*Grenze International Journal of Engineering and Technology, Jan Issue*

# Solar Power Generation Forecasting by using Artificial Neural Network and Back Propagation Algorithm

Shashikant[1] and Binod Shaw[2]
[1-2]National Institute of Technology, Raipur, India
Email: shashikantkaushaley20@gmail.com, binodshaw2000@gmail.com

***Abstract*—Accurate forecasting leads to minimal losses and maximum profit for Power Sector Companies. Hence, Forecasting is important for Power Sectors Company for bidding, co-ordination, planning, control and operation of other sources. The peaks demands on power system are met by alternate source of energy mostly diesel generator and non-conventional source of energy. Out of there two power generation predictions from non-conventional source of energy is very important since it is nature dependent and non-liner. Forecasting based on non-linear data itself is a challenging task and developing a model is also challenging. In this work machine learning based solar power generation forecasting model is presented which can predict non-linear data based on its training algorithm. Artificial Neural Network (ANN) with single hidden layer and Back propagation algorithm (BP) with multiple hidden layer is presented for a week ahead Solar Power Generation Forecasting (SPGF), and the results shows the machine learning with more number of hidden layers will give better forecasting accuracy, i.e. BP algorithm exhibit better performance over single layer Neural Network.**

***Index Terms*— Forecasting, Solar power generation Forecasting (SPGF), Artificial Neural Network (ANN), Back Propagation Algorithm.**

## I. INTRODUCTION

In recent years, power generation from solar has increased a lot because if its advantages such as freely available in nature, less maintenance, clean and pure energy, pollution free, etc. Apart from these advantages Solar Power Generation (SPG) is dependent on nature, which greatly affects the power sector company in terms of economy, planning and scheduling. One way to overcome this problem is by predicting SPG, which also contribute to several other advantages such as proper controlling of the devices associated with SPG i.e., controllability, energy trading and reliability to the smart cities. Forecasting solves a part of problem in grid operations such as balancing the energy between generation and demand. The crucial part in the process of forecasting is to gather useful data from raw data from a valid source, later it requires an algorithm to perform the operation for prediction. Once the prediction is done then the next assessment is to find out its accuracy of the prediction and it can be done by standard statistical measures. This work provides a forecasting tool for predicting solar power generation. The forecasting accuracy can be further enhanced by modifying the core of the forecasting tool.

Many researchers have done research on forecasting of solar irradiation on different times scales with artificial neural network (ANN), Fuzzy logic, Auto-Regressive (AR) based approach and hybrid system by considering historical data and weather forecast data. Based on Numerical Weather Prediction (NWPs) as input, AR and AR with exogenous input (ARX) model has been tested and ARX model shows 35% improvement in root mean

*Grenze ID: 01.GIJET.8.1.2*

square error [2]. Jie shi et al. proposed forecasting algorithm based on weather forecast and general learning method developed from statistical learning theory called as Support Vector Machine (SVM) [3] for a day-ahead prediction. Ercan Izgi et al. applied artificial neural network (ANN) for forecasting solar power for small scale at different time horizons [4]. ANN is also treated as black box modelling, since it provides output based on the mapping of input and output data through training. Based on the sensitivity to data sets, 48 hours ahead prediction based on ANN is illustrated in [5]. Forecasting application based on ANN in electricity markets for operational planning of transmission system operator is presented in [6]. To find out the effectiveness accuracy of all forecasting methods statistical comparison are used such as Mean absolute error (MAE), Mean Square Error (MSE), Mean Absolute Percentage error (MAPE), Mean Arctangent Absolute Percentage Error (MAAPE) and Correlation of Determination ($R^2$) as illustrated in **[7]**. In the present work the MAE, MSE, MAPE and $R^2$ are used for statistical comparison. This paper helps the reader to understand how the neural network is implemented and used for forecasting solar power generation.

