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SOLAR PHOTOVOLTAIC OUTPUT ENERGY FORECASTING USING LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORK

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Abstract

Sunlight based vitality is a perfect and sustainable power source asset that has progressively turned out to be imperative due to the diminishing utilization of fossil fuel resources over the world. Forecasting output power in a Solar Photovoltaic panel is one of the major challenges under outdoor conditions. In this work, the problem is considered and two methodologies for the estimation of solar photovoltaic output power is analysed. As it is an outdoor power prediction, a historical dataset is collected by considering various parameters such as wind speed, weather, temperature, wind direction, air pressure, and rainfall. The prediction is timed under 5 minute's basis. The linear regression model based on the Ordinary Least Square (OLS) method minimizes the sum of the squares error (SSE) and provides better results for forecasting. The error between the independent variables and the dependent variables is reduced by using linear regression model. On the other hand, artificial neural network is the method used for forecasting in the statistical approach. The implementation of ANN display is finished with Multilayer Perceptron (MLP) and the preparation technique for neural system is finished by Back Propagation calculation. After the prediction, the accuracy is measured by various error measurement criteria like Mean Absolute Percentage Error (MAPE), Mean Magnitude of Relative Error (MMRE) and Root Mean Square Error (RMSE) and at last MAPE is considered for analysis. The result shows that artificial neural network model brings out better prediction when compared to linear regression model for maximum power prediction.

Keywords:

Photovoltaic Module, Solar Energy, Linear Regression, Ordinary Least Square (OLS), Sum of the Squares Error (SSE), Artificial Neural Network, Multilayer Perceptron, Error Back Propagation (EBP)

1. INTRODUCTION

The sun powered photovoltaic framework is a framework that captures the sun's potential and converts it into a usable potential called Power. The sun is one of the essential sources of energy which is influenced by the other natural phenomenon like warmth, wind, pressure, and rain [2] [13].

Presently, mankind is primarily utilizing petroleum derivatives as the predominant means for generating power. But the use of such non-renewable energy sources is not the correct means for reaping energy [3]. So, this procedure prompts the utilization of sunlight, which, as of now, is an inexhaustible source of energy to deliver the power called solar power. The forecast on the incredible longevity of the availability of solar energy has opened wide avenues for the solar power oriented future projects. The first and foremost component for such projects is the photovoltaic framework, which converts solar energy into the usable format of electricity [4]-[6].

The photovoltaic set up comprised of a few components including sun oriented boards that assimilate and changes over daylight into power, and send it to a sun-based inverter that is utilized to change the electric flow from DC to AC [7]. Further, the mounting, cabling, and other electrical accompaniments come together to set up the working framework.

Solar photovoltaic forecasting involves the following process like the sun path, their atmosphere condition, their scattering processes and the characteristics of a solar energy plant that utilizes the sun energy to create solar power [8]-[11]. Solar photovoltaic system can transform solar energy into electric power. The output power relies upon the approaching sun powered radiation and the sun based board qualities [14].

The Artificial Neural Network (ANN), with the sunlight based radiation, draws out the best estimating outcomes and few days of preparing is important to give precise forecasting [5] [15]. Gauging data will be basic for an effective use and the administration of the power lattice. The ANN is utilized to foresee the irradiance. The re-enactment of this strategy will be contrasted with a few basic strategies, for example, Support Vector Regression (SVR) and Feed Forward Neural Networks (FNN) [1] [12]. The sun oriented vitality will get expanded consistently because of natural concerns and for the most part because of decreased expenses [16] [17].

The rest of the paper is organized as follows. Section 2 summarizes the dataset collection works. Section 3 describes the proposed method for Solar PV system. Section 4 analyses the experimental performance of the proposed method. Finally, this paper is concluded in section 5.

2. DATASET COLLECTION

The raw data is collected in its own format. The input variables like wind speed, weather temperature, wind direction, air pressure and rainfall are collected in the YULARA dataset are considered in the present analysis. Solar irradiance data collection was performed using a pyranometer. Temperature data were obtained using the temperature sensor. The data were collected and stored by means of spreadsheets at an interval of about 5 minutes' interval. The input variables were collected from January 2018 to July 2018, totaling 7 months of data, resulting in 59,083 measurements, since measurements were from 05:00 hours to 18:00 hours.

