Role of ANN in Functionality and Designing of Solar Photovoltaic Cell: A Review

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1 Introduction

The research on photovoltaic cell has increased widely due to its extensive uses. A photovoltaic cell converts the Sun's energy into usable energy without any impact on environment. The most important component of a solar panel is photovoltaic cell, which actually generates electricity.

These photovoltaic (PV) cells are mainly divided into two categories, monocrystalline and polycrystalline, as these are most commonly used for various commercial and residential applications. A single silicon crystal is used for monocrystalline PV cell, whereas many shards of silicon crystals are used in polycrystalline PV cells. On comparison, monocrystalline PV cell is more efficient than polycrystalline PV cells. The reason being, as monocrystalline PV cell, consists of a single silicon crystal, and there is an easier flow of electrons generated through the photovoltaic effect. In polycrystalline PV cells, there are many shards of silicon aligned in many different directions which makes electricity flow slightly difficult.

The primary objective of this study is to understand the basics of PV cell and to know-how neural networks (NN) can impact its computational characteristics. The remainder of the paper will be organized as follows. Sections 2 and 3 describe the functionality and design of a PV cell. Section 4 discusses ANN in brief; Sect. 4.1 describes the earlier studies based on ANN which have modelled PV cell parameters; Sect. 5 concludes the paper and highlights the future direction.

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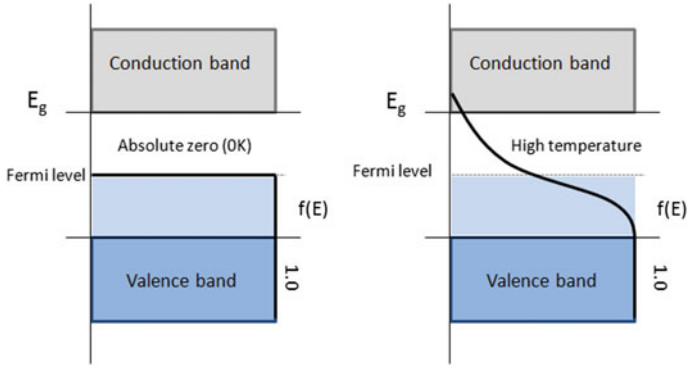

Fig. 1 Semiconductor Band Structure Plot

2 Functionality

A PV cell captures solar energy to produce electricity through a process called photovoltaic effect. Each cell operates as a semiconductor consisting of *p*-type and *n*-type semiconductor joined to form a *p*-*n* junction. Due to this, an electric field is formed causing negatively charged particles electrons to move in one direction and positively charged particles photons to move in other direction. When Sun rays are incident on these PV cells, photons transfer their energies to electrons in PV cell causing them to jump to a higher energy state known as the conduction band. This movement of electrons in conduction band generates an electric current in the cell.

Figure 1 demonstrates the semiconductor band structure plot. According to quantum theory, there exists a gap between valence and conduction bands of semiconductor. At absolute zero temperature, semiconductors behave as an insulator. At higher temperature, they become conductive as electrons and holes move from one band to another. This is due to the illumination of PV systems due to incident photons [1–4].

3 Designing

The PV cell design principles are affected by the working environment in which they are produced. For example, if it is developed for the research environment, then efficiency is more important, whereas for commercial environment cost weighs more.

The absorption coefficient of semiconductors also plays an important role in PV cell design. It is dependent on the material and also on the wavelength of light absorbed by the cell. The designers of PV cell use materials with higher absorption

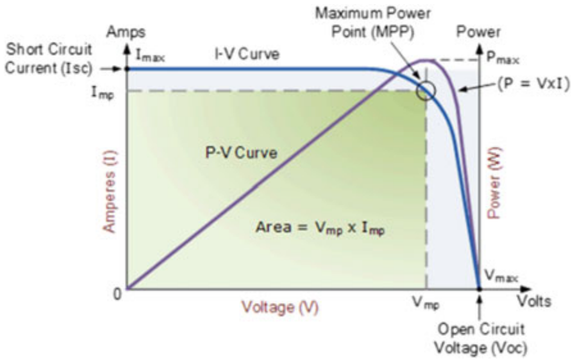

Fig. 2 *I–V* Curve of a PV cell

coefficients which can absorb photons readily and eventually excite electrons into the conduction band.

