Eksplorium *p*-ISSN 0854-1418
Volume 46 No. 1, May 2025: 586–595 *e*-ISSN 2503-426X

Optimizing Artificial Neural Network Configurations Using Multi-Factor Performance Ranking for Solar PV Systems

Pavan Gangwar[1], Sandhya Prajapati[2*], Amit Saini[3], Mohit Payal[4], Pravesh Belwal[5], Mukul Chaudhary[6]
[1] Department of Electrical Engineering, United College of Engineering and Research, Prayagraj, India
Email Id: pavan.bmas@gmail.com
[2] Department of Electrical and Electronics & Communication Engineering, DIT University, Dehradun, India
Email Id: sandhya.prajapati@dituniversity.edu.in
[3] Department of Electronics & Communication Engineering, Uttaranchal University, Dehradun, India
Email Id: saini291986@gmail.com
[4] Department of Electronics & Communication Engineering, Graphic Era Hill University, Dehradun, India
Email Id: mohitpayaal1986@gmail.com
[5] Department of Electronics & Communication Engineering, School of Engineering & Computing, Dev Bhoomi Uttarakhand University, Dehradun, India, Email Id: pravesh.belwal@gmail.com
[6] Department of Electrical Engineering, COER university, Roorkee, India, Email Id: cmukul76@gmail.com
[*] Corresponding Author: sandhya.prajapati@dituniversity.edu.in

Article Received: 26 Feb 2025, Revised: 27 April 2025, Accepted:08 May 2025

Abstract: Artificial Neural Networks (ANNs) are widely used for modelling nonlinear systems due to their adaptive learning capabilities. In this work, different combinations of ANN functions such as transfer functions, learning rules, and training algorithms are examined to determine their impact on prediction accuracy for solar photovoltaic (PV) modules. A dataset comprising input parameters including maximum power (Pm), open-circuit voltage (Voc), short-circuit current (Isc), irradiance (Ir), temperature (T), and fill factor (FF) from 34 different PV modules is used to predict output parameters: current (Im) and voltage (Vm) at peak power. We've developed a total of 84 ANN models by bringing together a variety of functions. Each model is trained using mean squared error (MSE), along with a set number of epochs and performance indicators. To compare the models effectively, we use a weighted ranking system. This approach helps to pinpoint the best ANN setup for accurately modeling how photovoltaic output behaves.

Keywords: ANN, Solar PV, Thermal heating, Cooling.

INTRODUCTION:

There is various research associated with the solar PV system in almost every sector like replacing conventional generation [1], improving renewable energy utilization [2], utilizing recycled grey water with rooftop solar PV [3-4], or in the transportation sector with the eco-friendly solutions [5-6]. Similarly, to make them more robust and predictable solar system artificial intelligence techniques are used in this field in the existing literature, for forecasting [7-16], power output estimation, energy forecasting, power quality improvement, for monitoring [17-21] The neuron model made up of complicated structure in which the output and the input data are connected through neurons to continue training the data to match the output and error is adjusted with the weights of the neuron layer.

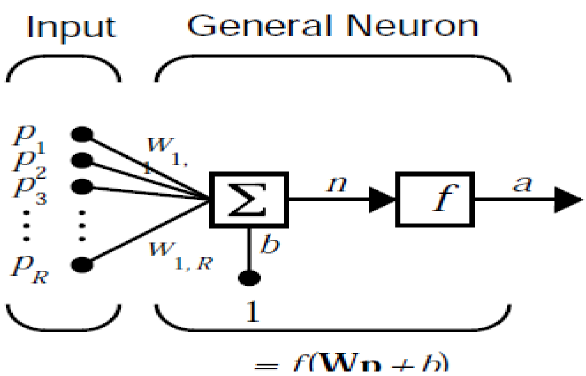
In the structure the input scalar p is multiplied by the corresponding weight w then the product wp is added with the bias which is a weight with the constant input 1. Figure 1 shows that this sum is the argument of the transfer function chosen for the network. The training is done to achieve the desired behavior of the network by adjusting the weight and the bias. The

Volume 46 No. 1, May 2025: 586–595 *e*-ISSN 2503-426X

number of transfer functions used for this purpose is shown in figure 2 which are used to generate the output.

