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Modelling Spatial Characteristics of Silicon Solar Cell: Artificial Neural Network Approach

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This research presents Artificial Neural Network (ANN) modelling of silicon solar cells' spatial characteristics. The dataset for the present study is acquired from the research on silicon solar cells carried out at Shivaji University, India. The silicon-based solar cells are exceptionally popular due to their high efficiency and longer lifetime. An ANN is a mathematical model based on biological neural systems skilled to capture relationship in data to provide higher forecast accuracy. The present investigation aimed at building best possible ANN architecture by tweaking the parameters such as learning algorithm, activation function and number of neurons in hidden neurons. Thus, derived ANN architecture involves three neurons in the hidden layer and logistic activation function for supervised learning. Root Mean Square Error (RMSE) estimate of error rate is used here for assessing the performance of the model.

Keywords: Artificial neural network, Silicon solar cell, Efficiency, R Programming.

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1. INTRODUCTION

Solar energy has become the forefront of the non-conventional energy sources due to its abundant availability, non-contaminating nature that at less cost [1]. Solar cells are the way to tap the solar energy. There are some issues related to their productivity and cost. The researchers all around the globe striving hard to come out with high efficiency, cost effective solar cells bearing their life expectancy significantly over extended time span [10-12]. Efficiency is the one of the most paramount metrics of crystalline solar cells.

Many researchers have carried out analysis of solar cell characteristics based on different approaches. Dongale et al. have explained the fact that the efficiency of silicon solar cell is strongly correlated with its size [1]. Their study showed that the *p*-type thickness, short circuit current and open circuit voltage are the notable features for the modelling of silicon solar cell. Kamath et al. have reported a modelling characteristics of randomly textured tandem silicon solar cells using decision tree approach [2]. This model was designed by adjusting features such as min split, min bucket, max depth and complexity. The study depicted that "fill factor" and "thickness of *a*-Si layer" are the determinants of "efficiency" of random textured silicon solar cells. A contribution of Dongale et al. presents ANN modelling for predicative synthesis and characterization of $Ni_xMn_xO_x$ based thermistor [3]. This study has exhibited the exploitation of modelling, simulation and soft computational approaches for forecasting the best appropriate chemical composition and thus establish the synergy between the soft computing paradigm and materials science.

Ghaitaoui et al. have reported ANN modelling and experimental verification of flexible organic tandem solar cell modules [4]. This study uncovered the application of ANN to automatically parameterize the voltage-current and the voltage-power characteristics of natural photovoltaic modules. Yet another paper by Dongale et al. has presented the quadratic complex rational function approach for time domain modelling of randomly textured tandem silicon solar cells [5]. The efficiency of randomly textured tandem silicon solar cells is forecasted using the ANN. Xiao et al. have introduced ANN model to predict the output power of various kinds of photovoltaic cells [6]. A contribution by Jakhrani et al. depicts an improved scientific model for computing power output of solar photovoltaic modules [7]. This model is seen as increasingly useful in terms of precise estimations of photovoltaic module power output for any required area and number of factors used. Yet another research by Goyal et al. has explored ANN modelling of surface passivation adequacy for solar cell applications [8]. This study had shown that ANN model can be used to anticipate the carrier lifetime for a given deposition condition.

In the backdrop of the research endeavours portrayed above, the present research explores ANN modelling of silicon solar cells spatial characteristics. The dataset for the present study is acquired from the research on silicon solar cell carried out using the PC1D numerical simulation program [1]. The present investigation is carried out in R environment. The experiment derives ANN model with three neurons in the hidden layer and logistic activation function. The performance of the model is assessed with reference to RMSE estimate of error rate.

The remaining part of the article is organized as follows. The introduction is followed by the theory of construction of ANN model for spatial characteristics of silicon solar cell. The third section explores the results and discussions with computational details of the ANN model. At the end aptness of the ANN for modelling the silicon solar cells spatial characteristics will be discussed.

