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An Improved Maximum Power Point Tracking Controller for PV Systems Using Artificial Neural Network

***Abstract**. This paper presents an improved maximum power point tracking (MPPT) controller for PV systems. An Artificial Neural Network and the classical P&O algorithm were employed to achieve this objective. MATLAB models for a neural network, PV module, and the classical P&O algorithm are developed. However, the developed MPPT uses the ANN to predict the optimum voltage of the PV system in order to extract the maximum power point (MPP). The developed ANN has a feedback propagation configuration and it has four inputs which are solar radiation, ambient temperature, and the temperature coefficients of I_{SC} and V_{OC} of the modeled PV module. Meanwhile, the optimum voltage of the PV system is the output of the developed ANN. Based on the results; the response of the proposed MPPT controller is faster than the classical P&O algorithm. Moreover, the average tracking efficiency of the developed algorithm was 95.51% as compared to 85.99% of the classical P&O algorithm. Such developed controller increases the conversion efficiency of a PV system.*

***Streszczenie.** W artykule zaprezentowano ulepszony układ śledzenia maksymalnej mocy w systemie fotowoltaicznym. Zastosowano sieć neuronową i klasyczny algorytm P&O. Sieć neuronowa w sprzężeniu zwrotnym ma cztery wejścia: promieniowanie słoneczne, temperatura otoczenia i współczynniki temperaturowe I_{SC} i V_{oc}. Wyjściem jest optymalne napięcie systemu. (**Ulepszona metoda śledzenia maksymalnej mocy systemu fotowoltaicznego z wykorzystaniem sieci neuronowej**)*

Keywords: MPPT, PV systems, ANN, P&O algorithm.
Słowa kluczowe: system fotowoltaiczny, kontroler.

Introduction

Photovoltaic systems are one of the direct solar energy systems. Whereas, photovoltaic systems collect light from the sun and convert it to electricity. PV systems are clean whereas it reduces greenhouse gases, and it is non-polluting. However, the typical photovoltaic system is consisted of PV modules, DC-AC inverter, charger controller and batteries. In a PV system, the PV modules generate D.C electricity which is used to charge batteries through a charge controller. Meanwhile, inverters convert the D.C current to A.C current. However, the main drawbacks of PV systems are the capital cost and the dependence on climate conditions such as solar radiation and ambient temperature.

As a fact, each photovoltaic module has an optimum operation point, called maximum power point (MPP). This point varies depending on cell temperature, solar radiation, and load impedance. However, the MPPT is a power electronic device located between the PV modules and the loads, in order to ensure the maximum power operation.

