Developing Intelligent MPPT for PV Systems Based on ANN and P&O Algorithms

H. I. Abdelkader, A. Y. Hatata, M. S. Hasan

Abstract— The maximum power point tracking (MPPT) in photovoltaic (PV) systems varies depending on the fluctuation of the solar radiation and temperature; while the energy transfer from the PV to the load is controlled by specific algorithms. Conventional techniques for MPPT (Perturb and observe (P&O)) are easy to implement but they suffer from oscillations at MPP and speed is less due to fixed perturb step. To achieve better energy efficiency conversion in PV systems, it is required to develop maximum power point tracking (MPPT) control techniques. This paper presents an improved MPPT controller for PV systems using two techniques namely; Artificial Neural Network (ANN) and developed P&O techniques. The proposed ANN and the developed P&O algorithm are modeled using MATLAB/SIMULINK. The proposed ANN has two inputs which are solar radiation and ambient temperature. The optimum voltage of the PV system is the output of the proposed ANN. The proposed ANN was evaluated under different irradiation conditions and temperature. The response of the proposed ANN for MPPT controllers found to be lesser oscillation at MPP and faster tracking response compared with the developed P&O algorithm.

Index Terms— Photovoltaic (PV), Maximum power point tracking (MPPT), Perturb and Observe (P&O), Artificial Neural Network (ANN).

1 INTRODUCTION

Solar energy is currently considered as one of the most important renewable energy sources. The incident light from the sun is a large source of energy. The photovoltaic (PV) systems are one of the most promising and attractive renewable energy sources due to their low operational and maintenance costs, pollution free power generation, long life cycles, and noise free operation [1-2].

The PV system characteristic is non-linear whose its output power varies as function of the irradiance and temperature. The main weakness of the PV system is high installation cost and low efficiency. There are different ways to increase the output power from the photovoltaic systems by directing the panel perpendicular to the solar radiation most of the time and also by extracting the optimal output power by using a maximum power point tracking control. Hence, it is essential to operate the PV system at its maximum power point [3, 4].

The tracking control of the MPP is complicated problem. Various MPP tracking methods have been proposed such as (perturb and observe [4-5], incremental conductance [6], parasitic capacitance [7], constant voltage [8], reactive power control [9],) and artificial intelligence methods (neural network [10–12] and fuzzy logic controller [13–15]. These strategies have some disadvantages such as high cost, difficulty, complexity and instability.

The P&O algorithms are common useed in photovoltaic (PV) systems due to its ease of implementation. It can be implemented by applying perturbation to the reference voltage or the reference current of the PV panel to track MPP. But it is not suitable for rapidly varying weather conditions. However, operation with fixed size perturbations results in a trade-off between speed of response and maximum power yield in the steady state[16].

Artificial neural networks are based on neurophysical models of human brain cells and their interconnection. Such networks are characterized by exceptional pattern recognition and learning capabilities. It can be described as a set of elementary neurons that are usually connected in biologically inspired architectures and organized in several layers. The multilayer feedforward neural network (MFFNN) architectures and algorithms are well suited for patterns classification problem. It has parallel distributed architecture for information processing this allows it to lean any complex input/output mapping. MPPT can be treated as a problem of input data pattern recognition which can be well handled by ANNs [17].

This paper presents a PV model with MATLAB/SIMULINK, and tracks the MPP using a developed P&O and Artificial Neural Network (ANN). It proposes multilayer feed forward neural network based MPP tracker for PV systems. The proposed MFFNN is trained using backpropagation algorithm and suitable training data. The ANN uses the irradiance and temperature as inputs. The PV model was simulated to generate training and testing data for PV module at various conditions to train and test the proposed neural network. Finally the results showing the performance of the MFFNN based MPP tracker compared with the developed P&O algorithm has been presented in the paper.

2. Modeling and simulation of the PV System

The PV array model should be constructed first; a practical model of PV system is modeled and simulated using MATLAB/SIMULINK. The model is connected to DC/DC converter with the industrial data from a solar panel manufacturer.

- Assoc. Prof. H. I. abdelkader is currently working as Associate Professor in Physics Dept., Science College, Mansoura Univ., Egypt, E-mail: Alisamer1980@yahoo.com.
- Dr. A. Y. Hatata is currently working as Lecturer in Electric Engineering Dept. Faculty of engineering, Mansoura Univ., Egypt, E-mail: a_hatata@yahoo.com.
- M. S. Hasan is currently pursuing masters degree program in Physics Dept., Science College, Mansoura Univ., Egypt.

ISSN 2229-5518

2.1 Practical PV model

The most popular model used to represent the PV module is the current source in parallel with a diode, with a parallel and series resistors (Rp, Rs) as illustrated in figure 1.

