International Journal of Electrical Components and Energy Conversion
2017; 3(1): 14-20
http://www.sciencepublishinggroup.com/j/ijecec
doi: 10.11648/j.ijecec.20170301.12
ISSN: 2469-8040(Print); ISSN: 2469-8059(Online)

Review Article

Electrical Characterization of a Photovoltaic Module Through Artificial Neural Network: A Review

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To cite this article:
Rashmi Galphade. Electrical Characterization of a Photovoltaic Module Through Artificial Neural Network: A Review. *American Journal of Electrical Power and Energy Systems*. Vol. 3, No. 1, 2017, pp. 14-20. doi: 10.11648/j.ijecec.20170301.12

Received: February 11, 2017; **Accepted**: March 9, 2017; **Published**: April 18, 2017

Abstract: The aim of this paper is to present a review of I-V characteristics of photovoltaic module using artificial neural network (ANN). The ANN approach has found to be the efficient tool over complex non-linear mathematical equations and complicated models for estimation of output power and energy of PV modules.

Keywords: Photovoltaic Module, ANN, Modeling, Simulation, Electrical Characteristics

1. Introduction

Power consumption has significantly increased in recent decades. Traditional energy resources such as oil, coal and nuclear has negative impact on day to day life. For these reasons researches have turned toward renewable energy resources such as solar energy which is the radiant light and heat from the sun, wind and marine energy. Renewable energy is recognized as clean and durable energy. Scientists have converted the solar energy into electricity, which reduces pollution due to fossil fuels in new millennium [1].

PV modules have numerous advantages such as quicker installation and longer life of exploitation, simpler circuits and safe source of renewable energy [2]. A PV module is a connected assembly of 6x10 solar cells. Solar PV panels constitute the solar array of a photovoltaic system that generates and supplies solar electricity in commercial and residential areas. Several models have been proposed in literature to consider various details of the PV systems. Different circuits with model photocurrent sources, current leakage paths and loss elements are also presented. Non-linear lumped parameter equivalent circuits and their parameters are found by experimental current-voltage characteristics using analytical or numerical techniques [3-5].

Most solar PV modules are produced for terrestrial applications and are made from crystalline silicon solar cells. These thin- film solar modules are made up of amorphous silicon (a-Si), cadmium telluride (CdTe), Copper Indium Selenide (CIGS) and Gallium Arsenide (GaAs). Due to which the thin-film technology becoming most promising.

However, the problem associated with the PV module is unpredictability of the output power due to variations in irradiance levels and solar cell temperature. Hence, solar energy obtained from PV module does not remain constant. The power in the PV module is a function of PV array and voltage [6].

2. Photovoltaic Module

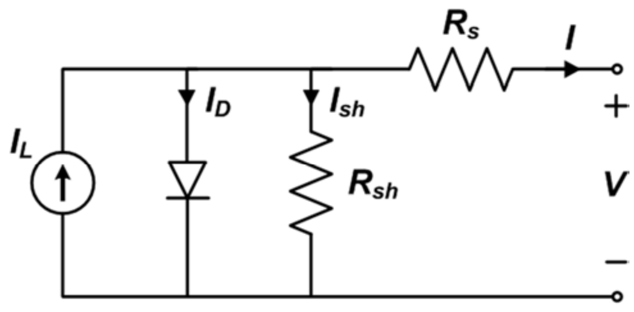

Figure 1. *Equivalent circuit of solar PV module.*

A well-known general equation for the diode current of the PV cell is given by,

$$I = I_L - I_D\left[e^{\frac{Q(V+IR_{sh})}{nkT}} - 1\right] - \frac{V+IR_s}{R_{sh}} \quad (1)$$

Where,

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

I_D is the diode saturation current (A).

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

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

R_s is the cell series resistance (Ω).

R_{sh} is the cell shunt resistance (Ω).

V_d is the diode voltage (V).

n is the ideality factor.

κ 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 [7]. The second component of a PV system is the converter, which is used to regulate the output of PV cells and/or convert the generated voltage waveforms from DC to AC [8].