Many methods proposed in the literature to track the MPP for a PV system. In [1] a MPPT is developed to avoid the oscillation in the classical P&O algorithm that compares only two points, which are the current operation and the subsequent perturbation point to observe their changes in power. Then, based on the difference in the output power the controller increase or decrease the PV module array output voltage. The authors of [1] developed an algorithm of three-point weight comparison, which runs periodically perturbing the solar array terminal points of the P-V curve. The three points are the current operation point A, a point B perturbed from point A, and a point C with doubly perturbed in the opposite direction from point B. If two points are positively weighted, the duty cycle of the converter must be increased. While, when two points are negatively weighted, the duty cycle of the converter should be decreased. In the other cases with one positive and one negative weighting, the MPP is reached or the solar radiation has changed rapidly and the duty cycle is not able to be changed. The authors of [1] claimed that the experimental test verified the tracking efficiency as well as avoided the oscillation in the classical P&O algorithm. In [2] a modified P&O based MPPT is presented to track the maximum power point of PV systems. The proposed algorithm is divided into two major parts; maximum power computation and direct power control of the power drawn from the PV module. The maximum power is computed online using a modified perturb and observe algorithm. The computed maximum power is compared with instantaneous actual PV power. Then, the error between the maximum power and the actual power is applied to a controller to drive the buck chopper of the PV system. In [3] an intelligent controller is used to extract the maximum power from the standalone PV system (SAPV) using genetic algorithm (GA). A feed forward neural network is trained using a set of solar radiation and temperature records to find the maximum voltage. The obtained voltage is compared with the PV array voltage and the error is applied to a PI controller. The output of the PI controller is compared to high frequency triangular wave, and this pulse is used to trigger the DC-DC converter to change the output voltage of the SAPV system. In [4] an optimization of the duty cycle of the triggering signal of the DC-DC converter is done. The main reason of this optimization is to extract the maximum power point from the PV module. Therefore, a theoretical analysis is proposed to customize the optimal choice of the duty cycle band width of the triggering signal of the DC-DC converter according to its dynamic behavior. In [5] an improved perturbation and observation (IP&O) algorithm is proposed. This algorithm automatically adjusts the reference step size of the PV voltage and the hysteresis bandwidth under rapidly atmospheric conditions change. However, a digital signal processor (DSP) was used to implement the proposed MPPT control system, whereas it controls the DC-DC boost converter in the 3kW grid-connected PV power system. The authors of [5] claimed that the dynamic response of the proposed (IP&O) algorithm was faster than the (P&O) algorithm. In [6] a modified MPP tracking algorithm using Artificial Neural Network is proposed. This algorithm aims to detect the atmospheric conditions variation in order to adjust the perturbation step for the next perturbation cycle. An ANN is used in predicting the power value during the next cycle of perturbation, the difference between the ANN output value and the measured value gives previous information about the atmospheric conditions evolution. As a result, the proposed algorithm was faster than classical P&O algorithm with a small oscillation around MPP. In [7] the incremental conductance (IC) technique is proposed to solve the drawbacks of P&O algorithm of a PV module. The proposed algorithm aims to deal with the cases of rapidly varying atmospheric conditions. The incremental conductance algorithm was developed on the fact that the array terminal voltage can always be adjusted towards the V_{max} value by comparing the incremental and the instantaneous conductance values of the PV array. However, a mathematical model was used to simulate the PV array in the evaluation of the algorithm performance under randomly varying atmospheric conditions. As a result, both simulation and experimental results showed that the developed incremental conductance based MPPT algorithm efficiency is about 90%.

The main objective of this paper is to present an improved P&O based MPPT in order to increase the tracking response and consequently increase the tracking efficiency. This work was done based on metrological records (solar radiation and ambient temperature) provided by Solar Energy Research Institute (SERI), University Kebangsaan Malaysia (UKM).

Modeling of PV Cell and PV module

Figure (1) shows the equivalent circuit of photovoltaic cell. The output current Ipv can be described as follows [8].

(1) $$I_{pv} = I_{sc} - I_d$$

(2) $$I_d = I_o\left\{\exp\left[\frac{V_{pv} + R_s I_{pv}}{V_T}\right] - 1\right\} - \left\{\frac{V_{pv} + R_s I_{pv}}{R_p}\right\}$$

Where $V_T = (KT/q)$ is the thermal voltage, q is the electron charge, K is Boltzmann constant, T (Kelvin) is the temperature of the cell, R_s is the series resistance of a solar module, and R_p its shunt resistance.

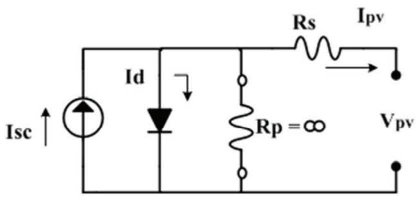

Fig. 1 Equivalent circuit of PV cell

The series resistance (R_s) indicates the losses of the solar cell, while the shunt resistance (R_p) is to represent the reverses current of the diode. However, in this research the R_p will be supposed infinite thus equation (2) will be;

(3) $$I_d = I_o\left\{\exp\left[\frac{V_{pv} + R_s I_{pv}}{V_T}\right] - 1\right\}$$

As for the model of a PV module, it can be described by the two following equations,

(4) $$I_{pv\,module} = N_p I_{pv}$$

(5) $$V_{pv\,module} = N_s V_{pv}$$

Where Ipvmodule and Vpvmodule are the PV module output current and voltage. Meanwhile N_p and N_s are the number of PV cells in parallel and the number of PV cells in series respectively.

