Perovskite Solar Cell Simulation using Artificial Neural Network

[1]K.G. Kharade,[2]R.R. Mudholkar,[3]R. K. Kamat, [4]S. K. Kharade

[1,4]Assistant Professor, [2,3]Professor

[1]Department of Computer Science, [2,3]Department of Electronics, [4]Department of Mathematics

[1,2,3,4]Shivaji University, Kolhapur, Maharashtra, India

Abstract: In the present investigation we report the effect of Perovskite solar cell over the other energy storage devices. A perovskite solar cell integrates a perovskite organized compound, commonly a half breed natural inorganic lead or tin halide-based material, as the light-reaping dynamic layer. perovskite solar cells have turned out to be economically appealing because it has higher efficiencies and extremely low creation costs. By emulating this solar cell in MATLAB, we predicated result eagerly facilitates with the test results. We have used an Artificial neural network (ANN). To get a streamlined solar cell we have resolute the errors, found at different estimations of covered neurons in ANN. Results confirm the stability of Perovskite solar cell over the other energy storage devices.

***Index Terms* - ANN, Mean-Square error, Perovskite solar cell, Simulation.**

I. Introduction

Humankind is requesting a greater amount of energy as its level of advancement is developing. Ordinary energy assets are constrained, so experts and governments are advancing energy investment funds and energetic effectiveness. Likewise, sustainable power sources have been managed and advanced by these specialists and governments as another option to constrained regular energy assets. Solar cell changes over the imperativeness of light into power by photovoltaic effect or photoelectric effect. The solar energy is the most infinite origin of energy. Metal halide perovskites have exceptional highlights that make them helpful for solar cell applications. The crude materials utilized, and the conceivable creation strategies are both minimal effort. Their high ingestion coefficient empowers ultrathin films of around 500 nm to assimilate the total obvious solar range. These highlights consolidated outcome in the likelihood to make minimal effort, high proficiency, lightweight and adaptable solar modules. Perovskite solar cells hold a preferred position over conventional silicon solar cells in the straightforwardness of their handling and their resistance to inner deformities.

Anyi Mei analyzes perovskite solar cell that uses a double layer of mesoporous by using Drop-casting method. The simulated results are compare with experimental results and concludes that perovskite solar cell has high stability[1]. Wanyi Nie uses Hot-casting method which concludes structure–property relationships play a crucial role for achieving photo-stable, reliable high efficiency perovskite-based thin-film optoelectronic devices [2]. Wu, W. Q examines fabrication and molecular doping of perovskite solar cell film. Their work represents a significant step towards the scalable, cost-effective manufacturing of PSCs with both high performance and simple fabrication processes [3]. Hyeonseok Lee observed the structure of perovskite solar cell by field emission scanning electron microscopy. He concludes that the performance of the perovskite solar cells was affected by the engineered optical and electrical properties of the NiO thin films. It showed highest performance owing to excellent optical properties (transmittance & bandgap) and moderate conductivity [4]. Jae Choul Yu revealed the enhancement in the efficiency and the excellent stability of inverted perovskite solar cells are promising for the eventual commercialization of perovskite optoelectronic devices [5]. You-Jyun Chen compared Fabrication of standard perovskite solar cells with Fabrication of Cu2O-based perovskite solar cells. He investigate that the Cu/Cu2O film serves as a protective layer against the penetration of humidity and Ag into the perovskite active layer [6]. Yicheng Zhao devise a perovskite seeding method that efficiently incorporates cesium and beneficially modulates perovskite crystallization by using MAFA method [7]. Pengyang Wang1 constructs a SCG (Solvent-controlled growth) method of inorganic perovskite films in dry environment for efficient and stable solar cells [8]. Bo Li provides the important results to progress towards understanding of phase stability in realization of large-scale preparations of efficient and stable inorganic PSCs [9]. Xiaoxia Xu, have successfully prepared highly efficient planar PSCs based on low-temperature solution-processed OA-capped well crystalline SnO2-NRs ETLs. Low-temperature arrangement prepared technique is a sort of low-vitality expending and straightforward approach for planning cost-effective planar perovskite solar cells [10].

