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A new MATLAB/Simulink model of triple-junction solar cell and MPPT based on artificial neural networks for photovoltaic energy systems

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Abstract This paper presents a new Matlab/Simulink model of a PV module and a maximum power point tracking (MPPT) system for high efficiency InGaP/InGaAs/Ge triple-junction solar cell. The proposed technique is based on Artificial Neural Network. The equivalent circuit model of the triple-junction solar cell includes the parameters of each sub-cell. It is also include the effect of the temperature variations on the energy gap of each sub-cell as well as the diode reverse saturation currents. The implementation of a PV model is based on the triple-junction solar cell in the form of masked block in Matlab/Simulink software package that has a user-friendly icon and dialog. It is fast and accurate technique to follow the maximum power point. The simulation results of the proposed MPPT technique are compared with Perturb and Observe MPPT technique. The output power and energy of the proposed technique are higher than that of the Perturb and Observe MPPT technique. The proposed technique increases the output energy per day for a one PV module from 3.37 kW h to 3.75 kW h, i.e. a percentage of 11.28%.

1. Introduction

Fueled by the advance in semiconductor technology, solar cells are one of the most promising candidates for alternate energy sources. Photovoltaic (PV) system is a green power source that converts sunlight to electricity. It has many applications as in space satellites and orbital stations, solar vehicles, power supply for loads in remote areas, and street lighting systems [1].

Motivated by superior performance and high efficiency, multi-junction solar cells have received much attention in the concentrated solar cell systems due to their ultimate feathers. A multi-junction solar cells used in concentrated PV systems are different from silicon PV cells as they are capable of converting very large amounts of sunlight into energy at high efficiency [1]. Multi-junction solar cells have high conversion efficiency with a record value of more than 40% [2].

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PV module represents the fundamental power conversion unit of a photovoltaic system. The output characteristics of PV module depend on the solar radiation, cell temperature and output voltage of PV module. Since a PV module has non-linear characteristics, it is necessary to model it for the design and simulation of a maximum power point tracking (MPPT) for PV system applications [3]. In order to get a maximum output power form the solar cells, a maximum power point tracker system is highly recommended. The output power delivered by a PV module can be maximized using MPPT control system. It consists of a power conditioner to interface the PV output to the load, and a control unit, which drives the power conditioner for extracting the maximum power from a PV array [4].

Many research efforts on MPPT have developed. Among these, Yusivar, and Tito [5] proposed a MPPT technique based on PI controller with error feedback in order to get a fast tracking time. Matsumoto et al. [6] illustrated MPPT a system using boost converter for ultra-low input voltage. Askarzadeh and Rezazadeh [7] proposed MPPT using bird mating optimizer-based parameters identification approach. However, there is a need for fast and accurate MPPT technique to follow the maximum power point of PV module. This paper proposes a software implementation of the maximum power point tracking solar cell system using artificial neural networks (ANN). An ANN based-tracker can handle these requirements because of its accuracy and fast performance [8]. The PV model based on a multi-junction solar cell is implemented in the Matlab/Simulink software package in the same way of Matlab block libraries or other component-based electronics simulation software packages.

This paper is organized as follows. Section 2 describes equivalent circuit of an InGaP/InGaAs/Ge triple-junction solar cell, modeling of boost converter and artificial neural network MPPT. Simulation results are illustrated in Section 3. Finally, conclusions are given in Section 4.

2. Modeling of the proposed PV system

The simulation of the proposed PV system has been carried out using MPPT based on artificial neural network. Also, for a comparison purpose, the Perturb and Observe (P&O) is also addressed. ANN based-tracker has been used to identify the value of the current (I_{mpp}) that gives a maximum power point. Simulation of the proposed PV system has been implemented using MATLAB/Simulink program that includes the proposed system sub-models explained in the following sections:

2.1. Equivalent circuit of an InGaP/InGaAs/Ge triple-junction solar cell

Triple junction InGaP/InGaAs/Ge solar cell consists of InGaP, InGaAs, and Ge subcells as shown in Fig. 1. The sub-cells are constructed with decreased energy gaps from the top to the bottom. This structure minimizes the losses due to thermalization of hot carriers and transmission of low energy photons that increases the solar energy converted into electricity more efficiently than single-junction cells [9]. Multi-junction InGaP/InGaAs/Ge solar cells are known to have an ultrahigh efficiency and are now used for space applications [10].

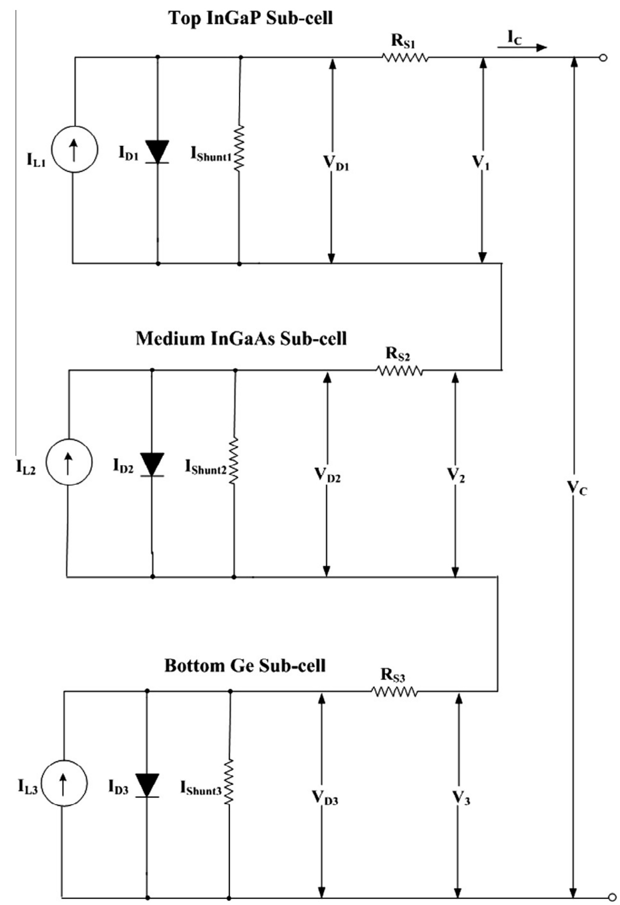

Figure 1 Equivalent circuit model of triple-junction solar cell.