Figures (2) and (3) show the I-V and P-V characteristic curves of a PV module respectively. The most important points on the I-V characteristic curve of a PV module are the short-circuit current I_{sc} , the open-circuit voltage V_{oc} , and the maximum power point. However, Figure (2) shows I-V characteristics of a PV module for different values of solar radiation and temperature respectively. From figure (2.a), it is clear that the current of the PV module increased linearly by increasing the solar energy, while the voltage of the PV module increased in a logarithmic pattern as the solar radiation increases. From figure (2.b), the voltage of the PV module decreases as far as the ambient temperature value increases, while the current of the PV increases in logarithmic pattern by the decrease in the ambient temperature [9].

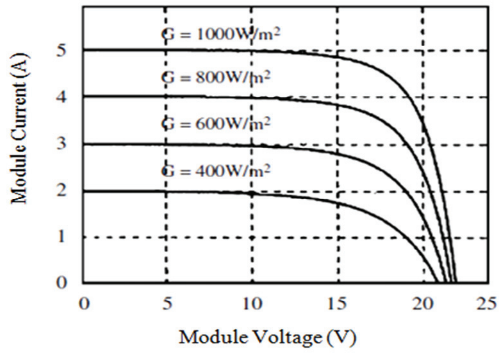

Fig 2.a solar radiationinfluence on the I-V characteristic

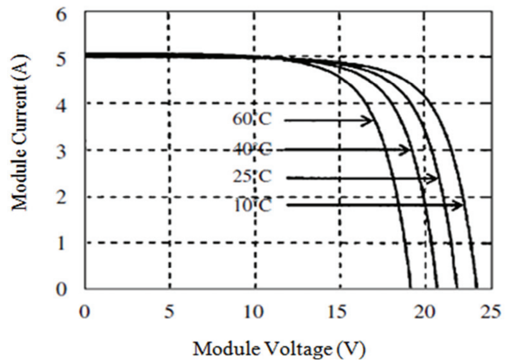

Fig 2.b ambient temperature influence on the I-V characteristic

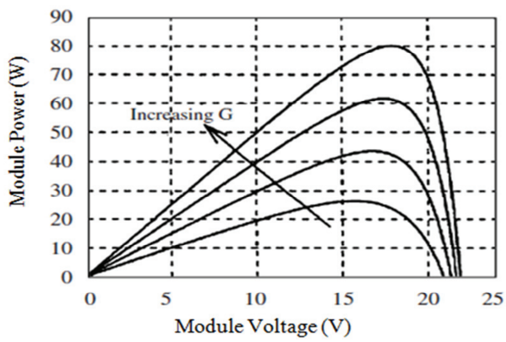

Fig 3.a solar radiation influence on the P-V characteristic

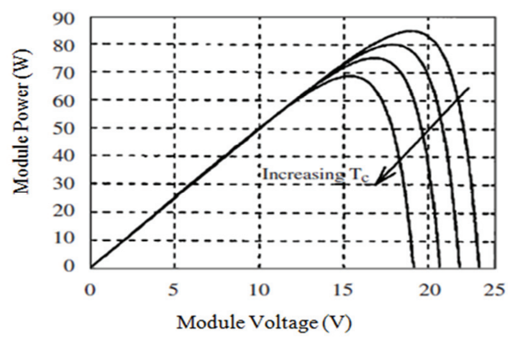

Fig 3.b ambient temperatureinfluence on the P-V characteristic

Figure (3) shows the P-V characteristic of the PV module. From figure (3.a), it is noted that the power of the PV module increases as the solar radiation value increased. Besides that, figure (3.b) shows that the voltage of the PV module decreases as the ambient temperature value decreased.

The effect of solar energy and the ambient temperature on a PV module output voltage and current can be described mathematically as follows [8].

(6) $$I_{sc} = I_{sc}^{*}\left(\frac{G}{G^{*}}\right) + \alpha i\left(T - T^{*}\right)$$

(7) $$V_{oc} = V_{oc}^{*} + \alpha v\left(T - T^{*}\right) - \left(I_{sc} - I_{sc}^{*}\right)$$

Where I_{sc}^{*} is short-circuit current of the PV module at the reference solar radiation **(**$G^{*} = 1000\ W/m^{2}$**)**, V_{oc}^{*} is the open-circuit voltage at the reference temperature ($T^{*} = 25\ c^{\circ}$**)**, αi is the temperature coefficient of I_{sc} **,** and αv is the temperature coefficient of V_{oc} **.**