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II. Computational tool

A neural system is a figuring model whose layered structure takes after the organized structure of neurons, with layers of associated nodes. A neural system can gain from information—so it very well may be prepared to perceive designs, arrange information, and conjecture future occasions. A neural system separates your contribution to layers of reflection. During examination of this exploration we have utilized MATLAB for computational counts.

Techniques Used with Neural Networks:

- Supervised Learning
- Classification
- Regression
- Pattern Recognition

- Unsupervised Learning
- Clustering.

III. ANN MODELING OF PEROVSKITE SOLAR CELL

For perovskite solar cell, we consider the following parameters or experimental data as an input to the neural - short circuit current (Jsc), Open circuit voltage (Voc), Fill factor (FF)and the output of the neural network contains efficiency(Ƞ). The Table 1 below shows the experimental results for perovskite solar cell.

Name of the Solar Cell	Experimental Results			
	J_{sc} (mA cm^{-2})	V_{oc} (mV)	FF	η (%)
perovskite solar cell [Material used: $MAPbI_3$, Synthesis Method used: Drop Casting Method, Spin Coating]	22.8	0.858	0.66	12.84
	14.83	0.964	0.706	11.3
	21.55	1.02	0.823	18.09
	19.85	1.036	0.76	16.37

Table 1: Experimental results for perovskite solar cell

To model the stability of perovskite solar cell, we have employed artificial neural network (ANN). Highly crystalline morphology is used for the experiment. The ANN prompts streamlined arrangements in some ongoing nonlinear issues. For the present examination, average feed-forward ANN is utilized. The system comprises of concealed layer and yield layer.

IV. WORKING MODEL

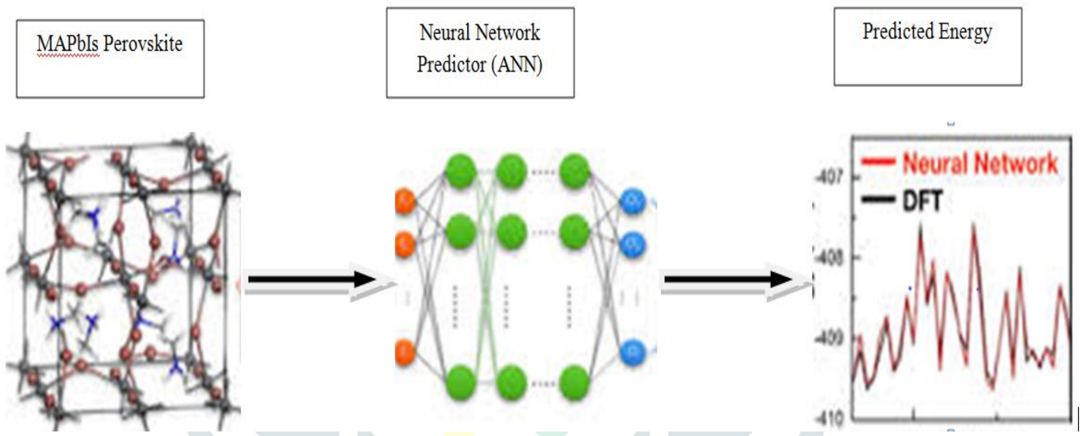

Figure 1: The Levenberg-Marquardt feed-forward algorithm is used to train the present architecture

The short circuit current (Jsc),Open circuit voltage(Voc),Fill factor(FF) of perovskite solar cell is considered as inputs to the network, whereas efficiency is considered as the output of the network. By measuring the performance of the ANN model perovskite solar cell in terms of mean square error (MSE) and the correlation coefficient. The MSE is defined as,

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad (1)$$

where Y_i is an actual value of the i^{th} observation and $\hat{Y}_i$represents the predicted value of the i^{th}observation. The difference $(Y_i - \hat{Y}_i)$ is termed as an error. The correlation coefficient between X and Y is,

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (2)$$

Where $\bar{X}$and $\bar{Y}$ denotes the arithmetic mean of the X and Y respectively.