Transfer Function: It is an activation function, a monotonically increasing differentiable function. The weightage sum of the input is applied to the transfer function for the final output. The three transfer functions shown in figure 2 are utilized for this study.

Fig1. Neural Network Structure



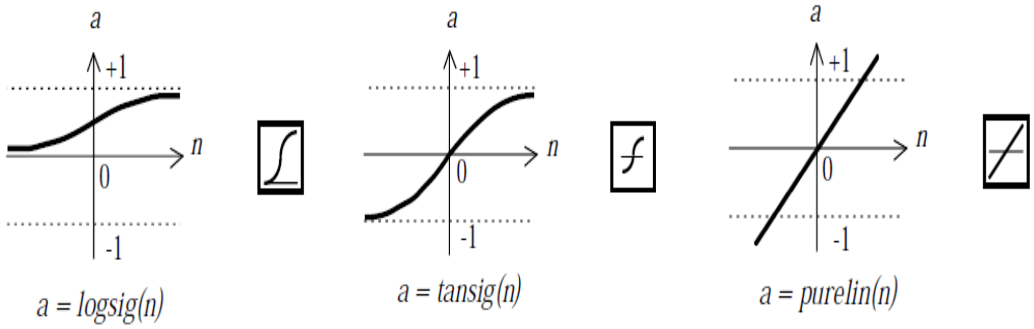


Fig2. Transfer Function and their graphs

Training Function: The training process can begin once the network's weights and biases have been established. During training, the weight and bias are changed over and over to make the network performance function as small as possible. In MATLAB's nntool, there are different training functions and their algorithms.

Batch Gradient Descent (traingd): Among training functions, traingd is the steepest decent batch. For the purpose of this function, the weight and bias are modified to counteract the negative gradient of the performance function.

Batch Gradient Descent with Momentum (traingdm): Momentum allows a network to respond by ignoring the small feature in the error surface and providing faster convergence.

Resilient Backpropagation (trainrp): The sign of the derivative, not its size, determines which way the weights will change.

Conjugate Gradient Algorithm (traincgf): In this algorithm weight is adjusted in the steepest descent direction in which performance function decreases most rapidly.

Powell Beale conjugate gradient (traincgb): The amount of space needed by this algorithm is slightly higher than that of traincgp. Quicker convergence is the norm.

Scaled conjugate gradient (trainscg): This algorithm combines the model trust region approach instead of a time-consuming line search algorithm.

BFGS Algorithm(trainbgf): It's very close to Newton's approach. Although it typically converges in fewer iterations than conjugate gradient algorithms, it does require approximate storage of Hessian matrices and more computation per iteration.
Levenberg-Marquardt (trainlm): This algorithm approaches the second-order training speed without additional computation of the hessian matrix.
One-step secant method (trainoss): It represents a compromise between conjugate gradient and quasi-Newton methods.
Scaled conjugate gradient (trainscg): This is the only method that eliminates the need for line search. Its general-purpose training algorithm is exceptional.
Rate of adaptive learning (traingdx): It allows for faster training than traingd, but only in batch mode.
Bayesian regularization (trainbr): Adaptation of the Levenberg-Marquardt training algorithm in order to generate networks that are capable of good generalization. It makes things easier in that regard.
Output evaluation parameter:
Mean Square Error (MSE): Mean square error is the sum of the square error between output of the neural network and the target value.

$$\mathrm{MSE} = \frac{1}{\mathrm{Q}}\sum_{\mathrm{k}=1}^{\mathrm{Q}}(\mathrm{t}(\mathrm{k}) - \mathrm{a}(\mathrm{k}))^2$$

Functions of Learning:
Learngd: Weight and bias gradient descent learning function.
Learngdm: Use of a bias-learning function based on a combination of gradient descent and momentum weighting. The nntool of MATLAB is used for the network training of the input and output data. With the training function, learning function and the output parameter of the mean square error as mentioned above.

