ARTIFICIAL NEURAL NETWORK APPROACH FOR MORE ACCURATE SOLAR CELL ELECTRICAL CIRCUIT MODEL

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ABSTRACT

The implementation of a neural network especially for improving the accuracy of the electrical equivalent circuit parameters of a solar cell is proposed. These electrical parameters mainly depend on solar irradiation and temperature, but their relationship is nonlinear and cannot be easily expressed by any analytical equation. Therefore, the proposed neural network is trained once by using some measured current–voltage curves, and the equivalent circuit parameters are estimated by only reading the samples of solar irradiation and temperature very quickly. Taking the effect of sunlight irradiance and ambient temperature into consideration, the output current and power characteristics of PV model are simulated and optimized. Finally, the proposed model has been validated with datasheet and experimental data from commercial PV module, Kotak PV-KM0060 (60Wp).The comparison show the higher accuracy of the ANN model than the conventional one diode circuit model for all operating conditions.

Keywords

Photovoltaic module, Generalized model, Matlab/Simulink, Equivalent circuit parameter, Artificial neural network; I–V characteristics; Modeling

1.INTRODUCTION

Different solar cell models have been developed to describe the electrical behaviors of solar cells, but the electrical equivalent circuit is a convenient and common way in most simulation studies. The five parameters of interest in the equivalent circuit are the photo-current (Iph), series resistance (Rs), parallel resistance (Rp), diode saturation current (Is) and the ideality factor (A). The current–voltage (I–V) relationship of a solar cell is described by a mathematical equation that is both implicit and nonlinear. Therefore, determination of the parameters requires more computational efforts for each operating condition [1–7]. However, all of the circuit parameters depend on both irradiation and cell temperature. Every assumption forces the model to fall into error. In this study, the dependence of all the circuit parameters on cell temperature and irradiance are included by using the neural network for improving the accuracy of the PV module model.
Blas et al. [4] present the use of analytical methods in determining the circuit parameters for the operation of a solar cell under conditions of high irradiance. Teng and Ping [1] present the

determination of the circuit parameters from experimental data by using the Q–R decomposition technique based on the least square method.

An artificial neural network (ANN) is accepted as a technology offering an alternative way to solve complex problems. In the last decade, significant progresses have been made in neural network technology to expand the range of potential applications into different areas because of the black box functionality of neural. The neural network can provide very good mapping if trained correctly. This makes it a good choice for such a task. The neural network is utilized to predict the equivalent circuit parameters by only reading the samples of irradiation and temperature. A number of available experimental data are used for training the neural network, which employs a back propagation algorithm.The main objective of this paper is to investigate the applicability of the neural network based PV equivalent circuit model for improving the model accuracy and to show the necessity of including the variation of all the parameters with varying operating conditions.

2. GENERAL SOLAR CELL MODEL

2.1 Conventional one diode electrical Model

A general mathematical description of I-V output characteristics for a PV cell has been studied for over the past four decades [8]-[10]. Such an equivalent circuit-based model is mainly used for the MPPT technologies. The equivalent circuit of the general model which consists of a photo current, a diode, a parallel resistor expressing a leakage current, and a series resistor describing an internal resistance to the current flow, is shown in Fig. 1.

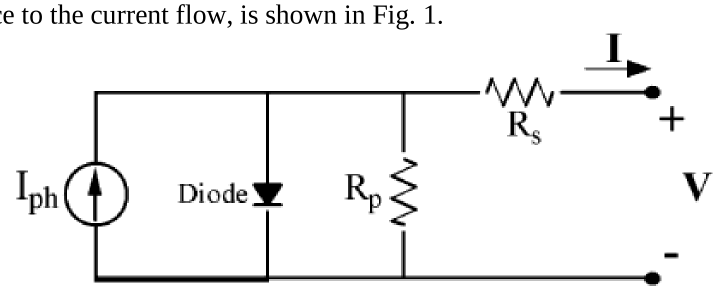

Fig. 1 One diode conventional solar cell model

The voltage-current characteristic equation of a solar cell is given as

$$I = I_{PH} - I_S\left[\exp\left(q\left(V + IR_S\right)/KT_C A\right) - 1\right] - \left(V + IR_S\right)/R_{SH}$$

where I_{PH} is a light-generated current or photocurrent, I_S is the cell saturation of dark current, q (= 1.6 ×10^{-19} C) is an electron charge, K (= 1.38 ×10^{-23} J/K) is a Boltzmann's constant, T_C is the cell's working temperature, A is an ideal factor, R_{SH} is a shunt resistance, and R_S is a series resistance. The photocurrent mainly depends on the solar insolation and cell's working temperature, which is described as

$$I_{PH} = \left[I_{SC} + K_I\left(T_C - T_{REF}\right)\right]\lambda$$

where I_{SC} is the cell's short-circuit current at a 25°C and 1kW/m2, K_I is the cell's short-circuit current temperature coefficient, T_{REF} is the cell's reference temperature, and λ is the solar insolation in kW/m2. On the other hand, the cell's saturation current varies with the cell temperature,

which is described as

$$I_S = I_{RS}\left(T_C / T_{REF}\right)^3 \exp\left[qE_G\left(1/T_{REF} - 1/T_C\right)/KA\right]$$

where I_{RS} is the cell's reverse saturation current at a reference temperature and a solar radiation, E_G is the bang-gap energy of the semiconductor used in the cell. The ideal factor A is dependent on PV technology [11] and is listed in Table I.