Referring to Fig. 1, the solar cell current can be expressed as

$$I_C = I_{Li} - I_{Di} - I_{shunti} \tag{1}$$

where $i = 1$ for top sub-cell, $i = 2$ for medium sub-cell, and $i = 3$ for bottom sub-cell.

The light generated current is given by [3]

$$I_{L_i} = RK_C[I_{sc_i} + a(T_c - T_{c,\mathrm{ref}})] \tag{2}$$

where $T_{c,\mathrm{ref}}$ is the reference temperature in °C, a is the temperature coefficient of the short circuit current in A/°C, K_C is the concentration ratio, and R is the solar radiation in kW m^2.

The diode current is given by [10]

$$I_{Di} = I_{Oi}\left[\exp\left(\frac{qV_{Di}}{n_i K_B T}\right) - 1\right] \tag{3}$$

$$V_{Di} = V_i + I_C \times R_{Si} \tag{4}$$

$$I_{Oi} = K_i \times T^{(3+\gamma_i/2)}\left[\exp\left(-\frac{E_{gi}}{n_i K_B T}\right)\right] \tag{5}$$

where q is the electron charge, n_i is the diode ideality factor, K_B is the Boltzmann's constant, E_g is the bandgap energy, K and γ are constants, T is the absolute temperature, and R_S is the cell series resistance.

The bandgap energy (E_g) is effected by the temperature. The variation of the bandgap energy with the temperature can be expressed as [11]:

$$E_g(T) = E_g(0) + \frac{\alpha T^2}{T + \beta} \tag{6}$$

If the shunt resistance is big enough, the shunt current can be neglected [10]. Substituting (3)–(5) in (1) gives:

$$I_C = I_{L1} - I_{D1} - I_{shunt1} = I_{L2} - I_{D2} - I_{shunt2} = I_{L3} - I_{D3} - I_{shunt3} \tag{7}$$

The output voltage of the cell, V_C, is given by

$$V_C = V_1 + V_2 + V_3 \tag{8}$$

Neglecting the shunt current, the voltage V_1, V_2, and V_3 can be expressed as:

$$V_1 = \frac{n_1 K_B T}{q} \ln\left[\frac{I_{L1} - I_C}{I_{O1}} + 1\right] - I_C \times R_{S1} \tag{9}$$

$$V_2 = \frac{n_2 K_B T}{q} \ln\left[\frac{I_{L2} - I_C}{I_{O2}} + 1\right] - I_C \times R_{S2} \tag{10}$$

$$V_3 = \frac{n_3 K_B T}{q} \ln\left[\frac{I_{L3} - I_C}{I_{O3}} + 1\right] - I_C \times R_{S3} \tag{11}$$

Substitute (9)–(11) in (8) gives:

$$V_C = \frac{n_1 K_B T}{q} \ln\left[\frac{I_{L1} - I_C}{I_{O1}} + 1\right] + \frac{n_2 K_B T}{q} \ln\left[\frac{I_{L2} - I_C}{I_{O2}} + 1\right] + \frac{n_3 K_B T}{q} \ln\left[\frac{I_{L3} - I_C}{I_{O3}} + 1\right] - I_C \times R_S \tag{12}$$

where;

$$R_S = R_{S1} + R_{S2} + R_{S3} \tag{13}$$

2.2. Modeling of DC–DC boost converter

The input power for the boost converter comes from the PV array outputs that are connected to battery storage. A boost converter is a DC to DC converter with an output voltage greater than the source voltage. It is sometimes called a step-up converter since it "steps up" the source voltage. The Simulink of a mathematical model of a boost converter was addressed in [8,12]. The voltage transfer function of a boost converter is expressed by the following:

$$V_i = V_b(1 - D) \tag{14}$$

where V_i is the terminal voltage of PV module, V_b is the battery voltage, and D is the duty cycle.

2.3. Artificial neural network MPPT

To minimize the energy cost figure of PV system, it is necessary to extract as much available energy as possible from the solar cell. So it is preferable to operate the PV system at the MPP through the sunshine hours. The output generated power from the PV module is changing with the operating voltage and current at each value of the radiation and temperature. A maximum power point tracker is used to track the point at which the maximum power point occurs.

Artificial neural network (ANN) is specified in finding the appropriate solution for the non-linear systems. A back propagation network technique is the most widespread artificial neural network technique [13]. ANN is well adapted for microcontrollers. It has three layers: input, hidden, and output layers as shown in Fig. 2. The number of nodes in each layer is variable and they are user-dependent. The input parameters are PV array parameters such as V_{OC} and I_{sc}, atmospheric data such as irradiance and temperature, or any combination of them. The output is usually one or several reference signals. It can be voltage, current, power at MPP or a duty cycle signal that is used to drive the power converter to operate at or close to the MPP [4]. The links between the nodes are all weighted. The link between nodes i and j is labeled with a weight of W_{ij}. To accurately identify the MPP, the weights have to be carefully determined through a training process.

