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Modeling of multi-junction solar cells for estimation of EQE under influence of charged particles using artificial neural networks

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ABSTRACT

External quantum efficiency (EQE) of a solar cell provides information on the internal operations of the solar cells which can be used in optimization of solar cell design. The EQE of solar cells for space applications is adversely affected by the influence of charged particles in space. Usually numerical model based software, e.g., PC1D, are used to estimate the EQE and fitted with the measured EQE to obtain degradation performance of space solar cells. However, the accuracy of these models may be limited due to complex phenomena and interactions occurring between the junctions of the solar cells and the nonlinear influence of charged particles. In this paper we propose an artificial neural network (ANN)-based model to estimate the EQE performance of triple-junction InGaP/GaAs/Ge solar cells under the influence of a wide range of charged particles. Using the experimental data from Sato et al. [1], it is shown that the ANN-based models provide a better estimate of the EQE than the PC1D model [1] in terms of mean square error and correlation coefficient.

1. Introduction

The spectral response of a solar cell is given by $SR(\lambda) = I_{ph}(\lambda)/P_{in}(\lambda)$, where I_{ph} is the photo-current generated under short-circuit condition and P_{in} is the illumination incident power as a function of wavelength λ [2]. Using a calibrated cell one can obtain the external quantum efficiency (EQE) as $EQE(\lambda) = SR(\lambda) \cdot hc/e\lambda$, where h, c and e represent Planck's constant, speed of light in vacuum and elementary charge of an electron, respectively. EQE computed from the spectral response is an important performance measure of a solar cell and is useful to characterize the emitter, whose dopant density profile must be carefully optimized in order to fit in the narrow compromise between designs for high short-circuit current and for low series resistance [3]. In addition, fitting of the EQE provides information on actual layer thickness, surface recombination velocities at key interfaces and minority carrier transport parameters such as the diffusion length, lifetime and mobility [2,4,5].

For space applications, e.g., satellites, and space vehicles, solar cell performance degradation in space is caused by incident charged particles, e.g., protons and electrons either trapped in the earth's radiation belts or ejected during solar events. The solar energetic protons cause major performance degradation of solar cells due to ionization and/or atomic displacement processes [6]. In addition, alpha particles, gamma rays, cosmic rays and neutrons also cause damage to the solar cells. Several studies on different performance degradation models of solar cells have been reported in [7–9]. Recently, Sato et al. [1] carried out detailed degradation modeling of triple-junction (3J) InGaP/GaAs/Ge solar cells under the influence of different proton energies using PC1D software [10]. They have shown that the PC1D-based model is able to accurately estimate the EQE and to predict the degradation behavior of the MJ solar cell under the influence of a wide range of proton energies and fluence levels.

Artificial neural networks (ANNs) have been successfully used in solving different nonlinear and complex problems in science and engineering [11]. The ANNs learn the problem space with the knowledge of training examples and have been endowed with certain unique properties, e.g., these networks can adapt to the changing environment; are capable of forming complex mappings between the multidimensional input–output spaces; are fault-tolerant in the sense that the performance degrades gracefully if some of the links break down or nodes malfunction; are able to generalize in the sense that ANNs can respond correctly to instances not seen previously; and are capable of processing with incomplete and noisy data [11]. The successful application of ANNs in instrumentation and measurement [12], classification of otoneurological data [13,14], digital communication channel equalization [15], nonlinear system identification [16] and nonlinear compensation for sensors [17] have been reported.

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Recently there have been several reports on the use of ANNs for solar cell modeling and photovoltaics (PV) applications. Abdulhadi et al. [18] have used a neuro-fuzzy-based model to predict I_{SC} and V_{OC} of solar cells. The ANNs have been applied for estimation of the maximum power generation from a PV module [19] and a PV system design [20]. A radial basis function-based ANN controller to increase PV plant efficiency [21] and ANN-based characterization of Si-crystalline PV modules [22] have been reported with impressive results. The effectiveness of the ANN-based techniques to obtain the electrical circuit parameter with high accuracies is evident from the article by Karatepe et al. [23]. Wide application of ANNs and artificial intelligence techniques for PV applications can be seen from the excellent review paper by Mellita and Kalogirou [24]. Recently, we have reported an ANN-based modeling technique for dual-junction solar cells and shown that the ANN-based model outperforms the ATLAS-based model [25] for estimation of EQE and solar cell parameters. It may be noted that EQE degradation of the Ge layer observed at low fluence of 10^{12} ion/cm^2 is mainly caused by the decrement of minority carrier diffusion length, and causing deterioration at long wavelengths ($\lambda > 1.6$ μm) [26]. Therefore, accurate estimation of EQE at higher wavelengths is more important than the lower wavelengths.

The main objective of the present paper is to develop an ANN-based model to estimate EQE of an InGaP/GaAs/Ge 3J solar cell under the influence of different proton energies and fluences. For this purpose a multi-layer perceptron (MLP) trained with a back-propagation (BP) algorithm has been proposed. In this study the measurement data and PC1D simulated results from the paper reported by Sato et al. [1] have been used. With extensive simulation studies using only 40% measurement data for training, it is shown that the proposed ANN-based model is able to estimate the EQE with better accuracy than the PC1D-based model proposed by Sato et al et al. [1] in terms of mean square error (MSE) and correlation coefficient (CC). Since the solar cell measurements are expensive and time consuming, the proposed ANN-based model can save about 60% on measurement cost.