Methodology:

Table 1 represents the different functions to train the ANN network. The different combinations of functions out of the four categories from table 1 are chosen for the neural network structure. The total combination made from the function is 84. Thus the 84 different ANN network is trained for performance comparison. For performance evaluation, all these networks are examined depending on three performance parameters (time, epoch and error). But due to the fact that when more than one performance parameter gets involved, it gets difficult to compare the overall network performance as different performance parameters show different trends.

Table 1: Different functions to train the ANN Network

Transfer Function	Learning Function	Training Function	Mean Square Error (MSE)
Tansig Logsig Purelin	LEARNGD LEARNGDM	TRAINBR TRAINCGB TRAINGDM TRAINRP TRAINGDA TRAINSCG TRAINBFG TRAINCGF TRAINCGP TRAINGD TRAINOSS TRAINR TRAINGDX TRAINLM	MSE

To analyze the different network combinations, the rank method has been utilized to generalize the results for all performance parameters. In this method the weightage is assigned to all the performance factors depending upon the performance requirement, the corresponding weightage is given according to each performance factor. Like for time factor the network taking less time get a high weightage than the network taking more time and accordingly for the epoch and error. W_{time}, W_{epoch}, W_{error} respectively for time, epochs and the error corresponding to the network function chosen. The weight assignment for the three parameters is shown in figure 3 for all the 84 networks formed.

Corresponding to this numbering the overall weightage W_{total} of each network is assigned by the addition of all the performance parameter weights as shown in the equation.