A multilayer feed-forward neural network is proposed in this paper. The number of neurons in the input and output layers is two and one, respectively. The number of neurons in the hidden layer would be determined by trial and error [8]. The neurons in the input layer get the input signal from the measurement of solar radiation and ambient temperature. The neurons in the hidden layer calculate their outputs using sigmoid activation function and pass them to the neurons in the output layer. The node in the output layer provides the identified current at MPP.

In the training process of the neural network, a set of input–output training data is needed. The training data are obtained with the help of the mathematical model of the PV module characteristics, which has been discussed in the above section. The training data should cover a wide spread of all possible environmental conditions in which the network could be expected. Once the network is trained, a desired output goal is found. Also, it must be tested with another data set.

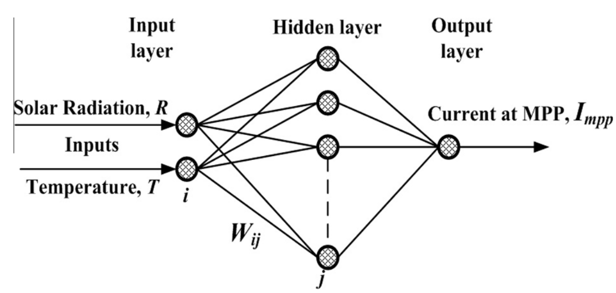

Figure 2 Construction of the artificial neural network.

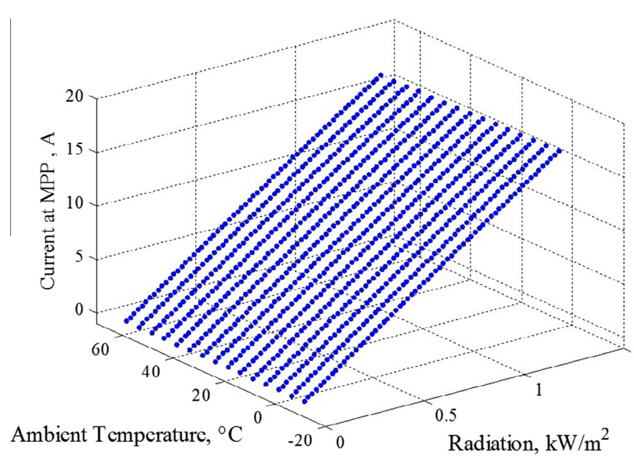

Figure 3 The training data calculated by the mathematical model.

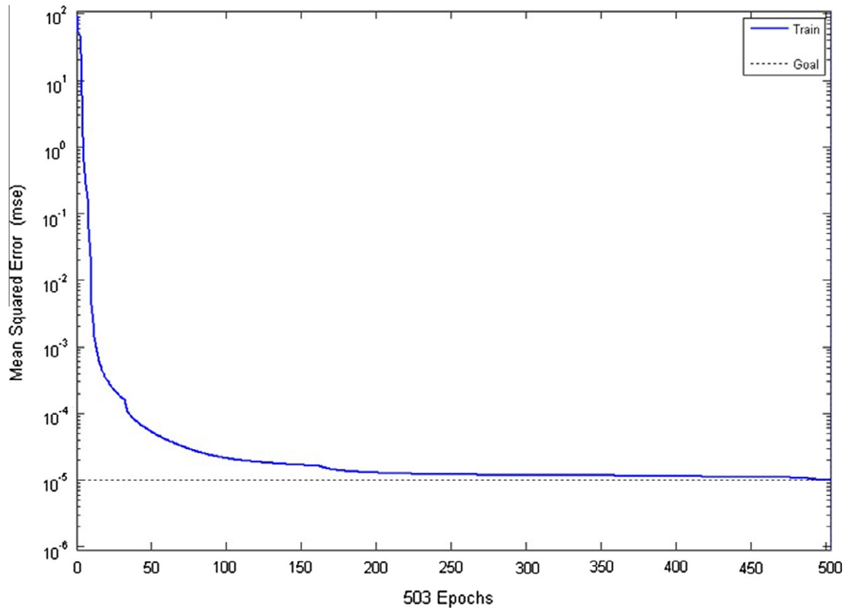

Figure 4 Convergence error for the neural network training process.

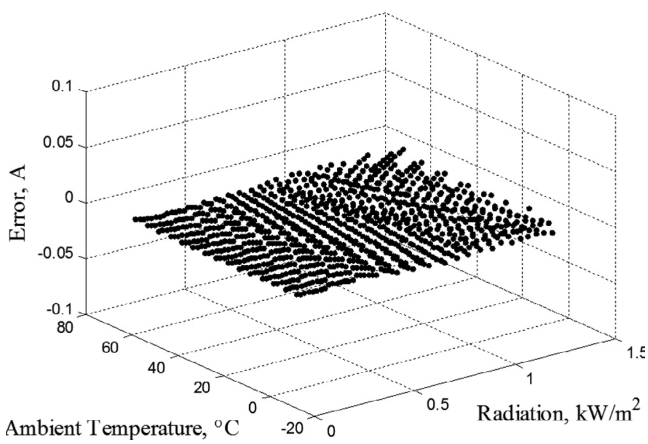

Figure 5 Neural network outputs error when it is tested with the testing data.

The output of the ANN and the target output at the kth instant are represented by $\{y_i(k)\}$ and $\{d_i(k)\}$, where $i = 1, 2, \ldots, N_L$. The error at the kth instant is given by [14]

$$e_i(K) = d_i(K) - y_i \tag{15}$$

The sum of square errors produced by the ANN is given by [14]

$$E(K) = \sum_{i=1}^{N_l} [e_i(K)]^2 \tag{16}$$

The back-propagation algorithm attempts to minimize the function $E(k)$ recursively by updating the weights of the network. After the network has been trained to the desired accuracy, a separate set of test patterns is supplied as an input to the ANN in order to evaluate its performance. It is necessary for the ANN to be able to generalize the situation from the provided training patterns and correctly identify the optimal operating point.