Table 1. Diode ideality Factor, A and PV Technology

PV Technology	A
Si-mono	1.2
Si-poly	1.3
a-Si:H	1.8
a-Si:H Tadem	3.3
a-Si:H Triple	5
CdTe	1.5
CIS	1.5
GaAs	1.3

An even more exact mathematical description of a solar cell, which is called the double exponential model which can be derived from the physical behavior of solar cell constructed from polycrystalline silicon. This model is composed of a light-generated current source, two diodes, a series resistance and a parallel resistance. However, there are some limitations to develop expressions for the V-I curve parameters subject to the implicit and nonlinear nature of the model. Therefore, this model is rarely used in the subsequent literatures and is not taken into consideration for the generalized PV model. The shunt resistance R_{SH} is inversely related with shunt leakage current to the ground. In general, the PV efficiency is insensitive to variation in R_{SH} and the shunt-leakage resistance can be assumed to approach infinity without leakage current to ground. On the other hand, a small variation in R_S will significantly affect the PV output power. The above equation can be rewritten as follows

$$I = I_{PH} - I_S\left[\exp\left(q\left(V + IR_S\right)/KT_C A\right) - 1\right]$$

For an ideal PV cell, there is no series loss and no leakage to ground, i.e., $R_S = 0$ and $R_{SH} = \infty$ [13]-[14].

The equation again can be simplified as

$$I = I_{PH} - I_S\left[\exp\left(qV/KT_C A\right) - 1\right]$$

2.2 Solar Module and Array Model

Since a typical PV cell produces less than 2W at 0.5V approximately, the cells must be connected in series-parallel configuration on a module to produce enough high power. A PV array is a group of several PV modules which are electrically connected in series and parallel circuits to generate the required current and voltage. The equivalent circuit for the solar module arranged in N_P

parallel and N_S series is shown in Fig.2. The terminal equation for the current and voltage of the array becomes as follows [15]-[18].

$$I = N_P I_{PH} - N_P I_S \left[\exp\left(q\left(V / N_S + IR_S / N_P\right) / KT_C A\right) - 1\right] - \left(N_P V / N_S + IR_S\right) / R_{SH}$$

In fact, the PV efficiency is sensitive to small change in R_S but insensitive to variation in R_{SH} . For a PV module or array, the series resistance becomes apparently important and the shunt down resistance approaches infinity which is assumed to be open. In most commercial PV products, PV cells are generally connected in series configuration to form a PV module in order to obtain adequate working voltage. PV modules are then arranged in series-parallel structure to achieve desired power output

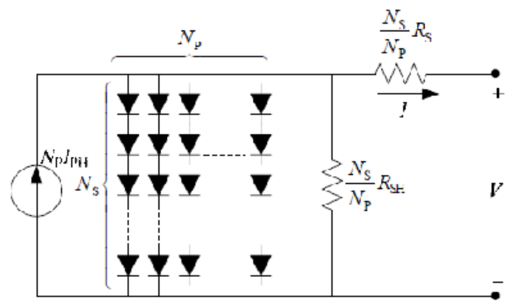

Fig. 2 A generalized model

It can be shown that N_S = N_P = 1 for a PV cell, N_P =1 and N_S : series number of cells for a PV module, and N_S and N_P : series-parallel number for a PV array. The mathematical equation of generalized model can be described as

$$I = N_P I_{PH} - N_P I_S \left[\exp\left(q\left(V / N_S + IR_S / N_P\right) / KT_C A\right) - 1\right]$$

The most simplified model [13], [19] of generalized PV module is depicted in Fig.2. The equivalent circuit is described on the following equation

$$I = N_P I_{PH} - N_P I_S \left[\exp\left(qV / N_S KT_C A\right) - 1\right]$$

2.3 Determination of Model Parameters

All of the model parameters can be determined by examining the manufacturer's specifications of PV products. The most important parameters widely used for describing the cell electrical performance is the open-circuit voltage V_{OC} and the short-circuit current I_{SC}. The aforementioned equations are implicit and nonlinear; therefore, it is difficult to arrive at an analytical solution for a set of model parameters at a specific temperature and irradiance. Since normally I_{PH} >> I_S and ignoring the small diode and ground-leakage currents under zero-terminal voltage, the short-circuit current *I*SC is approximately equal to the photocurrent I_{PH} , i.e.,

$$I_{PH} = I_{SC}$$

On the other hand, the V_{OC} parameter is obtained by assuming the output current is zero. Given the PV open-circuit voltage V_{OC} at reference temperature and ignoring the shunt-leakage current, the reverse saturation current at reference temperature can be approximately obtained as

$$I_{RS} = I_{SC} / [\exp(qV_{OC} / N_S K T_C A) - 1]$$

In addition, the maximum power can be expressed as

$$P_{MAX} = V_{MAX} I_{MAX} = FFV_{OC} I_{SC}$$

where *V*max and *I*max are terminal voltage and output current of PV module at maximum power point (MPP), and FF is the cell fill factor which is a measure of cell quality.

2.4 Building of Generalized PV Model

A model of PV module with moderate complexity which includes the temperature independence of the photocurrent source, the saturation current of the diode, and a series resistance is considered based on the Shockley diode equation. It is important to build a generalized model suitable for all of the PV cell, module, and array, which is used to design and analyze a maximum power point tracker. Bing illuminated with radiation of sunlight, PV cell converts part of the photovoltaic potential directly into electricity with both I-V and P-V output characteristics. A generalized PV model is built using Matlab/Simulink [20] to illustrate and verify the nonlinear I-V and P-V output characteristics of PV module. The proposed model is implemented in MATLAB SIMULINK and shown in Figs. 3(a) and 3(b).

