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Optimization of Silicon Tandem Solar Cells using Artificial Neural Networks

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Abstract. The demand for photovoltaic cells has been increasing exponentially in the past few years. The efficiency of the solar cell which has posed tremendous amount of constraints was solved by the concept of multi-junction solar cell. Since, multi-junction solar cell was developed, optimization of it posed a great challenge for the entire community. In the present paper, this challenge of optimization of multi-junction solar cells has been tackled with the use of Artificial Neural Network techniques. Silicon (Si) tandem cell was one of the initial developments in the domain of multi-junction solar cells. The present study has been conducted over Si tandem cell which is two junction three layered solar cell (a part from the tunnel layer). Bayesian Regularization algorithm is used for training the Artificial Neural Network. Input parameters are taken to as spectral power density, temperature, thickness of the layers of cells and the output parameters are I-V characteristics which are further used to calculate the open circuit voltage (V_{oc}), Fill Factor of the cell (FF), short circuit current density (J_{sc}) and Maximum Power Point (MPP). The implementation of this algorithm on any model of multi-junction solar cell can lead to the development of highly efficient solar cells keeping in mind the physical constraints of the environment where it is to be installed and hence, maximum amount of solar to electric conversion efficiency can be archived.

1 Introduction

The development of the photovoltaic cell is one of the most significant steps that mankind has taken towards research and practice on clean energy. The invention is a distinctive step towards the reduction in the carbon emissions being rendered by continually pronounced increments in carbon-based fossil fuel consumption by the post-modern economies. Apart from its potential to render zero carbon emissions, solar cell technology has also gained significant attention because of the economic benefits it poists. [1] At present, research has culminated in successful development and fabrication of the third generation photovoltaic cells which are multi-junction thin film solar cells. Yet, it is posited that the potential of this invention remains largely untapped and motivation for growth in the invention as well as further development in this field remains equivalent to what it was decades ago. [2]

The efficiency of a solar cell, i.e. its energy conversion ratio, because of weakly optimized and modestly efficient cells has emerged as a major challenge during the development of this technology. Furthermore, the economic output and adoption of the multi-junction solar cell remain significantly less than its theoretically calculated potential. [3] While it can be said that the efficiency of solar cells has been increased through the implementation of modern fabrication techniques. Yet there is a need to examine methods for further optimization of parameters in order to improve the outcomes and hence, bring out the best possible efficiency ratio in a particular solar cell.

On such method with high potential to address this problem is the integration of Artificial Neural Networks (ANN) in the field of solar cells. ANN has been successfully applied in prior studies of different parameters of solar cells, especially for tracking maximum power point prediction - a major measure of efficiency. [4] State-of-art research in the field is currently focused on training multiple neural networks by different techniques to predict best suited neural network model for a given solar cell [4]. The research community is rigorously working towards the development of a ANN which can optimize a multi-junction photovoltaic technology.

This study focuses on developing an ANN model by training data taken by multiple iterations of a Si tandem cell which is, as per our knowledge one of the most commonly fabricated multi-junction solar cell. [5] After performing multiple iterations on different training algorithms, Bayesian Regularization algorithm was found to give the best result with least error and the data received has been presented in this paper. The values extracted from the neural network model have been used to get IV curves and to report the optimized model. Fig. 1 shows the structure of the Si tandem cells on which the study has been done. This study can be taken further for utilization in various geographical regions, post - consideration of spectral power density and temperature of the location. Hence, a cell may be modeled according to different installment sites so as to get the most efficient and optimized output.