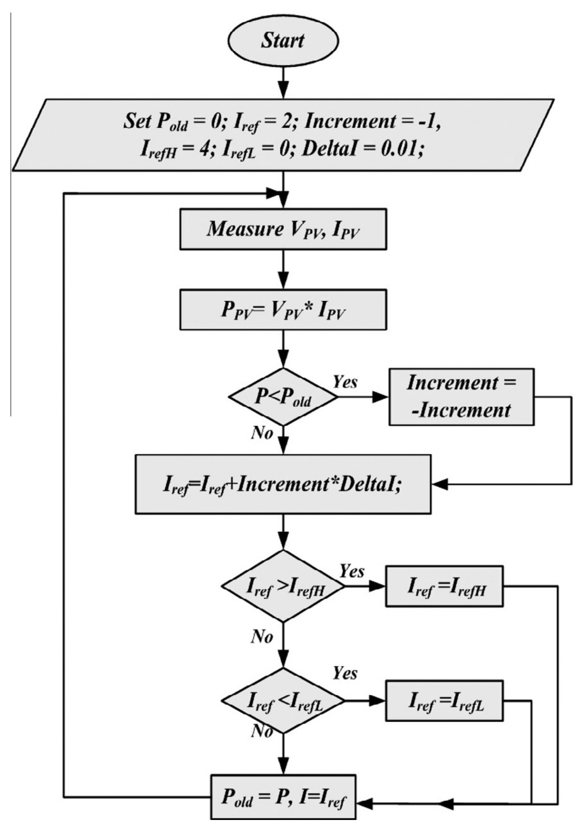

Figure 6 Flowchart of the proposed P&O MPPT Algorithm.

ANN has been trained with the data values obtained from the mathematical model of the PV module. The training parameters are as follows:

- Learning rate parameter $\eta = 0.1$.
- Number of training iterations = 1000.
- Error goal (performance) = $1e^{-5}$.

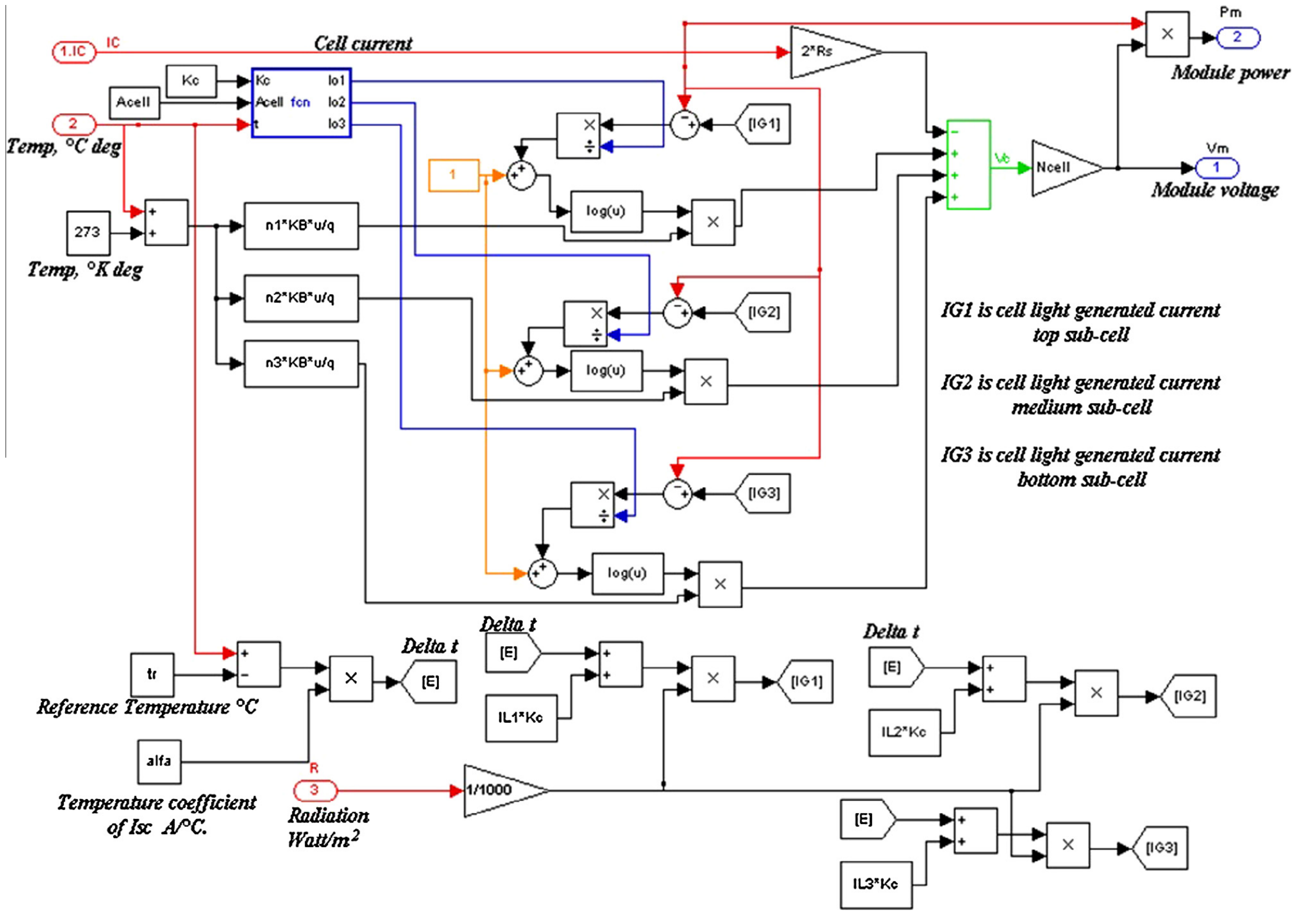

Figure 7 The proposed Matlab/Simulink model of the PV module based on triple-junction solar cell.