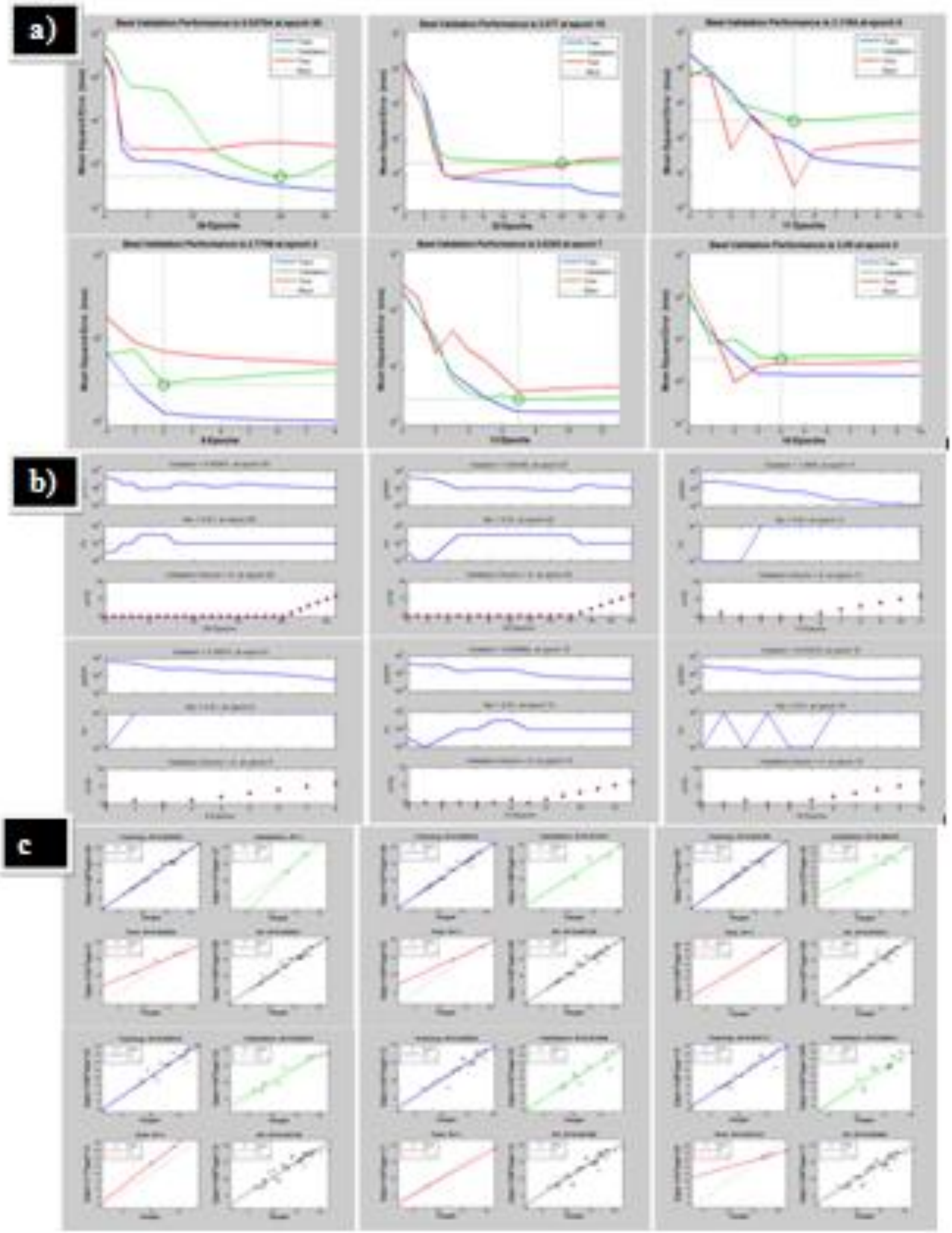

Figure 2: Performance of ANN model of perovskite solar cell. By changing the values of hidden neuron i.e.5,10,15,25,30,35 (a) mean square error of network provided by the network; (b) gradient, mu (), and validation checks parameters of the network; (c) The correlation coefficient of the output

IV. PERFORMANCE MEASUREMENT OF ANN MODEL

Figure 2 presents the performance of ANN model of perovskite solar cell. Figure 2(c) represents correlation coefficient of the output provided by the network. This is also called the Regression. Regression is a statistical metric used in finance, investment and other disciplines to determine the power of the connection between one dependent variable and a number of other factors.