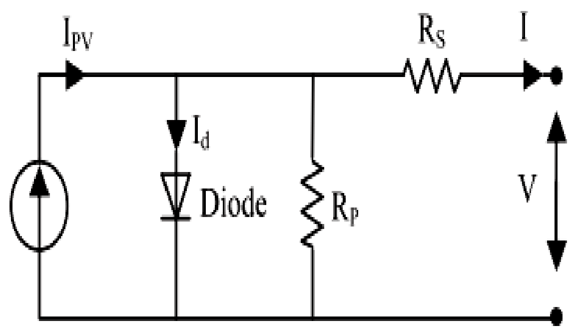


Fig. 1 Single-diode model of a practical PV cell

The output current of the PV module can be expressed by mathematical equation as [18-19]:

$$I = I_{PV} - I_d - \frac{V+IR_S}{R_P} \quad (1)$$

$$I_d = I_o\left(e^{\frac{V+IR_S}{\alpha V_T}} - 1\right) \quad (2)$$

Where:

I_{PV} is the PV current

I_o is the saturated reverse current

α is a constant known as the diode ideality factor

V_T is the thermal voltage of the cells $= \frac{N_S KT}{q}$

N_S is the number of cells connected in series

K is Boltzmann's constant

q is the charge of the electron

T is the absolute temperature of the p–n junction,

R_S and R_P are the series and parallel equivalent resistances of the solar panel respectively.

The PV current (I_{PV}) has a linear relationship with light intensity and also varies with temperature variations. I_o is dependent on temperature variations. Values of I_{PV} and I_o are calculated from the following equations:

$$I_{PV} = \left(I_{PV,n} + K_I \Delta T\right)\frac{G}{G_n} \quad (3)$$

$$I_o = \frac{I_{SC,n} + K_I \Delta T}{e^{(V_{OC,n}+K_V\Delta T)/\alpha V_T} - 1} \quad (4)$$

If the array is composed of NPparallel connections of cells the PV and saturation currents may be considered as NP times as above.

2.2 DC / DC Converter model

There are several types of DC/DC converters. A step up (boost) converter is chosen to control the PV module's output voltage. The boost converter can always work continuously without the power source being open-circuited. The discontinuous mode in a boost converter could be prevented with a relatively large inductor and the current could be kept steady within a switching period, as well [20]. Figure 2 shows the electrical circuit of the DC-DC boost converter. It contains two components for storing the energy, the inductor and the capacitor. The switch that is used here is an Insulated Gate Bipolar Transistor (IGBT).

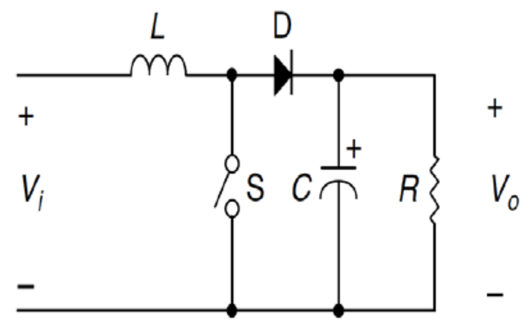


Fig. 2 circuit of the DC-DC boost converter.

The duty cycle, D = t_{on}/T where T is the period equal to $t_{on}+t_{off.}$ The relation between the input and output voltage is given from.

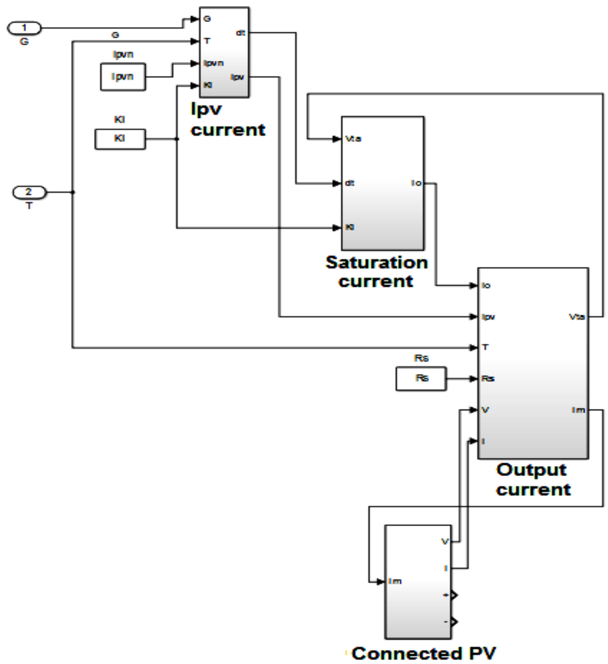
$$V_o = \frac{1}{1-D} V_i \quad (5)$$

The input voltage of the converter is the solar module output voltage that is changes all the time. However, its output voltage must be kept at a desired value. This is done by controlling the duty ratio, so that the operating point of the PV system can be adjusted to realize MPPT algorithm [21-22].