$$W_T^n = \left(W_{epoach}^n + W_{time}^n + W_{error}^n\right)$$

W_T^n = Total weightage of the nth network

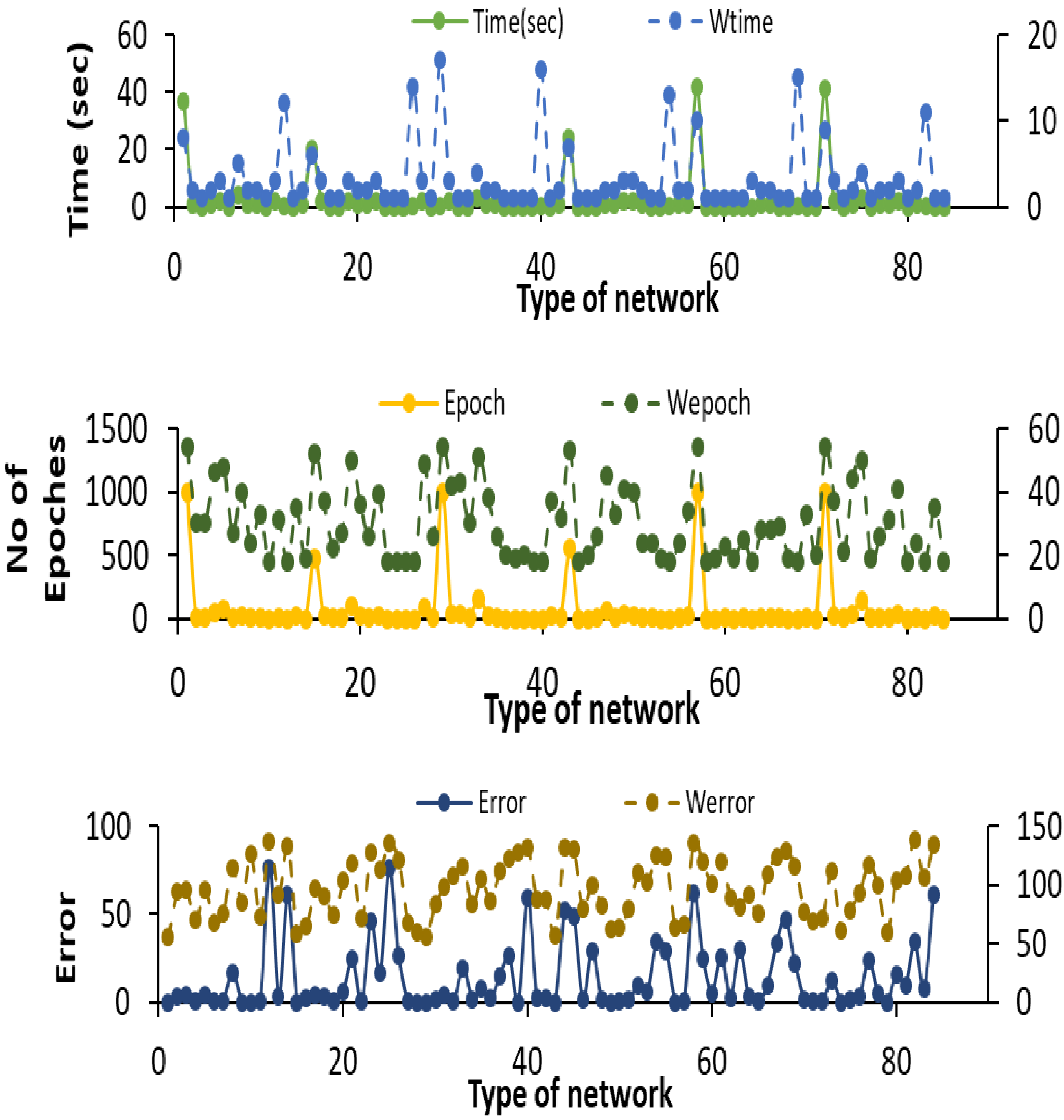


Fig3. Weight assignment for all the three performance parameters

All the 84 networks are trained with the six data input of Pm, V_{oc}, I_{sc}, I_r, T, FF the data consist of the 34 different panel rating with the output of V_m and I_m parameters. The ANN networks are trained with these input and output readings for best performance. The performance of the 7 randomly chosen network has been shown in figure 4 and figure 5 respectively.