When hidden neuron value is'5' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.98291, whereas for validation dataset, it becomes 1 and for testing dataset it to becomes approximately 1. The overall correlation coefficient of the output and provided by the network is equal to 0.98291. When hidden neuron value is'10' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.98138), whereas for validation dataset, it becomes approximately 1 and for testing dataset it becomes 1. The overall correlation coefficient of the output and provided by the network is equal to 0.98138.

When hidden neuron value is'15' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.97831), whereas for validation dataset, it becomes approximately 1 and for testing dataset it becomes 1. The overall correlation coefficient of the output and provided by the network is equal to 0.97831. When hidden neuron value is'25' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.94735), whereas for validation dataset, it becomes approximately 1 and for testing dataset it becomes 1. The overall correlation coefficient of the output and provided by the network is equal to 0.94735. When hidden neuron value is'30' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.94789), whereas for validation dataset, it becomes approximately 1 and for testing dataset it becomes 1. The overall correlation coefficient of the output and provided by the network is equal to 0.94789. When hidden neuron value is'35' then the correlation coefficient for training data set is approximately equal to 1(i. e. 0.94386), whereas for validation dataset, it becomes approximately 1 and for testing dataset it becomes approximately 1. The overall correlation coefficient of the output and provided by the network is equal to 0.94386.The mean-square error and mu () of the network have value 0.01 which is very small, and confirms the effectiveness of ANN in modeling perovskite solar cell. Following graph shows that the optimized results of perovskite solar cell found at '5' hidden neurons.

