

A comparative study of artificial intelligent-based maximum power point tracking for photovoltaic systems

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Abstract. Maximum power point tracking (MPPT) is normally required to improve the performance of photovoltaic (PV) systems. This paper presents artificial intelligent-based maximum power point tracking (AI-MPPT) by considering three artificial intelligent techniques, namely, artificial neural network (ANN), adaptive neuro fuzzy inference system with seven triangular fuzzy sets (7-tri), and adaptive neuro fuzzy inference system with seven gbell fuzzy sets. The AI-MPPT is designed for the 25 SolarTIFSTF-120P6 PV panels, with the capacity of 3 kW peak. A complete PV system is modelled using 300,000 data samples and simulated in the MATLAB/SIMULINK. The AI-MPPT has been tested under real environmental conditions for two days from 8 am to 18 pm. The results showed that the ANN based MPPT gives the most accurate performance and then followed by the 7-tri-based MPPT.

1. Introduction

Photovoltaic (PV) is considered a widely used renewable energy (RE) source because it is free, clean, and environmental friendly [1]. PV system may be installed in the form of stand-alone and grid-connected systems [2]. The drawbacks of a PV system are that it exhibits intermittent power generation under varying weather conditions and the amount of generated power from a solar cell depends on the nonlinear current–voltage (I–V) and power–voltage (P–V) characteristics, which vary with irradiance and temperature. However, there is a unique point on the P–V curve which is the maximum power point (MPP). To increase the performance of PV systems, it is crucial to operate near to the MPP [3].

Many MPPT algorithms have been developed such as the conventional MPPT techniques which include the incremental conductance (IC), perturb and observe (P&O), and constant voltage (CV) techniques [4]. The P&O technique has been widely utilized because of its simple control algorithm and minimal number of input parameters. However, the disadvantage of the P&O technique is that enormous oscillation is exhibited in the region of MPP and such oscillation leads to a certain loss in power. The IC technique can somehow eliminate oscillations in the region of MPP [5] but it requires accurate sensors for measuring either the voltage or current.

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Recently, AI based-MPPT has been applied because it is robust and easily adapted to complex systems without the need of a mathematical model [6]. In this paper, a comparative study for three AI-based MPPT is made for a PV system by considering three artificial intelligent techniques, namely, artificial neural network (ANN), adaptive neuro fuzzy inference system with seven triangular fuzzy sets (7-tri), and adaptive neuro fuzzy inference system with seven gbell fuzzy sets (7-gbell).

2. PV modelling

The equivalent electrical circuit of a PV cell shown in Figure 1 can be utilized to obtain the characteristics of a PV cell. From the mathematical model of the circuit, the output of the cell current (I), can be expressed as [7]:

$$I = I_{ph} - I_o \left(e^{\left(\frac{q(V+IR_s)}{n.K_B.T} \right)} - 1 \right) - \frac{V + I + R_s}{R_{sh}} \quad (1)$$

where I is the cell output current, I_{ph} is the light-generated current, I_o is the cell reverse saturation current or dark current, q is the electronic charge (1.6×10^{-19} C), V is the cell output voltage, R_s is the series resistance, n is the ideality factor, K_b is the Boltzmann's constant (1.38×10^{-23} J/K), T is the cell temperature (K), and R_{sh} is the shunt resistance.

The I_{ph} can be calculated as:

$$I_{ph} = [I_{sc,n} + \alpha(T - T_n)] \frac{G}{G_n} \quad (2)$$

where $I_{sc,n}$ short-circuit current at the nominal condition, α is short-circuit current temperature coefficient, T_n is nominal temperature, G is irradiance, and, G_n is the nominal irradiance.