Energy Analysis of Photovoltaic Module

The electrical efficiency of the photovoltaic panel is categorized as module and cell efficiency. The highest electrical loss of the panels occurs with temperature. The electrical efficiency is calculated as,

$$\eta_c = \eta_o[1-\beta\ (T_c\ -25)] \quad (2)$$

Where, η_o is the efficiency at standard test condition (I (t) = 1000 W/m^2, T_c= 25ºC), T_c is the solar cell temperature and β is the electrical efficiency thermal coefficient. The values of β depend on the features of the materials from which the PV module is produced. For crystal silicon 0.0045/K is taken. For CIS it is 0.0035/K. For CdTe it is 0.0025/K, for a-Si it is 0.02/K [8, 9].The output power of the PV module is calculated using,

$$P = VI \quad (3)$$

The electrical energy gain obtained from PV module is,

$$E_{l,net,electrical} = \eta_m A_m I(t) \quad (4)$$

Where, η_m is the module efficiency and A_m is the module surface area.

3. Artificial Neural Network

The working of the neural system depends upon neuron connection strength. Exposure to new ideas or learning can cause the change in the connection strength. The connection strength gives rise to new synaptic connections or losing the old information. The neuron response is determined by the transfer function. The transfer function describes the firing rate of the neuron. The firing rate varies with the input it receives. If the firing rate exceeds the activation then the neuron is off otherwise it is on. Though large number of neurons is required to carry information in human being, very few neurons are required in case of artificial neural network.

An artificial neural network is a network that attempts to perform brain functions. ANN has high speed, accuracy and accessibility. Neural networks performs specific task through learning process. When inputs and outputs are provided, they form a relationship between them. There are seven steps involved in the design and implementation of an ANN [9, 10]:

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

Armed with characteristics of ANN researchers have applied this mathematical theory to many complex problems [11-16].

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.

3.1. Feed Forward Networks

These networks are characterized by acyclic graph which describes the topological structure of network. Feed forward networks are the most commonly used networks. Figure 2shows simple feed forward network.

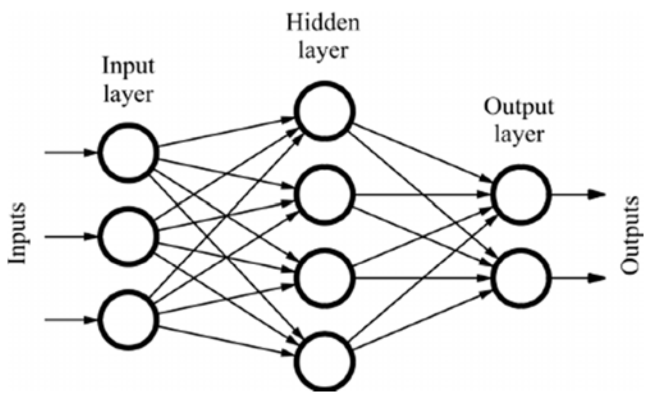

Figure 2. *Feedforward network.*

The feed forward network consists of number of processing units. They are organized in a series of two or more mutually exclusive sets of neurons or layers. The first layer holds the other layers applied in the network whereas the last layer consists of all the mapping. In the inner layers computing takes place. Weights connect each unit in one layer to that next higher layer. The output along with the weights is fed forward to provide the activation to the next higher layers. The role of the input layer is to provide the input values to the units of the higher layers. In the input layer there are no weights. The information flows from input layer to the output layer. Each layer based on its input computes an output vector and the process then proceeds towards the last layer. Thus feed forward network allows parallelism between each layer and interlayer information is serial. Fig. 3 consists of Feed forward net based strategy. The network consists of d inputs and c number of output units. Instead of input and output layers there are five "hidden" layers. The feed forward network allows parallelism within each layer but the flow of information is serial [17].

3.2. Radial Basis Network

Radial basis function (RBF) [18] is a branch of artificial neural networks, which has been applied in various fields for classical mechanics control, time series prediction, clustering etc. The RBF network is shown in figure 3

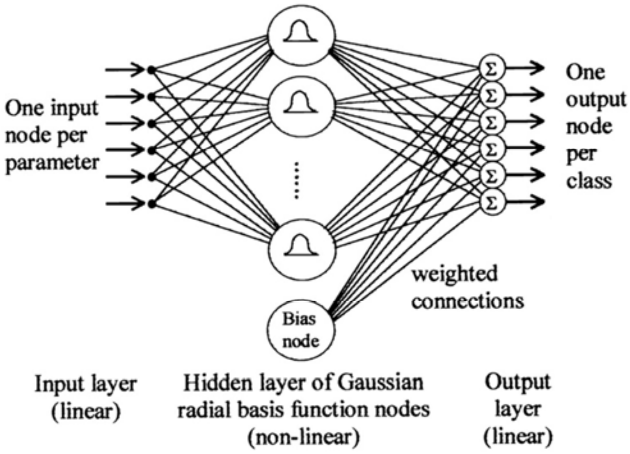

Figure 3. *Radial basis nework.*

The idea of RBF networks is derived from the theory of function approximation. Their main features are:

1. They are two layered feed-forward networks.
2. The neuron in the first layer does not use the weighted sum of inputs and the sigmoid transfer function.
3. The outputs of the first-layer neurons, each of which represents a basis function, are determined by the distance between the network input the center of the basis function.
4. As the input moves away from a given centre, the neuron output drops off rapidly to zero.
5. The second layer of the RBF network is linear and produces a weighted sum of the outputs of the first layer.
6. The neurons in the RBF networks have localized respective fields because they only respond to inputs that are close to their centers.

4. Literature Review

Literature review of application of ANN for estimation of electrical characterization of a photovoltaic module:

M. Hadjab et al. [2] have developed ANN for PV panel BP 3160 W to estimate the electrical current-voltage and power-voltage.

They observed that current of a solar cell is proportional to the solar illumination; and it increases slightly with temperature. The open circuit voltage of a solar panel varies slightly with the solar illumination and decrease with increasing temperature. Moreover, the optimal power increases mainly with increasing illumination and decreases rapidly with increasing temperature. A good agreement is obtained between model of the PV panel and neural technique.ANN is successful in predicting values of power, current and solar irradiance at different time, voltage and temperature.

F. Bonanno et al. [19] have developed radial basis function neural networks based module to improve the accuracy of the predicted output I-V and P-V curves and to keep in account the change of all parameters at different operating conditions. In this network they have taken input parameters as radiation and voltage. At the output current and voltage are there. The numerical values of the computed I-V and P-V characteristics match closely to those obtained from the experimental data.

L. Sindhura and K. Choudhary [20] developed ANN for MPPT of solar panel considering the variations in input levels of solar irradiation and temperature. The MPPT done using ANN has shown better result than the conventional PO controller.

M. U. Olanipekun et al. [21] used ANN to predict the output power generated from a single junction Cu (In, Ga) Se_2 (CIGS) thin film PV module by investigating the effect of the no. of input variables on the estimated accuracy. The input parameters are irradiance, module temperature, open circuit voltage (V_{oc}), short circuit current (I_{sc}). It is observed that thee predicted and observed values match perfectly.

M.T. Makhloufi et al. [22] propose an intelligent control method for MPPT of a photovoltaic system under variable temperature and solar irradiation conditions using ANN. They conclude that MPPT ANN controller which is initially based on the experience of the operator during the training stage has a very good transient performance. It improves the responses of the PV system. It not only reduces the time response to track the MPT but also eliminates the fluctuations around this time. The effectiveness of the ANN control for PV systems under varying environmental conditions is proved.

H. Rezk and El-Sayed Hasaneen [23] presented a new matlab/ simulink model of PV module and MPPT system for high efficiency InGap/InGaAs/Ge triple-junction solar cell. 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 output as I-V and P-V characteristics under various conditions and also includes the effect of the temperature variations on the cell characteristics. The simulation results of the proposed

MPPT technologies which are based on ANN are compared with perturb and observe MPPT technique. The output power and energy of the proposed technique are higher than that of perturb and observed MPPT technique.

B. Garcia-Domingo et al. [24] in their work applied multilayered perceptron models to generate I-V curves of one of the most extended commercial modules of concentrating PV technology using the influential atmospheric variables as input to the network. To train these networks they carried out experiments with real measurements in Jaen Spain from July 2011 to June 2012. They also presented procedure which is previous selection of the most representative samples from initial data set using kohonen-self organizing map. They observed that it is possible to obtain the characteristics curves of CPV modules under different meteorological condition with high accuracy and fidelity.

İlhanCeylan et al. [25] in their study predicted module temperature according to outlet air temperature and solar radiation. The study is made in open air. Solar radiation was measured and that data was used for training of ANN. They further calculated electrical efficiency and power depending on the predicted module temperature. They concluded that the outside temperature is a very important factor in terms of photovoltaic module temperature. A good correlation is observed between measured and predicted values. Solar radiation is inversely proportional to photovoltaic electrical efficiency; however power is directly proportional to solar radiation.