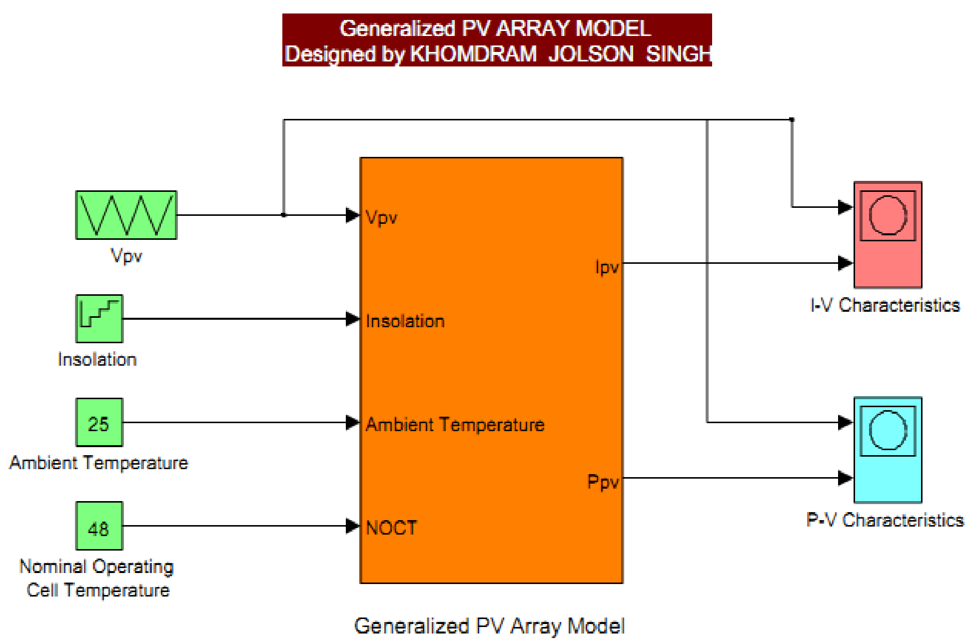

Fig. 3(a) Generalized SIMULINK based PV Array Model

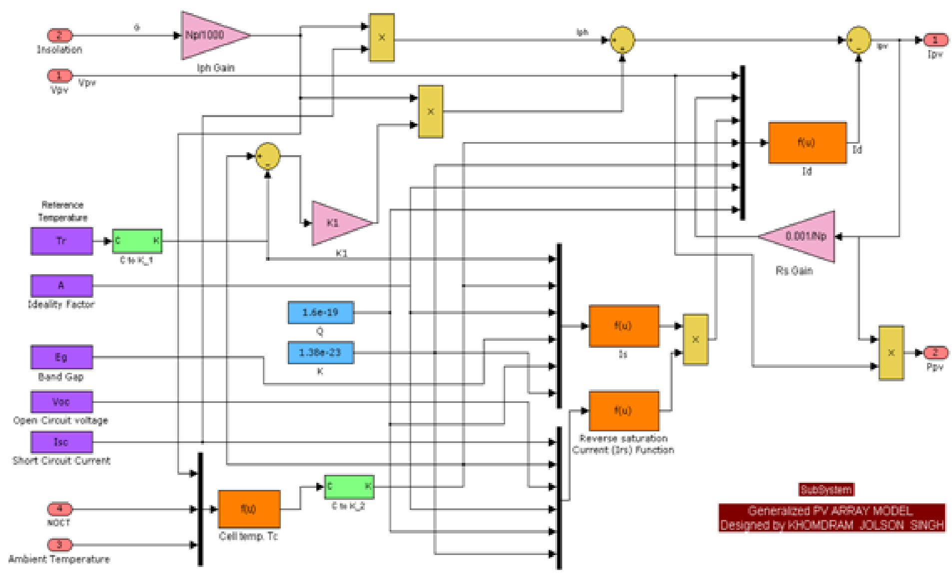

Fig. 3(b) Subsystem implementation of the Model

2.5 Simulation Results of PV Cell and Module

For a PV cell, $N_S = N_P = 1$. Both I-V and P-V output characteristics of conventional PV model for a cell are shown in Fig. 5. The nonlinear nature of PV cell is apparent as shown in the figures, i.e., the output current and power of PV cell depend on the cell's terminal operating voltage and temperature, and solar insolation as well.

The **Kotak KMOO60 60W** PV module is taken for example. The key specifications are listed in Table 2 in which the nominal operating cell temperature (NOCT) is the temperature that the cells will reach when they are operated at open circuit in an ambient temperature of 20°C under AM 1.5 irradiance conditions with λ=0.8kW/m2 and a wind speed less than 1 m/s. The electrical characteristics of PV module are generally represented by the current versus voltage and power versus voltage curves. Both I-V and P-V output characteristics of PV module at various insolation and temperatures are carried out and the results are shown in Figs. 5. We also see from Fig. 5(b) that with increase of working temperature, the short-circuit current of the PV module increases, whereas the maximum power output decreases. The increase in the short-circuit current is much less than the decrease in the open-circuit voltage, and the effect makes maximum power decreasing by about 0.45%/°C at high temperatures. On the other hand, from, we also observe that with increase of solar insolation, the short-circuit current and the maximum power output of the PV module increase as shown in Figs. 5(a) and 5(c). The reason is the open-circuit voltage is logarithmically dependent on the solar irradiance, yet the short-circuit current is directly proportional to the radiant intensity. Fig.4 show some input parametrs necessary for the simulink model.