3. SYSTEM MODEL

The primary goal of this work is to locate the most affecting input variables for the expectation of greatest power for sun oriented photovoltaic yield control estimating for diminishing the error. Here two strategies have been proposed. The usage of first strategy depends on Regression display premise. Direct Regression dependent on the Ordinary Least Square (OLS) is a basic technique that draws out the linear connection between both the reliant variable (dependent variable and independent variable) and the free factors to decrease the error and thereby expands the precision.

The execution of second system relies upon Artificial Neural Network (ANN) that draws out the better figure when stood out from first methodology which has been realized by Multilayer Perceptron (MLP). A preparing technique for neural network can be done by Back Propagation Algorithm which improves the exactness. The ANN demonstrates the error better then OLS display. The error criteria like, Mean Absolute Percentage Error (MAPE), Mean Magnitude Relative Error (MMRE) and Root Mean Square Error (RMSE) are utilized for most extreme power expectation and here Mean Absolute Percentage Error is considered for investigation.

4. IMPLEMENTATION OF OLS DESIGN PROCEDURE

Structuring an OLS regression model draws out the precise procedure. Ordinary Least Square is a type of linear least squares method utilized for evaluating the obscure parameters directly dependent on relapse investigation. OLS picks the parameters of a direct capacity as a gathering of autonomous factors by the least squares guideline. OLS limits the squares of the contrasts between the dependent variable i.e. estimations of the variable being anticipated for the given dataset and those anticipated by the linear regression. The steps involved reducing error by implementing ordinary least square regression involves the following,

- **Step 1:** The execution of OLS technique comprises of various mixes of input factors such as wind speed, weather temperature, wind direction, air pressure and rainfall. Here from two to five distinct blends of input factors were picked dependent on their significance for estimating.
- **Step 2:** Construct the different combinations of input variables in a matrix format [X]
- **Step 3:** Now to find the adjoint of X (i.e. X*) where $X* = X-T$ (i.e. Transpose of complex conjugate of X)
- **Step 4:** Then to compute ($X*X$) and hence find ($X*X$)−1 (i.e. inverse of ($X*X$)
- **Step 5:** Again compute X0= ($X*X$)−1$A*T$ where T is the target value
- **Step 6:** At last the error can be calculated by the formula $E=\|XX_0-T\|^2$ i.e. the total of the squares of the contrast between the independent factors and dependent variable (Target esteem).

4.1 NEURAL NETWORK DESIGN PROCEDURE

The implementation of a neural network follows the systematic procedure. In general, neural networks can be used for varieties of functions such as recognition, prediction and regression etc. In this paper neural networks are used for designing the forecasting models using five important steps that are involved in designing a common neural network. The process used in designing a neural network can be specified by a block diagram in Fig.1.

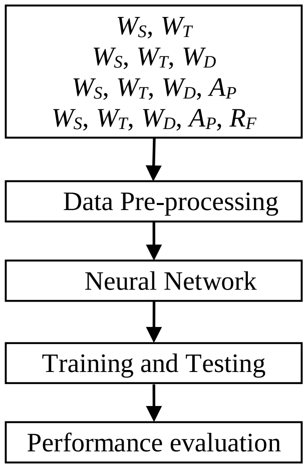


Fig.1. Flow of designing Neural Network

4.1.1 Data Preprocessing:

The data pre-processing includes the data cleaning, data normalising and data option. The steps involved in data pre-processing are as follows.

4.1.2 Data Cleaning:

Data cleaning makes sure by hand that all the labels are really correct. There may be several repetitions of the same data, hence that should be pruned out. Next, the collected dataset should be checked for well balanced, i.e. if all the classes contain the same amount (count) of data or not. Henceforth the data cleaning is to fill the opening estimation of the data, wipe out the commotion data and right the irregularities information in the data.

4.1.3 Data Normalizing:

The data should all have the same size. This file will contain all the features as well as the labels in a row, thus multiple rows for multiple data. The main data pre-processing is given by the data scaling or time normalising. Here, in this project, data normalising is used and it involves the transformation of chronological series of data values in the range [0,1] or [-1,1]. The de normalization is made by linear transformations on the components.