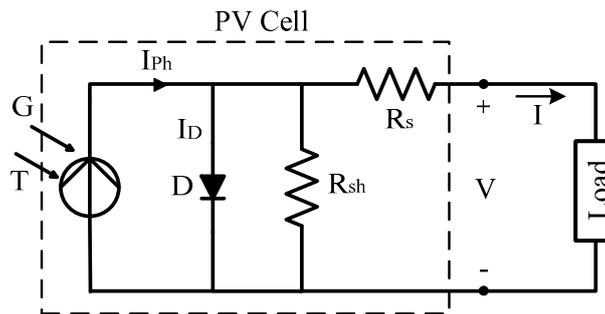


Figure 1. Equivalent electrical circuit of a PV cell

3. Artificial intelligent based-MPPT

Three AI based-MPPT techniques are used in this study, namely, ANN, adaptive neuro fuzzy inference system (ANFIS) with seven triangular fuzzy sets (7-tri), and ANFIS with seven gbell fuzzy sets (7-gbell). ANN is a distributed processing system consisting of neurons which are simple connected elements. The ANN model considered in this study is the multi-layer feedforward model with back propagation (BP) algorithm. The ANN model consists of three layers, namely, the input, hidden, and output layers with 2, 20 and 1 neurons, respectively. The ANFIS considered in this study uses a fuzzy inference system model to transform a given input into a target output.

Since electric power is the product of current and voltage, therefore a power-voltage (P-V) characteristic curve of a solar cell can be obtained for a given radiation level as shown in Figure 2. However, there is one particular point at which the solar cell can deliver maximum power for a given radiation intensity, and this operating point is the maximum power point (MPP). From Equations (1) and (2), the cell output current is shown to be nonlinear and dependent on irradiation and temperature. These equations can be used to calculate reference current (I_{MPP}) which eventually provides MPP by considering the cell output voltage.

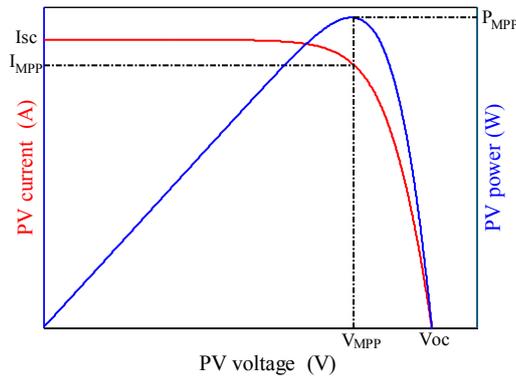


Figure 2. Current-Voltage (I-V) and Power-Voltage (P-V) characteristic curves of a solar cell

In this work, 300,000 input data samples which correspond to G and T have been generated using the following equations (3) and (4).

$$G_i = rand * (G_{max} - G_{min}) + G_{min} \quad (3)$$

$$T_i = rand * (T_{max} - T_{min}) + T_{min} \quad (4)$$

where i from 1 to 300,000. The minimum and maximum limits for the G and T are selected based on the historical data. In Malaysia, G typically varies between 0 to 1200 W/m^2 , while the T fluctuates in the range of 20 to $40 \text{ }^\circ\text{C}$. Therefore G_{min} , G_{max} , T_{min} , and T_{max} in (3) and (4), are chosen as 0, 1500 W/m^2 , 0, and $45 \text{ }^\circ\text{C}$, respectively so as to ensure that the generated data covers the typical data range.

4. Results and Discussion

In this study, 25 SolarTIFSTF-120P6 PV modules were employed to supply a 3 kW peak. The modules were arranged in series-connected configuration to produce a DC output voltage of 435 V. To evaluate the performance of the developed AI-based MPPT, field input data, namely, G and T , were collected from Universiti Kebangsaan Malaysia on the 9th and 10th of August 2014, from 8 am to 6 pm at a sampling rate of 30 s. The goal is to compare the performance of the three developed AI-based MPPT under the same strict conditions. Data acquisition was performed with the HOBOWarePro. Figures 3 and 4 show the meteorological conditions (G and T) and the output maximum electrical power registered from the developed AI-based MPPT for the studied cases.