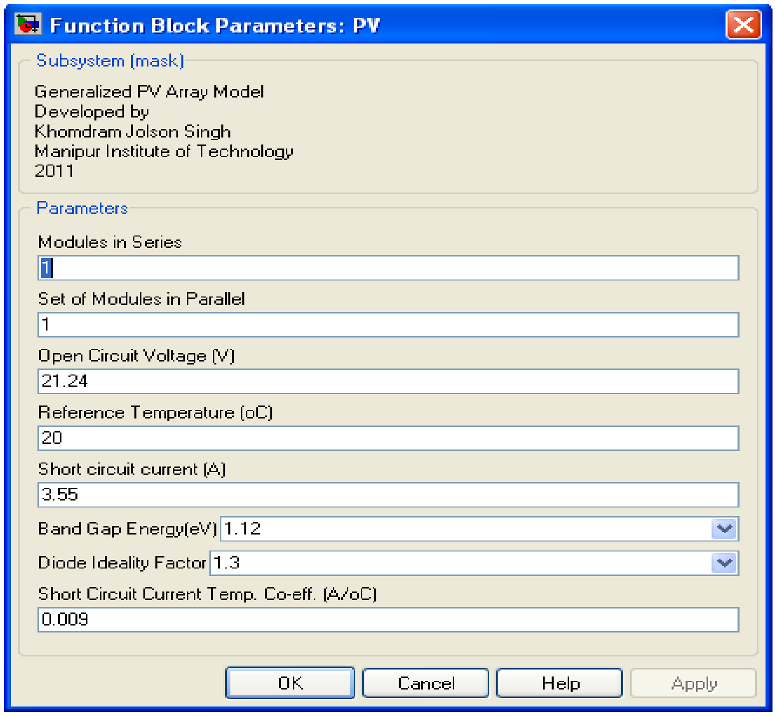

Fig. 4 Input Parameter dialog box of the model

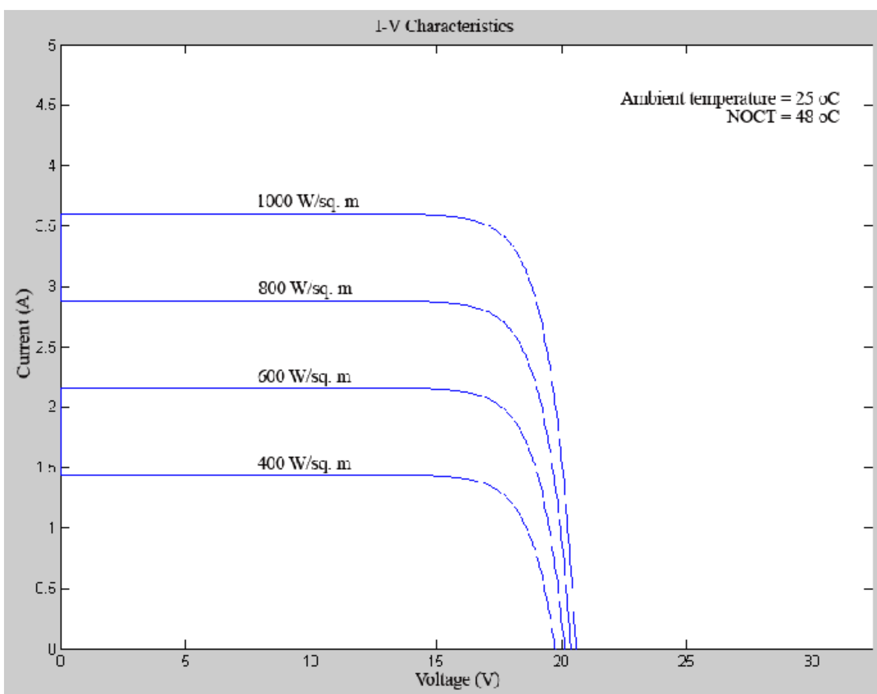

Fig. 5(a) I-V output characteristics with different λ.

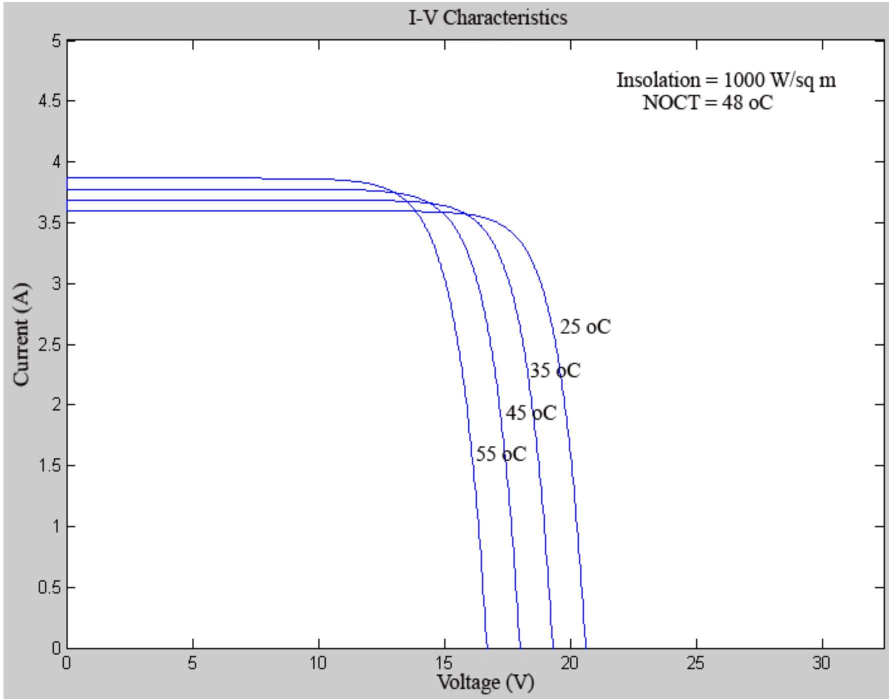

Fig. 5(b)I-V output characteristics with different *Tc*.

