Fill Factor Estimation for a Photovoltaic Module: An ANN based Approach

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Abstract: The Fill Factor (FF) of a Photovoltaic (PV) module is usually specified in the ratings of the module by the manufacturer. However, this value is specified at certain standard or operating conditions of solar insolation and temperature. Determination of the FF at any other operating condition requires detailed experimental data or, alternatively, involved analytical computation.

A novel alternative methodology is to develop a generalized ANN model that can serve the same purpose, with minimal computational effort. The present paper attempts to develop an ANN model that can be used to predict the FF at any value of operating condition other than the value specified at rated conditions. ANN models with different configuration have been tested successfully and shows an average error in estimation of <1%, thereby validating their use for simulated investigations in general.

Keywords: PV module, Photovoltaics, ANN, Fill Factor evaluation, Non- standard operating conditions.

Introduction

Photovoltaic (PV) systems generate electricity by conversion of solar radiation into electrical energy. The output of a PV system depends on light intensity, cell temperature, orientation of the panel and atmospheric conditions.(temperature, wind velocity etc) The light intensity primarily affects the amount of produced current, and the cell temperature controls the cell voltage. Although the electrical characteristics of PV panels are evaluated and published under the standard test conditions (STC) [1000W/^{2}, 25ºC], under actual operation conditions (i.e., varying solar insolation as well as large temperature variations) most panels do not behave as indicated in the datasheets. At most certain manufacturers provide alternative performance outputs at Normal Operating Cell Temperature (NOCT) conditions [800 W/m^2, temperature 45±3ºC,wind speed of 1m/sec and air at 20ºC] The performance of PV panel under actual operating conditions different from the datasheet information is sometimes necessary for proper sizing of the PV plant, converter, design of the maximum power point tracking (MPPT) and associated control strategy. However, the field testing of PV arrays is expensive, time consuming, and difficult under non sunny weather conditions. It becomes thus necessary to develop simulation models to predict the performance of PV modules.

Literature Studies

Various analytical models are available in the literature for simulating the behavior of solar cells under restricted irradiance and temperature conditions. A brief overview of some of these studies is presented: Azzouzi et al [1]examined the simulated performance of the single diode PV model in three stages- an ideal stage with no parasitic resistances, then the model with additional series resistance and finally the model with both series and shunt resistances. They found that the model with the addition of series resistance only gave best performance results.A similar conclusion was arrived at by an earlier investigation by Bikaneria et al [2] . Benghanem and Alamri [3] examined different explicit models with different number of parameters for simulating the PV cell. They also proposed experimental methods to extract the series and shunt resistance parameters that are present in the model. Other attempts to examine the results of simulations using the single diode model were reported by Rodigues et al [4],[5]. To improve the accuracy of the model simulations, a second diode has been used by some researchers [6]-[7]. Single diode model is simple and easy to implement, whereas double diode model has better accuracy which acquiesces for more precise forecast of PV systems performance. Ahmad et al [8] investigated the performance of the single and double diode models on a comparative basis. MATLAB tool is used to serve this purpose They found that the double diode model has superior performance compared to single diode model.

In most of the analytical models, there is a need to estimate accurately certain model parameters such as the series and shunt parasitic resistances and the ideality factor. A proper estimation of these will yield a reasonably good model that can be applied for performance evaluation under varied operating conditions. In the literature, a variety of methods have been evolved to accomplish this. These methods include the, double exponential method [9], conductance method [10] and pattern search technique.[11],[12] The problem that a researcher faces is to estimate these parameters accurately. An alternative approach is to use the Artificial Neural Network (ANN) concept in which a minimal of input data is needed. Artificial Neural Networks (ANNs) are being applied to study engineering systems that are governed by non linear relationships. This is also true of the solar cell on account of its non linear I-V characteristics. Some reports that deal with the application of ANNs are available in the literature [13]-[20]. In these reports, the use of the ANN model has been demonstrated suitable and better than the use of the conventional diode equivalent circuit model. Further, in most of these cases the back propagation algorithm has been generally adopted.

Motivation for Present Research

The Fill Factor is a measure of the performance of the cell and is given as:

$$\textit{Fill Factor (FF)} = P_{peak}/(Voc*Isc)$$

Where: P_{peak} is the peak output of the module/array, *Voc* is the open circuit voltage and *Isc* the short circuit current.