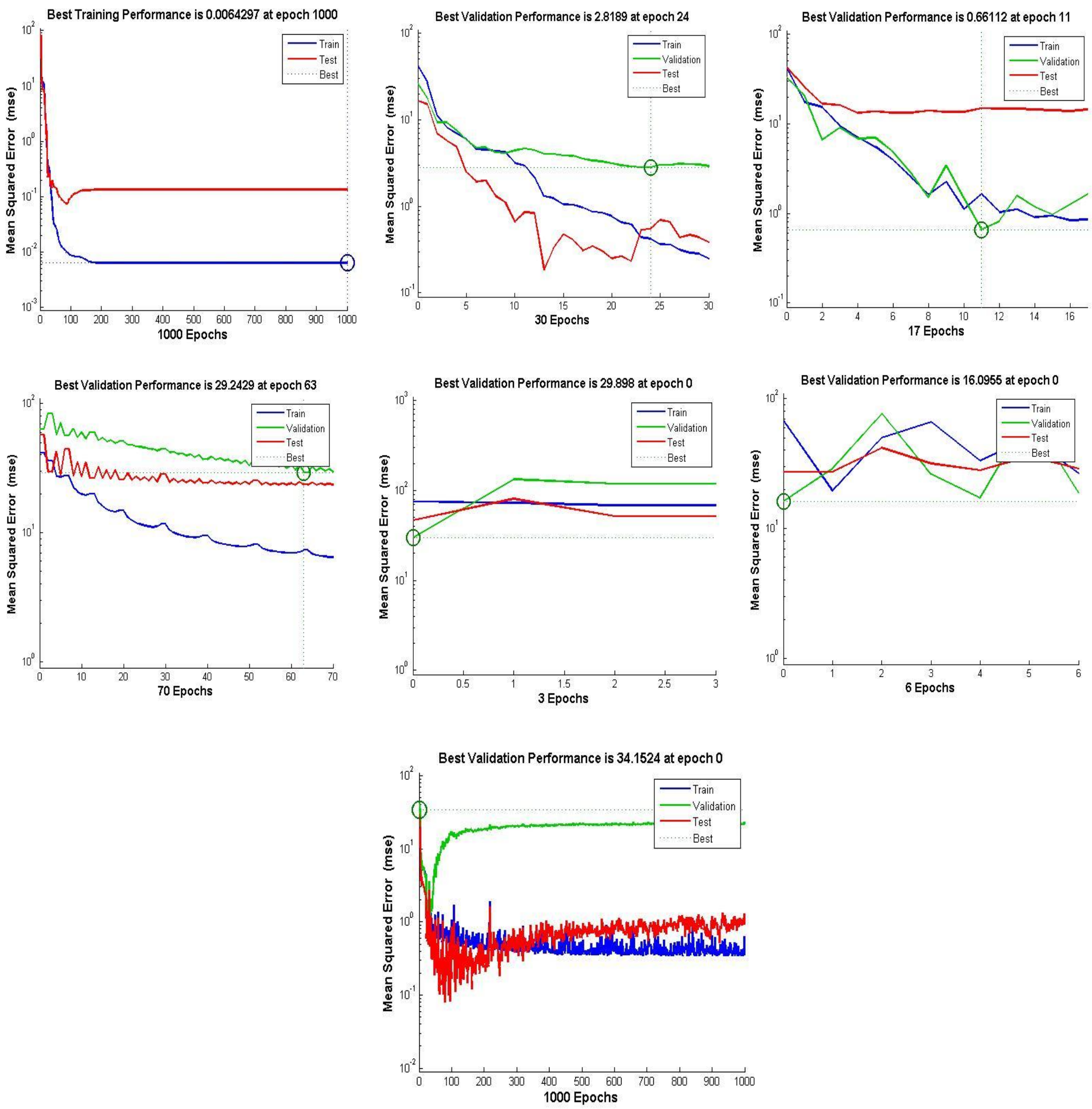


Fig4. Performance graph of the 7 randomly chosen ANN network respectively a). ADFT b). AEGT c). BDIT d). BEJT e). CDLT f). CEOT g). CEQT

Result and Discussion: Each network is assigned with the weightage number depending upon the three performance parameters. Now the summation of all these weightages corresponding to each network represents the total weightage of the network. Now depending upon this total weightage all the networks can be compared as the weightage represents the performance corresponding to the three-performance factor. The network weightage from higher to low value can be identified as the best to worse network. In this case the ranking is done from the lower weight to the high weight. The total weightage obtained for all the 84 networks is shown in figure 6. The ranking determines the overall network performance depending upon the three performance parameters. From the ranks obtained the frequency distribution curve has been plotted as shown in figure 7 for the total weightage of the different networks.