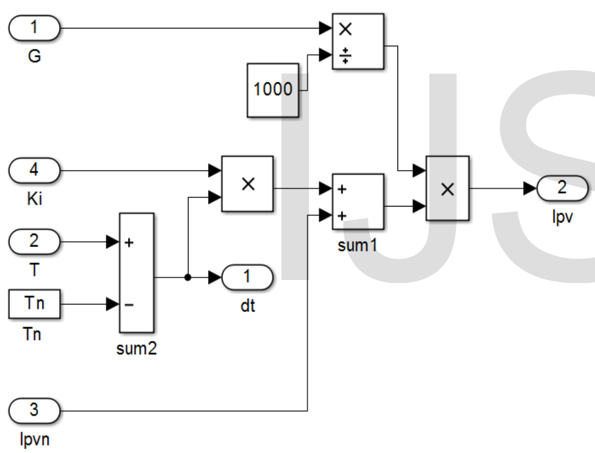
2.3 Simulink Model for the PV System

The model discussed above has been implemented in MATLAB/SIMULINK environment. According to the equations discussed above, all the important parameters' models are built separately as displayed below. The whole PV system model is illustrated in figure 3. It consists of four subsystems; photovoltaic current (I_{PV}) calculation block, saturation current calculations block, output current calculation block and electric PV circuit connection block. The PV module was connected to DC/DC converter as shown in figure 4.

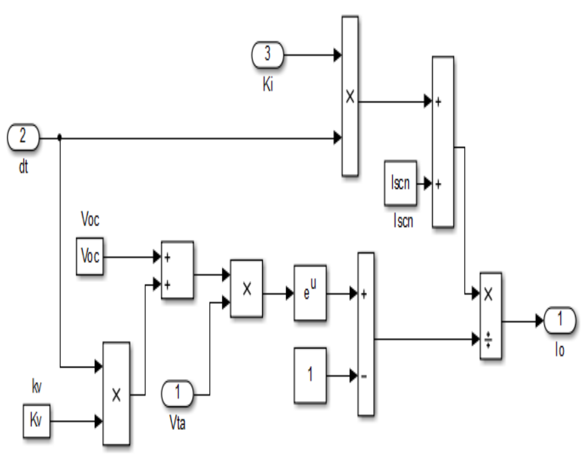
The PV module has two inputs (solar irradiance level and temperature) and two outputs (output voltage and current). The output data, the I-V curve and P-V curve are available to observe. The system and the module configuration are shown below.



