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Investigation of Different Designs of Artificial Neural Network for Maximum Power Point Tracking of Grid Connected PV System

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***Abstract*-This paper aims at increasing the PV system efficiency through the design of the Artificial Neural Network (ANN) for maximum power point tracking (MPPT) of grid connected PV systems. The main effective factors for efficiency increase is to design an accurate tracker of maximum power point. Some conventional methods, such as the perturb-and-observe (P&O) and the incremental conductance (IC), are widely used for MPPT. The artificial intelligence can substitute these conventional methods to produce a precise MPPT system. The artificial neural network (ANN) is investigated, in this paper, to compare between different designs to maximize the output dc power of PV array. One hidden layer with different number of neurons, two hidden layers and a modified criterion for improving the learning process are the proposed designs of ANN for MPPT. The IC method is used as a base case to be compared for the clarification of the improvement achieved using the ANN as an MPP tracker.**

***Keywords* - Artificial neural network, Incremental Conductance, Grid connected PV system, Maximum power point tracking.**

I. INTRODUCTION

The PV systems are widely incorporated into the electric power utilities. The PV system efficiency is closely related to operating these systems at their maximum power point. While the Sun tracker is a way to get the maximum irradiation from the sun, the maximum power point tracking (MPPT) system manipulates the PV voltage to match the maximum output dc power for various environmental and load conditions. As the accuracy of the MPPT system increases, more output dc power is gained and hence the PV system efficiency increases. Maintaining the PV system efficiency as high as possible essentially encourages the exploiting of PV systems [1].

The MPPT system commands the PV voltage through adjusting the duty cycle of the dc-dc boost converter for different environmental conditions, e.g., the solar irradiance (G) and the cell temperature (Tc). The incremental conductance (IC) and the perturb-and-observe (*P&O*) are the main widely used conventional MPPT methods [2-5]. The artificial intelligence (AI) control can effectively promote the performance of the MPPT control system. The fuzzy logic control [6, 7] and the genetic algorithm (GA) [8, 9] were exploited for advancing MPPT. Some optimization techniques, e.g., particle swarm optimization [10] and Ant colony optimization [11], were applied to improve the MPPT efficiency. Some hybrid MPPT techniques exploit both the classical methods and artificial intelligence [12, 13]. An evaluation of classical techniques is introduced in [14]. Comparative evaluations of the conventional and AI based MPPT were presented in [2] [3] [15] [16], which assert the advantage of using the AI algorithms for MPPT systems. The artificial neural networks (ANNs) were effectively used for MPPT of standalone and grid connected PV systems [17-20].In this paper, investigations and comparisons of different designs of feed-forward back propagation ANN for MPPT are presented. The effect of increasing the number of neurons in one hidden layer, increasing the number of hidden layers are introduced and compared. The training algorithm used is the Leven berg-Marquardt algorithm, where it is the fastest and most accurate training algorithm for this type of problems [21].

It is noted that, although the learning process stops as the validation checks satisfies the required mean square error (MSE), some outputs have considerable errors with respect to the corresponding targets. A proposed criterion is added to the learning process of the ANN to get better learning of the ANN from the training data. So the criterion is proposed to relearn the ANN to satisfy that all individual output match its corresponding target with a maximum error of $1*10^{-5}$. This leads to an improvement of the operation of the ANN based MPPT control system. The inputs of the ANN are chosen in such a way that they are the most effective factors on the operation of the PV system, which are the solar irradiance (G) and the cell temperature (Tc). The output of the ANN is chosen that it controls the PV array voltage to maintain the maximum power generation from the PV array, which is the duty cycle of the dc-dc boost converter. The conventional incremental conductance MPPT method is used as a base case to be compared with the different architectures of ANN for MPPT.