The maximum power point (MPP) of a PV cell depends on three factors; solar radiation, load impedance, and ambient temperature. When a PV generator is directly connected to the load, the system will be operated at the intersection of the I-V curve and the load line, which may be far from the maximum power point (MPP). Therefore, the maximum power point operation is based on the load impedance adjustment under the varying of atmospheric conditions [10], as shown in figure (4). However, to adapt the load resistance and extract maximum power from a PV module, DC-DC converter is used by set the duty cycle of its triggering signal. Therefore, to determine the optimum power from a PV system, it is necessary to take into account the optimum voltage V_{op} and the optimum current I_{op} which are given by [9].

(8) $$V_{optimum} = K_{v} V_{oc}$$

(9) $$I_{optimum} = K_{i} I_{sc}$$

Where K_v and K_i are proportional factors with typical values in the ranges of (0.75-0.85) and (0.9-0.92) respectively.

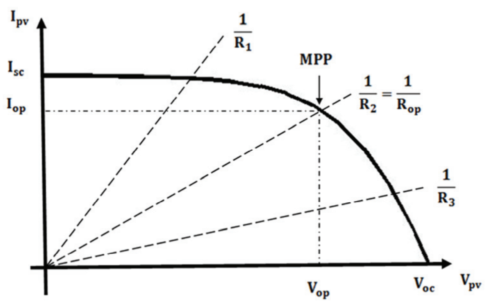

Fig. 4 PV system operating points with varying loads

Classical P&O algorithm

The P&O algorithm is most commonly used in PV systems applications due to its ease of implementation and simplicity. It is an iterative method for obtaining MPP. Whereas, it measures a PV module current and voltage, then perturbs the operating point of a PV module to encounter the change direction. Figure (5) shows the flow chart of the classical P&O algorithm. As a fact, when dP_{pv}/dV_{pv} = 0 then the maximum power point of a PV module will reach a maximum value. From that, it's necessary to measure the instantaneous values of a PV module current $I_{pv}(t_1)$ and voltage $V_{pv}(t_1)$. At the same time, measure the previous situation of the current $I_{pv}(t_1 - 1)$ and the voltage $V_{pv}(t_1 - 1)$ so as to calculate the power of a PV module at both cases. After that, the changing of ΔP_{pv} is measured to check whatever positive or negative. If ΔP_{pv} is greater than zero, the perturbation of the operating voltage should be in the same direction of the increment. Otherwise, the operating point obtained of the PV module moves away from the MPPT and the operating voltage should be in the decrement direction [11].

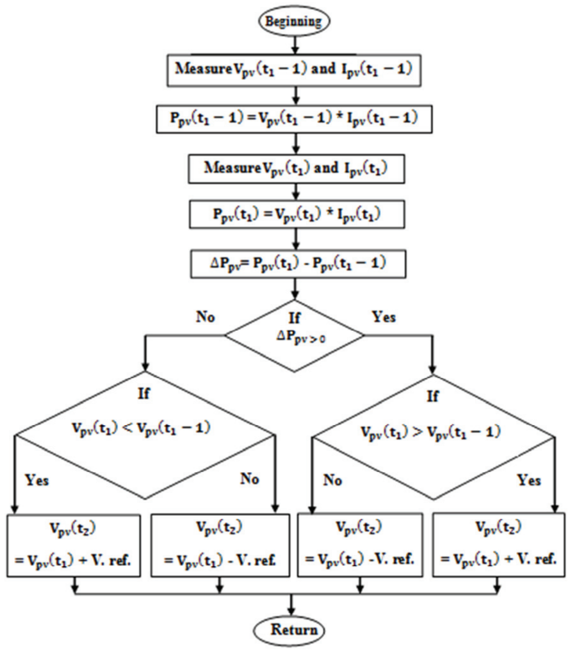

Fig 5 Flow chart of Classical P&O algorithm

The main problem of this method can be seen when atmospheric conditions (mainly solar radiation) rapidly change [7]. In addition, P&O techniques may caused many oscillation around the MPP, and this slows down the response of the system

The proposed MPPT System

Figure (6) shows the proposed PV system, which is consisted of a PV module, boost DC-DC converter, controller, and load. A feedback propagation artificial neural network based controller is used to predict the instantiations optimum voltage Voptimum of the PV system in order to ensure the maximum power operation.