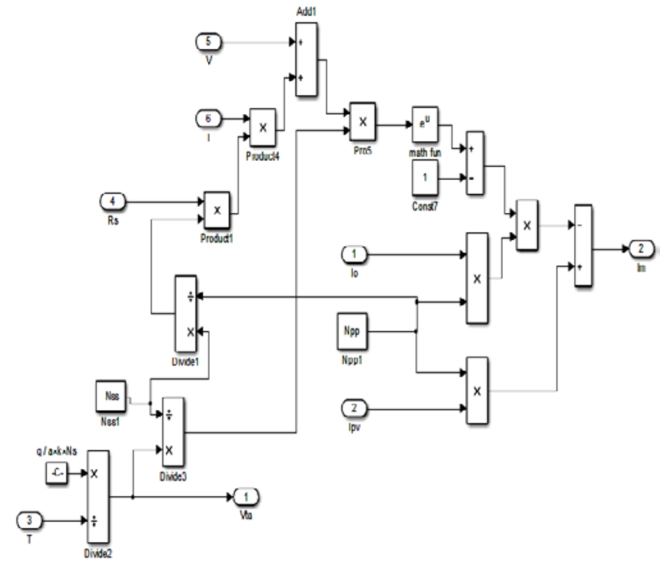
(a) The whole PV system model



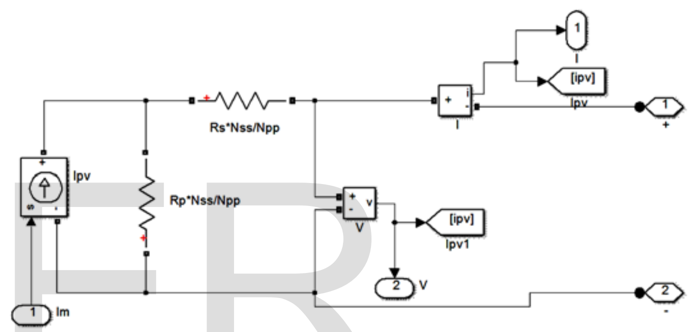
(b) IPV calculation module



(c) Saturation current calculation modules



(d) Output current calculation module



(f) Electric PV circuit connection

Fig. 3 Block diagram of the modeled PV system

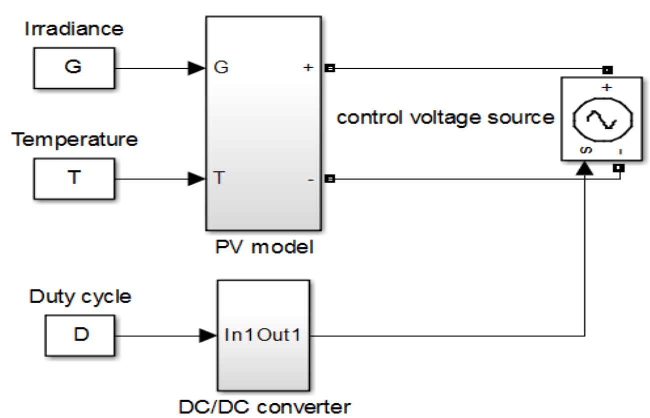


Fig. 4 PV model connected to DC/DC converter

The PV module used in the simulation is composed of 72 solar cells in series, and the electrical specification of Sun-Power E19 PV Panel are shown in table 1. The voltage V is considered varying from zero to open circuit voltage Voc corresponding to the variation in current from short circuit current Isc to zero. With the model set up in Simulink, sets of curves (I-V and P-V) are achieved under different weather conditions: Irradiation change from1000W/m2 to 200W/m2 and temperature change from 25°C to 70°C. The performance of a PV module for different solar irradiance and fixed temperature at 25oC are shown in figure 5 and 6. It can be seen that the short circuit current and the power increases with the increase of the irradiance level, while very small change in the open-circuit voltage.

Table 1. Electrical specification of SunPower E19 PV Panel

Parameter	Value
Maximum Power P_{max}	240W
Maximum Power Voltage V_{mp}	40.5V
Maximum Power Current I_{mp}	5.93A
Open Circuit Voltage V_{oc}	48.6V
Short Circuit Current I_{sc}	6.30A
Maximum System Voltage	600V
Temperature Coefficient of V_{oc}	132.5 mV/K
Temperature Coefficient of I_{sc}	3.5 mA/K
Number of series cells in one panel	72

The performance of a PV module at a constant level of irradiance (800 W/m2) and different temperature are given in figure 7 and 8. There is a reduction in Voc as the temperature increases. There is significant reduction in the power output of the PV system as cell temperature increases. Since achieving the maximum power output is the purpose, the P-V characteristic is relatively more important.