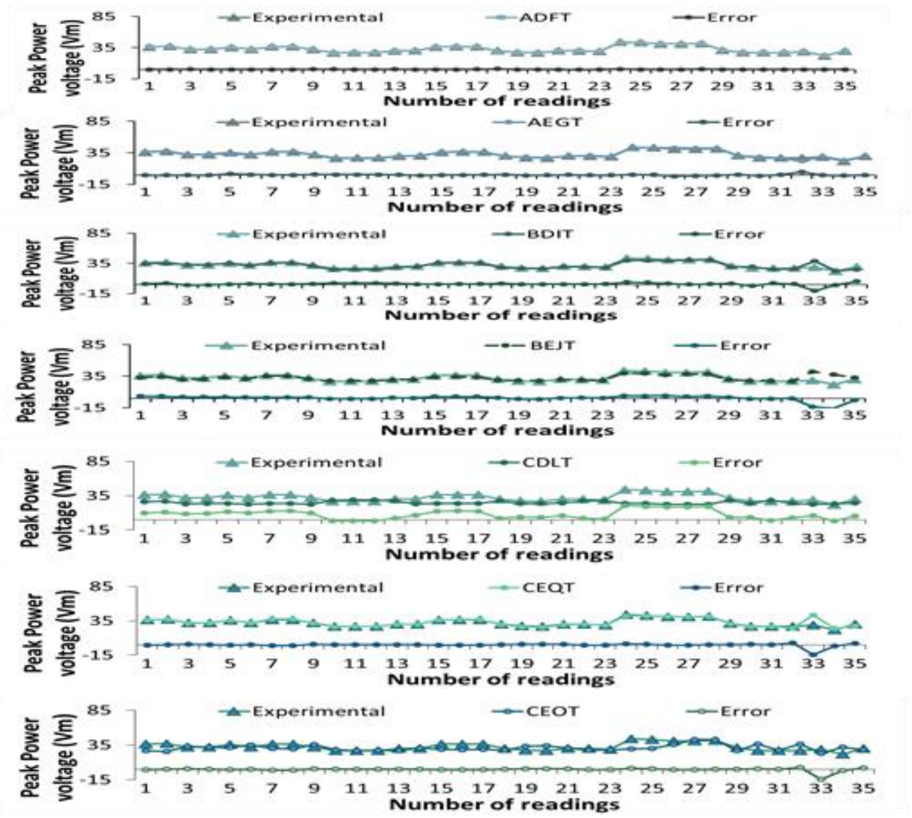


Fig5. Simulated results and error of seven randomly chosen ANN network respectively a) ADFT b) AEGT c) BDIT d) BEJT e) CDLT f) CEOT g) CEQT

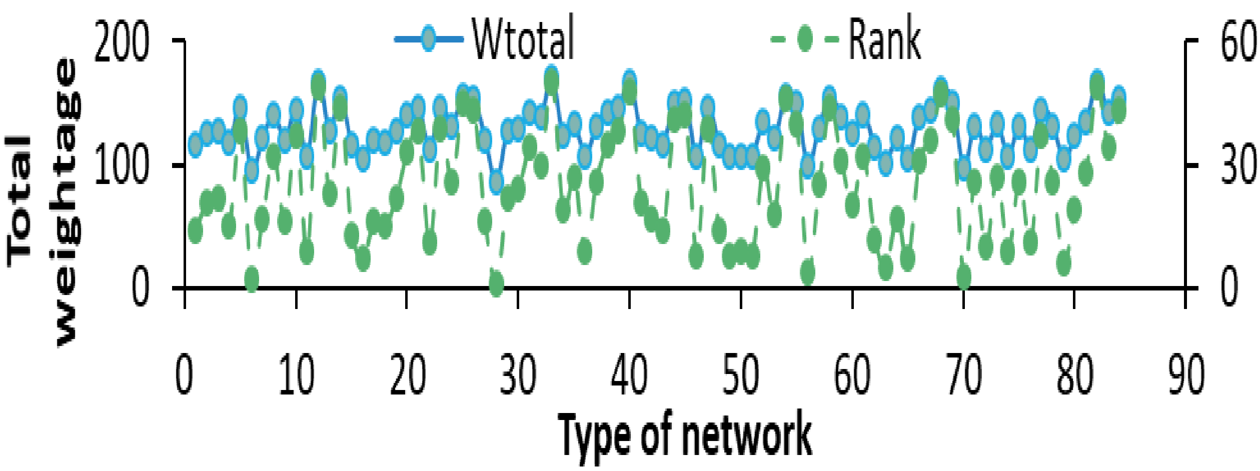


Fig6. Total weightage and ranking of all the networks based on three performance parameters