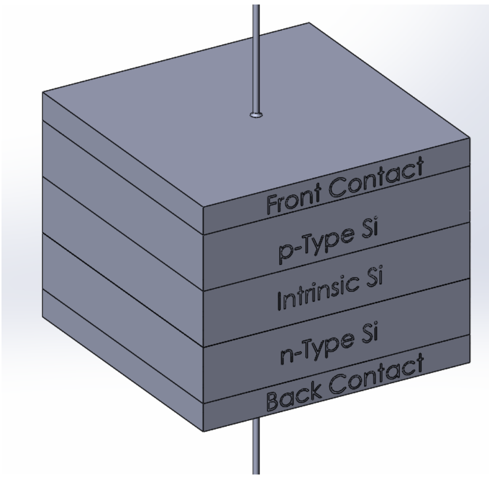

Figure 1 Si Tandem Cells used for the Development of datasets which has been used to train the ANN.

2 Previous Works

A considerable amount of research has been conducted to optimize several performance parameters of photovoltaic systems in different contexts with efficient use of an artificial neural network (ANN). For instance, maximum power point tracking algorithms based on ANN may force photovoltaic modules to operate at their maximum power points for all environmental conditions (Kulaksiz and Akkaya, 2012) [11]. Further, an ANN-based algorithm may correctly track the maximum power point even under abrupt changes in solar irradiance and improve the dynamic performance across the DC capacitor in the power converter that serves as an interphase to connect photovoltaic power plants into the AC grid (Carrasco, Mancilla-David, Fulginei, Laudani and Salvini, 2013) [7]. A summary of important studies related to the use of ANN in optimizing the performance of photovoltaic systems in chronological order is presented in table 1. However, the extant literature suggests that almost all of the experiments have been conducted with single-junction solar cells. Therefore, there is a paucity of research on optimizing performances of multi-junction solar cells, and the present study aims to address the same.

Table 1: Summary of important past studies

Author(s) (year)	**Study objective**	**Study findings**
Kalogirou (2004) [9]	Use of artificial intelligence methods like neural networks and genetic algorithms in optimizing a solar-energy system	A system was modeled using a TRNSYS computer program where weather conditions were embedded in input data used to train the model. Such methods pioneered the optimization of complicated solar-energy systems.
Karatepe, Boztepe and Colak (2006) [10]	An application of artificial neural networks to photovoltaic module modeling	The dependence on environmental factors of the circuit parameters involveed a set of nonlinear relationships difficult to express by analytical equations. However, a neural network could overcome the difficulty.
Bae, Jeon, Kim, Kim, Kim, Han and May (2010) [6]	Techniques for optimizing processes in cascaded solar cell fabrication following neural networks and genetic programming modeling	Texturing time, amount of nitrogen, DI water, diffusion time, and temperature found to be key variables for solar cell fabrication. Repeated applications of particle swarm optimization yielded process conditions with smaller variations, and, greater consistency in recipe generation.
Rai, Kaushika, Singh and Agarwal (2011) [12]	An artificial neural network based maximum power point tracking controller to predict maximum power voltage and maximum power current under varied atmospheric and load conditions	A model for the energy generation by a photovoltaic array was developed to capture the effect of solar irradiance, atmospheric temperature, wind speed and variability of the load in the circuit. Its maximum power point tracking performance excels over the conventional PID controller and avoids the tuning of controller parameters.
Subiyanto, Mohamed and Hannan (2012) [13]	A method for maximum power point tracking of a photovoltaic module by using the Hopfield neural network optimized fuzzy logic controller	Simulation and experimental results showed proposed study method to be more robust and accurate compared to conventional methods. Further, this method successfully tracked global maximum power point of a photovoltaic energy harvesting system.

Chen, Gooi and Wang (2013) [8]	Use of fuzzy and neural networks to forecast solar radiation accurately at different weather conditions	Mean absolute percentage error produced by study technique was much smaller compared to that of the other methods when used in grid-connected photovoltaic systems
Yuan, Xiang and He (2014) [14]	A mutative-scale parallel chaos optimization algorithm using crossover and merging operation to optimize photovoltaic system performance	This technique outperforms other meta-heuristic algorithms commonly deployed for extracting different parameters of solar cell models, such as double diode, single diode, and photovoltaic module, among others.