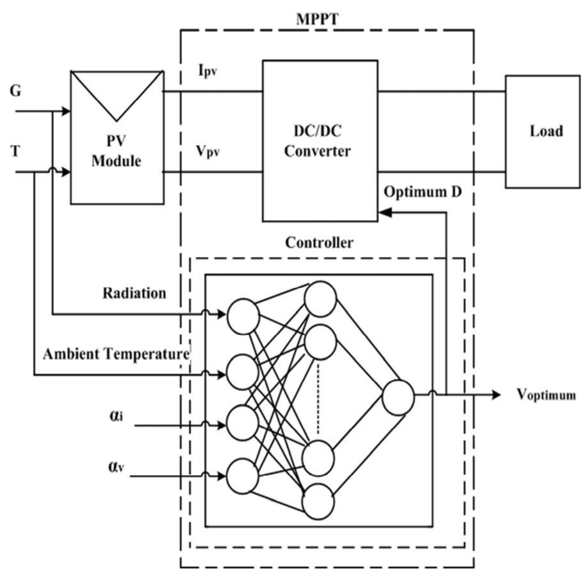

Fig. 6 Proposed MPPT system

In practice, to extract the maximum power point from the PV module corresponding with a load resistance, a boost converter is used. A boost converter is a power converter with an output DC voltage greater than its input DC voltage. It is a class of switching-mode power supply containing at least two semiconductor switches (uncontrolled and controlled switches like a diode and a transistor respectively) and at least one energy storage element. In addition, a capacitor is often added to the converter output to reduce the ripple of its output voltage [12]. The following equation describes the relation between the input and the output voltage of a boost DC-DC converter as a function of the duty cycle. In this research the output voltage is supposed to be the PV output voltage (V_{pv}) while the input voltage is supposed to be the optimum voltage ($V_{pv\ optimum}$) of the PV module.

(10) $$\frac{V_{pv}}{V_{pv_{optimum}}} = \frac{1}{D}$$

Proposed ANN using classical P&O algorithm

A neural network is an artificial representation of the human body that tries to simulate its learning process. In other words, ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. However, the advantage of using ANN here is to make the response of the proposed MPPT is faster than the classical P&O algorithm in order to increase the tracking efficiency. To do so an ANN has been developed using MATLAB and trained using solar radiation and ambient temperature records. The developed ANN aims to predict the instantaneous optimum voltage of a PV module/ Array by obtaining the instantaneous solar radiation and ambient temperature.

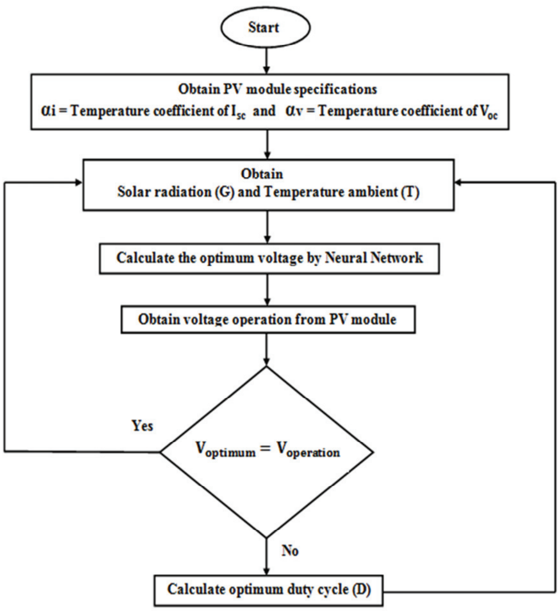

Fig 7 proposed algorithm

The classical P&O algorithm and a model for PV module were modeled using MATLAB and used to calculate the maximum voltage(V_{mp}) for set values of solar radiation and temperature. Then, the obtained optimum voltages set was as supposed the target of proposed ANN while the used solar radiation and ambient temperature data and the temperature coefficients of the modeled PV module were supposed as the inputs of the developed ANN. However, in this research Levenberg-Marquardt backpropagation function is used to train the developed ANN using the supposed inputs and targets. The proposed ANN has three layers; input layer, hidden layer and output layer as shown above in figure (6). The input layer has 4 neurons which are solar radiation G (W/m^2), ambient temperature T (C°), temperature coefficient of I_{sc} , and the temperature coefficient of V_{oc} . Meanwhile, the output layer is the predicted optimum voltage, which is supposed to be applied to the DC-DC boost converter.