C. B. Salah and M. Quali [26] proposed in their paper two methods of maximum power tracking using a fuzzy logic and neural network controllers for photovoltaic systems. The two inputs for the two maximum power point tracking controllers is solar radiation and photovoltaic cell temperature. The output was the optimum duty cycle corresponding to maximum power. The method was a 100 Wp PVP (two parallels SM50-H panel) connected to a 24 V dc load.They concluded that fuzzy logic and neural networks can model dynamical complex systems that change with time following non-linear laws. These two MPPT gives a simplified system and low cost to implement it also it gives a good power maximum power operation of any photovoltaic array under different conditions such as changing solar radiation and PV cell temperature.

L.Thiaw et al. [27] in their work used ANN technique and showed how efficiency of MPPT of photovoltaic generators can be improved and how it is possible to assess the available and recoverable wind energy potential of the site by means of finding an adequate distribution law of the wind speeds based on neural model. The efficient neural controller enables to find the optimal value of the DC-DC converter’s duty cycle, starting from load voltage, the output value of the short circuit current and the open circuit voltage of monitoring cells which reflect environmental conditions as compared to classical MPPT controllers with low error. Through this work importance of using ANN in renewable energy systems is exhibited.

H. Parmar [28] constructed ANN to predict outlet voltage and outlet current of PV module with inputs solar radiation and ambient temperature. For this model Feed-forward neural network with Leverberg-Marquardt algorithm is used. It was observed that the output current is proportional to the solar radiation. He concluded that the experimental output and neural output are in close agreement.

H. Mekki et al. [29] introduced the preliminary result of the modeling and simulation of the photovoltaic panel based on neural network and VHDL language. The inputs of the ANN-PV panel are the daily total irradiation and mean average temperature while the outputs are the current and the voltage generated from panel. The NN (Multilayer Perceptron) corresponding to the PV- panel is simulated using VHDL language based on saved weights and bias of the network. It is observed that the advantage of using the proposed PV-panel based on ANN and VHDL can be used for estimating the performance of the PV-panel and is able to predict the output electrical energy based on the environmental data. Also it evolves less computational efforts.

K. J. Singh et al. [30] in their paper proposed implementation of neural network especially to improve the accuracy of the electrical equivalent circuit parameters of solar cell. For this network, effect of sunlight irradiance and ambient temperature are taken as inputs whereas at the output current and voltage are taken. They concluded that, the trained network is sufficiently accurate in representing the circuit parameters when compared with conventional PV model as the dependency of the solar irradiance and cell temperature of all the model parameters are not included. Therefore, the accuracy and the performance estimation cannot be sufficient for all operating conditions.

F. Dkhichi and B. Oukarfi [31] in their paper they have used steepest descent algorithm in the training of artificial neural network to determine the internal parameters of solar cell. The prediction of the values of these parameters is made for various values of temperature and irradiance.

A. Shahat [32] proposed general and specific modeling and simulation for Schott ASE-300-DGF PV panel for smart grid applications. They have performed modeling of PV module at nominal conditions at 25°C, and 1 KW/m^2 with I-V curves at 0°C, 25°C, 50°C, 75°C also power and irradiance. They presented a non-specific modeling and simulation at more probable situations for various values of temperature and irradiance in 3-D figures. It is observed that the PV model using the equivalent circuit in moderate complexity provides good matching with the real module.

M. S. AïtCheikh et al. [33] proposed a control method for the maximum power point tracking of a photovoltaic system using ANN, so that the output power should increase. For this they built an electronic controller between the photovoltaic generator and the load. The electrical level output of the converter are estimated through three variables namely, solar insulation, the temperature of the junction and information on the dynamics of the charging voltage if it exists. It is observed that power output of control panel is compared with another maximum power point tracking scheme and showed improvement in power response and in the time response.

Nagarjuna Reddy J. et al. [34] observed that a photovoltaic generator exhibits nonlinear characteristics and its maximum power point varies with solar radiation. In their paper, they have developed an application of a neural network for the identification of optimal operating point of PV module and continuous control of boost converter to achieve the maximum output efficiency. It is observed that the network gives accurate predictions over wide variety of operating modes.

R. Ramaprabha and S. P. Chitra [35] in their paper quoted that the major drawbacks exists in PV systems are mismatching effects due to partial shaded conditions. Hence they formed neural network to predict maximum power tracking point under partial shaded conditions. They observed that scanned maximum power point training system is more efficient than distributed maximum power point training system. Results are validated with experimental results and good match is observed.