4.1.4 Data Option:

The last step in data pre-preprocessing is the information choice. Data option is to choose the information run that are utilized in this sunlight based forecasting. Here from 59,083 data samples, only 500 samples are chosen for this analysis.

5. NEURAL NETWORK IMPLEMENTATION

After the information pre-handling step, the following stage is to structure the neural network by determining the quantity of input layer, hidden layers and number of output layer. The ANN is utilized dependent on the idea of Back Propagation algorithm.

5.1 BACK PROPAGATION ALGORITHM

The neural network learning can be isolated into supervised learning and unsupervised learning models. The Back Propagation (BP) calculation is a standout amongst the most dominant directed learning calculations. The accompanying advances are completed for the procedure of usage of neural network with the relating Yulara dataset.

- In this undertaking all the input variable combinations have been considered from two to five. Subsequently, the quantity of neuron in input layer shifts from two to five are considered.
- The number of hidden layer in this work is one and it is viewed that the total number of neuron in hidden layer is 8.
- The number of output layer in this work is one, and so number of neuron in output layer is one. The weight can be fixed arbitrarily in the neural network. In this manner the neural network was intended for determining the sun powered photovoltaic system. In this work Multilayer Perceptron is utilized for forecasting.
- The neural network execution was accomplished for the Yulara dataset. Here there are six parameters that have been chosen from this dataset. In this task, five parameters are considered as input, and one parameter is considered as output.

The implementation of neural network takes place for different combinations for input variables in this venture, from two to five mixes of input factors are picked dependent on their significance for determining the most extreme power forecast of sun based photovoltaic yield control under open air conditions.

6. TRAINING/TESTING OF ANN

The neural network was prepared by Back Propagation Algorithm. The Matlab code for the BP has been composed by giving the dataset as input and target output. Amid training distinctive activation function has been utilized. The back propagation algorithm utilizes supervised learning, and afterward the error is determined. The steps engaged with preparing a neural network by back-propagation calculation involves the accompanying advances,

- The neural network is given with the training sample.
- Compare the neural network's output to the desired (ideal) output from that sample.
- Calculate the error in each output neuron.
- For every neuron, calculate the output, so that the desired output is calculated from the actual output by adjusting the sample values.

The weights are adjusted for each neuron to lower the error. Here 500 data are partitioned in the ratio 70:30, where 70% of the data i.e. 350 data are utilized for training the neural network and remaining 30% of data i.e. 150 data is utilized for testing the neural network.

7. PERFORMANCE EVALUATION

The last advance is to test the execution of the created device for both the OLS strategy and ANN technique. The execution assessment is done to accurately characterize the precision of the expectation and to relate error and subsequently picking impacting input factors of the conjecture show for greatest power forecast. Error is the contrast between the deliberate output power and the predicted output power given by the gauging model.

In this work, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Magnitude Relative Error (MMRE) is calculated and MAPE is considered for analysis purpose. Mean Absolute Percentage Error (MAPE %) is utilized for forecast of PV control under open air condition is given in Eq.(1),

$$MAPE = \left(\frac{1}{n} \sum_{i=1}^{n} \left| \frac{PV_{\max.power_{i(predicted)}} - PV_{\max.power_{i(measured)}}}{PV_{\max.power_{i(measured)}}} \right| \right) \quad (1)$$

where, $PV_{max.power}$ (predicted) is the most extreme power anticipated by OLS and ANN and $PV_{max.power}$ (measured) is the deliberate esteem real power. Additionally n speaks to the quantity of samples. (i.e.) 350 samples are utilized for training the neural network and 150 samples for testing the neural network. Root Mean Square Error (RMSE %) is utilized dependent on the observed power output is given in Eq.(2),

$$RMSE = \left(\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(PV_{\max.power_{i(predicted)}} - PV_{\max.power_{i(measured)}} \right)^2} \right) \times 100 \quad (2)$$