Figure (7) shows the proposed ANN algorithm. The algorithm starts by obtaining solar radiation and ambient temperature, and then the optimum voltage is predicted using the developed ANN. Here, a comparison between the predicted optimum voltage and the operating voltage is done to find whatever the system is optimally operated or not. Eventually, and in the case of non optimal operation the optimum duty cycle is calculated using the predicted voltage using equation (10).

Simulation Results and Discussion

Evaluating the proposed ANN

To evaluate the proposed neural network three error statistics are used. These statistics are mean absolute percentage error (MAPE), mean bias error (MBE), and root mean square error (RMSE). MAPE is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage, and is defined by the formula:

(11) $$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{I - I_p}{I}$$

where I is the actual value and I_p is the forecast value. The difference between I and I_p is divided by the actual value I again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted points (n). This makes it a percentage error so one can compare the error of fitted time series that differ in level.

In addition, Most ANN models being evaluated quantitatively and ascertain whether there is any underlying trend in the performance of the ANN models in different climates using MBE and RMSE. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on the long term performance of the models. A positive MBE value indicates the amount of overestimation in the predicted global solar radiation and vice versa. On the other hand, RMSE provides information on the short term performance and is a measure of the variation of predicted values around the measured data. It indicates the scattering of data around the linear lines. Moreover, RMES shows the efficiency of the developed network in predicting a future individual values, large positive RMES means big deviation in the predicted value from the real one. However, MBE and RMSE are given as follows:

(12) $$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(I_{pi} - I_i\right)$$

(13) $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_{pi} - I_i\right)^2}$$

where I_{P_i} is the predicted value, I_i is the measured value and n is the number of observations

In this research 1500 values of solar radiation and temperature were used to train, validate and test the proposed ANN. These data is divided into two parts; 1300 values for training and 200 values for testing. However, the MAPE, RMSE and MBE values for the developed ANN are 0.16%, 0.0774 (0.32%) and -0.0369(0.15%). These values ensure the accuracy of the developed network as well as the ability of the network to predict a future value with slight over/under estimation.

Figure (8) shows the predicted optimum voltage values compared to the calculated optimum voltage values by the classical P&O method. The obtained results were for 200 solar energy and ambient temperature records. However, from the figure the prediction accuracy is acceptable.

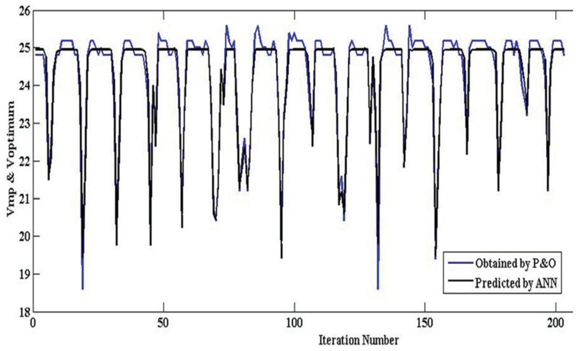

Fig 8 Simulated waveforms of maximum voltage and predicted voltage

Evaluation of the proposed PV system

The simulation results of the PV system using an Artificial Neural Network and Classical P&O algorithm are discussed in this section. Figure (9) compares the obtained P-V characteristics of the PV module from using the classical P&O algorithm and the proposed ANN algorithm. From the figure, it is shown that by using the proposed ANN algorithm, the location of the maximum power point (MPP) of the PV module is the nearest to the theoretical power as compared to the classical P&O algorithm.