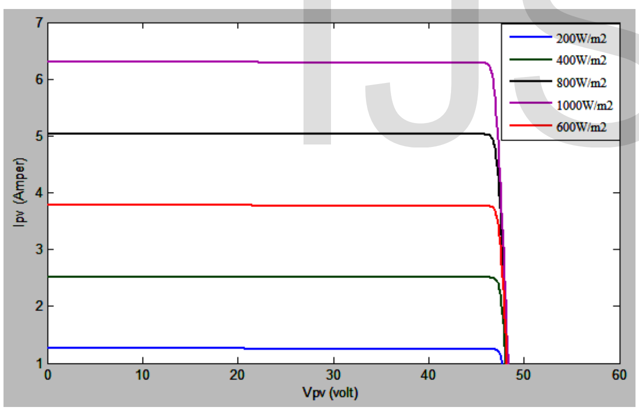


Fig. 5 I-V curves at different irradiation conditions

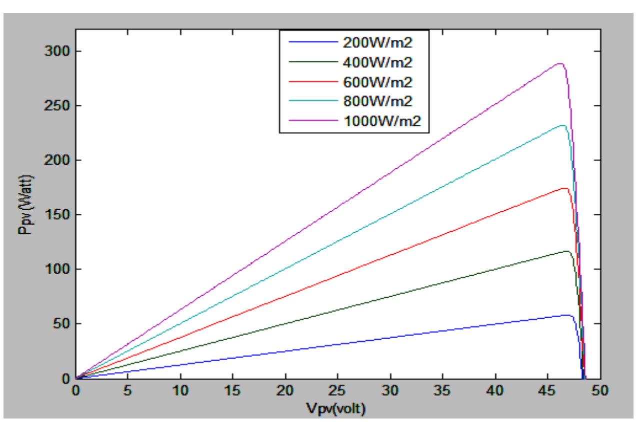


Fig. 6 P-V curves at different irradiation conditions

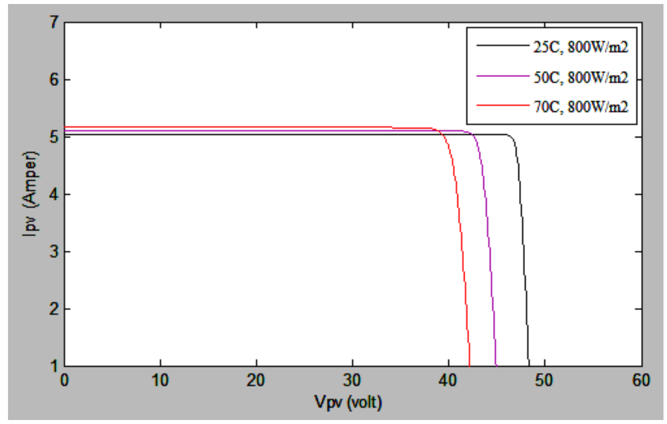


Fig. 7 I-V curves at different temperature conditions

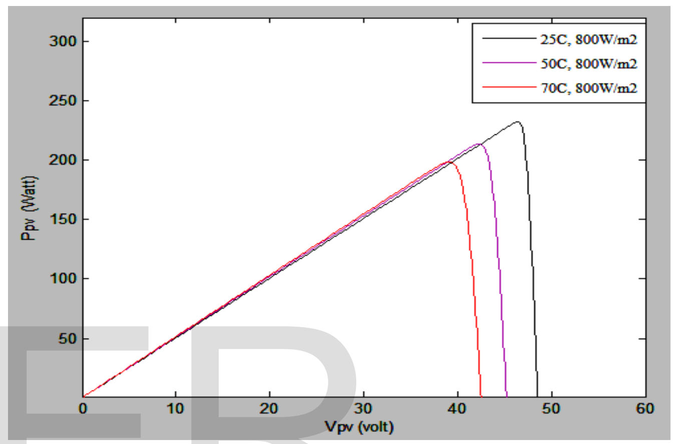


Fig. 8 P-V curves at different temperature conditions

3. Developing MPPT Algorithm

Maximum power point tracking plays an important role in photovoltaic system because of their role in maximizing the power output from a PV system for a given set of conditions.

3.1 Developed Perturb and Observe Algorithm

Conventional P&O algorithm operates by periodically perturbing the array terminal voltage or current and comparing the PV output power with that of the previous perturbation cycle. If the PV array operating voltage changes and power increases, the control system moves the PV array operating point in that direction; otherwise the operating point is moved in the opposite direction. In the next perturbation cycle the algorithm continues in the same way [4-5]. A common problem in P&O algorithms is when the MPP is reached; the output power oscillates around the maximum, resulting in power loss in the PV system. This is especially true in constant or slowly-varying atmospheric conditions. Furthermore, P&O methods can fail under rapidly changing atmospheric conditions [3].

In this paper a developed P&O algorithm is considered by adapting the step size of P&O based MPPT. The step size of perturbation will be increased when the system operates far from the MPP, and when the actual working point starts to fluctuate near the MPP, the algorithm will be reduce the step size to change the reference voltage, so the fluctuation is reduced to a large extent. It solves the oscillation at the MPP and tracking speed problems effectively. The developed algorithm improves the drawbacks of conventional P&O.

The flow chart of the developed P&O based MPPT is shown in figure 9.

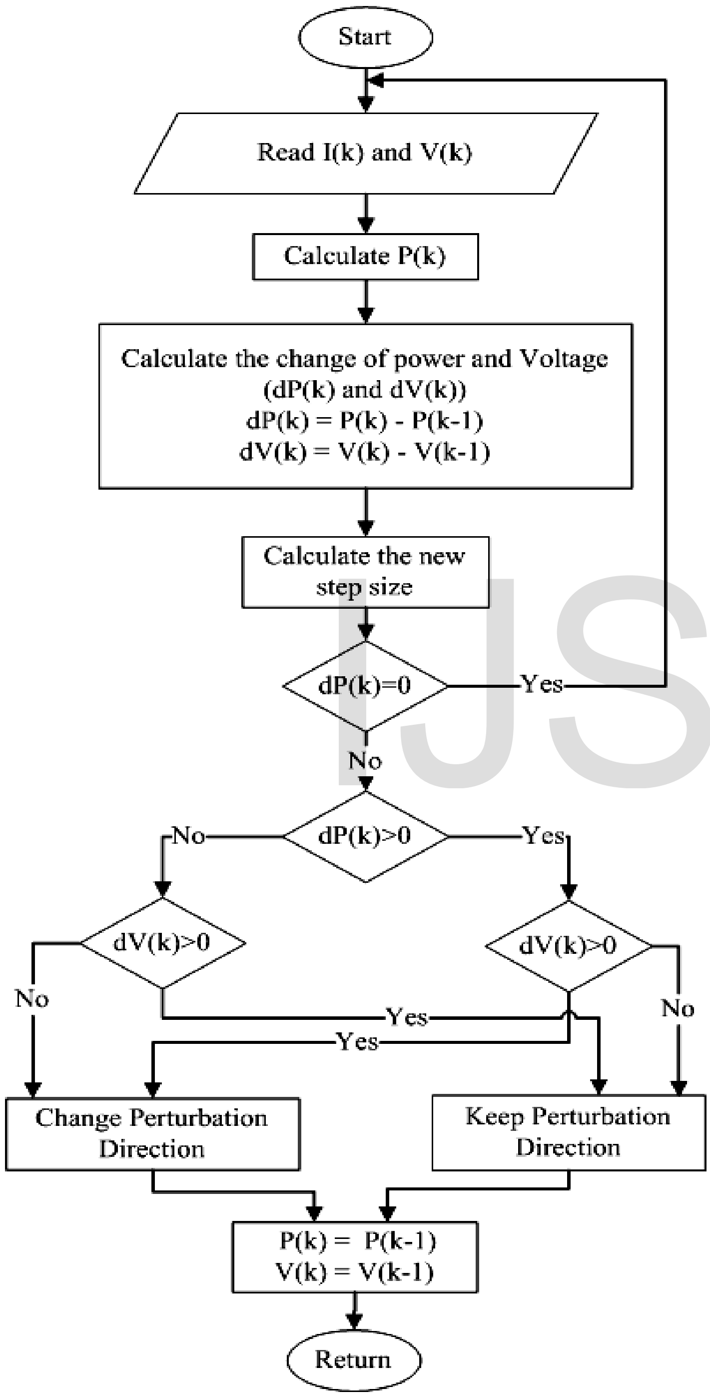


Fig. 9 Flow chart of the developed P&O MPPT algorithm

The proposed algorithm is implemented using Matlab/M-file. The input signal of the algorithm block is the PV current and output voltage, the output signal adjusted the duty ratio (D) of the converter to track the MPP. Figure 10 shows the block diagram of the developed P&O algorithm.