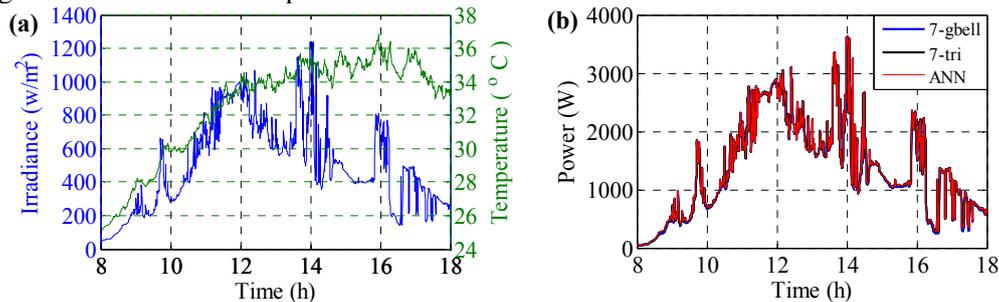


Figure 3. Metrological conditions (a) and extracted electrical power (b) on 9th of August 2014

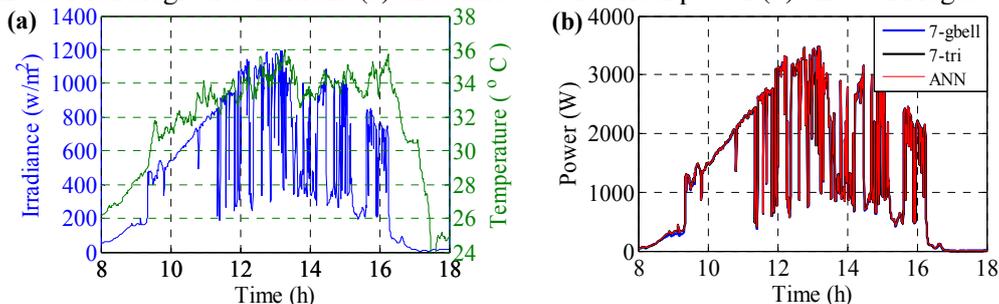


Figure 4. Metrological conditions (a) and extracted electrical power (b) on 10th of August 2014.

To evaluate the performance of the developed AI-based MPP trackers, three indices are used, namely, standard deviation (SD) for the error, mean absolute error (MAE), and correlation (R^2) using the q-q plot. The comparison of results is shown in Table 1. A low SD indicates that the data points tend to be very close to the mean, whereas a high SD indicates that the data points are spread out over a large range of values. The best performance is boldfaced. Table 1 clearly shows that the ANN based MPP tracker performs better than the other two ANFIS-based MPP tracker in terms of SD. For the second index, MAE, the decrease in its value mean the output is moving closer to the MPP. In terms of MAE values, the ANN based MPP tracker performs better than the ANFIS-based MPP tracker as depicted in Table 1. A statistical analysis was conducted to calculate the correlation (R^2) using the q-quantile (q-q) plots for two days. The q-q plot is an exploratory graphical method to ensure the validity of a distributional assumption for a set of data. When the data deviate from the assumed distribution, the points on the q-q plot fall on a straight line. As shown in Table 1, the ANN-based MPPT and 7-tri based MPPT perform better than the 7-gbell based MPPT which achieved $R^2=1$.

Table1. Performance indicators of the three AI-based MPP trackers.

Experiment data	Standard deviation (SD)			Mean absolute error (MAE)			Correlation (R^2)		
	7-gbell	7-tri	ANN	7-gbell	7-tri	ANN	7-gbell	7-tri	ANN
9 th of August	11.6390	1.14178	0.04199	10.2166	0.37268	0.01735	0.9997	1	1
10 th of August	11.7489	2.72587	0.08046	7.49826	1.42912	0.03517	0.9998	1	1

5. Conclusion

Three AI-based MPP trackers using ANN, ANFIS with seven triangular fuzzy sets (7-tri), and ANFIS with seven gbell fuzzy sets for a PV system were developed and the performances were evaluated using SD, MAE and correlation (R^2). Actual field data were used to measure the performance indices. Based on the results, the ANN-based MPP tracker is found to perform better than the two ANFIS-based MPP tracker in which it gives the lowest SD and MAE. A comparative analysis based on R^2 value reveals that the ANN and ANFIS with 7-tri achieved a robust correlation, which is ($R^2=1$).

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