2. ANN MODELLING OF SILICON SOLAR CELL

An Artificial Neural Network (ANN) is a mathematical model which includes interconnected artificial neurons. ANN has the capacity to learn from the data, either in a supervised or an unsupervised manner [13]. A conceptual diagram of ANN model designed in the present investigation is shown in Fig. 1. The model is

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perceived as a multi-input single output ANN system. It consists of five inputs namely *p*-type thickness (μm), *n*-type thickness (μm), short circuit current (A), open circuit voltage (V) and Fill Factor (FF). Efficiency η (%) is an output variable. Fig. 2 provides basic statistical summary of the dataset used for the present investigation. The data is divided into training and test set as shown in Fig. 3. This division is done using random sampling. Training set is used to find the relationship between dependent and independent variables by adjusting weights while the test set assesses the performance of the model [14].

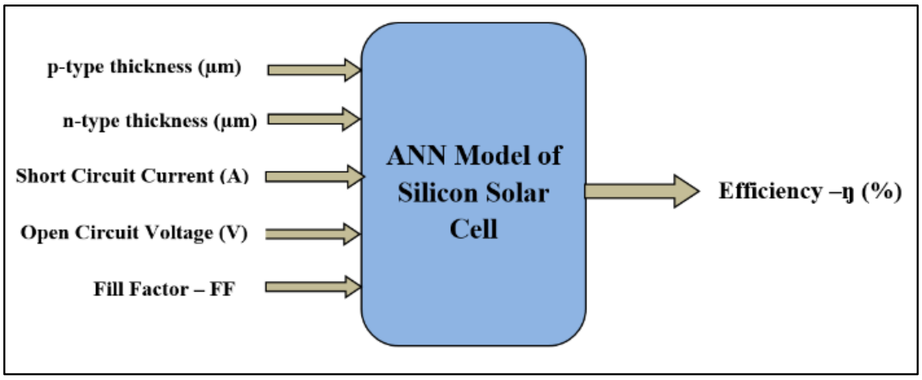

Fig. 1 – Conceptual ANN model of silicon solar cell's spatial characteristics

```
p_type_thickness n_type_thickness Short_Circuit_Current
Min.   :100      Min.   : 2.0     Min.   :0.01670
1st Qu.:100      1st Qu.: 4.0     1st Qu.:0.02082
Median :200      Median : 7.0     Median :0.02480
Mean   :190      Mean   : 6.2     Mean   :0.02603
3rd Qu.:275      3rd Qu.: 8.0     3rd Qu.:0.03148
Max.   :300      Max.   :10.0     Max.   :0.03610
Open_Circuit_Voltage  Fill_Factor      Efficiency
Min.   :0.6567       Min.   :0.7715   Min.   :0.0890
1st Qu.:0.6626       1st Qu.:0.8067   1st Qu.:0.1145
Median :0.6665       Median :0.8195   Median :0.1350
Mean   :0.6724       Mean   :0.8150   Mean   :0.1431
3rd Qu.:0.6806       3rd Qu.:0.8263   3rd Qu.:0.1770
Max.   :0.6964       Max.   :0.8376   Max.   :0.2010
```

Fig. 2 – Basic statistical summary of the dataset

```
> train_data
   p_type_thickness n_type_thickness Short_Circuit_Current Open_Circuit_Voltage Fill_Factor Efficiency
11              200                8                0.0218               0.6637      0.8252      0.119
15              300               10                0.0186               0.6567      0.7715      0.094
14              200               10                0.0180               0.6579      0.7868      0.093
1               100                2                0.0347               0.6964      0.8240      0.199
6               300                4                0.0325               0.6775      0.8301      0.182
4               100                4                0.0305               0.6810      0.7964      0.165
2               200                2                0.0361               0.6936      0.8043      0.201
10              100                8                0.0205               0.6642      0.8355      0.113
3               300                2                0.0367               0.6906      0.8364      0.211
8               200                6                0.0266               0.6706      0.8330      0.148
> test_data
   p_type_thickness n_type_thickness Short_Circuit_Current Open_Circuit_Voltage Fill_Factor Efficiency
5               200                4                0.0318               0.6795      0.8376      0.181
7               100                6                0.0252               0.6715      0.7916      0.133
9               300                6                0.0272               0.6689      0.8267      0.150
12              300                8                0.0224               0.6623      0.8149      0.120
13              100               10                0.0167               0.6581      0.8139      0.089
```