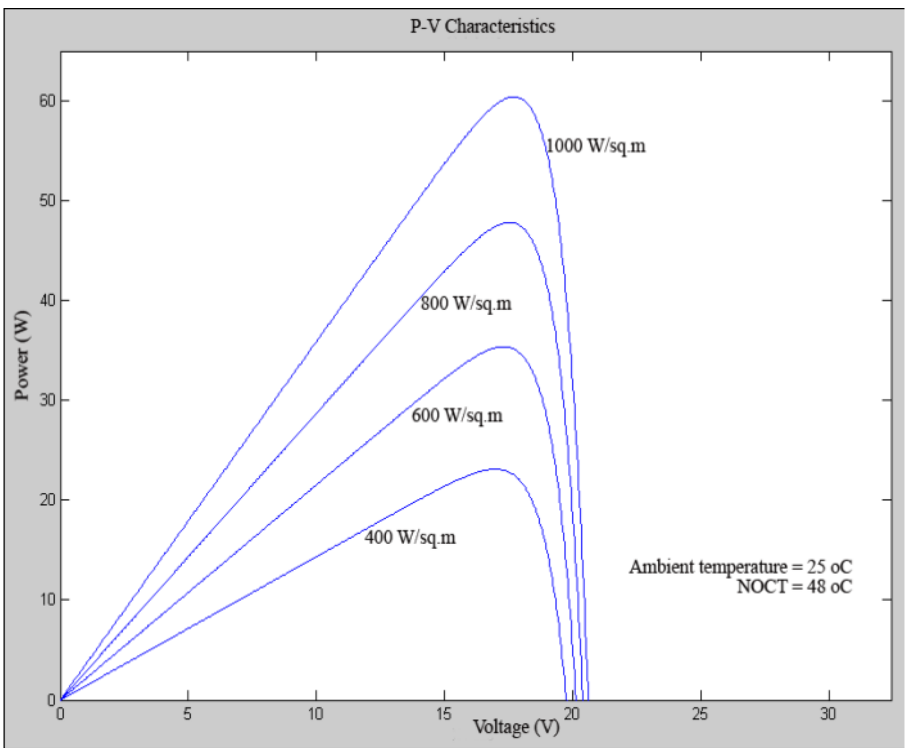

Fig.5(c) P-V output characteristics with different λ.

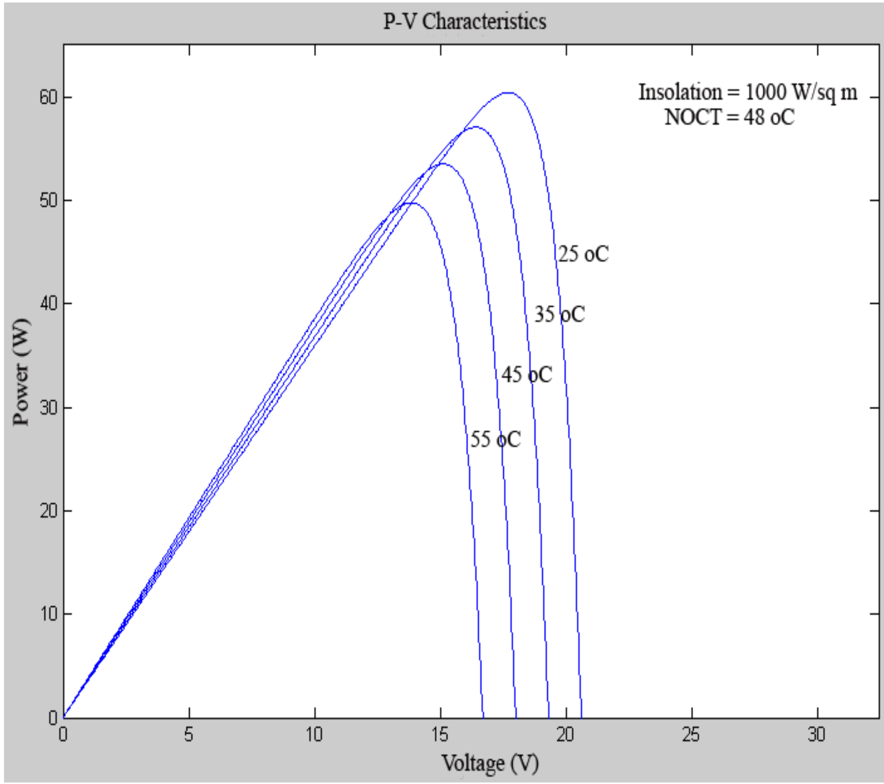

Fig.5(d)P-V output characteristics with different Tc

3. VARIATION OF ONE DIODE MODEL PARAMETERS

To characterize a PV module as a power source in studying its performance, it is very important to take into consideration the dependence of all the equivalent circuit parameters of the PV module on irradiation and cell temperature. The five equivalent circuit parameters can be determined using the available operating points on the I–V curve of the module. To be able to obtain the changes of the parameters over the whole range of operating conditions, Sandia's PV module electrical performance model [21] is used for generating the required five points on the I–V curve.