Mean Magnitude Relative Error (MMRE %) is used to measure the accuracy of prediction in the given Eq.(),

$$MMRE = \left(\frac{1}{n} \sum_{i=1}^{n} abs \left(\frac{PV_{\max.power_{i(measured)}} - PV_{\max.power_{i(predicted)}}}{PV_{\max.power_{i(measured)}}} \right) \right) \times 100 \quad (3)$$

8. SIMULATION RESULTS

The MATLAB code for both the Ordinary Least Square Regression method and the Error Back Propagation (BP) algorithm for Yulara dataset for various input combinations (from two to five input variables) of photovoltaic yield control estimating is executed and the anticipated yield is measured with the deliberate yield control. In order to find the relevant influencing input variables combinations, certain error esteems are determined for Yulara dataset. The implementation of OLS method and ANN method for different input combinations such as two input variable combinations, three input variable combinations, four input variable combinations, five input variable combinations was executed utilizing MATLAB programming and the error esteem was assessed.

In this work, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Magnitude Relative Error (MMRE) are calculated for both the OLS regression model and ANN model that depend on the net limit of the PV plant and MAPE is considered for investigation.

- *Mean Absolute Percentage Error (MAPE)*: Mean Absolute Percentage Error is used for prediction of PV power under outdoor conditions. It tends to be determined dependent on the net furthest reaches of plant from which the dataset is gathered.

Table.1. MAPE values for OLS method and ANN method

No of Variables	Variables combination	MAPE		
		OLS Method	ANN Method	
			Training	Testing
2	Wind speed, weather temperature	2.1569	0.1786	0.4230
3	Wind speed, weather temperature, Wind Direction	1.4627	0.1671	0.3783
4	Wind speed, weather temperature, Wind Direction, Air Pressure	1.2564	0.0615	0.0920
5	Wind speed, weather temperature, Wind Direction, Air Pressure, Rainfall	1.2320	0.0924	0.2014

At the point when MAPE esteem is lower, the precision of expectation will be higher and consequently for the lower esteem, most extreme power can be anticipated. The result of Mean Absolute Percentage Error (MAPE) is given in table.2 for both OLS method and ANN method.

- *Mean Magnitude Relative Error (MMRE)*: Mean Magnitude Relative Error measures the difference between actual power and estimated power relative to the actual power. The mean value is taken into account for every observation in the dataset. MMRE value brings out sensitive to individual predictions with large MREs.

Table.2. MMRE values for OLS method and ANN method

No of Variables	Variables combination	MMRE		
		OLS Method	ANN Method	
			Training	Testing
2	Wind speed, weather temperature	3.6304	1.1559	9.6165
3	Wind speed, weather temperature, Wind Direction	4.4046	1.1073	24.3251
4	Wind speed, weather temperature, Wind Direction, Air Pressure	6.7867	0.6198	468.1058
5	Wind speed, weather temperature, Wind Direction, Air Pressure, Rainfall	3.7688	0.6927	9.4315

The result of Mean Magnitude Relative Error (MMRE) is given in Table.2 for both OLS and ANN method.

- *Root Mean Square Error (RMSE)*: The RMSE value represents the square root of the particular function that gives the difference between predicted value power and observed value power. RMSD is a proportion of exactness, to look at forecasting errors for various factors of a given dataset.

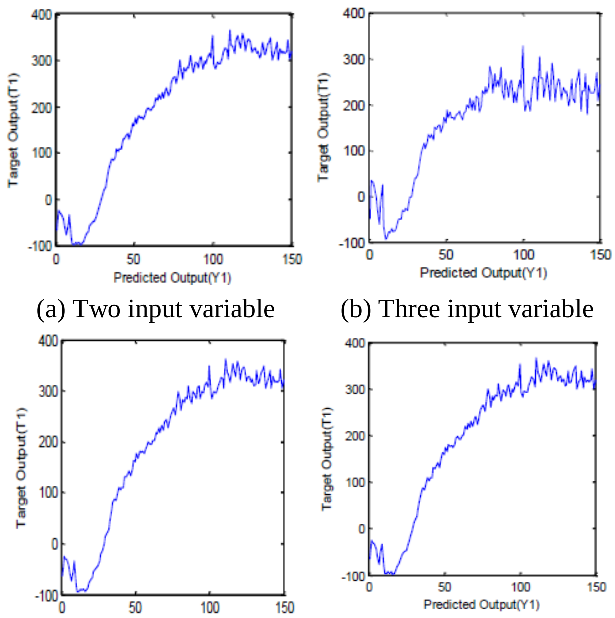
Table.3. RMSE values for OLS method and ANN method