Computation of the FF can be useful to compare the performance of the PV system under different operating conditions of solar insolation and /or cell temperature. Under rated standard or rated operating conditions, the values of P_{peak}, *Voc* and *Isc* are provided by the manufacturer. However, at any other operating condition involving different solar radiation levels or cell temperatures, the characteristics of the PV module will be altered and the FF will change. Estimation of the FF under such circumstances requires either complex analytical computations or else additional field data. It is here that a developed ANN model will be found useful.

The Problem Domain

The present paper develops a generalized ANN model for the estimation of the FF of a PV module and tests its performance. The equivalent circuit model is first discussed to acquaint the reader with the classical approach of PV simulation. This is then followed by the alternative approach of PV simulations in which the basics of the ANN model are highlighted. The next section discusses the basic analytical model use extensively in the literature, followed by elementary details of the ANN methodology and the architecture of the proposed model. The rest of the paper discusses the training, and testing of the ANN model so developed and shows its superiority in predicting accurate outputs.

The PV Model

Figure 1(a) and (b) shows the basic One-diode/ Two diodes models of the PV cell that has been mostly used for simulation studies .

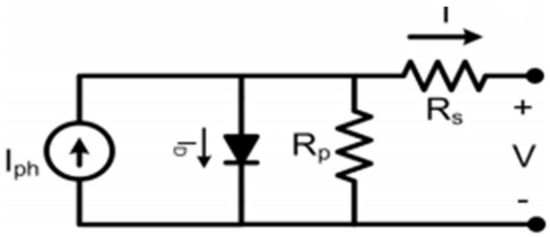

Fig.1 (a) The one diode PV model [6]

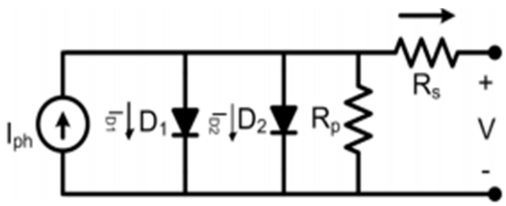

Fig. 1(b) The two diode PV model [6]

The relevant equations describing the performance are ;

For One diode model

$$I = I_{PH} - I_0\left[EXP\left(\frac{V + R_S * I}{Vt * \alpha}\right) - 1\right] - \frac{V + R_S * I}{R_P}$$

For Two diode model

$$I = I_{PH} - I_{D1} - I_{D2}$$

$$I_{D1} = I_{01}\left[\exp\left(\frac{q*V}{\alpha 1 * k * T}\right) - 1\right]$$

$$I_{D2} = I_{02}\left[\exp\left(\frac{q*V}{\alpha 2 * k * T}\right) - 1\right]$$

and after combining

$$I = I_{PH} - I_{01}\left[EXP\left(\frac{V + R_S * I}{Vt * \alpha 1}\right) - 1\right] - I_{02}\left[EXP\left(\frac{V + R_S * I}{Vt * \alpha 2}\right)\right] - \frac{V + R_S * I}{R_P}$$

Where:

I_L is the current generated by the incident light at the cell (A)

I_D is the diode saturation current (A). (I_{D1}, I_{D2} for the two diode model)

I is the overall diode current produced by the cell (A).

Q is the electron charge (1.60217646 x 10-19 C).

Rs is the cell series resistance (Ω).

Rp is the cell shunt resistance (Ω).

α is the diode D ideality factor.

$\alpha 1=1$ is the diode D1 ideality factor.

$\alpha 2 \geq 1.2$ is the diode D2 ideality factor

K is the Boltzmann constant (1.3806503 x 10-23 J/K).

T is the temperature of the PV cell measured in Kelvin.

V is the voltage across the cell.

PV systems mainly consist of PV cells, which are connected in a series and/or parallel to form a PV module, and a PV panel consists of a group of PV modules. A group of PV panels are arranged to structure a PV array.

Using the above expression, it is possible to obtain the I-V and P-V characteristics of the module for a particular temperature and insolation level. However, the characteristics of the PV cell module using the above equations will involve the determination of parameters i.e. *Rs, Rp* . These parameters have to be extracted from the data sheet of the PV module through complex calculations involving either complicated analytical expressions or some iterative algorithm.