Table 2: Kotak KMOO60 60W Specification (1kW/m2, 25°C)

KOTAK SOLAR MODULE - 60 Wp

DATA SHEET

Electrical Specifications		
Open Circuit Voltage	(Voc)	21.24 V
Short Circuit Current	(ISC)	3.55 A
Maximum Voltage	(Vmp)	17.64 V
Maximum Current	(Imp)	3.40 A
Maximum Power at STC	(Pmax)	60 Wp
Maximum System Voltage		600 V
Operating Temperature/Humidity		40° C to +85 C/ 85%

Temperature Coefficients		
NOCT		48°C±2°C
Current Temperature Coefficient	α (I_{sc})	0.09%/°C
Voltage Temperature Coefficient	β (V_{mp})	-0.34%/°C
Power Temperature Coefficient	λ (P_{max})	-0.37%/°C

Module Information			
Mode	: KM0060	Oblong Hole	: 7 x 11mm
Solar Cel	: Multi Crystalline	Terminal Box	: 600V Rating
Solar Cel Shape	: Fu l Square	Bypass Diode	: 6A
Co our Class of Cells	: Blue (Bright or Medium or Dark)	Cable & Connector	: Not Provided
Ce l Geometry	: 156mm x 78mm	Frame Materia	: Anodized Aluminium
Ce l Configuration	: 36 Cells in Series	Frame Type	: Screwed Ends
Modu e Dimensions	: 1005mm x 505mm x 30mm	Packing Method	: Unit & Master Carton
Modu e Weight	: 6 Kgs. Approximate	Qty. per Container	: 20HC-600Nos/40HC-1200Nos

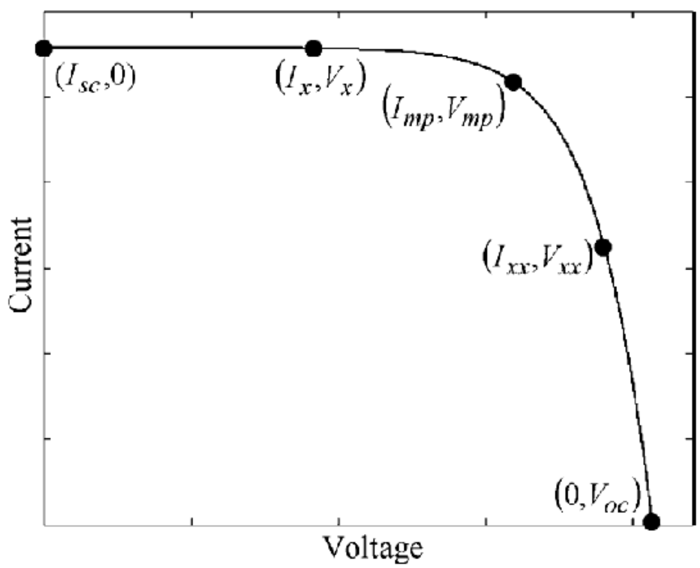

Fig.6 The used five operating points on the I–V curve of PV module to solve the nonlinear implicit I–V equation for a single operating condition [21]

These points are shown in Fig. 6 for one operating condition. These points are generated for 209 operating conditions between 15–65°C and 100–1000 W/m2 to solve the five coupled implicit nonlinear equations for the **Kotak KMOO60 60W** PV module that consists of 36 series connected mono-crystalline silicon solar cells. Solving the nonlinear implicit system of equations involves finding a solution such that every equation in the nonlinear system is 0. That is, we have five equations and five unknowns for each operating condition and we want to find x ε R^5 such that F(x) = 0, where

$$F_i = -I_i + x_1 - x_2(\exp(q(V_i + I_i x_4)/x_3 N_s kT) - 1) + (V_i + I_i x_4)/x_5$$

$$F(x) = \begin{bmatrix} F_1(x) \\ F_2(x) \\ F_3(x) \\ F_4(x) \\ F_5(x) \end{bmatrix}$$

Different optimization methods are tried for solving the system of equations. Numerical exercises seem to indicate that the trust region method [19] is considerably better than the others, so this method is used. In general, trust region methods are faster than gradient methods and guarantee stability regardless of the initial conditions. Good initial values are important for solving nonlinear system equations. An initial value that satisfies or closely satisfies many of the constraints reduces the work involved in finding a first feasible solution. At each different operating condition, initial values of the photo-current, series resistance and parallel resistance are estimated from their corresponding I– V curves. Initial values of the parameters are denoted by the subscript 0 and are given as

$$\begin{aligned} I_{ph0} &= I_{sc} \\ R_{s0} &= (V_{oc} - V_{xx}) / I_{xx} \\ R_{p0} &= V_x / (I_{sc} - I_x) \end{aligned}$$

where Isc is the short circuit current, Ix is the current at Vx = 0.5Voc, Ixx is the current at Vxx = 0.5(Voc + Vmp), Voc is the open circuit voltage and Vmp is the voltage at the maximum power point. The initial value of the diode ideality factor is taken as 1.5 for all cases. An initial value of the diode saturation current is determined by using above equations.

The solution of the system equations showed that all the parameters depend on both irradiation and temperature. On the other hand, it is necessary to include the variation of the parameters properly if accurate and reliable performance estimation is required in simulation studies. Obviously, it is quite difficult to determine the parameters for each irradiation and temperature in running simulation studies or on line PV system applications. For this reason, all parameters are estimated by using the neural network.