No of Variables	Variables combination	RMSE		
		OLS Method	ANN Method	
			Training	Testing
2	Wind speed, weather temperature	3.6394	1.1559	9.6165
3	Wind speed, weather temperature, Wind Direction	4.4046	1.1073	24.3251
4	Wind speed, weather temperature, Wind Direction, Air Pressure	6.7867	0.6198	468.1058
5	Wind speed, weather temperature, Wind Direction, Air Pressure, Rainfall	3.7688	0.6927	9.4315

The result of Root Mean Square Error (RMSE) is given in Table.3 for both the OLS method and ANN method.

8.1 ANALYSIS OF OLS METHOD

The Yulara dataset is used for analysis. The input and target outputs are given for different input variable combinations and it is separated by 70:30 ratio.



(a) Two input variable (b) Three input variable

(c) Four input variable (d) Five input variable

Fig.2. OLS method data plot for different input variables

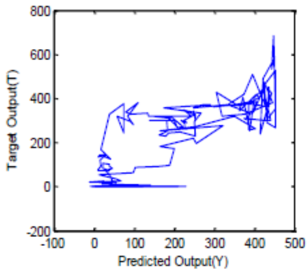
The Fig.2 is the graph plotted for different input variable combinations against the target yield (T_1) and the predicted yield (Y_1) of the sun oriented photovoltaic dataset by utilizing OLS relapse strategy.

The data plot for two input variables such as wind speed and weather temperature is shown in Fig.2(a). The data plot for three input variables such as wind speed, weather temperature and wind direction is shown in Fig.2(b). The data plot for four input variable combinations such as wind speed, weather temperature, wind direction and air pressure is shown in Fig.2(c).The data plot for five input variable combinations such as wind speed, weather temperature, wind direction, air pressure and rainfall is shown in Fig.2(d). The contrast between the actual yield of power and the measured yield of power is given for 150 time slots for all the above input variable combinations.

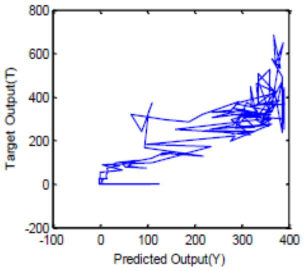
8.2 ANALYSIS OF ANN USING BACK PROPAGATION METHOD

The Yulara dataset is utilized for analysis. The input and target outputs are given for different input variable combinations and it is separated by 70:30 ratios. By dissecting Yulara dataset the following error graph for both training data and testing data were obtained. The Fig.4 is the graph plotted that shows the variations against the predicted output (Y) and the target output (T) for different input variable combinations of the sun powered photovoltaic dataset collection amid preparing the neural system.

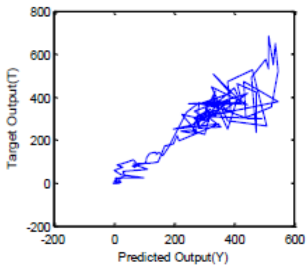
The measured output power was calculated for different input variable combinations. The training data plot for two input variables such as wind speed and weather temperature is shown in Fig.3(a). The training data plot for three input variables such as wind speed, weather temperature and wind direction is shown in Fig.3(b). The training data plot for four input variable combinations such as wind speed, weather temperature, wind direction and air pressure is shown in Fig.3(c).The training data plot for five input variable combinations such as wind speed, weather temperature, wind direction, air pressure and rainfall is shown in Fig.3(d). The amount of data used for training is 350.