Table 1 Parameters for triple-junction InGaP/InGaAs/Ge solar cell.

	Top sub-cell InGaP	Medium sub-cell InGaAs	Bottom sub-cell Ge
E_g (eV) at 298 K	$E_{g1} = 1.976$	$E_{g2} = 1.519$	$E_{g3} = 0.744$
I_{sc} (mA)	$I_{sc1} = 6.7522$	$I_{sc2} = 7.7126$	$I_{sc3} = 10.094$
K (A/cm^2 K^4)	$K_1 = 1.86 \times 10^{-9}$	$K_2 = 1.288 \times 10^{-8}$	$K_3 = 10.5 \times 10^{-6}$
n	$n_1 = 1.97$	$n_3 = 1.75$	$n_3 = 1.96$
γ	2	2	2
α	7.5×10^{-4}	5.405×10^{-4}	4.774×10^{-4}
β	500	204	235

The training data calculated by the mathematical model are shown in Fig. 3. The convergence error for the training process is shown in Fig. 4. After learning the neural network, it is important to test it to ensure that it is actually able to predict the desired output values with another input data that are not used in learning process.

A relative error (ΔE) is used as a validation criterion for the neural network. It is defined as follows:

$$\Delta E = \frac{I_{cal} - I_{ann}}{I_{cal}} \tag{17}$$

where I_{cal} is the current calculated by the mathematical model and I_{ann} is the simulated current by ANN under test.

The percentage error between the desired outputs calculated by the mathematical model of the PV module and the outputs of ANN is shown in Fig. 5. It is clear that the 2 + 4 + 1 feed-forward ANN is the suitable arrangement for the case under study because it gives an acceptable error. The absolute value of percentage error in the current is 0.11% that indicates the effectiveness of the artificial neural networks. The Weights and Biases for the used 2 + 4 + 1 ANN are illustrated in the following:

$$\mathrm{W1} = \begin{bmatrix} 1.4123 & 0.00130 \\ 0.6212 & -0.0008 \\ -1.7984 & 0.0287 \\ 0.6797 & 0.0001 \end{bmatrix}, \quad \mathrm{B1} = \begin{bmatrix} -1.3750 \\ -1.5392 \\ 1.5260 \\ 0.1708 \end{bmatrix},$$

$$\mathrm{B2} = [14.6650]$$

$$\mathrm{W2} = [1.2729 \quad 18.0364 \quad 0.0229 \quad 17.0485]$$

Table 2 Electrical specifications of the proposed simulated PV module.

Characteristics	Specification
Maximum power	480 W
Short circuit current	11.12 A
Open circuit voltage	60 V
Current at MPP	10.7 A
Voltage at MPP	45 V

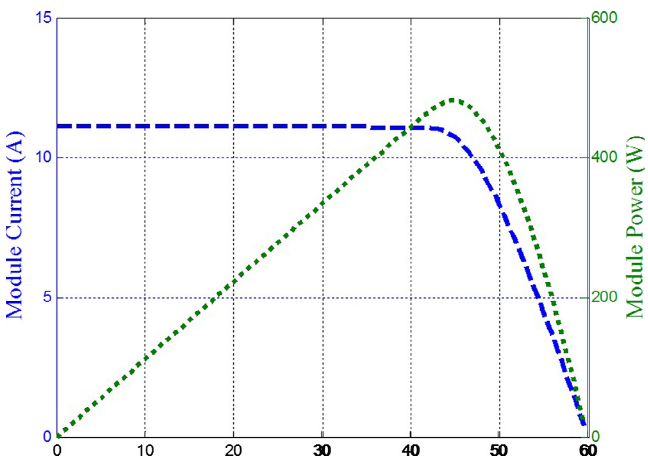

Figure 8 *P–V* and *I–V* characteristics of the proposed PV Module at standard conditions (800 W/m^2 and 20 °C).

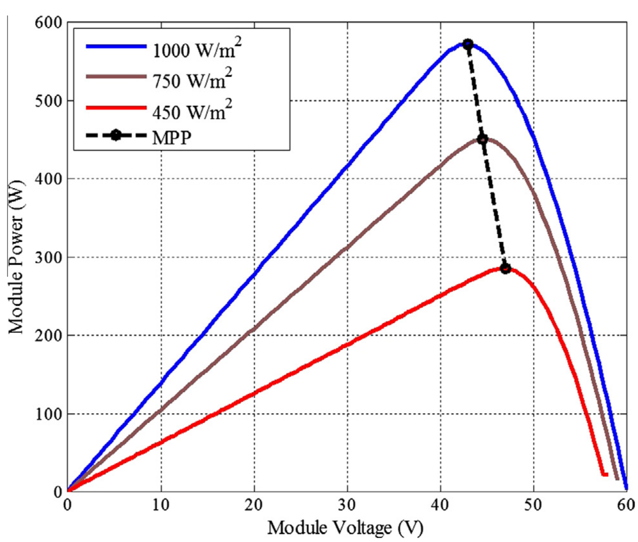

Figure 9a PV module power–voltage curves under different radiations and constant temperature 25 °C.