3. Training Dataset and Modelling of Neural Networks

SCAPS (a Solar Cell Capacitance Simulator) is a one dimensional solar cell simulation program developed at the Department of Electronics and Information Systems (ELIS) of the University of Gent, Belgium. [5] The cell was iterated for various spectral densities, temperature and thickness of the layers and hence, the IV characteristics along with Jsc, Voc and FF of the cell was noted. In total, 5143 iterations were run and 61,716 values were calculated that were used to train the neural network model for generating the presented output.

MATLAB was used to perform the ANN modelling. The Neural Network toolbox of MATLAB has been used for the fitting of the curve and creation of a successful model of the network. [15] Multilayer Perceptron (MLP) Feed Forward Fully Connected Neural Network has been modelled for optimization of parameters. In MLP networks, there is an input layer, an output layer and hidden layers. The hidden layers are associated by the weights which are calculated during the training of the model.

The transig function (Hyperbolic tangent sigmoid transfer function) has been used as the activation function for the neural network. This hyperbolic tangent transfer function is related to a bipolar sigmoid which has an output in ranging from of {-1 to +1}. Transig function is given by the following equation:\newline

$$n = \frac{2}{1+ e^{-2n}} - 1$$

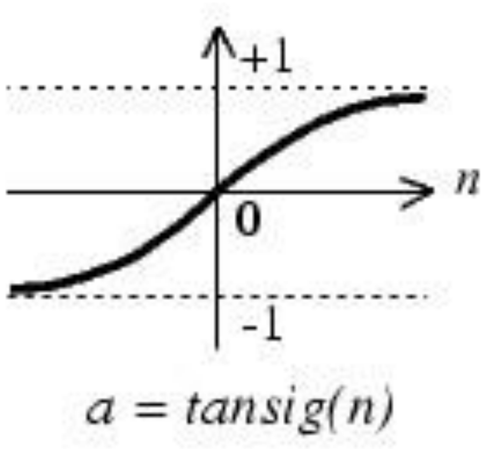

Figure 2 The graph of transig function.

Purelin function has been used in the network as the transfer function of the output layer. The purelin is a linear transfer function which is given by:

\begin{equation}
\psi(n) = n
\end{equation}

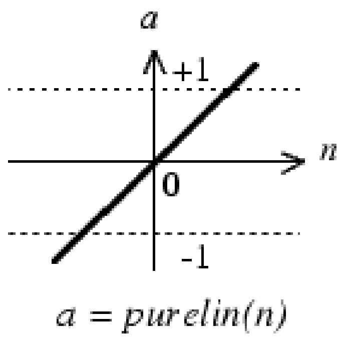

Figure 3 The Graph of purelin function.

Multilayer Perceptron network was trained with 40 hidden layers which has 6 inputs and one output of current. At present, the series and shunt resistance has been taken