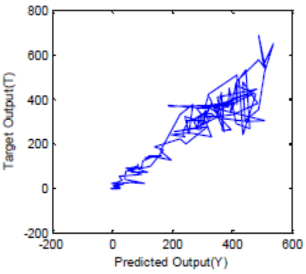
(a) Two input variable



(b) Three input variable



(c) Four input variable

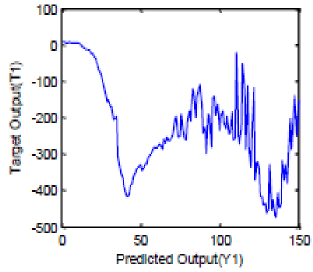


(d) Five input variable

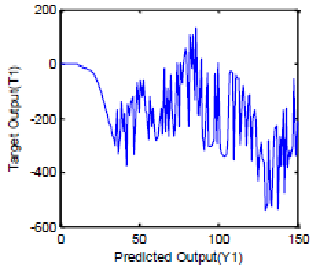
Fig.3. Training data plot for different variable combinations

The Fig.4 is the graph plotted that shows the variations against the predicted output (Y_1) and the target output (T_1) for different input variable combinations of the sun powered photovoltaic dataset collection amid testing the neural network. The measured output power was calculated for different input variable combinations.

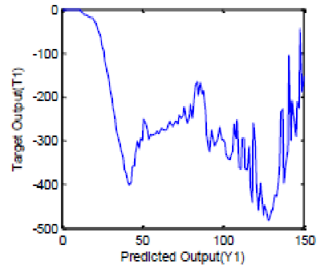
The testing data plot for two input variables such as wind speed and weather temperature is shown in Fig.4(a). The testing data plot for three input variables such as wind speed, weather temperature and wind direction is shown in Fig.4(b). The testing data plot for four input variable combinations such as wind speed, weather temperature, wind direction and air pressure is shown in Fig.4(c). The testing data plot for five input variable combinations such as wind speed, weather temperature, wind direction, air pressure and rainfall is shown in Fig.4(d). The amount of data used for testing is 150.



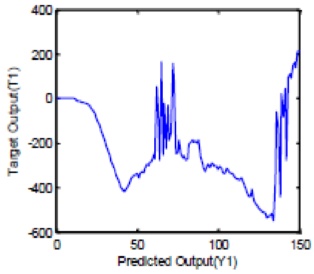
(a) Two input variable



(b) Three input variable



(c) Four input variable



(d) Five input variable

Fig.4. Testing data plot for different variable combinations

8.2.1 Analysis of Error Graph for ANN Training:

The analysis of error graph for training set by using ANN method is shown in Fig.5. The variation in both the anticipated yield esteem and the objective yield esteem is shown in the Fig.5 for two input variable combinations, three input variable combinations, four input variable combinations and five input variable combinations.

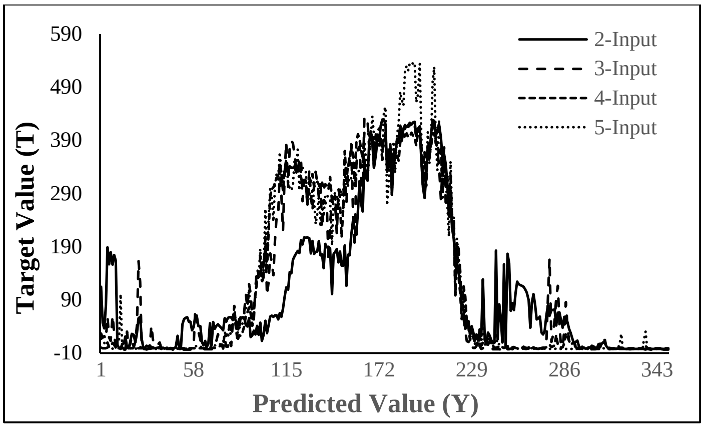


Fig.5. Analysis of Error Graph – ANN Method (Training)

8.2.2 Analysis of Error Graph for ANN Testing

The analysis of error graph for testing set by using ANN method is shown in Fig.6. The variation in both the anticipated yield esteem and the objective yield is shown in the Fig.6 for two input variable combinations, three input variable combinations, four input variable combinations and five input variable combinations.