Fig. 3 – Sampling of dataset for training and testing

3. ANN DETAILS, RESULTS AND DISCUSSION

The best possible ANN architecture is constructed by tweaking the parameters such as learning algorithm, activation function, number of epochs, dataset splitting, number of neurons in hidden layer and error combinations. Thus, inferred ANN model has three neurons in its hidden layer. Logistic activation function was utilized for smoothing the result of the cross product of the neurons and weights. Table 1 explains the ANN architecture for modelling silicon solar cells' spatial characteristics. Fig. 4 visualizes the derived neural network model. The black lines demonstrate the connections with weights. The weights are calculated using the back propagation algorithm. The blue line displays the bias term.

The root mean square error for the model is found to be 0.00111. Efficiency of solar cell is predicted using the derived neural net model. Table 2 compares actual and predicted efficiency of solar cell test cases. Fig. 5 compares the ANN predicted efficiency with the actual efficiency for test data. The result suggests that the ANN has the potential to exhibit as the best tool for modelling of silicon solar cell characteristics, thus learning by examples can be achieved [17].

Table 1 – ANN architecture for silicon solar cell modelling

ANN design parameters	ANN model specifications
Network type	Feed forward backpropagation
Activation function	Logistic function
Performance function	Root mean square error
Data division	Random
No of hidden layer	One
No of hidden neurons	Three