4. ANN BASED PARAMETERS PREDICTION

The artificial neural network structure is one of the important factors that influence the learning performances of networks. It is a natural hope to employ as small structures as possible under the conditions that they meet the performance requirements. Experience has shown that using the smallest network that can learn the task is better for both practical and theoretical reasons. It is necessary for the proper interpretation of your figures. If you want reprints of your color article, the reprint order should be submitted promptly.

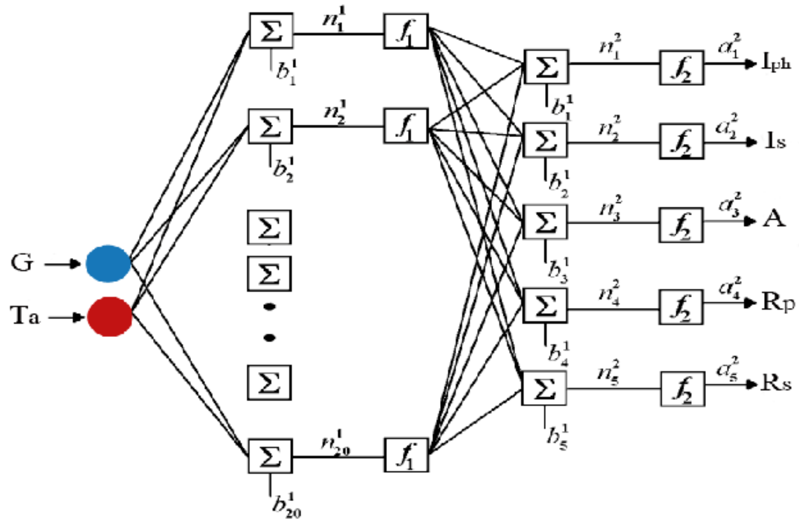

Fig. 7. Artificial neural network model

Training a smaller network usually requires less computation because each iteration is computationally less expensive. Unfortunately, the structures of multilayer feed forward perceptron networks are mainly determined by experience, and there has not been found a valid formula that is suitable for the different situations [23–26]. Architecture selection of ANN techniques can be divided into two categories. In the first category, a big network is selected, and the unnecessary nodes or connections are gradually eliminated [23].

The second category begins with a small network and gradually adds nodes or connections as needed. In this study, to map the relationship between A, Is, Rs, Rp, Iph and the irradiation and cell temperature, the second category was used when an appropriate neural network size is selected. Finally, sufficient results were obtained for a three layer feed forward neural network (input, single hidden and output layers) as shown in Fig. 7.The number of nodes in the input and the output layers are based on the input and output dimensions, respectively. The number of hidden layer nodes is determined empirically as we stated above. The 20 hidden nodes gave the most accurate estimation, and therefore, only the results of this case are given in the paper. Consequently, the input layer has 2 nodes, the hidden layer has 20 nodes and the output layer has 5 nodes (see Fig. 7). The input layer in this case consists of a two dimensional vector, irradiation and temperature, and the output vector is a five dimensional vector comprising A, Is, Rs, Rp and Iph. To reduce the computational effort, we take into consideration a small size network when we find an appropriate network size. This is very important during the testing phase of the network where fast responses are usually required. The outputs of the input layer nodes are weighted, summed, and passed through an activation function that acts as an amplitude limiting function. Three basic types of activation functions exist: threshold functions, piece wise linear function and sigmoid function [25]. The activation functions are used to limit or squash the input to the next neuron layer. The learning signal is a function of the error multiplied by the gradient of the activation function. For training, the activation function must be monotonically increasing from left to right, differentiable and smooth. In this study, all data are scaled to the range {_1; 1}, and a hyperbolic tangent sigmoid transfer function is used as the activation function of the single hidden layer [24]. A pure linear function was used as the activation function of the output layers of the neural network of Fig. 7, similar to Ref. [28]. Using a linear function in the output node of the neural network reduces the resulting computations. The relations between the inputs and outputs are given as follows: The input vector x = [irradiation, cell temperature] is applied to the input layer of the network as shown in Fig. 7. The net input of the jth hidden unit is

$$n_j^1 = \sum_{i=1}^{2} w_{ji} x_i + b_j^1$$

where Wji is the weight on the connection from the ith input unit, bhj for j = 1,2,. . .,20 represent the bias for the hidden layer neurons. The output of the neurons in the hidden layer is

$$a_j^1 = f_1(\sum_{i=1}^{2} w_{ji} x_i + b_j^1)$$

$$f_1(n) = \tan sig(n) = \frac{2}{1-e^{-2n}} - 1$$

and the net input to the neurons in the output layer is written as

$$n_k^2 = \sum_{i=1}^{20} w_{kj} a_j^1 + b_k^2$$

where Wkj is the weight on the connection from the jth input unit, b^2_k for k = 1,2,. . .,5 represent the bias for the second layer neurons. The output of the second layer, a^2_k , is the network outputs of interest, and these outputs are labeled yk.

$$a_k^2 = y_k = f_2(\sum_{j=1}^{20} w_{kj} a_j^1 + b_k^2)$$

$$f_2(n) = purelin(n) = n$$

The learning stage of the network is performed by updating the weights and biases using a back propagation algorithm with the Levenberg-Marquardt optimization method (see e.g. [29]) in order to minimize the sum of squared differences between the network targets and actual outputs for a given input vector. In order to avoid the network losing its generalization ability, training was stopped when the error on the test set was beginning to rise considerably (roughly after about 1000 training epochs). As can be seen clearly in Fig.9, the ANN can be used to identify the PV model parameters excellently. The basic configuration of the proposed PV model is summarized in Fig. 8. It is composed of a two stage process. Firstly, a neural network is used to predict the five parameters by reading only the samples of irradiation and temperature. Secondly, these parameters are put into the one diode electrical equivalent circuit model.