This paper is organized as follows. In Section II, the PV array modeling is introduced, with the one diode model representing the PV cell. In Section III, the IC method is presented as a conventional method to be the base case of comparison. The ANN for MPPT are presented. Section IV presents the results of the application of the ANN for MPPT and the comparison with the IC method. The application of different architectures of the ANN for MPPT and the effect of the proposed criterion for improving the learning process are presented. In Section V, the conclusion is presented.

II. PV ARRAY MODELING

The modeling of PV arrays is essential to estimate their response for different environmental and loading conditions. Generally, PV cells are connected in series or parallel to construct a PV panels. These panels are also connected in series and parallel to get PV arrays according to the required power and voltage. The modeling of the PV cells is the core for modeling of PV arrays. PV cells are generally represented by one diode or two diode models. The one diode model is simpler and sufficient for the modeling requirements, which is shown in Fig.1 [1, 22, 23].

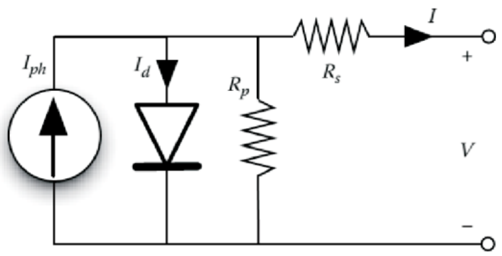

Fig.1. Representation of PV cell of one diode model[22]

The relation between the PV current (I) and the PV voltage (V) of a PV cell is presented in the following equations:

$$I = I_{ph} - I_s(exp(\frac{q(V+IR_s)}{akTc}-1)) - \frac{V+IR_s}{R_p} \quad (1)$$

$$I_{ph} = \frac{G}{G_n}(I_{sc_n} + K_I(Tc - Tc_n)) \quad (2)$$

$$I_s = I_{s_n}(\frac{Tc_n}{Tc})^3 exp(\frac{qE_g}{ak}(1/Tc_n - 1/Tc)) \quad (3$$

$$I_{s_n} = I_{sc_n} / (exp(\frac{qV_{oc_n}}{akTc_n}) - 1) \quad (4)$$

I_{ph} is the photo current, I_s is the saturation current, I_{sc} is the short circuit current in A, V_{oc} is the open circuit voltage in V, G is the solar irradiance in W/m^2, Tc is the cell temperature in Kelvin, and E_g is the band gap of the semiconductor material. For crystalline silicon $E_g = 1.124eV = 1.8*10^{-19}J$.

$k = 1.3806503*10^{-23}J/K$ is the Boltzmann constant, $q = 1.60217646*10^{-19}C$ is the electron charge and a is the ideal factor [22]. At standard test conditions (STC), with the subscript n, the solar irradiance is 1000 W/m^2, the cell temperature is $25^{\circ}C$, and the air mass (AM) is 1.5. The series resistance (R_s) represents the internal cell and the contact resistance, whereas the parallel resistance (R_p) is for accounting the leakage current.

The variation of the environmental conditions, especially the solar irradiance and cell temperature has a considerable effect on the point of maximum power. As an illustration of these effects, a PV panel, which is the SUNPOWER 305, with 96 solar cells connected in series, is simulated using the previous equations. The relations between the output power and voltage of the PV panel, for different solar irradiance, at standard cell temperature, and for different cell temperatures, at standard irradiance, are shown in Fig.2 and Fig.3, respectively. The maximum power points are marked in these figures to demonstrate their changes with the environmental conditions. As shown in these figures, the point of maximum power varies with the variation of G and Tc, which imposes an accurate tracking system to keep acquiring the maximum power for the variation of the environmental conditions.