The ANN Model

The ANN is a modeling method to simulate complex systems (especially nonlinear systems), using learning algorithms involving a set of training data. The relationships so extracted are not stored as equations, but are distributed throughout the network in the form of connection weights between neurons the basic units that comprise the ANN network. The structure of ANN is important factor that influences the learning performance of networks. The multilayer perception (MLP) known as feed-forward back propagation neural network (FFNN) has the capability of providing the best mapping of the input–output data matching, and so they are most commonly used type of ANN for most studies. The same will be used in the present study.

Figure 2 shows the basic structure of a typical multi input-multi output back propagation ANN model:

The inputs are $x_1, x_2, \ldots x_n$, while the outputs can be $y_1, y_2 \ldots y_n$.

A back propagation network is usually arranged in at least three layers: an input layer, the one or more hidden layer(s), and an output layer. The number of input neurons is equal to the number of independent variables ($x_1, x_2, \ldots x_n$), while the output neuron(s) represent the dependent variable(s)[$y_1, y_2 \ldots y_n$.]. The number of hidden layer and neurons within each layer can vary depending on the size, complexity and nature of the dataset.

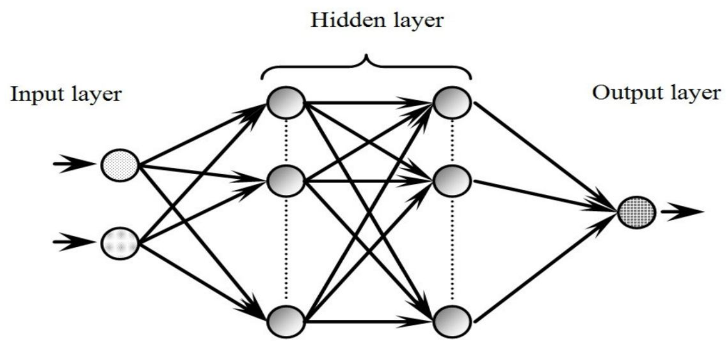

Figure 2: Schematic diagram of a Back Propagation ANN Model [20]

Figure 3 shows the information processing in a neural network unit.

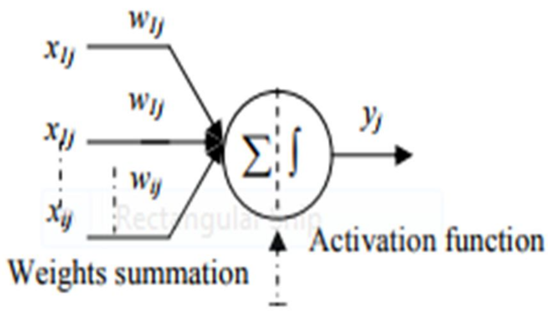

Figure 3: Information processing in a neural network unit [13]

The neurons carry out the same operation; the sum of their weighed inputs. Then they apply the result to a non-linear function such as hyperbolic tangent (TANH) named activation function to produce output as governed by the relationships:

$$y_j = f\left[\left(\sum_i w_{ij} x_{ij}\right) + b_j\right]$$

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

where *yj* is the output of the neuron, *wij* is the synaptic weight coefficient of the x_{ij} th input of the neuron, and *bj* is the bias, if involved.To objectively evaluate the performance of the networks, different statistical indicators may be used. Some of these indicators are mean squared error (MSE), coefficient of determination (R^2) and mean absolute per percentage error (MAPE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_{estimated} - Y_{target})^2$$

$$R^2 = \frac{\sum_{i=1}^{n}(Y_{estimated} - Y_{target})^2}{\sum_{i=1}^{n}(Y_{estimated} - Y_{mean})^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{estimated} - Y_{target}}{Y_{target}}\right|$$

where Y_{target} and $Y_{estimated}$ are measured and predicted current values respectively. Amongst the above statistical measures, *MAPE* is the most important statistical property in that it makes use of all observations and has the smallest variability from sample to sample. Moreover, it is easy to understand. Hence, its use is quite popular.