This paper is organized as follows: Introduction and literature survey in section I, Architecture of Neural Network and Deep Neural Network in section II, Statistical comparison in section III, Result and discussion in section IV and at last conclusion in section V followed by references.

## II. ANN AND BACK PROPAGATION

The concept of ANN in cell model was first introduced in 1943 [8]. It is a set of logical statement later the researcher focused on human learning ability and then it gets fame in engineering field on ANN in 1950 [9], but the development of ANN appeared after 1980 by researcher as illustrated in literature [10]-[12].

In this work, prediction from back propagation algorithm is compared with general neural network and their architecture is shown in figure. (2) and (3). The nomenclature used in fig (2), (3) and equation are illustrated in Table I. To understand the working of BP algorithm or deep neural network, we need to know the basic understanding of simple neural network and it can be done mathematically which is represented in equation (1)-(4) for architecture as portrayed in figure (1). The same calculation is done for BP algorithm and ANN.

Input to the output node in given by the summation of product of input weights to the input as represented in (1), in the present work bias is not considered.

$$V(i) = W_{11}X_1 + W_{21}X_2 + W_{31}X_3 \quad (1)$$

Where i=1, 2, 3,..n, n is the number of samples. In the work total number of sample is 3738 out of which 3000 samples is used for training and the rest is used for testing, but the prediction is done for a week.

The final output Y can be calculated by applying activation function to the values obtained by (1). Sigmoid activation function is used to calculate the output which can be represented by (2).

$$Y = P_i = F(V(i)) = \frac{1}{1+e^{-V(i)}} \quad (2)$$

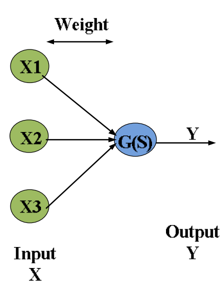


Fig 1. Simple ANN architecture.

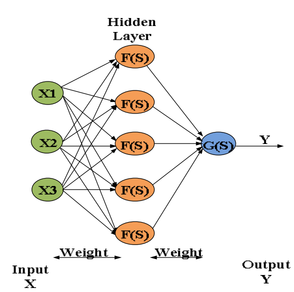


Fig 2. Single layer ANN.

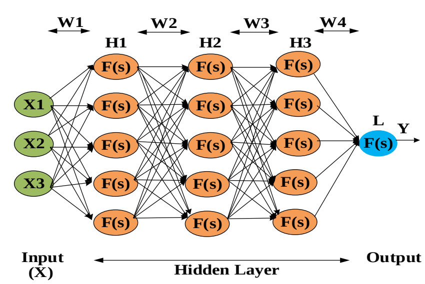


Fig 3 Architecture of Back Propagation.

Error can be calculated by subtracting actual value ($A_i$) to the predicted value ($P_i$), and it is represented by (3), and the weight can be updated by (4)

$$E_i = A_i - P_i \quad (3)$$

$$W_{new} = W_{old} + alpha * E_i * delta * X(i) \quad (4)$$

During the training process our aim is to obtain weight values with respect to minimum square error, and the obtained weight matrix is used for testing.

*BACK PROPAGATION ALGORITHM:* The architecture of BP algorithm consists of five layers namely one input layer, three hidden layer (HL) and one output layer. Total weight can be calculated by subtracting one from total number of layers present in the architecture. The feed forward calculation of BP algorithm is as follows:

Input to the 1st hidden layer can be obtained by (5).

$$IH1 = W1 * X \tag{5}$$

$$OH1(x) = \max(0, x) \tag{6}$$

Where, W1 is the randomly generated weight matrix of 5x3 in which number of rows is equal to number of neurons in hidden layer 1 i.e. H1, and X represents input matrix containing (X1, X2, X3)

Output of 1st hidden layer can be obtained by applying activation function to the input of 1st hidden layer as expressed in (6), which will be the input of 2nd hidden layer with respect to weight matrix w2 and it can be expressed in (7) and by applying activation function to it we get the Output of 2nd HL as expressed in (8).