III. MAXIMUM POWER POINT TRACKING

1. MPPT using incremental conductance method

The incremental conductance (IC) method is widely used for maximum power point tracking [2] [23]. The method is based on the fact that at the maximum power, the slope of the power voltage curve is zero. If the slope is negative then the PV voltage is required to be decremented and if the slope is positive the voltage is required to be incremented. The equations clarify the IC method:

$$P = VI \quad (5)$$

$$dP/dV = I + VdI/dV \quad (6)$$

where P is the output dc power. At maximum power point dP/dV=0, therefore:

$$dI/dV = -I/V \quad (7)$$

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When dP/dV>0, i.e., dI/dV>−I/V, the PV voltage requires to be increased, and when dP/dV<0, i.e., dI/dV<−I/V, the PV voltage requires to be decreased. A flowchart of the IC method for MPPT is shown in Fig.4, where ε is a small amount of voltage for increment or decrement. The IC method is presented to be the base case for comparison to clarify the improvement achieved when using the ANN for MPPT.

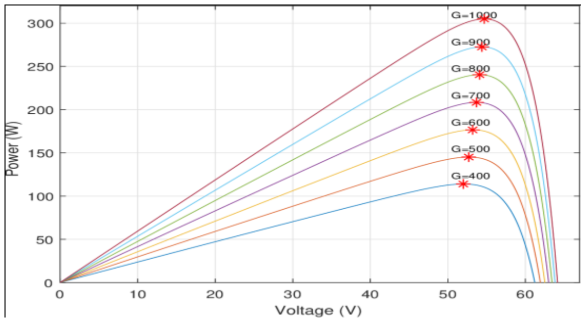

Fig.2 The relation between PV panel power and voltage for different solar irradiance at $Tc = 25^{\circ}C$

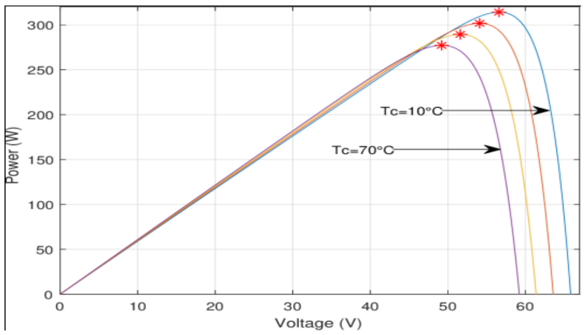

Fig.3 The relation between PV panel power and voltage for different cell temperature at G=1000W/m^2.

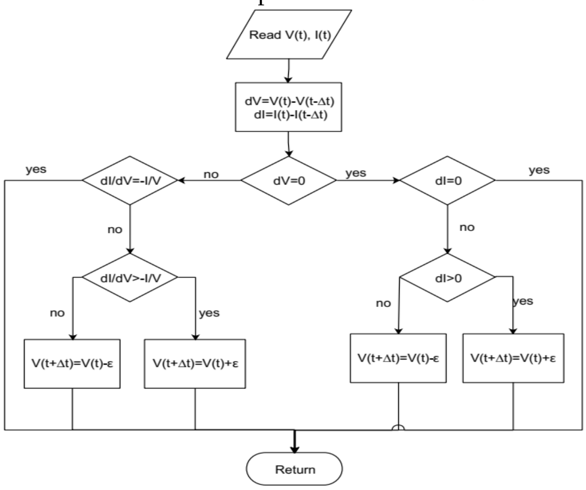

Fig.4. A flowchart of the IC method for MPPT.

2. Application of Artificial neural networks for MPPT

The artificial neural networks have the advantages of fast response and accuracy when they are well-trained [24]. The ANNs are used, in this paper, for accurate and fast MPPT system [17] [18]. One neuron model is shown in Fig.5 [24]. The activation function used is the hyberbolic tangent function. The neuron output can be expressed as:

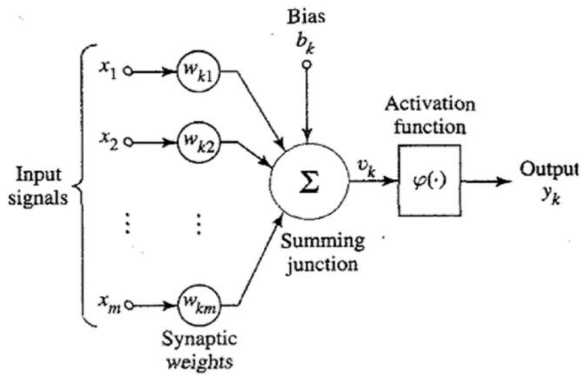

Fig.5 One neuron model [24].

