Electrical equivalent model of intermediate band solar cell using PSpice

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Abstract. Intermediate band solar cells (IBSCS) is a relatively new solar cell concept. The theoretical conversion efficiency limit for IBSCS is predicted to be 63.2% with blackbody illumination and 65.1% with AM1.5 spectrum, comparable to the theoretical efficiency for optimized triple junction solar cells with efficiencies of 63.8% and 67.0% under blackbody and AM1.5 illumination, respectively. This paper presents a structure of IBSC based on ZnTe:O. The proposed model uses irradiance and temperature as input parameters and the output characteristics of the structure are used as a prototypical example. So, in this work the artificial neural networks (ANNs) and the analog behavior modeling (ABM) of PSpice are implemented in order to model the IBSC. In addition, we have used the bias matrix and the weights matrix obtained by training to establish the IBSCS model on PSPICE simulator. This method represents an advantage by using a small representative database. Therefore, the obtained results of our model can be used in an electrical simulator. Thus, this method can be extended to other solar cells for motivating experimental efforts to realize these promising photovoltaic devices for low cost and high efficiency.

Keywords. PSpice simulator; IBSCS; neuronal network; analog behavior modeling (ABM).

1. Introduction

Worldwide photo-voltaic (PV) research is continuing in order to produce a low-cost and high-efficiency device for solar energy conversion. Power conversion efficiency has been improved for tandem and multi-junction solar cells, but these devices are more complex and are accompanied by higher manufacturing costs. Many techniques have been proposed to increase the efficiency of solar cells. They are based on different processes and properties such as photon recycling,

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impact ionization, angle dependent selectivity, down-conversion and up-conversion (Schokley & Queisser 1961; Luque & Martí 1997; Bremner & Honsberg 2012; Luque *et al* 2013). In recent years, intermediate-band solar cells (IBSCS) have been proposed to exceed efficiency limitations of conventional single-junction cells (Nozik 2006). In these devices, electron states are introduced in the forbidden band gap of a conventional semiconductor to provide three optical absorption bands to respond to incident solar energy. The theoretical conversion efficiency limit for IBSCS is predicted to be 63.2% with blackbody illumination and 65.1% with AM1.5 spectrum, comparable to the theoretical efficiency for optimized triple junction solar cells with efficiencies of 63.8% and 67.0% under blackbody and AM1.5 illumination, respectively (Luque *et al* 2001, 2004; Martí & Luque 2004). Several approaches have been proposed to practically realize an intermediate band solar cell including quantum dots, dopant impurities (often termed impurity-band photovoltaic), and dilute semiconductor alloys (Huan-Liang *et al* 2008; Khelifia *et al* 2008; Stanko *et al* 2008; Lin *et al* 2009).

Recently, artificial neural networks (ANNs) have been successfully employed in solving complex problems in various fields of applications including pattern recognition, identification, classification, speech, vision, prediction and control systems (Moufidi *et al* 2012). It is emerged as a highly effective learning technique suitable for performing nonlinear, complex, and dynamic tasks with a high degree of accuracy. Neural models are, therefore, much faster than physics/electro-mechanical models and have a higher accuracy than analytical and empirical models. Furthermore, they are easy to develop for a new device or technology (Kalogirou 2000; Tobías *et al* 2011; Mekki *et al* 2007; Lopes & Lienhardt 2003). The MATLAB interface was used during the design phase and optimization; the results (optimal architecture, bias, and weights of the network) are used for the implementation of the model as a component in the PSpice simulator library. The proposed technique keeps its validity also when applied to other systems for motivating experimental efforts to realize these promising photovoltaic devices.

2. Intermediate band solar cell modeling

2.1 Implementation of IBSCS model

The schematic structure of ZnTe-based IBSCS is presented in figure 1. Material parameters for ZnTe are chosen in this analysis as a prototypical material for IBSC due to recent interest in oxygen-doped ZnTe as an active region for IBSC devices.

Neural network is mostly used to find the appropriate solution for the non-linear and complex systems. Among its classes, there is the Multi-Layer perceptron (MLP) which is the most used, where the simpler architecture of MLP contains three layers as shown in figure 2. The input layer receives the external data. The hidden layers contain numerous hidden neurons that receive data from the input layer and send them to the third layer. Finally, the output layer gives the desired response according to the target system (Rahman *et al* 2011; Kouda *et al* 2011a, b; Phani & Mummadi 2005).

This research was applied by the use of sigmoid function as an activation function in order to calculate the hidden layer output and the linear function to calculate the output (Kouda *et al* 2011a, b; Giordano *et al* 2011; Han *et al* 2004).

In order to model electrical properties of solar cell, ANNs have been used to approximate the desired output. The flowchart of our proposed approach to find the optimal parameters using experimental data is detailed in figure 3. Approximation technique consists of three steps (Choice of neuronal structure, Learning and Validation).