There are seven steps involved in the design and implementation of an ANN, which are as follows: [21]

1. Creating the network
2. Configuring the network
3. Initializing the weights and biases
4. Training the network
5. Validating the network
6. Using the network

Using ANNs, researchers have applied this mathematical theory to many complex problems, prominent among them being:

1. Function approximation: In this method, the relationship between multiple inputs and single output is developed with adaptive model-free estimation of parameters.
2. Pattern association and pattern recognition: ANN’s are used to solve difficult problems in sound, image, video recognition.
3. Associative memories: In this method a problem is recalled when only a subset is given for clue. The network structures are complicated containing of many interacting dynamical neurons.
4. Generation of new meaningful patterns: This field is totally new and claims are made that neuronal structures can exhibit rudimentary elements of creativity

Problem Definition

The Main purpose of the present paper is to demonstrate that ANN models can be used as an alternative to conventional equivalent circuit PV models for estimating the Fill Factor. This approach has been preferred due to need of lesser input data measurements and lower computational effort. The remainder of the paper is structured to justify this claim.

Specifications of the ANN Model Developed

Various ANN architectures were tried to arrive at the most suitable ANN model which gave the highest accuracy. The ANN model architectures used are is: 5 or 7 nodes in the input layer; a single hidden layer of 10 nodes or 15 nodes and an out layer of a single output. The Neural Network Toolbox algorithm of MATLAB ® is used. The input variables for the 5- input model are: Open circuit voltage, Short circuit current, module cell temperature, insolation level, peak power. The 7- input model has two additional variables i.e. voltage and current at maximum power point. These input data are readily available in the manufacturer's supplied data sheet specifications of the module. The output is the Fill Factor (FF).
Table 1 provides the brief details of the developed ANN models.

Table 1: Architecture of the ANN models for the study

Feature	Number	Details
Input layer nodes	05, 07	Open circuit voltage, Short circuit current, temperature, insolation level, power at peak power conditions.[additionally, voltage and current at maximum power point]
Output layer nodes	01	Fill Factor (FF)
Hidden layers used	01	--
Hidden layer nodes	10,15	---
Convergence level	--	0.001
Type of ANN	--	Feed Forward Back propagation type ANN
Convergence algorithm used	--	Levenberg-Marquardt
Statistical Indicator used		Mean Square Error (MSE)

Training of the ANNs involves the use of a database of required inputs and output created from data specifications of PV cell modules obtainable from different manufacturers. Additionally, practical field/ laboratory data reported in certain research papers are also included in the database. The developed ANN models are tested for accuracy.

Results of ANN Model Testing

The ANN model with specifications as given earlier was trained using the MATLAB neural network tool box. A snapshot of the training performance is given for the ANN with 7 input nodes and 10 neurons in the hidden layer in Figures 3-5.