$$IH2 = W2 * OH1 \tag{7}$$

$$OH2(x) = \max(0, x) \tag{8}$$

Similarly, the input of 3rd hidden layer is obtained by the product of weight matrix W3 to the output of 2nd hidden layer and by applying activation function we get output of 3rd hidden layer which is expressed in (9) and (10).

$$IH3 = W3 * OH2 \tag{9}$$

$$OH3(x) = \max(0, x) \tag{10}$$

Finally the input of the output node L is expressed in (11) and final output is obtained by applying sigmoid activation function to (11) as expressed in (12).

$$IL = W4 * OH3 \tag{11}$$

$$Y = P_i = OL = \frac{1}{1+e^{-IL}} \tag{12}$$

Error is calculated by subtracting actual value to the predicted value of (12) and is expressed in (13)

$$E_i = A_i - P_i \tag{13}$$

The error is propagated back from output to input through hidden layers. Each layer will have an error with respect to their respective weights as represented in (14), (16), (18) and (20) and the new update weight matrix with learning ability or learning rate alpha is incorporated in error of each layer as shown in (15), (17), (19) and (21).

$$\frac{\partial E}{\partial W4} = E_i * \left(P_i * (1 - P_i)\right) * W4 \tag{14}$$

$$W4_{new} = W4_{old} - \left(alpha * \frac{\partial E}{\partial W4}\right) \tag{15}$$

$$\frac{\partial E}{\partial W3} = \frac{\partial E}{\partial W4} * \left(OH3 * (1 - OH3)\right) * W3 \tag{16}$$

$$W3_{new} = W3_{old} - \left(alpha * \frac{\partial E}{\partial W3}\right) \tag{17}$$

$$\frac{\partial E}{\partial W2} = \frac{\partial E}{\partial 34} * \left(OH2 * (1 - OH2)\right) * W2 \tag{18}$$

$$W2_{new} = W2_{old} - \left(alpha * \frac{\partial E}{\partial W2}\right) \tag{19}$$

$$\frac{\partial E}{\partial W1} = \frac{\partial E}{\partial W2} * \left(OH2 * (1 - OH2)\right) * W1 \tag{20}$$

$$W1_{new} = W1_{old} - \left(alpha * \frac{\partial E}{\partial W1}\right) \tag{21}$$

TABLE I. NOMENCLATURE OF THE ALGORITHM USED IN THE WORK

| Parameter | | Name | Description |
|---|---|---|---|
| ANN | X | Input [3x1] | Temperature, irradiation, time. |
| | W | Weight [1x3] | Connection between input nodes to output node. |
| | Y | Output | Final output |
| | E | Error | Actual value - predicted value |
| | F(ΣXW) | Activation function (A.F) | Sigmoid activation function. |
| BACK PROPAGATION | W1 | Weight [5x3] | Connection between input node to nodes of 1st Hidden Layer (HL) |
| | W2 | Weight [5x5] | Connection of nodes between 1st HL to 2nd HL. |
| | W3 | Weight [5x5] | Connection of nodes between 2nd HL to 3rd HL. |
| | W4 | Weight [1x5] | Connection of nodes between 3rd HL to output node. |
| | IH | IH1, IH2, IH3 | Input of 1st HL, 2nd HL and 3rd HL. |
| | OH | OH1, OH2, OH3 | Output of 1st HL, 2nd HL and 3rd HL. |
| | F(s) | HL activation Function | ReLU activation function |
| | G(s) | Output A.F | Sigmoid activation function. |
| | L | Output node | Final Output |