$$v_k = \sum_{x=1}^{x=m} (w_{ki}.x_i + b_k) \tag{8}$$

$$y_k = \psi(v_k) = \frac{1-e^{-v_k}}{1+e^{-v_k}} \tag{9}$$

The general architecture of the ANN is shown in Fig.6. The ANN has two inputs, which are the solar irradiance (G) and the cell temperature (Tc) and the output is the duty cycle of the dc-dc boost converter used for controlling the PV voltage.

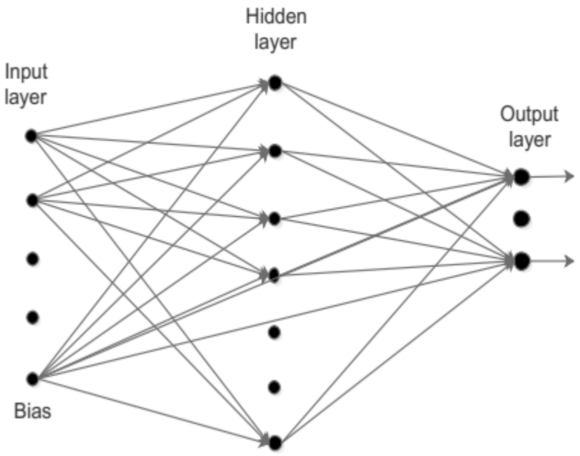

Fig.6 The general architecture of the ANN.

For the training of the ANN for MPPT, the sequence starts by acquiring the training data (the inputs and targets) from the simulation of the PV array. When a specified performance is reached, i.e., the mean square error reaches a certain small value, the trained ANN becomes suitable for using as MPPT system. A flowchart, shown in Fig.7, presents the sequence of learning process of the ANN for MPPT.

IV. SIMULATION AND RESULTS

For the application of different architectures of the ANN based MPPT, a grid connected PV system model, which is the detailed model of a 100-kW grid connected PV array from MATLAB SIMULINK library, whose block diagram is shown in Fig.8, is used. This system comprises a PV array, whose maximum output dc power is 100.7 KW at a solar irradiance of 1000 W/m^2 and a cell temperature of 25 $^\circ$C, a dc-dc boost converter, an inverter and the grid. The dc-dc boost converter is used to control the dc voltage of the PV array at different environmental conditions to track the maximum output power of the array.

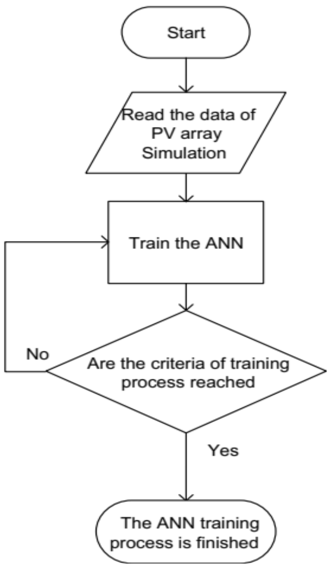

Fig.7A flowchart for learning the ANN for MPPT.

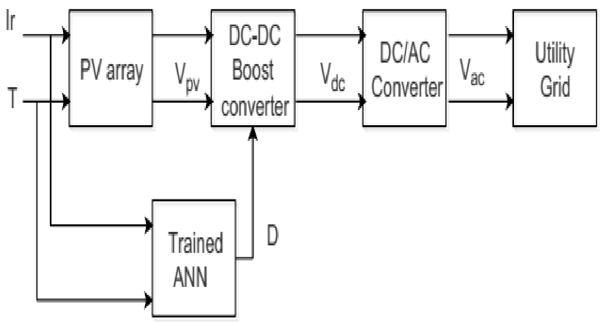

Fig.8A block diagram of the model of the grid connected PV system.