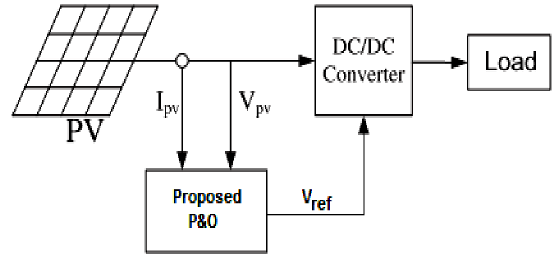


Fig. 10 block diagram of proposed P&O algorithm

3.2 Proposed MPPT Algorithm Based on ANN

A multi layer feed-forward neural network (MFFNN) will be used to track the MPP. The network is consists of three layers; input layer, hidden layer and output layer. The number of neurons in hidden layer will be determined by trial and error.

I. Input Selection of the NN

In our network, Two-input network with one neuron in output layer was chosen as the MPPT network. The network needs one output to show the value of reference output voltage to adjust the duty ratio (D) of the converter to track the MPP. The reference output voltage is dependent on solar irradiance (G) and cell temperature (T). The simulated cases are divided into three groups. The first is the training group and its patterns are selected randomly and normally distributed in order to make ANN to generalize and prevent skew learning. The second group is used to validate the ANN during the training process and the last one is the test group. Training and testing patterns are generated by simulating the PV model at different solar radiations, temperature and loads using MATLAB/SIMULINK. The training sets consist of 500 patterns. The block diagram of the proposed MFFNN with the booster converter is shown in figure 11.

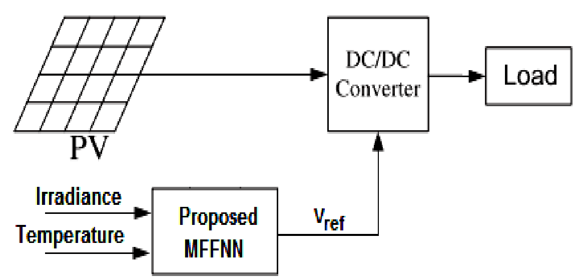


Fig. 11 block diagram of proposed MFFNN algorithm

III. The Structure and Training of ANN

Many different MFFNN structures, having 2-inputs and one output but with different number of neurons in their hidden layers were considered and trained. These networks were trained both with back propagation (Bp) and Marquardt-Levenberg (ML) algorithms. The criterion for determining the number of neurons in each hidden layers was based on a combined consideration of the training error (accuracy) and speed.

The program used for implementing the algorithm is developed by applying the MATLAB neural network toolbox. Several tests were performed to determine the optimum number of hidden neurons based on the mean square error (MSE) and number of training epochs. It was found that the network trained with ML algorithm provides better results compared with the results of the networks trained with the Bp algorithm. Moreover, different training functions were examined for convergence. The sigmoid transfer function is used for hidden and output layers. Table 2 shows some of these different networks.

Table 2. Comparison between different proposed MFFNN based MPPT

Network Structure	Epoch	MSE	Training time
2-3-2-1	35	0.462	10 sec
2-4-3-1	42	0.1412	15 sec
2-5-5-1	101	7.391E-5	45 sec
2-7-5-1	450	4.621E-5	03:15
2-10-7-1	260	8.233E-4	1:50

The network which showed satisfactory results, while not was having a big size had 7 neurons in first hidden layer, 5 neurons in second hidden layer. The proposed MFFNN structure of the MPPT is (2-7-5-1) as shown in figure 12. The output layer is capable to minimize the MSE of the MFFNN to a final value less than 4.621E-5 within 450 epochs. The MSE training error convergence diagrams for the MFFNN using "trainlm" training function is shown in figure 13.