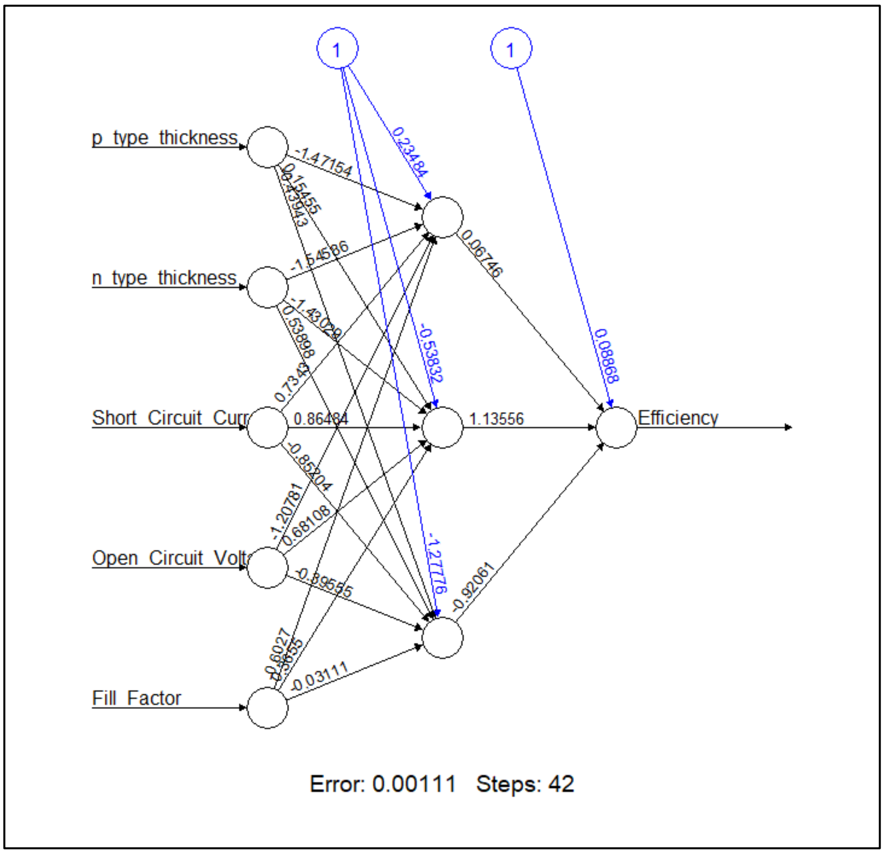

Fig. 4 – Computed ANN model for silicon solar cell characteristics

Table 2 – Actual and predicted efficiency of silicon solar cell test data

Actual efficiency	ANN predicted efficiency
0.181	0.17975919
0.133	0.13385813
0.15	0.15231108
0.12	0.12273294
0.089	0.08678449

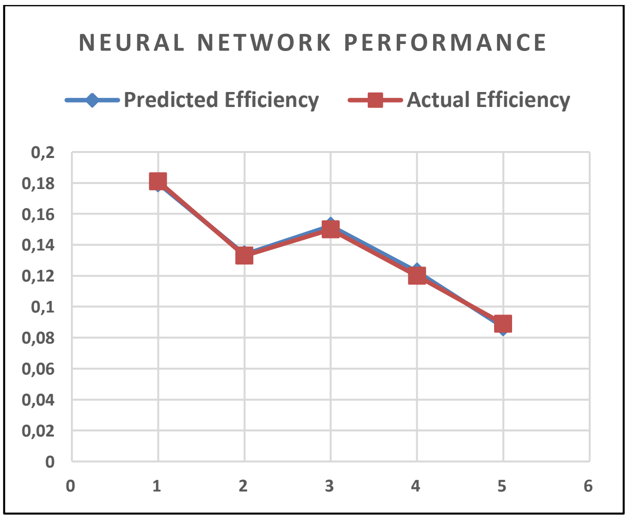

Fig. 5 – Actual and predicted efficiency of solar cell test data

4. CONCLUSIONS

In the present paper, we have reported modelling of spatial characteristics of silicon solar cell using ANN. The dataset for the present study is acquired from the research on silicon solar cell carried out using the PC1D numerical simulation program. The present study demonstrated optimum ANN architecture by varying its various attributes such as network algorithm, activation functions, number of hidden layers, number of neurons in hidden layer, number of epochs, dataset splitting and performance combinations. The resulted ANN architecture with logistic activation function for training the model reveals preeminent performance at single hidden layers with three hidden neurons. Thus, derived neural network proficiently predicts solar cell efficiency with very less error. The result concludes that the ANN has the potential to exhibit as the best tool for modelling spatial characteristics of silicon solar cell, thus learning by examples can be accomplished.

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Моделювання просторових характеристик кремнієвого сонячного елементу: підхід штучної нейронної мережі

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У цьому дослідженні представлено моделювання штучної нейронної мережі (ANN) просторових характеристик кремнієвих сонячних елементів. Набір даних отримано з досліджень кремнієвих сонячних елементів, проведених в університеті Шиваджі, Індія. Сонячні елементи на основі кремнію надзвичайно популярні завдяки високій ефективності та більш тривалому терміну експлуатації. ANN – це математична модель на основі біологічних нейронних систем, призначених для збору взаємозв'язків даних для забезпечення більшої точності прогнозування. Представлене дослідження спрямоване на створення найкращої можливої моделі ANN шляхом налаштування таких параметрів, як алгоритм навчання, функція активації та кількість нейронів у прихованих шарах. Таким чином, створена модель ANN включає три нейрони у прихованому шарі та функцію логістичної активації для керованого навчання. У роботі також знайдено середньоквадратичну помилку (RMSE) для оцінки працездатності моделі.

Ключові слова: Штучна нейронна мережа, Кремнієвий сонячний елемент, R програмування, Ефективність.