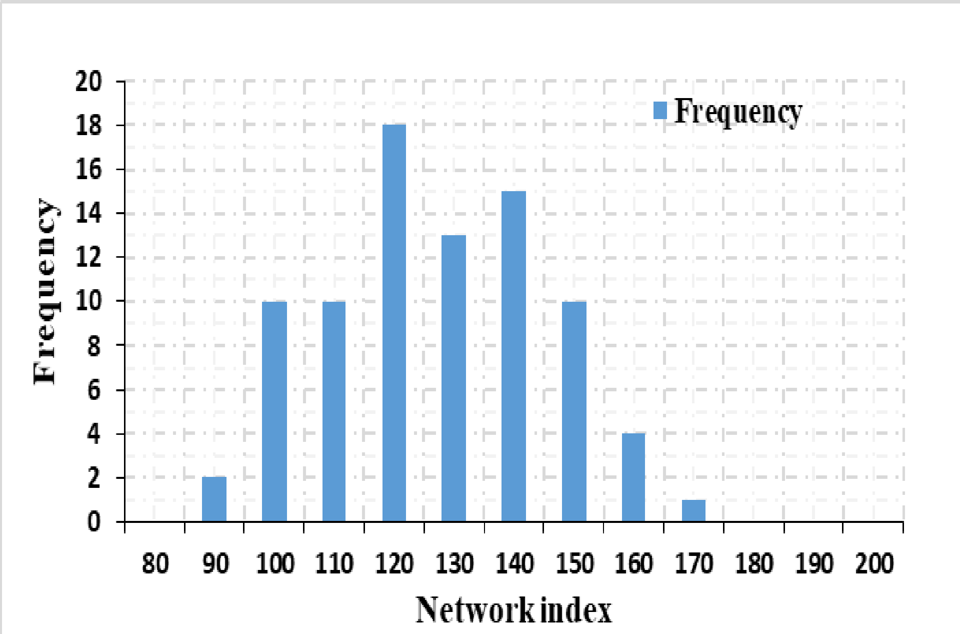


Fig7. Frequency distribution of the network weight

Funding This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors**.**

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References:

[1] Sandhya Prajapati and Eugene Fernandez," Capacity Credit Estimation for Solar PV Installations in Conventional Generation: Impacts with and without Battery Storage", Energy sources part A: Recovery, Utilization and Environmental Effects, Taylor and Francis, DOI 10.1080/15567036.2019.1676326.

[2] Sandhya Prajapati, Eugene Fernandez, "Relative Comparison of Standalone Renewable Energy System Battery Storage Requirement for Residential, Industrial and Commercial Loads", International Journal of Renewable Energy Technology, Inderscience, Vol. 11, No. 2, 2020.

[3] Sandhya Prajapati, Eugene Fernandez, "Residential load management with grey water recycling to maximize Rooftop solar PV usage," Energy Sources Part A: Recovery,

Utilization and Environmental Effects, Taylor and Francis, DOI 10.1080/15567036.2019.1687618.

[4] Sandhya Prajapati, Eugene Fernandez" Standalone solar PV system for grey water recycling along with electric load for domestic application", International Journal of Sustainable Engineering, Taylor and Francis DOI: 10.1080/19397038.2020.1739168.

[5] Sandhya Prajapati, Eugene Fernandez, "Rooftop Solar PV System for Commercial Office Buildings for EV Charging Load", IEEE 6th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA 2019) 27-29 August 2019, Kuala Lumpur, Malaysia.