The main ingredient of a PV cell is silicon which causes an electric current to flow. All the PV modules are rated against standard test conditions (STC) which includes three factors: (a) Irradiance, i.e. sunlight intensity or power. The measurement standard is 1 kW per m^2. (b) Airmass, i.e. clarity and thickness of the air which affect the Sun's angle. The standard is 1.5. (c) Cell temperature. The standard is 25 °C.

The performance of solar panels can be represented by an "*I–V* curve". Every solar panel has multiple *I–V* curves which shows the relationship between current (I) and voltage (V) under prevailing conditions of, temperature, air mass and irradiance. Maximum peak power point (MPP) also depicts when a PV cell generates maximum power.

Figure 2 describes the *I–V* curve of a PV cell. At open-circuit voltage (V_{oc}), the voltage across the cell is maximum and the current is at its minimum, whereas when the cell is short circuited, the current is at its maximum known as short-circuit current (I_{sc}) and the voltage is at its minimum. As the PV cell is a *p-n* diode, the diode equations are inculcated in its designing. For achieving good conduction, the bottom layer of a PV cell should be completely covered and the topmost layer should be transparent so that the incident photons aren't blocked. A metallic cell grid is also used within the semiconductor to increase its conduction which reduces electron travel distance and thereby decreases resistance [4].

4 Artificial Neural Networks (ANN)

ANN works just like our human brain to solve a particular problem. The basic unit of brain and nervous system is the biological neurons which receives the input from the external world via dendrites, process it and gives the output through Axons. In the similar way, ANN also uses neurons to process the inputs. These neurons are connected to one another using connection link with weights assigned to them. This

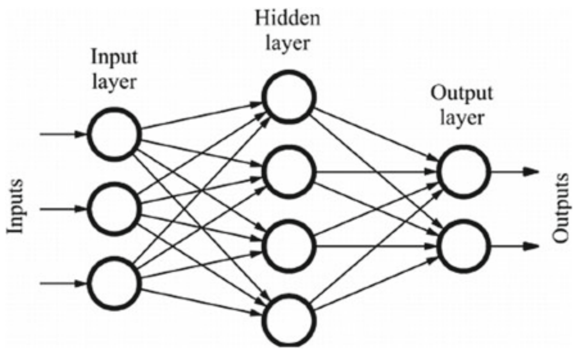

Fig. 3 An ANN with three layers

is required to solve a problem by a neural network. Every neuron has an internal state denoted by an activation function. There are many activation functions few of them are, binary step, sigmoid, tan h, ReLu, etc. There exist different kinds of ANN. The simpler one is called "perceptron" which is a single layer neural network. Later on, multilayer perceptrons with backpropogation learning algorithms are developed consisting of input, hidden and output layers. These ANNs are based on supervised learning and are used in variety of problems. Figure 3 shows a feed-forward ANN with three layers.

4.1 ANN Approaches Used in PV Cells

This section discusses various ANN approaches applied to PV cells. It also presents the discussion on various parameters of PV cell predicted through ANN modelling and the ANN framework used. The ANN modelling of a PV cell mainly uses two approaches [5, 6]: the first approach uses various irradiation and temperature values to predict the equivalent circuit parameters and then calculates current or voltage using analytical model; the second approach generates *I–V* curves using irradiance and module cell temperature as inputs to ANN.

Zhang and Bai [7] used genetically trained radial basis function neural networks (RBFNN) to predict the maximum power points (MPPs) and corresponding *I–V* curves of photovoltaic (PV) panels. The inputs to the network were radiation, ambient temperature and load voltage; and the output was load current. The hidden layer consisted of radial basis function which were trained using genetic algorithm. This model provided better results than conventional RBFNN which uses *k*-means algorithm in radial basis function. The genetically trained RBFNN were used to find optimal power points in PV panels.