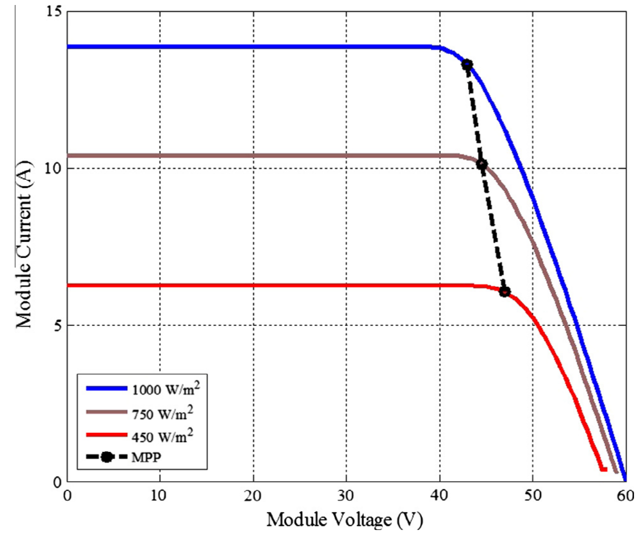

Figure 9b PV module current–voltage curves under different radiations and constant temperature 25 °C.

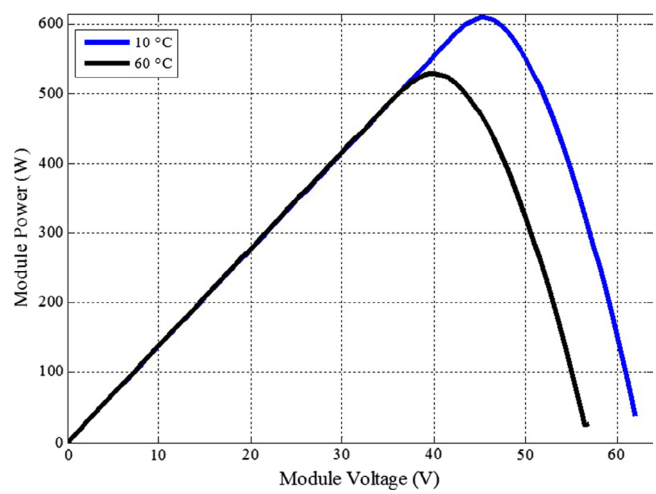

Figure 10a PV module power–voltage curves under different temperatures and constant radiation 1000 W/m^2.

2.4. Perturb and Observer P&O MPPT

P&O MPPT [8,15] is the most popular technique. It is based on the tracking MPP by comparing the power at different samples and perturbing current periodically. This process continues until the MPP is reached, where the change in the power with respect to the current is equal to zero. The algorithm used in this study tracks the current I_{mpp}. However, it tracks directly the maximum possible power P_{max} that can be extracted from the PV. The flowchart of the P&O MPPT technique is shown in Fig. 6. After one perturb operation, the power is calculated and compared with the previous value to determine the change of power $\Delta P = P - P_{old}$. If the change in the power $\Delta P < 0$, the operation continues in the same direction of perturbation. Otherwise, the operation reveres the perturbation direction.

3. Simulation results

3.1. Simulation of solar PV module in MATLAB/Simulink

The model of triple-junction solar cell is implemented in the MATLAB/Simulink as shown in Fig. 7. The proposed PV module is made of 20 triple-junction solar cells in series and provides 480 W of nominal maximum power at 800 W/m^2

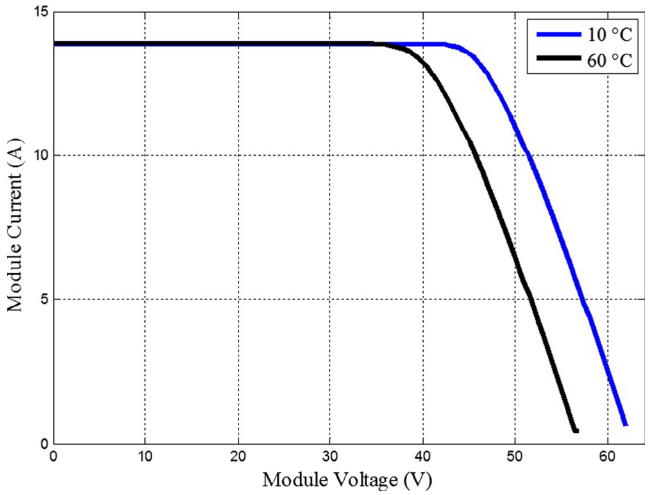

Figure 10b PV module current–voltage curves under different temperatures and constant radiation 1000 W/m^2.

and 20 °C (standard conditions). Table 1 shows the values of the triple junction InGaP/InGaAs/Ge solar cell parameters [16,17]. Table 2 shows the electrical specifications of the proposed simulated PV module.

The photovoltaic power characteristic is shown in Fig. 8. It varies with the level of solar radiation and temperature. The proposed PV module under standard conditions has the characteristic shown in Fig. 8. There is a unique point on the curve, called the maximum power point, at which the PV module operates with maximum efficiency and produces maximum output power.

By taking the effect of solar radiation and cell temperature into consideration, the simulation results of output power–voltage characteristics and output current–voltage characteristics of PV model under increasing solar radiation and at constant temperature are shown in Figs. 9a and b. The maximum power point is strongly affected by varying the solar radiation. MPP is changed from 280 W to 570 W as the solar radiation varies from 450 W/m^2 to 1000 W/m^2. On the other hand, *I–V* characteristics of the cell are highly changed by varying the solar radiation before the cell output voltage reaches the point at which the maximum power point occur after that it is slightly affected by varying the solar radiation. Figs. 10a and b show *P–V* characteristics and *I–V* characteristics at different temperature and constant solar radiation. The MPP is affected by varying the cell temperature. The value of the MPP is changed from 530 W to 612 W as the temperature changed from 60 °C to 10 °C. For a given solar radiation, when the cell temperature increases, the *I–V* characteristics are remain constant until the value of the open circuit voltage reaches the value at which the maximum power point occurs. The *I–V* characteristics are shifted down as the temperature decrease.