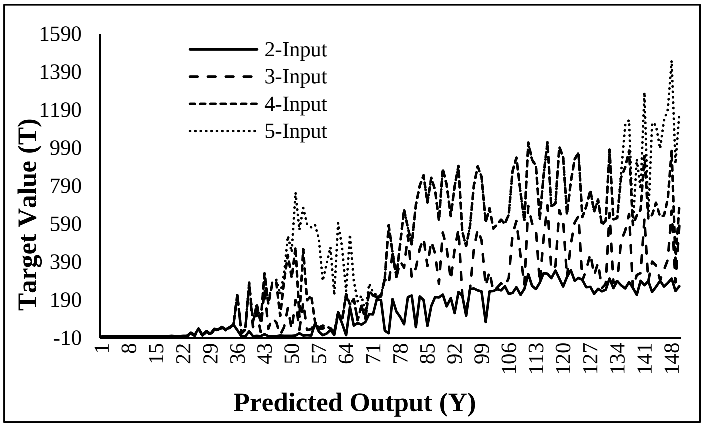


Fig.6. Analysis of Error Graph – ANN Method (Testing)

8.3 COMPARISON OF OLS METHOD AND ANN METHOD

A comparison is made for both OLS regression method and ANN method. The Mean Absolute Percentage Error (MAPE) values are resolved for examination, since it is utilized for estimation of sun powered photovoltaic plant under open air conditions. For low estimations of MAPE, the precision of expectation will be high and most extreme power can be anticipated.

Table.4. Comparison of OLS method and ANN method

No. of Variables	Variable combination	OLS	ANN
2	W_S, W_T	2.150	0.4230
3	W_S, W_T, W_D	1.427	0.3783
4	W_S, W_T, W_D, A_P	1.2564	0.0923
5	W_S, W_T, W_D, A_P, R_F	1.2330	0.2020

From Table.4, it is analysed that ANN method brings out better prediction when compared to OLS method. The accuracy of MAPE is high in ANN method since the error values get reduced when compared to OLS method. Also it is observed that wind speed, wind temperature, wind direction and air pressure are considered as most relevant influencing input variables for maximum power prediction of Solar Photovoltaic forecasting under outdoor conditions.

9. CONCLUSION

Solar photovoltaic forecasting under outdoor condition based on OLS method and ANN method was developed. The Yulara dataset from 1st January to 24th July was collected and used for photovoltaic forecasting. Here, various information variable combinations are picked to discover the most significant effect factors for the generation of maximum power. The error assessment was done to feature the exactness of prediction. The error analysis result shows that when a value of error is low, then the accuracy of prediction will be high.

It is discovered that rainfall is a less impacting variable for the forecast of maximum power, while wind speed, weather, temperature, wind direction, and air pressure are the most affecting factors in PV module for maximum power generation using the ANN strategy. It is also analyzed that the MAPE of ANN method provides better prediction when compared to MAPE of OLS method.

In the future, both multiple linear regression and different ANN techniques could be connected to PV modules using diverse advances to make maximum power forecasts in outdoor conditions through the use of diverse datasets. The datasets have to be implemented in the new advanced learning algorithm or hybrid evolutionary algorithm.

REFERENCES

[1] Ahmad Alzahrani, PouryaShamsi, CihanDagli and Mehdi Ferdowsi, “Solar Irradiance Forecasting using Deep Neural Networks”, *Procedia Computer Science*, Vol. 114, No. 3, pp. 304-313, 2017.

[2] H.A. Al Waeli, K. Sopian, Hussein A. Kazem, Jabar H. Yousif, Miqdam T. Chaichan, Adnan Ibrahim, Sohif Mat and Mohd Hafidz Ruslan, “Comparison of Prediction Methods of PV/T Nanofluid and Nano -PCM System using a Measured Dataset and Artificial Neural Network”, *Solar Energy*, Vol. 162, pp. 378-396, 2018.

[3] Amit Kumar Yadav and S.S Chandel, “Identification of Relevant Input Variables for Prediction of 1-Minute Time-Step Photovoltaic Module Power using Artificial Neural Network and Multiple Linear Regression Models”, *Renewable and Sustainable Energy Reviews*, Vol. 77, pp. 955-969, 2017.