## III. STATISTICAL MEASURES

The objective of statistical measures is to find out the closeness of predicted data ($P_i$) to actual data ($A_i$). In this paper four statistical measures are used namely MAE, MSE, MAPE and $R^2$ as represented from (22)-(25). In the first three performance indices, the minimum value represents the predicted is closer to the actual value but in the fourth performance indices i.e. $R^2$ maximum value represents the predicted value closer to the actual value, and its range lies between 0-1.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_i - P_i| \qquad (22)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2 \qquad (23)$$

$$MAPE = \frac{1}{N}\sum_{i=i}^{N}\left|\frac{A_i - P_i}{P_i}\right| * 100 \qquad (24)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(A_i - P_i)^2}{\sum_{i=1}^{N}\left(A_i - mean(P_i)\right)^2} \qquad (25)$$

## IV. RESULT AND DISCUSSION

In this work, solar data is collected from Chhattisgarh State Power Distribution Company Limited (CSPDCL), February 2020 to December 2020, in which temperature, irradiation, time and power is taken for training and testing purpose as shown in figure 3. This data is used for training ANN and BP algorithm as illustrated in section III.. Total number of samples considered during training is 3000 out of 3738, and it is run for 4000 epochs. After the training the model is tested and the solar power generation prediction is done for a week and the result associated with it is portrayed in the figure 4, which represents the comparison of actual data with ANN and BP algorithm. The statistical observation is tabulated in table II. In statistical comparison, minimum value for MAE, MSE, MAPE represents the best value i.e. close to the actual value, whereas maximum value in $R^2$ represents the best value.

The difference in the architecture of ANN and BP is, number of hidden layer and its neuron. The predicted value from ANN with single hidden layer with five neurons has some disadvantage as it is observed in the table II, the statistical value of $R^2$ is very low, the reason for this is unknown and depend on many factors such as number of hidden layer, number of neurons present in each hidden layer, unable to handle uncertainties and non-linearity, insufficient data-sets, etc. Hence, in the architecture of BP, number of hidden layers is increased and the effect is propagated on the result which has a significant improvement in forecasting accuracy. Hence, it can be concluded that the working of ML depends on the type of problem, data-sets and number of hidden layer and its neuron.

## V. CONCLUSION

Solar Power Generation Forecasting is essential for power sectors for bidding, planning, scheduling, and also control for grid operations. In this paper an attempt has been made to solve those problems by creating a model for forecasting. The model presented here uses machine learning which learns itself and adapts the changes in

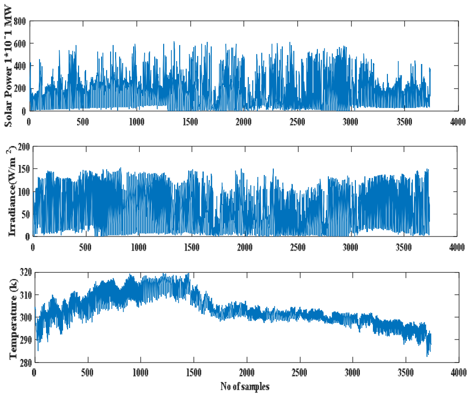


Fig 3. SPG per day average data under observation

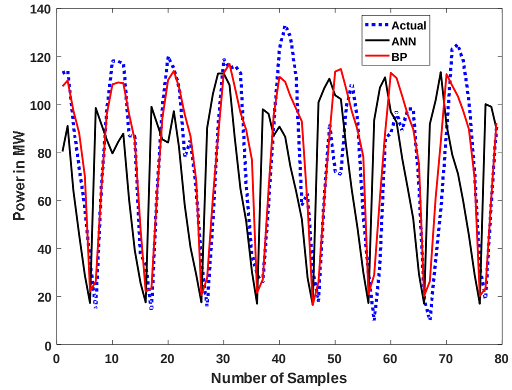


Fig 4. Comparison of actual data with ANN and BP prediction for a week.