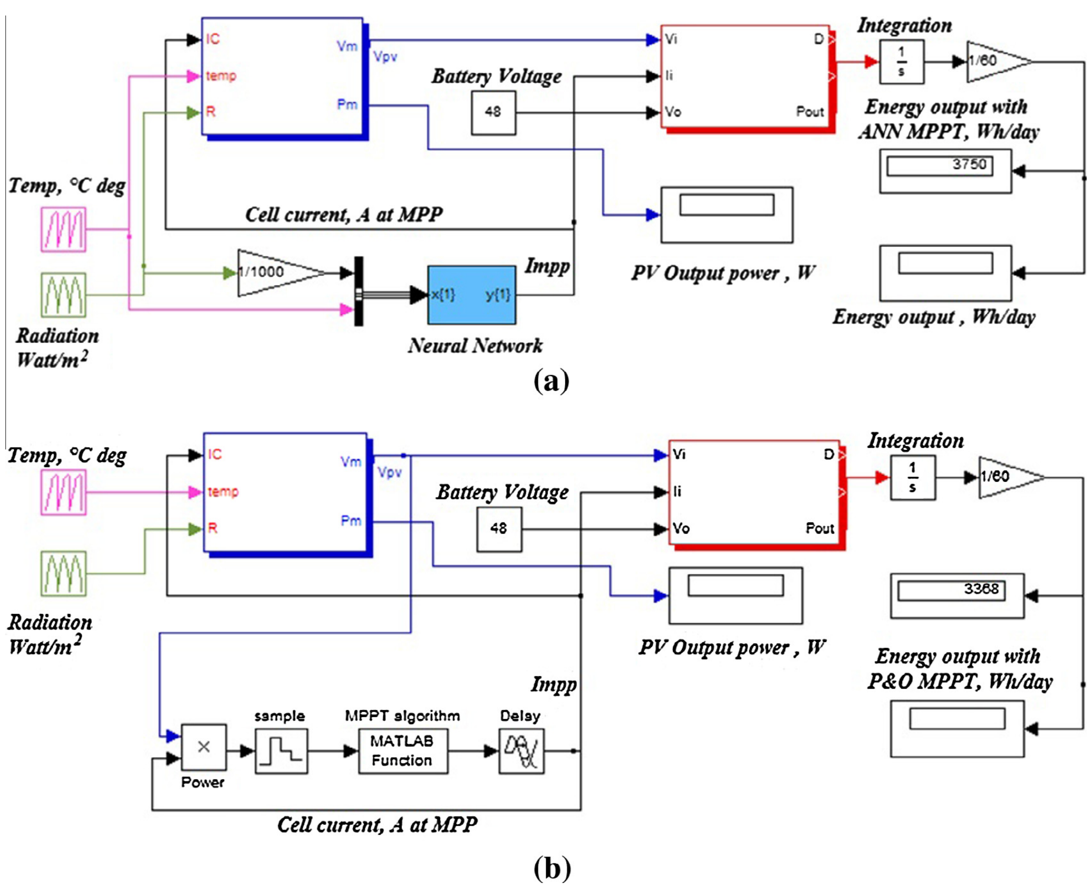

Figure 11 (a) Matlab/Simulink model of PV system with ANN MPPT technique. (b) Matlab/Simulink model of PV system with P&O MPPT technique.

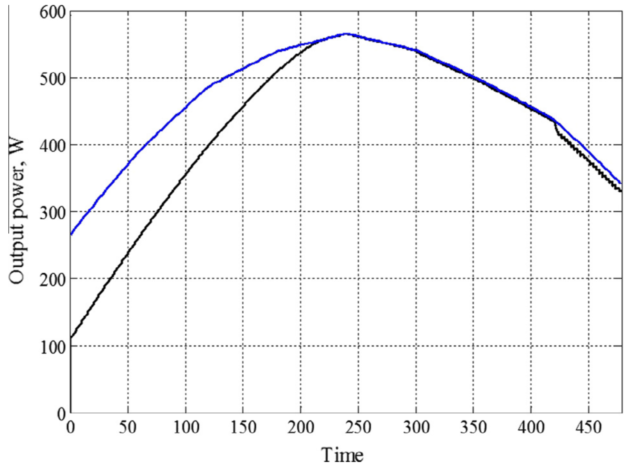

Figure 12 The output power from PV system with and without using ANN MPPT technique.

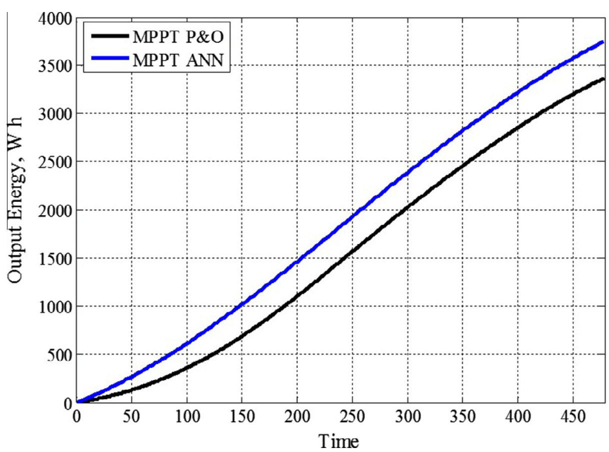

Figure 13 The output energy from PV system of the proposed ANN MPPT technique compared with MPPT P&O technique.