Karatepe et al. [5] proposed feed-forward neural network with three layers. The inputs were irradiation and temperature, and the outputs were *n*, Is, Rs, Rp and Iph. The three kinds of activation function were used, and they were piecewise linear function, sigmoid function and piecewise linear function. In order to check the accuracy of the proposed model, the experimental setup was used. It was found that the model provided accuracy than the conventional model.

Mekki et al. [8] proposed simulation and modelling of a PV module using ANN and VHDL language. The inputs to the model were total irradiation and mean average temperature, and the outputs were current and voltage. The NN is implemented using VHDL language. The proposed model predicted the energy from the PV panel using only the environmental factors and required less computational efforts.

Rehman and Mohandes [9] proposed feed-forward ANN for the estimation of global solar radiation (GSR). The inputs to the network were air temperature and relative humidity values of Abha City in Saudi Arabia from 1998 to 2002. The authors classified the inputs in three categories and found that ANN provided good prediction for GSR based on temperature and relative humidity.

Ghanbarzadeh et al. [10] predicted daily global solar radiation (GSR) in future time domain using ANN for Dezful City in Iran. The inputs were measured air temperature, relative humidity and sunshine hours values between the years 2002 and 2006. The entire dataset was divided into three categories. They found that the ANN model used provided promising results for GSR.

Behrang et al. [11] used MLP and radial basis function network for GSR modelling. They divided the input dataset into six categories. The inputs were daily mean air temperature, relative humidity, sunshine hours, evaporation and wind speed for Dezful City in Iran between 2002 and 2006. The training data used by them was for the year 2002–2005, and the rest of the data was used as a testing data. The results provided by ANN were good in comparison with conventional GSR prediction models.

Celik [12] used generalized regression neural network (GRNN) model to estimate the operating current of a 120 Wp of monocrystalline photovoltaic module. The inputs used in the model were solar radiation on the module, cell temperature and the operating voltage of the system. The learning algorithm used was Levenberg–Marquardt (LM) algorithm. The model's performance to estimate current was evaluated using mean absolute percentage error (MAPE). The results of GRNN model were also compared with the results of actual experiments carried out in Iskenderun, Turkey, and with the analytical model. It was found that the current predicted by GRNN model was more accurate than the analytical model and close to the real-time experimental results.

Salah and Ouali [13] proposed neural network and fuzzy logic models to estimate maximum power point (MPP) for photovoltaic modules. The inputs to both the models were solar radiation and cell temperature. The model was validated on a 100Wp PVP SM50-H panel connected to a 24 V DC load. The models were adaptable to changing solar radiations and cell temperature. The results concluded that the fuzzy logic model was better than the neural network model in estimation of maximum power point (MPP).

Bonanno et al. [14] et al. used radial basis function neural networks (RBFNN) to predict the load current. The inputs to the model were solar radiation, ambient temperature and load voltage. The model has input, hidden and output layers and, used backpropagation learning algorithm. It improved the *I*–*V* and *P*-*V* curves of a PV module. Guede et al. [15] approximated the I–V curve using ANN. They modelled ATERSA A55 photovoltaic module using feed-forward network with backpropagation learning. The temperature, irradiance and the voltage were the inputs, and the current was the output. The prediction accuracy of the model is measured using mean square error (MSE). Ceylan et al. [16] used backpropagation neural network to predict the temperature of a PV module. The inputs to the ANN model were ambient air temperature and solar radiation. These inputs were determined from the experimental studies at Aegean region of Turkey with ambient air temperature at 10, 20, 30 and 40 °C and at different solar radiations. The predicted module temperature was then used to calculate the electrical efficiency and power.

Dumitru et al. [17] used multilayer perceptron and Elman neural networks to estimate the solar photovoltaic energy production. A two-year data of energy production of photovoltaic cells was analysed, and it was found that the energy production level increases in summer. This energy production was analysed using different parameters of ANN like learning rate, number of neurons and number of epochs. The accuracy prediction can also be increased by considering several factors like meteorological conditions, seasons and by increasing the dataset.

Parmar [18] used feed-forward network with Levenberg–Marquardt backpropagation (*trainlm)* as the learning algorithm. The inputs to the network were solar radiation and ambient temperature, and the outputs were voltage and current value. The network performance was measured using mean square error (MSE), and it can be used in any climatic conditions to predict the output from photovoltaic panels. The network with two hidden layers provided the best prediction performance with minimum error.