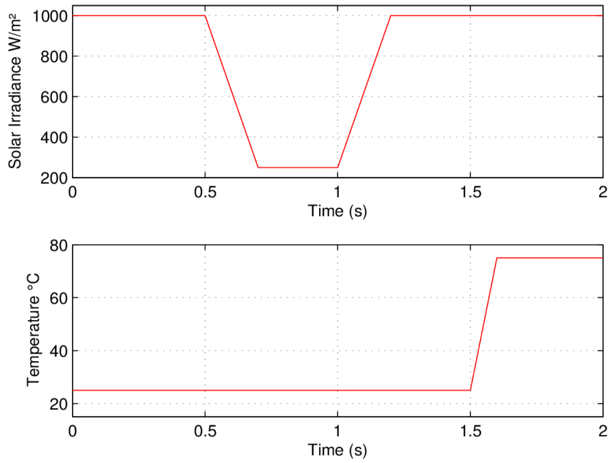

Fig.9 The solar irradiance and cell temperature used for ANN testing.

To check the capability of the ANN to be used for MPPT, proposed variations of the solar irradiance and the cell temperature, which are the inputs of the ANN, are shown in Fig.9. These environmental variations are used to test the response different architectures of the ANN compared to the IC method. Starting with the first ANN architecture, which has 10 neurons in one hidden layer, the output dc power of the PV array when using the ANN based MPPT method is compared to using the IC based MPPT method, which is shown in Fig.10. If the hidden layer neurons are increased to 20 neurons, the comparison of the output dc power of the PV array is presented in Fig.11.

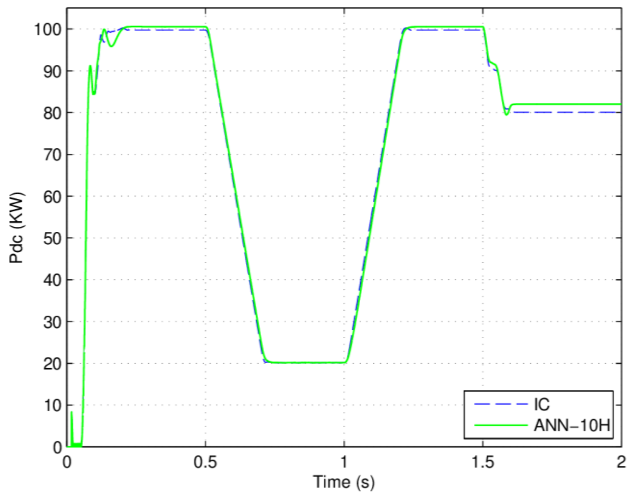

Fig.10A comparison between the output dc power when using the IC method and the ANN of 10 neurons in a hidden layer for MPPT.

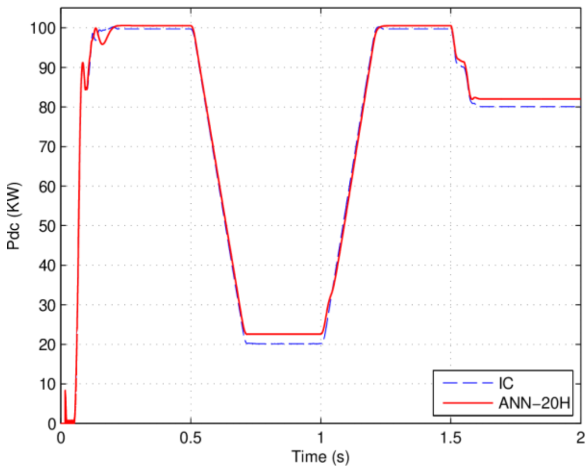

Fig.11 A comparison between the output dc power when using the IC method and the ANN of 20 neurons in a hidden layer for MPPT.