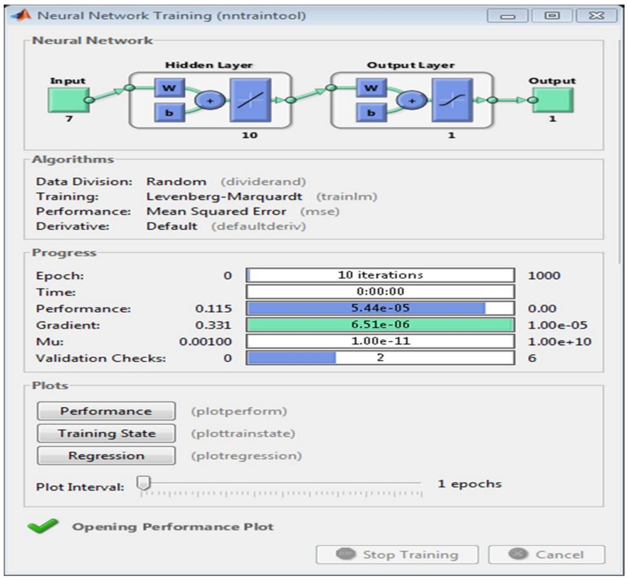

Figure 3: ANN Architecture & Training convergence

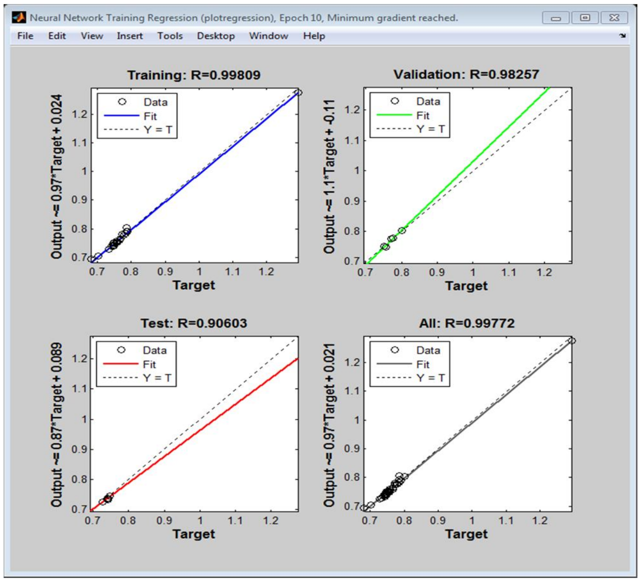

Figure 4: Training Regression Results

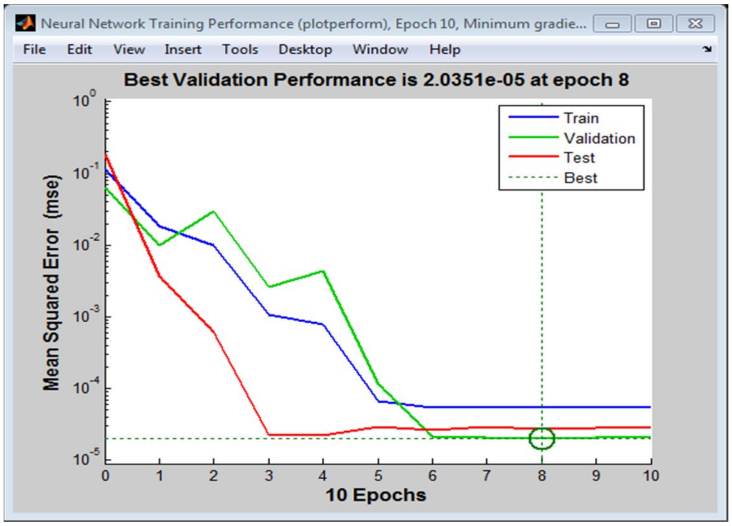

Figure 5: Training Convergence Results

The developed ANN models were tested with random input data from the created database.

Table 2 shows the levels of accuracy obtained taking a total of 20 random samples of the training data comparing the actual output with that obtained from the different constructed ANN models. It is seen from these results that a good level of accuracy can be achieved. This will justify the use of the ANN model in general for further simulation studies.

Table 2: Level of accuracy of the various ANN models under testing mode

Testing sample no.	Output (actual)	Output (ANN model)	% error
1	0.757673	0.75184	0.769857
2	0.747359	0.7437	0.489591
3	0.7592	0.7587	0.065859
4	0.778166	0.77569	0.318184
5	0.750958	0.73536	2.07708
6	0.769034	0.76739	0.213775
7	0.759387	0.75853	0.112854
8	0.764868	0.76115	0.486097
9	0.787758	0.78255	0.661117
10	0.774294	0.77095	0.431877
11	0.751562	0.75126	0.040183
12	0.767606	0.76419	0.44502
13	0.726901	0.72485	0.282157
14	0.785667	0.7814	0.543105
15	0.772436	0.77227	0.02149
16	0.767014	0.76638	0.082658
17	0.789407	0.78327	0.777419
18	0.760413	0.75142	1.182647
19	0.760148	0.75807	0.273368
20	0.737419	0.73644	0.13276
		Average % Error	0.470355

Conclusion

The paper proposes an alternative method of estimating the Fill Factor (FF) of a PV module with different operating conditions. The model chosen is the ANN and is developed as a generalized one that will save effort and computational labour in obtaining performance under different ambient conditions without the necessity of any additional field data measurements. Combinations of models with different number of input and hidden layer nodes have been tested and the results give a net mean error of lesser than 1%. The major advantage of this method for PV performance evaluation is that it requires merely the manufacturer's datasheet which is readily available. The high accuracy of the model for estimation thus makes it suitable as an alternative to field experimental efforts or the use of analytical models.

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