3.2. Simulation of PV system in MATLAB/Simulink

The simulation of the proposed system has been implemented using MATLAB/Simulink program as shown in Fig. 11. The simulation is carried out to study the effect of the PV system operates with ANN MPPT technique on the output power and energy. Fig.12 shows the output power of the PV system as a function of time with and without ANN MPPT technique. Fig. 13 shows the output energy from PV system as a function of time for the proposed ANN MPPT compared with P&O MPPT technique. It is clear from the figures that using the proposed ANN MPPT technique, the output power and energy from PV module are greater than the output power and energy in case of using P&O MPPT technique. The output energy per day from one PV module increases from 3.37 kW h to 3.75 kW h, i.e. a percentage of 11.28%.

In order to illustrate the merits of the proposed ANN tracking technique, the performance of the proposed MPPT technique is compared with P&O MPPT technique at different irradiance conditions. The irradiance rate is changed from 700 W/m^2 to 800 W/m^2, 300 W/m^2 to 800 W/m^2 and also 500 W/m^2 to 800 W/m^2. Fig. 14 shows the dynamic response

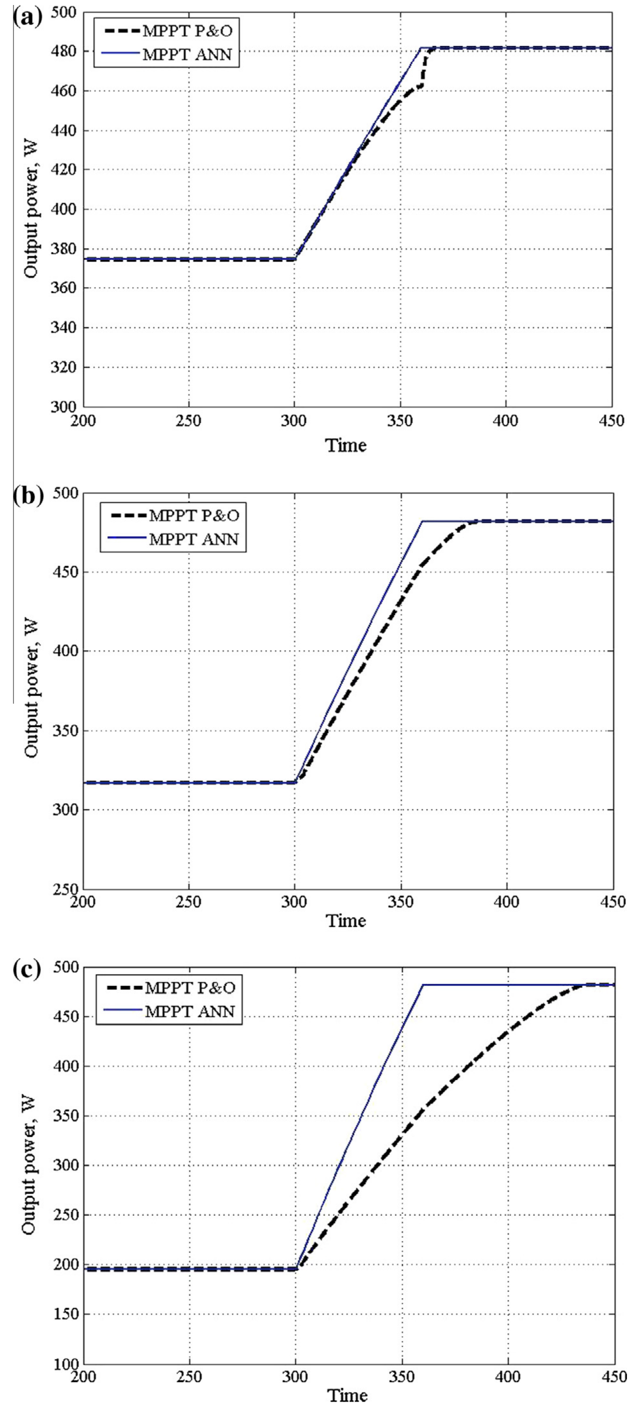

Figure 14 Dynamic response of the PV module output power for the proposed ANN technique compared with P&O technique under different irradiance conditions.

of the PV module output power for the proposed ANN tracking technique compared with P&O MPPT technique under different irradiance levels. At low radiation change rate, there is a little difference between the performance of the proposed technique and P&O technique as shown in Fig. 14a. On the other hand, at high radiation change rate especially in tropical environment, the P&O MPPT takes longer time to follow the maximum power point compared with the proposed ANN technique that reduces the energy captured from the

PV system as shown in Figs. 14b and c. The proposed ANN tracking technique is superior with respect to P&O MPPT technique. It is effectively improved the tracking speed and increased the output energy of the PV system.

4. Conclusion

A new Matlab/Simulink model of PV module based on high efficiency InGaP/InGaAs/Ge triple-junction solar cell is proposed. The proposed model represents the PV cell, module, and array for easy use on the simulation platform. The model takes solar radiation and cell temperature as input parameters and outputs I–V and P–V characteristics under various conditions and also includes the effect of the temperature variations on the cell characteristics. Artificial Neural Network based tracker technique is proposed. The overall PV system with MPPT is implemented in MATLAB/Simulink. The output power and energy from PV system with ANN are compared with those obtained by the commonly used P&O technique. The simulation results reveal that, using the ANN MPPT technique effectively improves the tracking speed and increases the output energy per day from one PV module from 3.37 kW h to 3.75 kW h, i.e. a percentage of 11.28%. This increase in the output energy from PV proves the superiority of the proposed technique that can be translated to considerable cost reduction of the generated kW h.

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