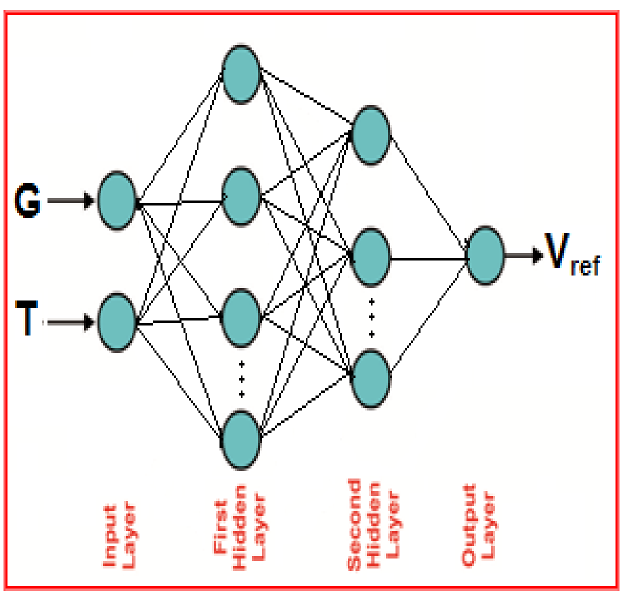


Fig.12 Structure of proposed MFFNN based MPPT

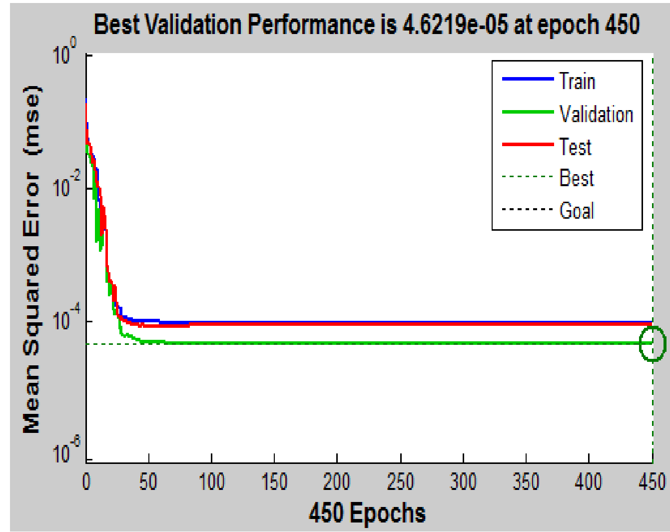


Fig.13 MSE Training Convergence of the MFFNN

4. Simulation and Results

The proposed MFFNN was trained off-line. Once the desired performance was achieved, the weights of the MFFNN were frozen. The proposed MFFNN and the developed P&O methods are tested with different irradiation test patterns as shown in figure 14.

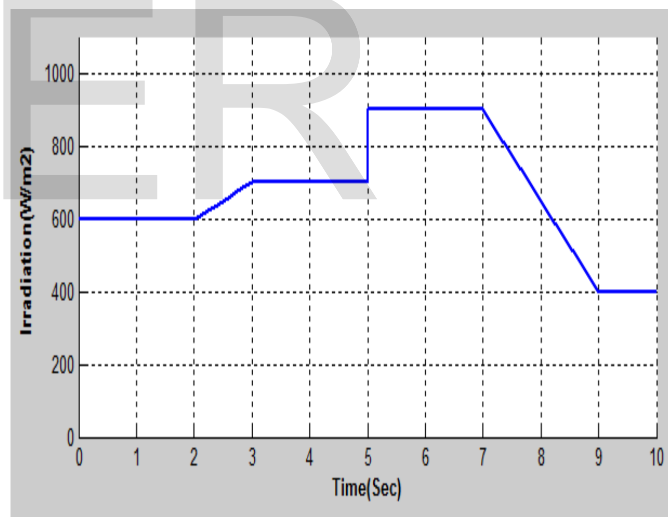


Fig.14 Variable test irradiation with respect to time

Figure 15 illustrates the predicted maximum power value by MFFNN compared to the calculated maximum power values by the developed P&O algorithm. The results show that the MFFNN predicts correctly the MPPT for all the studied cases and the MFFNN outputs are more stable under all different conditions and less oscillation. This clearly confirms the effectiveness and the speed of the proposed MFFNN method.

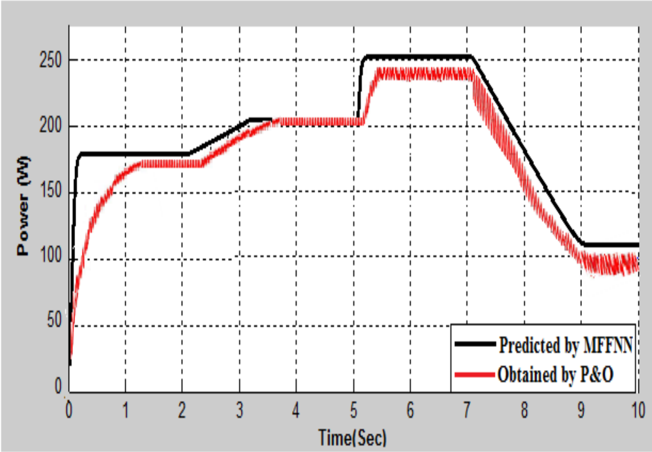


Fig. 15 Power tracking using proposed MFFNN and developed P&O method

5. Conclusion

This paper presents an improved approach for tracking the MPP algorithm for PV system under different weather conditions based on MFFNN and P&O techniques. The conventional P&O technique was developed by using variable perturb step. The performance of the developed P&O technique was validated in terms of tracking speed and efficiency using simulation studied. The response of the developed P&O algorithm become faster and the average tracking efficiency was increased. Also an efficient MFFNN based MPPT algorithm has been proposed in this paper. The results demonstrate the ability of MFFNNs to generalize the situation from the provided patterns and to accurately track the MPP. Its tracking performance was compared with the developed P&O method. The presented test results demonstrate the effectiveness and the speed of the proposed MFFNN under various solar radiations and temperature.