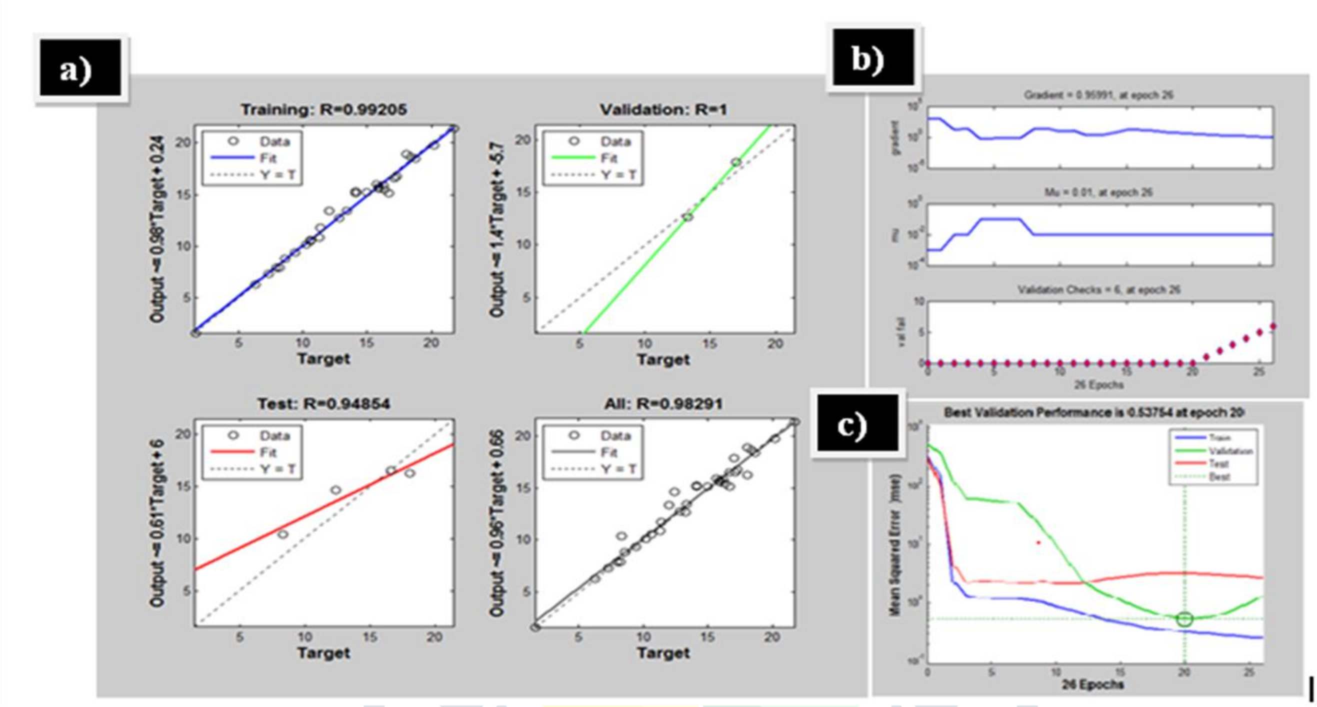

Figure 3: Performance of ANN model with '5' hidden neuron value of perovskite solar cell. (a)correlation coefficient of the output provided by the network; (b)gradient, mu (μ), and validation checks parameters of the network; (c) mean square error of network

V. IMPACT OF HIDDEN NEURONS PEROVSKITE SOLAR CELL

For different neuron values we found different average errors of perovskite solar cell. These values are in between -0.930226 to 0.42589.

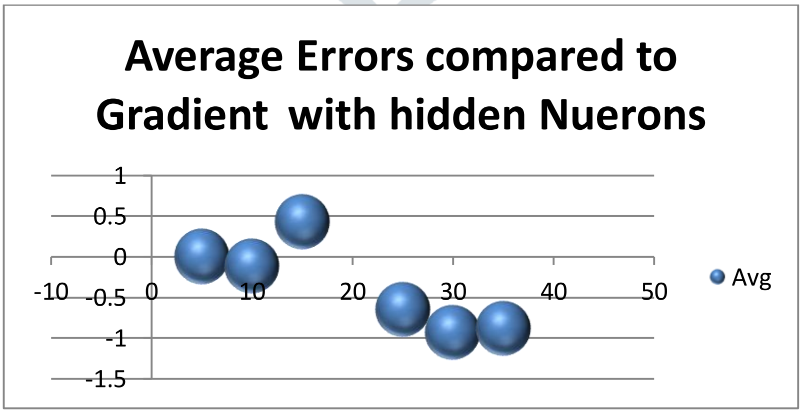

Figure 3: Average Errors found in different values of hidden neuron

Above graph shows that the negative average error values of perovskite solar cell found at '10', '25', '30', '35' hidden neurons. When Value of hidden neuron was '5' then average value was 0.95991. When Value of hidden neuron was '10' then average value was -0.11653. When Value of hidden neuron was '15' then average value was 0.42589. When Value of hidden neuron was '25' then average value was -0.65018. When Value of hidden neuron was '30' then average value was -0.930226. When Value of hidden neuron was '35' then average value was -0.885598. So above graph represents the minimum error found at '10' hidden neurons. From above predictions we can conclude that this result is useful for optimization of perovskite solar cell parameters.

Figure 4: Predictive model for perovskite solar cell

Figure 4 describes the relationship between durability, cost and efficiency of perovskite solar cell. Eventhough the cost of perovskite solar cell is very low, the durability and efficiency of the solar cell remains high.

VI. CONCLUSION

In the present examination, we have effectively displayed the properties of perovskite solar cell utilizing the artificial neural network (ANN The current ANN architecture is helpful for software development identified as a smart block for anticipating the characteristics of perovskite solar cells. For different neuron values we found different average errors of perovskite solar cell. For the hidden neuron we got the effective result. So, we can assume that at hidden neuron level '5' the stability of perovskite solar cell is high as compared to other hidden neurons

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