TABLE II. STATISTICAL COMPARISON PREDICTING SPGF FOR A WEEK

| NN | MAE | MSE | MAPE | $R^2$ |
|---|---|---|---|---|
| *ANN* | 34.4348 | 1689.7 | 58.2092 | 0.3847 |
| *BP* | 11.4922 | 225.4531 | 19.2523 | 0.8288 |

the nature of input and provides good result. ANN with single hidden layer and BP with three hidden layer as presented in the paper. From the statistical comparison in table II it is observed that the BP algorithm have minimal values as compared to ANN in MAE, MSE and MAPE, whereas for perfect forecasting accuracy $R^2$ has to be one but in practical scenario it's not possible, hence model objective is that $R^2$ should be close to one. From observation in table II, forecasting accuracy from BP is 82.88%. Hence it can be concluded that the BP algorithm has better prediction accuracy in comparison with ANN.

## REFERENCES

[1] Rahim, D. Rifai, K. Ali, M. Zeesan, A. N. Abdalla, and M. A. Faraj, "Science of the Total Environment Solar irradiance measurement instrumentation and power solar generation forecasting based on Artificial Neural Networks (ANN): A review of five years research trend," *Sci. Total Environ.*, vol. 715, p. 136848, 2020, doi: 10.1016/j.scitotenv.2020.136848.

[2] P. Bacher, H. Madsen, and H. A. Nielsen, "Online short-term solar power forecasting," *Sol. Energy*, vol. 83, no. 10, pp. 1772–1783, 2009, doi: 10.1016/j.solener.2009.05.016.

[3] J. Shi, W. J. Lee, Y. Liu, Y. Yang, and P. Wang, "Forecasting power output of photovoltaic systems based on weather classification and support vector machines," *IEEE Trans. Ind. Appl.*, vol. 48, no. 3, pp. 1064–1069, 2012, doi: 10.1109/TIA.2012.2190816.

[4] E. Izgi, A. Öztopal, B. Yerli, M. K. Kaymak, and A. D. Şahin, "Short-mid-term solar power prediction by using artificial neural networks," *Sol. Energy*, vol. 86, no. 2, pp. 725–733, 2012, doi: 10.1016/j.solener.2011.11.013.

[5] 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," *Math. Comput. Simul.*, vol. 131, pp. 88–100, 2017, doi: 10.1016/j.matcom.2015.05.010.

[6] Chen, S. Duan, T. Cai, and B. Liu, "Online 24-h solar power forecasting based on weather type classification using artificial neural network," *Sol. Energy*, vol. 85, no. 11, pp. 2856–2870, 2011, doi: 10.1016/j.solener.2011.08.027.

[7] R. K. Sahu, B. Shaw, and J. R. Nayak, "Engineering Science and Technology , an International Journal Short / medium term solar power forecasting of Chhattisgarh state of India using modified TLBO optimized ELM," *Eng. Sci. Technol. an Int. J.*, vol. 24, no. 5, pp. 1180–1200, 2021, doi: 10.1016/j.jestch.2021.02.016.

[8] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *Bull. Math. Biophys.*, vol. 5, no. 4, pp. 115–133, 1943, doi: 10.1007/BF02478259.

[9] Attneave, F., & M. B. (1950). [Review of *The Organization of Behavior; A Neuropsychological Theory*, by D. O. Hebb]. *The American Journal of Psychology*, *63*(4), 633–642. https://doi.org/10.2307/1418888.

[10] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," *Feynman Comput.*, vol. 79, no. April, pp. 7–19, 2018, doi: 10.1201/9780429500459.

[11] J. A. Anderson, "Cognitive and Psychological Computation with Neural Models," *IEEE Trans. Syst. Man Cybern.*, vol. SMC-13, no. 5, pp. 799–815, 1983, doi: 10.1109/TSMC.1983.6313074.

[12] E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning Internal Representations by Error Propagation," *Readings Cogn. Sci. A Perspect. from Psychol. Artif. Intell.*, no. V, pp. 399–421, 2013, doi: 10.1016/B978-1-4832-1446-7.50035-2.