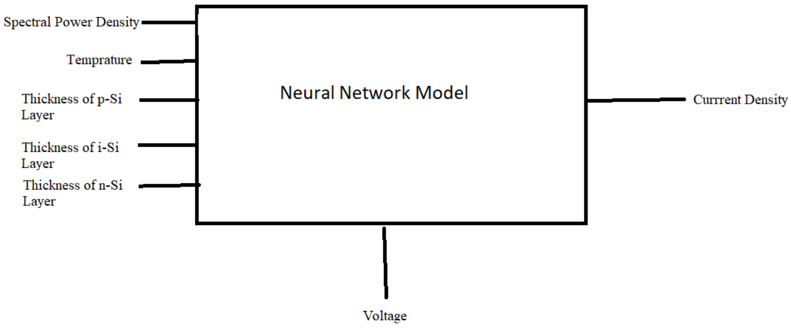

Figure 4 Neural Network Model Developed with Inout and Output Parameters

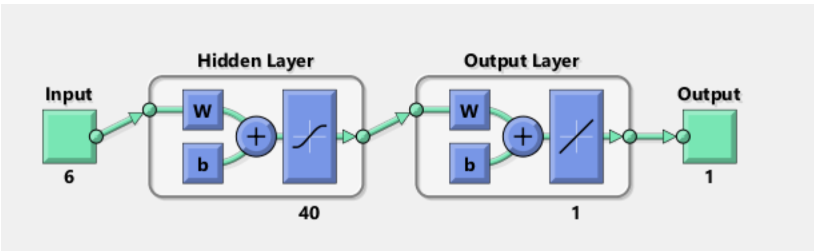

Figure 5 The neural Network with 40 Hidden Layer and output layer with transig and purelin function respectively

as zero but in the final paper, the series and shunt resistances will also be included as a output parameters.

4. Results

Multilayer Perceptron (MLP) Feed Forward Fully Connected Neural Network with 40 hidden layers was trained with Bayesian regularization algorithm. After the training the network outcomes were reported as per the information presented in Table 1.

Table 2 Values of the Neural Network after training.

Training Samples	3600
Validation Samples	1028
Testing Samples	514
Mean Square Error for Training	0.00313071
Mean Square Error for Test Samples	0.00377475
Regression Values for Training Samples	0.9998
Regression values for Test Samples	0.99978
Time Taken	30 seconds

Figure 6 illustrates the performance of the Neural Network trained for the prediction. Figure 7, shows the training states of the network and gives a clear idea about the gradient descent and mu (μ), which represented the control parameter of the neural network, Figure 8, represents the error histogram of the model and it can be noticed that most of the values lie between -0.078785 to +0.05701 which represents a low occurrence of error.

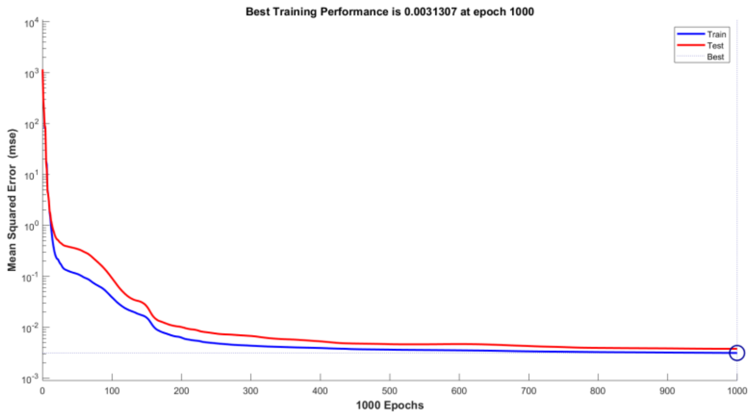

Figure 6 Performance graph for Neural Network Trained.

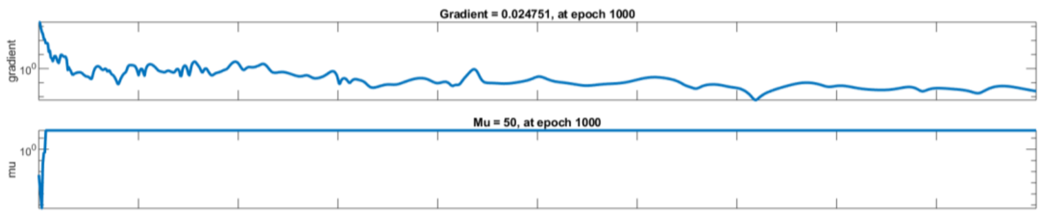

Figure 7 Training state of Neural Network Model.