[6] Sandhya Prajapati, Eugene Fernandez,"Green Energy for Residential Loads with Electric Vehicle Charging: Cost Analysis for a Rooftop Solar PV system", International Conference on Artificial Intelligence & applications, College of Engineering Roorkee, Roorkee, 20-21 Nov,2019

[7] Azadeh, A., R. Babazadeh, and S. M. Asadzadeh. 2013. Optimum estimation and forecasting of renewable energy consumption by artificial neural networks. Renewable and Sustainable Energy Reviews 27:605–12. doi:10.1016/j.rser.2013.07.007.

[8] Rocha, A. S. F., F. K. D. O. M. V. Guerra, and M. R. B. G. Vale. 2020. Forecasting the performance of a photovoltaic solar system installed in other locations using artificial neural networks. In Electric Power Components and Systems 48:1–12, 201–212. UK: Taylor & Francis. doi:10.1080/15325008.2020.1736211

[9] Perveen, G., M. Rizwan, N. Goel, and P. Anand. 2020. Artificial neural network models for global solar energy and photovoltaic power forecasting over India. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 1–26. doi:10.1080/15567036.2020.1826017.

[10] Yona, A., T. Senjyu, A. Saber, T. Funabashi, H. Sekine, and C. Kim. 2007. Application of neural network to one-day-ahead 24 hours generating power forecasting for photovoltaic system. 2007 International Conference On Intelligent Systems Applications To Power Systems, Niigata, Japan

[11] P. Mathiesen and J. Kleissl, "Evaluation of numerical weather prediction for intra-day solar forecasting in the CONUS," Solar Energy, vol. 85, no. 5, pp. 967–977, May 2011.

[12] P. Bacher, H. Madsen, and H.A. Nielsen, "Online short-term solar power forecasting, vol. 83, no. 10, pp. 1772–1783, Oct. 2009

[13] F.-V. Gutierrez-Corea, M.-A. Manso-Callejo, M.-P. Moreno-Regidor, and M.-T. Manrique-Sancho, "Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations," Solar Energy, vol. 134, pp. 119-131, Sep. 2016.

[14] C. Tao, D. Shanxu, and C. Changsong, "Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement", Proc. 2nd IEEE Int. Symp. Power Electron. Distrib. Gener. Syst. (PEDG), pp. 773-777, Jun. 2010.

[15] L. Mazorra Aguiar, B. Pereira, P. Lauret, F. Díaz, and M. David, "Combining solar irradiance measurements, satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting," Renewable Energy, vol. 97, pp. 599-610, Jun. 2016.

[16] Ashraf, I., and A. Chandra. 2004. Artificial neural network based models for forecasting electricity generation of grid connected solar PV power plant. International Journal of Global Energy Issues 21 (1–2):119–30. doi:10.1504/IJGEI.2004.004704.

[17] Hiyama, T., and K. Kitabayashi. 1997. Neural network based estimation of maximum power generation from PV module using environmental information. IEEE Transactions on Energy Conversion 12 (3):241–47. doi:10.1109/60.629709.

[18] Huang, C., A. Bensoussan, M. Edesess, and K. L. Tsui. 2016. Improvement in artificial neural network-based estimation of grid connected photovoltaic power output. Renewable Energy 97:838–48. doi:10.1016/j.renene.2016.06.043.

[19] Malik, P., and S. S. Chandel. 2020. A new integrated single-diode solar cell model for photovoltaic power prediction with experimental validation under real outdoor conditions. International Journal of Energy Research. doi:10.1002/er.5881.

[20] Lo Brano, V., G. Ciulla, and M. Di Falco. 2014. Artificial neural networks to predict the power output of a PV panel. International Journal of Photoenergy 2014:1–12.

[21] Rehman, S., and M. Mohandes. 2008. Artificial neural network estimation of global solar irradiance using air temperature and relative humidity. Energy Policy 36 (2):571–76. doi:10.1016/j.enpol.2007.09.033.

[22] G. Reikard, “Predicting solar radiation at high resolutions: a comparison of time series forecasts,” Solar Energy, vol. 83, no. 3, pp. 342– 349, Mar. 2009.