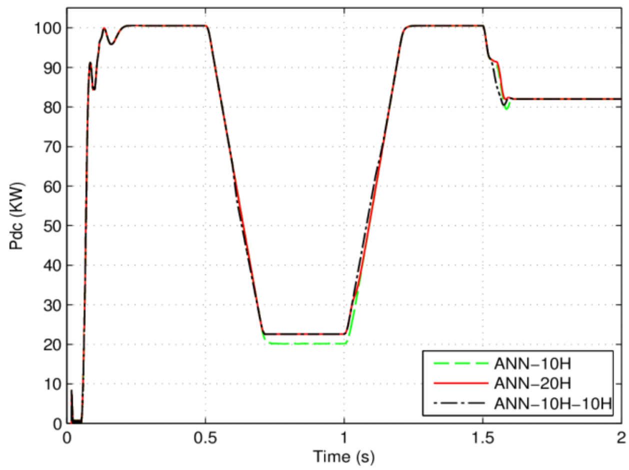

Fig.13A comparison between the output dc power when using the three proposed architectures of the ANN MPPT method.

If another hidden layer is added and a 10 neurons are used in each hidden layer, i.e., 2 hidden layers have 20 neurons, the comparison of the output dc power of the PV array is presented in Fig.12

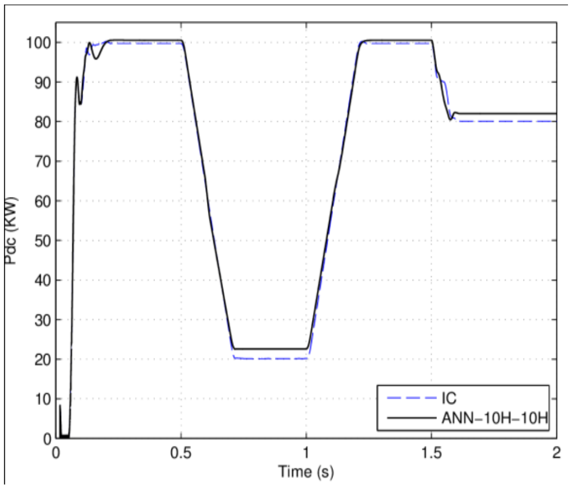

Fig.12 A comparison between the output dc power when using the IC method and the ANN of 10 neurons in each of two hidden layers for MPPT

Fig.13 clarify the comparison of the output dc power of the PV array of the three ANN architectures. This figure demonstrates that using 20 neurons in one hidden layer provides a slight improvement over using two hidden layer with 20 neurons and these two ANN architectures provide better responses over using one hidden layer with 10 neurons.

The learning process of the ANN can be improved if another criterion is added to the already existed criteria. Although the mean square error (MSE) is used as a criterion for stopping the learning process, some outputs have significant deviation from their corresponding targets. A criterion is proposed to relearn the ANN to satisfy that each output match its corresponding target with a certain small acceptable error, in addition to the criterion of small mean square error (MSE) already used as shown in the flowchart in Fig.14. Applying this criterion to the learning process of the ANN of one hidden layer with 10 neurons provides an appreciable improvement in the ANN response as shown in Fig.1.

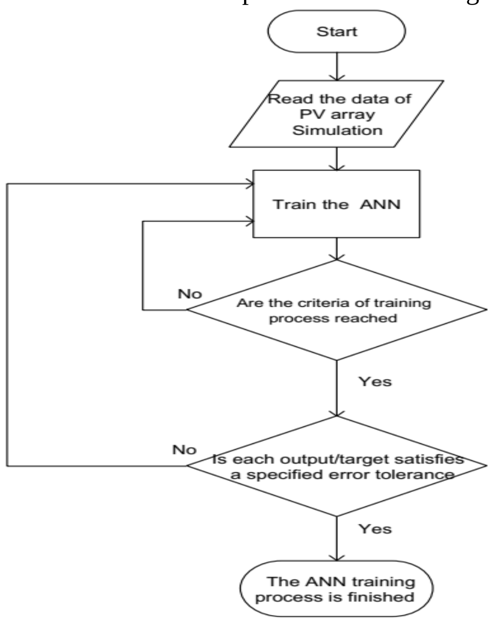

Fig.14 A flowchart of the IC based ANN for MPPT with modifying the learning process.