REFERENCES

[1] Q. Li and P. Wolfs, "A review of the Single Phase Photovoltaic Module Integrated Converter Topologies With Three Different DC Link Configurations," *IEEE Trans. on Power Electron.*, Vol. 23, no. 3, pp. 1320-1333, May 2008.

[2] E. Koutroulis, K. Kalaitzakis, N. Voulgaris, "Development of a Microcontroller Based Photovoltaic Maximum Power Point Tracking Control System," IEEE Trans. on Power Electron., Vol. 16, no. 1, pp. 46-54, January 2001.

[3] T. Esram and P. L. Chapman, "Comparison of Photovoltaic Array Maximum Power Point Tracking Techniques," IEEE Trans. Energy Convers., Vol. 22, no. 2, pp. 439–449, Jun. 2007.

[4] A. Reza Reisi, M. Hassan Moradi, 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.

[5] AK. Abdelsalam AM. Massoud, S. Ahmed, PN. Enjeti, "High-Performance Adaptive Perturb and Observe MPPT Technique for Photovoltaic-Based Micro-Grids," IEEE Trans. on Power Electronics Vol. 4, 2011.

[6] S. Zahra Mirbagheri, Saad Mekhilef, S. Mohsen Mirhassani," MPPT with Inc.Cond Method Using Conventional Interleaved Boost Converter." Energy Procedia, Vol. 42, PP. 24 – 32, 2013.

[7] DP. Hohm, ME. Ropp, "Comparative study of maximum power point tracking algorithm using an experimental, programmable, maximum power point tracking test bed," In: Proc 28th IEEE photovoltaic specialist conf; 2000.

[8] W. Swiegers, J. Enslin, "An integrated maximum power point tracker for photovoltaic panels," In: Proc IEEE int. symp ind. electron; 1998.

[9] Oshiro Masato, Tanaka Kenichi, Senjyu Tomonobu, Toma Shohei, Yona Atsushi, Saber Ashmed Yousuf, et al., "Optimal voltage control in distribution systems using PV generators," Int. J. Electr. Power Energy Syst. 2011; 33:485–92.

[10] A. Mellita, M. Benghanemb, S. Kalogirou, "Modeling and simulation of a stand-alone photovoltaic system using an adaptive artificial neural network," proposition for a new sizing procedure. Renew Energy 2007; 32.

[11] Ahmed M. Kassem," MPPT control design and performance improvements of a PV generator powered DC motor-pump system based on artificial neural networks," Electrical Power and Energy Systems, Vol. 43, PP. 90–98, 2012.

[12] K. Punitha, D. Devaraj, S. Sakthivel, "Artificial neural network based modified incremental conductance algorithm for maximum power point tracking in photovoltaic system under partial shading conditions," Energy Vol.62, PP 330-340, 2013.

[13] TL. Kottas, YS. Boutalis, AD. Karlis, "New maximum power point tracker for PV arrays using fuzzy controller in close cooperation with fuzzy cognitive network," IEEE Trans. Energy Convers. 2006; 21(3).

[14] Swati Singh, Lini Mathew, Shimi S.L." Design and Simulation of Intelligent Control MPPT Technique for PV Module Using MATLAB/ SIMSCAPE," International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, Issue 9, PP. 4554-4566, September 2013.

[15] N. Mazouz, A. Midoun, "Control of a DC/DC converter by fuzzy controller for a solar pumping system," Int J Electr Power Energy Syst. 2011;33:1623–30.

[16] D'Souza, N. S., Lopes, L.A.C., Liu, X., 2010, " Comparative study of variable size perturbation and observation maximum power point trackers for PV systems," Electric Power Systems Research 80, 296–305.

[17] E.A. Feilat and K. AI-Tallaq, "A New Approach for Distance Protection Using Artificial Neural Network," Developments in Power System Protection, Conference Puplication No. 479@ IEE 2001

[18] G. Ari, "Dynamic Modeling of Single Phase Grid Connected Photovoltaic System," University of Nevada, Las Vegas, May 2012.

[19] M. G. Villalva, J. R. Gazoli and E. R. Filho, "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays," IEEE Trans. on Power Electronics, Vol. 24, No. 5, MAY 2009.

[20] X. Wang, "The Research of the Stand-Alone Photovoltaic System and It's Maximum Power Point Tracking (MPPT)," Nanjing University of Aeronautics and Astronautics.

[21] C. Hua and C. Shen "Study of Maximum Power Tracking Techniques and control of DC/DC Converters for Photovoltaic Power System," IEEE, PESC, Vol.1, pp.86-93, 17-22 May 1998.

[22] J. L. Durán-Gómez, E. García-Cervantes, D. R. López-Flores, "Analysis and Evaluation of a Series-Combined Connected Boost and Buck-Boost DC-DC Converter for Photovoltaic Application," IEEE, pp 979-985, 19-23 March 2006.