After many tests of different ANN architectures, multilayer perceptron (MLP) with two hidden layers have been considered for best results; four neurons and Logsig as transfer function for the first layer, five neurons and the Logsig as transfer function for the second layer and the Linear transfer function for the output layer.

Table 1 summarizes parameters of neural networks where the data loading is: training base, test base, validation base, number of layers and neurons, type of the transfer functions, number of iteration and estimate threshold.

2.2 Implementation ANN in PSpice

By using the Analog Behavioral Modeling (ABM) PSpice Library components and the results (optimal architecture, bias and weights of the network), the Solar cell model designed previously is implemented as a component in the PSpice simulator library. In order to test its effect on electrical environment, figure 4 shows the model of ABM architecture where each neuron of the ANN is replaced by one ABM which is characterized by the neuron equation. Therefore,

Figure 1. Intermediate band solar cells structure.

Figure 2. A typical layer neural network.

Figure 3. Training program flowchart.

Table 1. Parameters of the neural networks model.

Database		Number of neurons		Transfer function
Training base	300	Input layer	02	Log sig Log sig Linear
Test base	100	1st hidden layer	04	
Validation base	100	2nd hidden layer	05	
		Output layer	01	

the general form of equation in the first and second hidden layers of ABM's can be given as

$$\text{Out } i = 1 / (1 + \exp(- (B_{ni} + W_{nij} * V(IN_j) + W_{nij} * V(IN_j) + \dots + W_{nij} * V(IN_j)))) \quad (1)$$

For example the equation of ABM1 can be given as

$$\text{Out } 1 = 1 / (1 + \exp(- (B_{11} + W_{111} * V(IN_1) + W_{112} * V(IN_2)))) \quad (2)$$

The equation exponential form is due to the choice of the transfer function in the first hidden layer, B_{11} is the first bias of the first hidden layer in the bias matrix "Bni", where n represents the number of hidden layers and i is the number of ABM in the first hidden layer ($i = 1 \dots 4$). W_{111} , and W_{112} are respectively the first and the second weight for the first hidden layer in the weights matrix "Wnij", where j varies from 1 to number of inputs ($j = 1 \dots \text{number of input}$). IN_1 and IN_2 represent input parameters which are temperature and irradiance respectively. Thus we have 10 equations with 10 bias ($4+5+1$) and 33 weights [$(4 \times 2) + (5 \times 4) + (1 \times 5)$].

3. Results and discussion

In order to validate our proposed ANN model, we have introduced it on PSpice simulator with fixed parameters (the temperature is fixed at 300 K and under AM1.5 illumination E), experimental set was compared with ANN model. Figure 5 represents a comparison of the variation of current as function as output voltage using ANN model and one reported in (Weiming *et al* 2009) at fixed parameters. We can see that proposed model provides a good agreement between them. Figure 6 shows the variation of current versus output voltage by implementation of our proposed ANN model in PSpice simulator. Using PARAMETRIC DC SWEEP analysis, we can also observe a good agreement between experimental and results provided by PSpice simulator.

The obtained results of our proposed model are presented in table 2, where MSE is the mean square error, Th is the estimate threshold “Test MSE”, I_{sc} represents the short circuit current and V_{oc} represents the open circuit voltage. As can be seen from the table a good agreement

Figure 4. ABM architecture model in PSPICE.

Figure 5. Variation of current density as function as output voltage with fixed parameters; $T=300K$ and $E= AM1.5$.

Figure 6. Variation of current density as function as output voltage with fixed parameters; $T=300\text{K}$ and $E= \text{AM1.5}$ using PSpice simulator.

Table 2. Comparison with simulation results and experimental one.

Input		Our proposed model		Experimental results		Mean square error	
Illumination (E)	AM1.5	V_{oc} (v)	0.39	V_{oc} (v)	0.38	Test MSE	3.910^{-4}
Temperature (T)	300 K	I_{sc} (mA/cm ²)	3.5	I_{sc} (mA/cm ²)	3.6	Training MSE	10^{-4}

is obtained between simulation results and experimental one. Hence, the proposed model can be used to predict other combinations of input variables (temperature and illumination) in full range. Further, the parametric simulation shows that our proposed model can be implemented as a circuit in a PSpice library to study the IBSCs-based devices for low cost and high efficiency.

4. Conclusion

The paper presents the modeling of I–V characteristics of IBSC based on Zn–Te:O depending on temperature and irradiance of the environment. The proposed model helps to realize the contribution of the inputs and activity of complete solar cell. The simulation results presented in this work are the evidence of the models validity and it is performed by considering an approach for modeling of IBSCS which can be done by implementation of ANN model in PSPICE. The model results have been verified and validated using experimental measurements, where a good agreement is observed between them. In addition, our study can be extended and improved by including the effect of other parameters such as serial and shunt resistances where new models must be considered. Moreover, this model may serve as a basis for a further efforts to develop Zn–Te:O and other dilute alloys or impurity materials for enhanced solar cell conversion efficiency.

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