V. Lo Brano et al. [36] in their paper illustrated an adaptive approach based on different topologies of artificial neural networks (ANNs) for the power energy output forecasting of photovoltaic (PV) modules. They collected the data by a dedicated weather monitoring system. They obtained power output forecast using three different types of ANNs: a one hidden layer Multilayer perceptron (MLP), a recursive neural network (RNN), and a gamma memory (GM) trained with the back propagation. The inputs taken for ANN modeling are weather data (air temperature, solar irradiance, and wind speed) along with the output as power output data available for the two test modules. The results obtained from the network indicated the short-term power output forecasting problem has solved with greater accuracy and ANN was identified as the best topology which takes less computational time.

E. Velilla et al. [37] presented the results from monitoring the electrical power after exposure to external weather conditions of two different solar modules technologies, one of them mono-crystalline 55 W silicon and the other a flexible organic solar module of 12.4 W. The temperature, relative humidity, and irradiance were taken as input parameters and the electrical power was taken as output. With the recorded data an artificial neural network model was trained, validated and tested. A sensitivity analysis for better performance for the organic flexible module was achieved specially under conditions of higher relative humidity, higher temperatures and lower irradiances. They concluded that this tool helps for prediction of the performance of these photovoltaic technologies at broad different environmental conditions.

J. Zeng and Wei Qiao [38] proposed a radial basis function (RBF) neural network-based model for short-term solar power prediction (SPP). In that, they have not predicted solar power directly, but the model predicts transmissivity, which is then used to obtain solar power according to the extraterrestrial radiation. For the proposed model, they have taken inputs has two-dimensional (2D) representation for hourly solar radiation and uses historical transmissivity, sky cover, relative humidity and wind speed. Meanwhile they compared the performance of the RBF neural network with that of two linear regression models i.e. an autoregressive (AR) model and a local linear regression (LLR) model. They observed that RBF neural network significantly outperforms the AR model and is better than the LLR model. Furthermore, they concluded that use of transmissivity and other meteorological variables, especially the sky cover, can significantly improve the solar power prediction performance.

According to F. Almonacid et al. [39], to carry out correct photovoltaic engineering, a suitable characterization of PV module electrical behavior is important. Hence, they formed ANN for electrical characterization of si-crystalline PV modules for any irradiance and module cell temperature. Their results showed that good predictions are observed when compared with the measured values.

A. Mellit et al. [40] described a methodology to estimate the profile of the produced power of a 50 Wp Si-polycrystalline. For this, they formed two artificial neural networks (ANNs) developed for use in cloudy and sunny days respectively. For the model, measured data was solar irradiance, air temperature, PV module voltage and PV module current. Their results confirmed the ability of the developed ANN-models for estimating the power produced with reasonable accuracy. Also they analyzed that the ANN-models perform better than polynomial regression, multiple linear regression, analytical and one-diode models. Another advantage of ANN they observed was it requires less number of parameters or complicate calculations unlike implicit models. Their developed models could be used to forecast the profile of the produced power. According to them, this methodology has been applied for large scale photovoltaic plants as well as for other PV technologies.

S. Leva et al. [41] in their paper formed ANN for photovoltaic plant energy forecasting and analyzed in term of its sensitivity with respect to the input data sets. The analysis of the results was based on experimental activities carried out on a real photovoltaic power plant accompanied by clear sky model. Their paper deals with the hourly energy prediction for all the daylight hours of the following day, based on 48 hours ahead weather forecast. Their trends of error showed that the predictions are more accurate for sunny days.

5. Conclusion

In the present study, the I-V characterization of photovoltaic module and output power using ANN is reviewed. In various I-V models, input parameters are time, temperature and solar irradiance. It is observed that, organic cells do not require high levels of radiation whereas humidity played a very important role in the behavior of the performance of the solar cell.

Moreover, the current of the solar cell is proportional to the solar irradiance, it increases with the slightly with the temperature. The open circuit voltage of a solar cell varies with the solar irradiance and inversely proportional to the temperature. The output power increases with increase in solar irradiance and inversely proportional to the temperature. For modeling of ANN data that represents past history, data taken on present PV module is required. The performance of the ANN depends on the model which compares the predicted data with the past history of the real system. ANN is observed as useful technique over conventional techniques. It is observed that ANN is found to be suitable tool for the prediction of electrical characterization of PV module. Like all other approximation techniques, ANN has relative advantages and disadvantages. It requires a huge data to train the network. There are no rules in which cases FF network and RBF network is suitable for an application. In some cases, RBF network is found faster than FF network.

Acknowledgement

The author is thankful to Dr. Anil Kottantharayil, Prof. IIT-B, for providing library access.

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