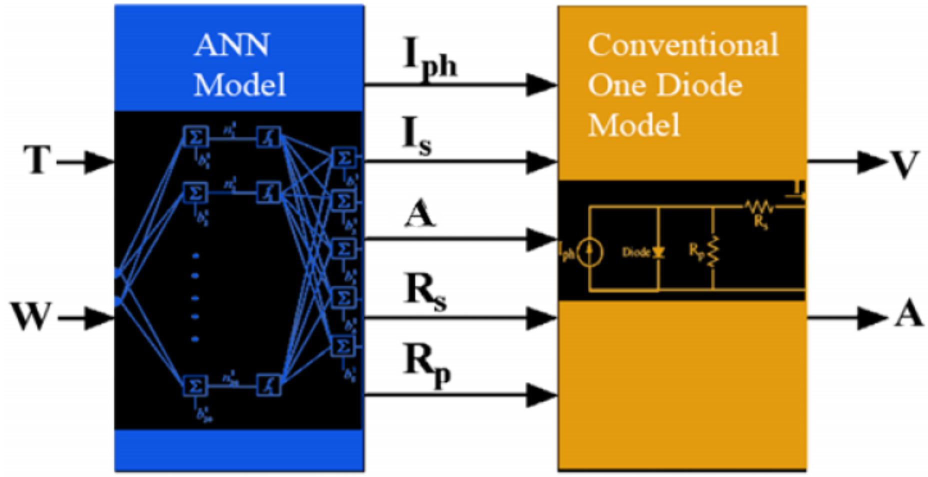

Fig. 8 A more accurate ANN proposed model

5 . RESULT FROM APPLICATION OF THE PROPOSED MODEL ON EXPERIMENTAL DATA

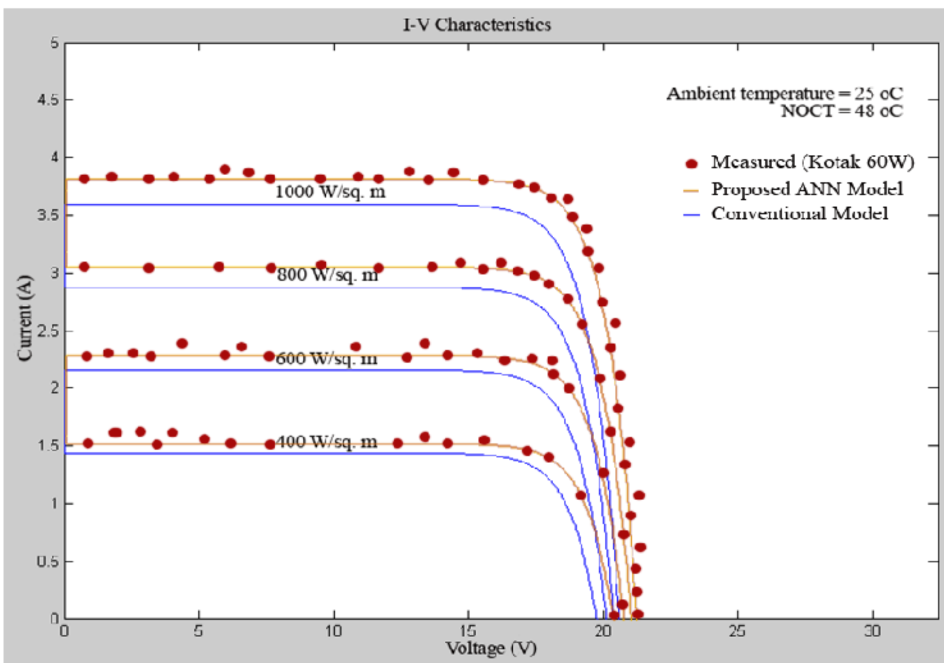

Fig. 9 The comparison of conventional model and the proposed model for testing data set with measured I–V curves of the Kotak 60W PV module

The comparative result is shown in Fig.9.It is observed that the proposed model for a solar cell model significantly decreases the error in simulation studies and also offers a compact solution to include the dependence of the equivalent circuit parameters on solar irradiation and cell temperature. The proposed model I-V data closely overlap with that of actual experimental measured data indicating the more accuracy of this ANN based model than conventional one.

6. CONCLUSIONS

This work studies the implementation of artificial neural networks to PV module modeling and analysis of their electrical parameters. The accuracy and generalization of the proposed model is validated by comparing test results with actual data from commercial module. In the conventional PV model, the dependency on solar irradiation and cell temperature of all the model parameters are not included, so the accuracy and the reliability of performance estimation cannot be sufficient for all operating conditions. This paper accepts irradiance and temperature as variable parameters for all the parameters of the PV module equivalent circuit model. They are predicted by reading only samples of radiation and temperature by using an artificial neural network. After that, these parameters are presented to the current–voltage equation of the PV module to obtain the electrical characteristics. The trained network is sufficiently accurate in representing the variation of the parameters when compared with other methods. The proposed model can be used for any type of PV module design, simulation and application in various energy studies.

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