The uncertainty and reproducibility are inherent problems in EQE measurement. However, careful design of measurement system can minimize such problems. The EQE measurement system reported in [27] shows that a set of spectral response measurements systematically made over one year on the same solar cell, has resulted in an average deviation of only 0.25%. In such cases the ANN-based modeling techniques can be helpful to minimize the uncertainty and reproducibility problems. It is true that the PC1D-based models provide some information on the physical relationship of MJ solar cell and EQE measurement. Whereas, the ANN-based models provide accurate estimation of EQE using only a small set of measurement data. Since ANNs can model the system dynamics based on a learning algorithm, it provides intelligence. Thus, the major advantage of ANN-based modeling technique is that once trained with sufficient data, the ANN model can predict the EQE for the unknown set of input parameters. Thus, the ANN-based model can complement the PC1D model for better design and development of MJ solar cells.

The rest of this paper is as follows. In Section 2, the MLP and basic scheme of ANN-based modeling of solar cell is provided. A brief description of the PC1D model and experimental setup as reported in [1] is given. In Section 4, the proposed ANN-based modeling scheme and the datasets used in this study are provided. Performance comparison between the MLP-based model, experimental, and PC1D simulated results are given in Section 5, and conclusions of this study are made in Section 6.

2. MLP and modeling scheme

In this section a brief description of the MLP and ANN-based modeling scheme is provided.

2.1. Multi-layer perceptron and back-propagation algorithm

The multi-layer perceptron, as shown in Fig. 1, is a feed-forward network which consists of one or more hidden layers besides the input and the output layers. Each layer contains one or more nonlinear processing units called ‘neuron’, or ‘node’. All layers except the output layer contain a bias or threshold node whose output is set to a fixed value of 1.0. Each node of a lower layer is connected to all the nodes of the upper layer through links called weights. The BP algorithm, a generalized steepest descent algorithm, is the most popular learning technique used to train the MLP. The weights of the MLP are updated using the BP algorithm during the training phase. The knowledge acquired by the network after learning is stored in its weights in a distributed manner. The MLP and the BP algorithm are briefly discussed below. For more details on MLP and BP algorithm, one may refer to [11].

Consider an L-layer MLP as shown in Fig. 1. In this network, the number of nodes (excluding the threshold unit) in the input and output layers are denoted by N_0 and N_L, respectively. The number of nodes (excluding the threshold unit) in the hidden layers is denoted by N_l, where $l = 1,2,\ldots,L-1$. Thus, the architecture of an L-layer MLP is denoted by $\{N_0-N_1-\ldots-N_L\}$. During the *training phase*, an input pattern, and its corresponding desired or target pattern is applied to the network. At the kth instant, let the input pattern applied to the MLP be denoted by $\{u_i(k)\}$, where $i = 1,2,\ldots,N_0$. Since no computation takes place in the input layer of the MLP, the node output for this layer is given by $x_i^{(0)} = u_i(k)$. The node outputs for other layers at the kth instant are given by:

$$x_i^{(l)} = \rho\left(S_i^{(l)}\right), \tag{1}$$

for $l = 1,2,\ldots,L$, and $i = 1,2,\ldots,N_l$, where,

$$S_i^{(l)} = \sum_{j=0}^{N_{l-1}} x_j^{(l-1)} w_{ij}^{(l)}, \tag{2}$$

$x_i^{(l-1)}$ is the ith node output of the $(l-1)$th layer, $w_{ij}^{(l)}$ is the connection weight from the jth node of $(l-1)$ th layer to ith node of lth layer, and $x_0^{(l-1)}$ is the bias unit whose output is set to 1. The nonlinear function $\rho(\cdot)$ is given by

$$\rho(z) = \tan h(z) = \frac{1-\exp(-2z)}{1+\exp(-2z)}. \tag{3}$$

This tanh function is continuously differentiable, provides an output ranging from −1.0 to 1.0 and has been used in many highly nonlinear modeling applications [11,16,17].

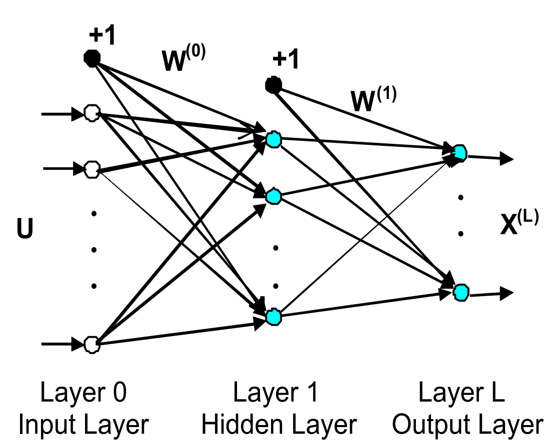

Fig. 1. Structure of an L-layer multi-layer perceptron ($L = 2$).