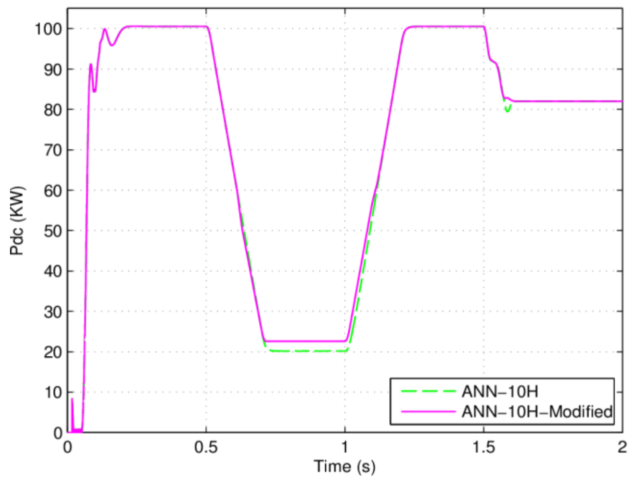

Fig.15 The output dc power of the PV array when using the 10 hidden layer ANN MPPT compared to the modification of the training process.

V.CONCLUSION

The maximum power point tracking is crucial for the operation of the PV system to enhance their efficiency. Different classical methods are used to track the maximum power, however they lack either accuracy or fast response. The artificial neural networks are used to substitute these classical methods as they can provide accurate and fast tracking. It is summarized from the simulation results that the increasing of the number of neurons in one hidden layer and the increasing of the number of hidden layers improve the tracking accuracy. However, the increased number of neurons in one hidden layer is preferable. The proposed criterion to limit the individual deviation between each output and the corresponding target, improves the ANN performance even with small number of neurons. The simulation results demonstrate that the well-trained ANN can successfully replace the classical methods and even provides greater output dc power.

REFERENCES

[1] D. Rekioua and E. Matagne, Optimization of photovoltaic power systems: modelization, simulation and control. Springer Science & Business Media, 2012.
[2] T. Esram, P. L. Chapman et al., “Comparison of photovoltaic array maximum power point tracking techniques,” IEEE Transactions on Energy Conversion EC, vol. 22, no. 2, pp. 439–449, 2007.
[3] A. R. Reisi, M. H. Moradi, and S. Jamasb, “Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review,” Renewable and Sustainable Energy Reviews, vol. 19, pp. 433–443, 2013.
[4] B. Subudhi and R. Pradhan, “A comparative study on maximum power point tracking techniques for photovoltaic power systems,” IEEE Transactions on Sustainable Energy, vol. 4, no. 1, pp. 89–98, 2013.
[5] Y.-H. Liu, J.-H. Chen, and J.-W. Huang, “A review of maximum power point tracking techniques for use in partially shaded conditions,” Renewable and Sustainable Energy Reviews, vol. 41, pp. 436–453, 2015.
[6] B. N. Alajmi, K. H. Ahmed, S. J. Finney, and B. W. Williams, “Fuzzy-logic-control approach of a modified hill-climbing method for maximum power point in microgrid standalone photovoltaic system,” Power Electronics, IEEE Transactions on, vol. 26, no. 4, pp. 1022–1030, 2011.
[7] M. Tajuddin, M. Arif, S. Ayob, and Z. Salam, “Perturbative methods for maximum power point tracking (mppt) of photovoltaic (pv) systems: a review,” International Journal of Energy Research, vol. 39, no. 9, pp. 1153–1178, 2015.
[8] R. Ramaprabha, V. Gothandaraman, K. Kanimozhi, R. Divya, and B. Mathur, “Maximum power point tracking using ga-optimized artificial neural network for solar pv system,” in the 1st international conference on electrical energy systems (ICEES), IEEE, pp. 264–268, 2011.
[9] A. Messai, A. Mellit, A. Guessoum, and S. Kalogeria, “Maximum power point tracking using a ga optimized fuzzy logic controller and its fpga implementation,” Solar energy, vol. 85, no. 2, pp. 265–277, 2011.
[10] Y.-H. Liu, S.-C. Huang, J.-W. Huang, and W.-C. Liang, “A Particle Swarm Optimization-Based Maximum Power Point Tracking Algorithm for PV Systems Operating Under Partially Shaded Conditions,” IEEE Transactions on Energy Conversion, vol. 27, no. 4, pp. 1027–1035, Dec. 2012.
[11] S. Titri, C. Larbes, K. Y. Toumi, and K. Benatchba, “A new mppt controller based on the ant colony optimization algorithm for photovoltaic systems under partial shading conditions,” Applied Soft Computing, vol. 58, pp. 465 – 479, 2017.
[12] K. Sundareswaran, V. Vignesh kumar, and S. Palani, “Application of a combined particle swarm optimization and perturb and observe method for MPPT in PV systems under partial shading conditions,” Renewable Energy, vol. 75, pp. 308–317, 2015.
[13] Ö. Çelik and A. Teke, “A Hybrid MPPT method for grid connected photovoltaic systems under rapidly changing atmospheric conditions,” Electric Power Systems Research, vol. 152, pp. 194–210, 2017.
[14] A. C. Zamora, G. Vazquez, J. Sosa, P. R. Martinez-Rodriguez, and M. A. Juarez, “Efficiency based comparative analysis of selected classical MPPT methods,” in 2017 IEEE International Autumn