Kazem et al. [19] proposed support vector machine (SVM) for predicting the photovoltaic current. The inputs to the technique were solar radiation and ambient temperature, and the output was the photovoltaic current. The proposed model provided good accuracy in comparison with other related works.

Yassin and Harb [20] proposed neural network with differential evolution (NN-DE) technique to predict the cell operating temperature. The inputs to the network are: ambient temperature (T_{amb}), wind speed, air mass and solar radiation intensity. They used cell operating temperature to evaluate the maximum power output P_{Max} of photovoltaic modules. The obtained results of the model performed well when compared with conventional regression trees model. Durrani et al. [21] used neural networks to predict daily PV power for residential grid connected PV systems. Two forecasts models were developed for irradiation; one used multiple feed-forward networks and the other was persistence based. The NN-based irradiance forecast model performed better than persistence forecast model for all the accuracy measures used.

Sun et al. [22] used convolution neural network to relate PV cell output with the climatic conditions. The images of the sky were used to relate the current generated by the PV cell. They tested their approach with different CNN structures and proposed the future use of their model. Yousifa et al. [23] did comparative study from 2008 to 2017 on PV/T (photovoltaic thermal) energy data prediction systems which used

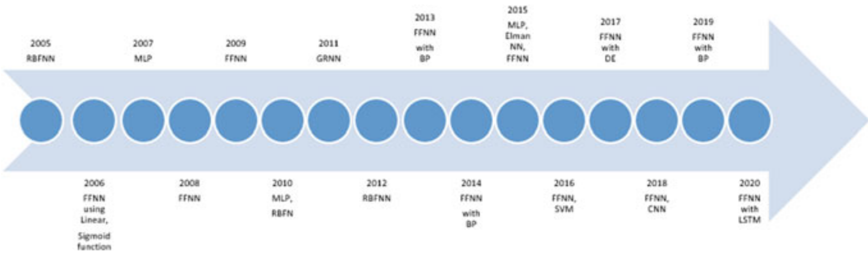

Fig. 4 Timeline of the ANNs used in the study for modelling PV cell

ANN to predict global solar radiation. The published study used different kinds of ANN and the model performed well in all the evaluation measures used.

Al-Dahidi et al. [24] proposed PV power predictions using small computational time and used ten ANN learning algorithms to train 23 datasets. They found correlations between various factors affecting PV power generation and developed an efficient prediction model. Cortés et al. [25] used multilayer perceptron network to estimate the parameters based on manufacturers datasheet. The inputs to the network are I_{sc} (short-circuit current), V_{oc} (open-circuit voltage), MPP (photovoltaic cell maximum power point), I_{mpp} (current value at the maximum power point) and V_{mpp} (voltage value at the maximum power point); the estimated parameters are I_{ph} (generated current due to photons), R_s (photovoltaic cell series resistance)and I_0 (diode reverse saturation current); the network consisted of two hidden layers and used Bayesian regularization learning method. The model can be used with any polycrystalline silicon cell, and there is no need to retrain the neural network for different PV modules made up with these cells. The synthetic data is used for training the neural network. Chen et al. [26] used long short-term memory (LSTM) learning algorithm to design a radiation classification coordinate method to select the similar time periods which are impacted by various PV power generation meteorological factors. Their proposed model was at par than the four other models compared in the work.

The ANNs used in all the above studies provided the results which were at par than the conventional models and were good in predicting the PV modules output. Figure 4 shows the timeline consisting of various ANNs used to model the PV cell. This timeline is based on the studies used in the current work.

5 Conclusion

The use of photovoltaic modules is rapidly increasing as they are based on renewable energy of sun with number environmental impact. The current study provided the base for research on photovoltaic modules and modelling their characteristics using ANN. ANNs are more capable in estimating the parameters of a PV module. The published work on PV modules with ANN is used different types of networks. But as the new soft computing techniques are introduced, every year the future work can comprise of using these techniques in modelling PV cell characteristics.

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