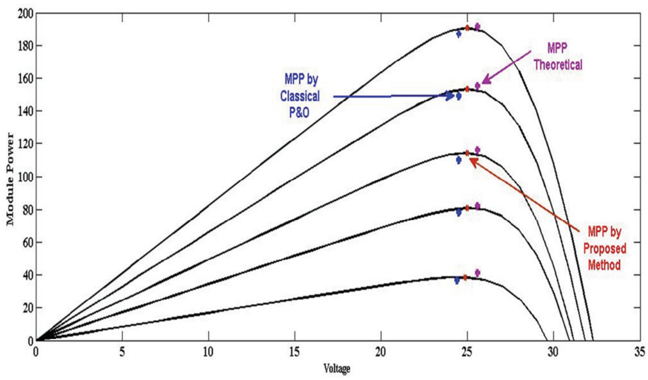

Fig 9 Comparing P-V characteristics

To evaluate the performance of the proposed system, a comparison between the classical P&O algorithm and the proposed ANN algorithm is carried out for a set of solar radiation and the results are plotted in figure (10). From this figure, it is noted that the power of the proposed algorithm is higher than the classical P&O algorithm.

In terms of an efficiency, the efficiency of classical P&O algorithm is calculated by dividing the obtained power by the theoretical maximum power of PV module, while the efficiency of the proposed algorithm is obtained by dividing the predicted power by the theoretical maximum power of PV module. According to the results, the tracking efficiency of proposed algorithm is not less than 92% as compared to using the classical P&O algorithm as shown in figure (11). Therefore, the proposed ANN algorithm is efficient under different values of solar radiation.

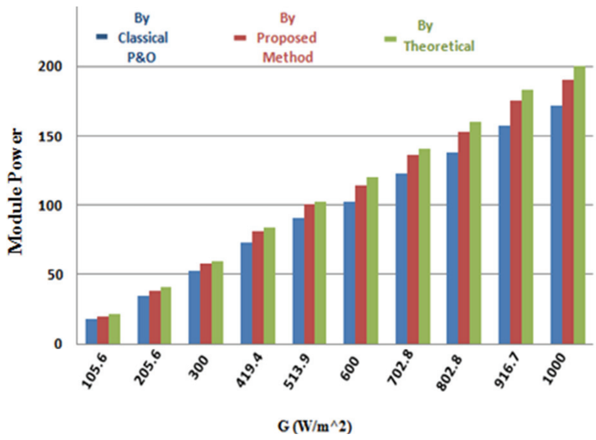

Fig 10 Comparing PV module powers

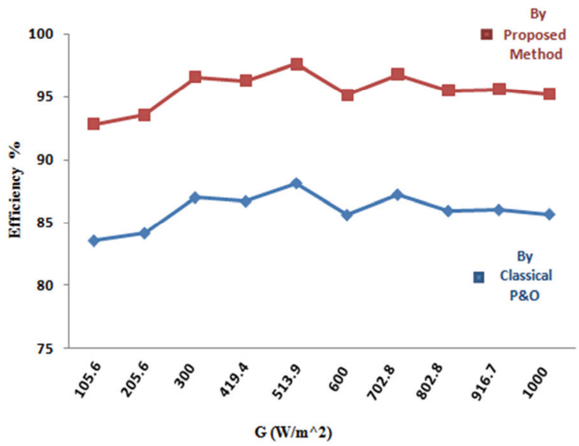

Fig 11 Comparing efficiency of PV system

Finally, TIC and TOC functions are used to determine the CPU time (elapsed time) needed to calculate the optimum voltage by the proposed MPPT algorithm and the classical P&O algorithm whereas the TIC is called before the program and the TOC afterwards. As a result, the execution time of the proposed algorithm is 4.98 second to calculate the optimum value of the voltage as compared to using the classical P&O algorithm. Meanwhile the execution time of the classical P&O algorithm is 9.7 second, this to say that the improved algorithm is faster than the classical P&O method.

Conclusion

An improved MPPT algorithm has been proposed in this research. An Artificial Neural Network and the classical P&O algorithm were employed to achieve this objective. MATLAB models for the used neural network, the PV module, the classical P&O algorithm are developed. The improved MPPT algorithm extracts the maximum power point from the PV module corresponding with a load resistance in terms of solar radiation and ambient temperature. Simulation results showed that the response of the improved MPPT algorithm was faster than the classical P&O algorithm. Moreover, the average tracking efficiency of the developed algorithm was higher than the classical P&O algorithm.

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