[4] Amit Kumar Yadav, Vikrant Sharma, Hasmat Malik and S.S. Chandel, “Daily Array Yield Prediction of Grid-Interactive Photovoltaic Plant using Relief Attribute Evaluator based Radial Basis Function Neural Network”, *Renewable and Sustainable Energy Reviews*, Vol. 81, pp. 2115-2127, 2017.

[5] Emanuele Ogliari, Alberto Dolara, Giampaolo Manzolini and Sonia Leva, "Physical and Hybrid Methods Comparison for the Day Ahead PV Output Power Forecast", *Renewable Energy*, Vol. 113, No. 3, pp. 11-21, 2017.

[6] Florencia Almonacida, Eduardo F. Fernandeza, Adel Mellitb and Soteris Kalogirouc, "Review of Techniques based on Artificial Neural Networks for the Electrical Characterization of Concentrator Photovoltaic Technology", *Renewable and Sustainable Energy Reviews*, Vol. 75, pp. 938-953, 2017.

[7] Guido Cervone, Laura Clemente Harding, Stefano Alessandrini and Luca DelleMonache, "Short-Term Photovoltaic Power Forecasting using Artificial Neural Network and Analog Ensemble", *Renewable Energy*, Vol. 108, No. 2, pp. 274-286, 2017.

[8] HadiKalani, Mohammad Sardarabadi and Mohammad Passandideh Fard, "Using Artificial Neural Network Models and Particle Swarm Optimization for Manner Prediction of a Photovoltaic Thermal Nanofluid Based Collector", *Applied Thermal Engineering*, Vol. 113, pp. 1170-1177, 2017.

[9] Kian Jazayeri, Moein Jazayeri and Sener Uysal, "Artificial Neural Network-Based All-Sky Power Estimation and Fault Detection in Photovoltaic Modules", *Journal of Photonics for Energy*, Vol. 7, No. 2, pp. 1-18, 2017.

[10] Z. Li, L. Liping and Y. Dongmei, "Comparison of Two Regression Models for Predicting Crop Yield", *Proceedings of IEEE International Symposium on Geoscience and Remote Sensing*, pp. 1521-1524, 2010.

[11] Masoud Vakili, Saeed Reza Sabbagh Yazdi, Soheila Khosrojerdi and Koosha Kalhor, "Evaluating the Effect of Particulate Matter Pollution on Estimation of Daily Global Solar Radiation using Artificial Neural Network Modeling based on Meteorological Data", *Journal of Cleaner Production*, Vol. 141, pp. 1275-1285, 2016.

[12] Mohammed Bou Rabee, Shaharin A. Sulaiman, "Magdy Saad Saleh and Suhaila Marafi, Using Artificial Neural Networks to Estimate Solar Radiation in Kuwait", *Renewable and Sustainable Energy Reviews*, Vol. 72, No. 3, pp. 434-438, 2017.

[13] Mohammad Hossein Dehghan, Farhad Hamidi and Mahsa Salajegheh, "Study of Linear Regression Based on Least Squares and Fuzzy Least Absolutes Deviations and its Application in Geography", *Proceedings of 4th Iranian Joint Congress on Fuzzy and Intelligent Systems*, pp. 1-6, 2015.

[14] Oveis Abedinia, Nima Amjady and Noradin Ghadimi, "Solar Energy Forecasting based on Hybrid Neural Network and Improved Metaheuristic Algorithm", *Computational Intelligence*, Vol. 34, No. 1, pp. 241-260, 2017.

[15] Prasis Poudel and Bongseog Jang, "Solar Power Prediction Using Deep Learning Technique", *Advanced Science and Technology Letters*, Vol. 146, No. 2, pp. 148-151, 2017.

[16] S. Leva, A. Dolara, F. Grimaccia, M. Mussetta and E. Ogliari, "Analysis and Validation of 24 Hours ahead Neural Network Forecasting of Photovoltaic Output Power", *Mathematics and Computers in Simulation*, Vol. 131, No. 1, pp. 88-100, 2017.

[17] Yuchi Sun, Gergely Szucs and Adam R. Brandt, "Solar PV Output Prediction from Video Streams using Convolutional Neural Networks", *Energy and Environmental Science*, Vol. 11, No. 7, pp. 1811-1818, 2018.