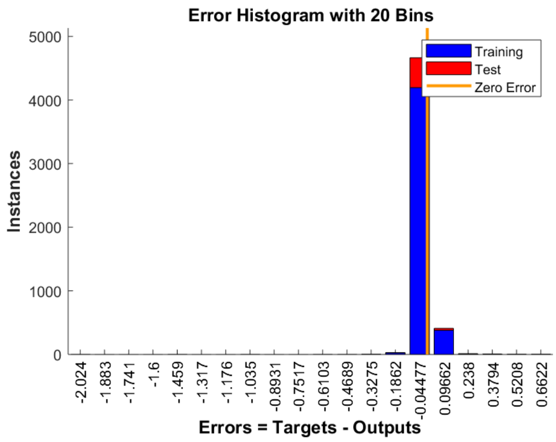

Figure 8 Error Histogram of the Trained Model.

5. Discussion

The network was trained as per the setup mentioned above. Figure 9, represents the regression curve of the model where it can be seen that a linear line passes through almost 90% of the data which indicates that the regression model is efficient enough to give a reliable data.

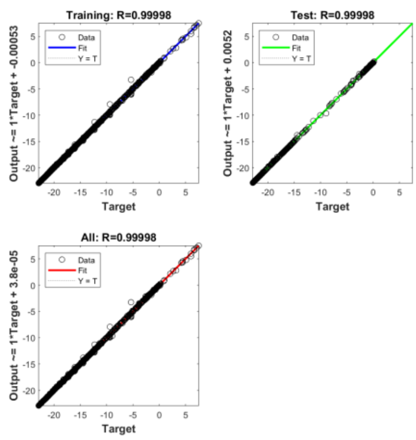

Figure 9 Regression Plot of the Trained Neural Network

After fitting the curve, the optimized points obtained were as follows:

Table 3 Points of optimization obtained from the trained model.

Spectral Power Density (W m^{-2})	1100
Temperature (K)	349.3
Thickness of p-layer (μm)	9.45
Thickness of i-layer (μm)	1.61
Thickness of n-layer (μm)	8.5

Using these points, a simulation of the Si tandem solar cell was performed on SCAPS and figure 9, shows the IV characteristic of the cell. It can be very clearly observed that the curve is optimized and which is also proven by various parameters on which efficiency is directly dependent. Table 4 shows the data obtained from the IV characteristics of the optimized cell.

Table 1 Measurements from the IV charcteristics.

Open Circuit Voltage (Voc)	0.813608 V
Short Circuit Current Density	16.44667824 (mA cm^{-2})
Fill Factor	64.1839 %
Maximum Power Point Voltage (**Vmpp**)	0.622477 V
Maximum Power point current density (Jmpp)	13.79758731 (mA cm^{-2})

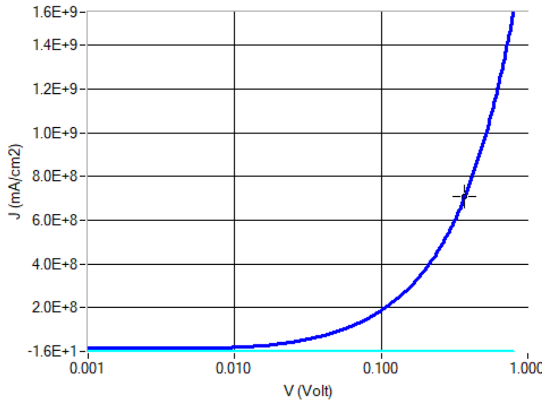

Figure 10 IV characteristic of the optimized solar cell as from the output of Neural Network Model.

6. Conclusion

This study was based on the present need for the optimization of a multi-junction solar cell where Si tandem cell was taken and a modelling was done on the data obtained by it using Artificial Neural Network. A network with 40 hidden layers was developed on MATLAB which was trained using Bayesian Regularization algorithm through 61,716 values obtained by iterations done on the cell. This trained network was used to predict the values of the input parameters to generate the most optimum model of the solar cell. These values were tested on the Si tandem cells and the obtained IV characteristic proved that the algorithm worked well and implicates efficient capability of predicting highly optimized multi-junction solar cells. A detailed study of the algorithm with other parameters like series and shunt resistances will be presented at a later stage.

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