Meeting on Power, Electronics and Computing (ROPEC), pp. 1–6, Nov. 2017.

[15] B. Bendib, H. Belmili, and F. Krim, “A survey of the most used MPPT methods: Conventional and advanced algorithms applied for photovoltaic systems,” Renewable and Sustainable Energy Reviews, vol. 45, pp. 637–648, 2015.

[16] H. Rezk and A. M. Eltamaly, “A comprehensive comparison of different MPPT techniques for photovoltaic systems,” Solar Energy, vol. 112, pp. 1–11, 2015.

[17] A. Mellit and A. M. Pavan, “Performance prediction of 20 kwp grid-connected photovoltaic plant at Trieste (Italy) using artificial neural network,” Energy Conversion and Management, vol. 51, no. 12, pp. 2431–2441, 2010.

[18]A. Bahgat, N. Helwa, G. Ahmad, and E. El Shenawy, “Maximum power point traking controller for pv systems using neural networks,” Renewable Energy, vol. 30, no. 8, pp. 1257–1268, 2005.

[19] F. Sedaghati, A. Nahavandi, M. A. Badamchizadeh, S. Ghaemi, and M. Abedinpour Fallah, “Pv maximum power-point tracking by using artificial neural network,” Mathematical Problems in Engineering, vol. 2012, 2012.

[20] S. Subiyanto, A. Mohamed, and M. Hannan, “Intelligent maximum power point tracking for pv system using hopfield neural network optimized fuzzy logic controller,” Energy and Buildings, vol. 51, pp. 29–38, 2012.

[21] M. Beale, M. Hagan, and H. Demuth, “Neural network toolbox,” MATLAB Users guide, The Math Works, Inc., 2017.

[22] N. Femia, G. Petrone, G. Spagnuolo, and M. Vitelli, Power electronics and control techniques for maximum energy harvesting in photovoltaic systems. CRC press, 2012.

[23] M. G. Villalva, J. R. Gazoli et al., “Comprehensive approach to modeling and simulation of photovoltaic arrays,” Power Electronics, IEEE Transactions on, vol. 24, no. 5, pp. 1198–1208, 2009.

[24] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd ed. Prentice Hall, 1999.