Prediction the Photovoltaic System Performance via Artificial Neural Network (ANN) Technique

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***Abstract*—Population growth and industrialization are driving up global energy consumption, which is expected to soar in the near future. However, the predominant use of fossil fuels exacerbates environmental pollution and greenhouse gas emissions, which are primary contributors to global warming. To address this, this study proposes an artificial neural network (ANN) model designed to forecast the power output of both monocrystalline and polycrystalline photovoltaic (PV) panels. The aim is to assess the performance and efficiency of these two PV panel types. Data spanning from 2018 to 2020 was gathered, with meteorological parameters serving as input for the ANN model. Polycrystalline panels exhibit higher voltage output, whereas monocrystalline panels typically yield greater current. The model's mean square error (MSE) for training, testing, and validation equated, indicating robust learning during training without overestimation. Both models demonstrate an excellent fit to the data, evident from the correlation coefficient (R) reaching 1. The predicted values closely align with actual trends for both panel types, with insignificant disparities in estimated voltage, current, and power. Overall, the polycrystalline panel outperforms the monocrystalline panel, boasting efficiencies of 0.999% and 0.997%, respectively.**

Keywords—photovoltaic, artificial neutral network, voltage, current.

I. INTRODUCTION

In recent years, the expansion and use of renewable energy have emerged as an inescapable path in the global energy revolution. As such, renewable energy is characterized as a sustainable and environmentally friendly source. It has the capacity to mitigate environmental impacts, minimize or eradicate secondary waste, and provide enduring energy solutions aligned with energetic, economic, and social needs [1]. Despite renewable energy being sustainable and inexhaustible, unlike finite fossil fuels, the prominence of photovoltaic (PV) power has been steadily rising in recent years, emerging as a pivotal component of the energy transition [2]. As fossil fuel prices escalate and their reliability wavers, photovoltaic systems are gaining traction in the global market. Moreover, with the advancement of green energy technologies and increased accessibility, photovoltaics are recognized as a viable cleaner energy option, despite being inherently reliant on sunlight. Solar energy production is affected by solar irradiance, which in turn is influenced by weather variables such as cloud cover, wind speed, and wind direction. In certain scenarios, customers may seek insights into the performance of deployed PV systems across various weather conditions. Artificial neural networks (ANNs) stand out as one of the most commonly utilized prediction methods for this purpose [3]. The fundamental form of artificial neural networks (ANNs) mimics the functionality of the human brain. Similar to the human brain, which can learn new abilities and adjust to varying situations, ANNs possess the capacity to analyse incomplete, unclear, and uncertain data and draw conclusions autonomously [4].

The anticipated surge in energy demand is attributed to global population growth and industrialization. However, the extensive reliance on fossil fuels for energy generation significantly contributes to environmental pollution and greenhouse gas emissions, exacerbating global warming. To address these challenges, a blend of renewable and non-renewable energy sources can help mitigate the drawbacks associated with fossil fuel usage. Solar energy, harnessed through photovoltaic (PV) technology, presents a sustainable alternative. The use of PV systems for power generation began in the 1970s and is currently experiencing fast global development [5]. Photovoltaic module efficiency is determined by a variety of environmental parameters, including solar irradiation, cell temperature, ambient temperature, and local climate conditions. Manufacturers generally produce module specifications based on conventional test conditions, which may not correctly represent practical performance, thus leading to overestimates of productivity. Accurately forecasting PV module power output and selecting optimal modules require reliable data and a thorough understanding of module performance under a wide range of operating scenarios. Therefore, the artificial neural network model employed in this study must be suitable and precise to facilitate the selection of the most suitable technology for the given location.

The objective of this paper is to assist solar energy operators in effectively managing, estimating, and strategizing electricity pricing to enhance their electricity generation capacity. The specific goals of this study are: to construct an artificial neural network (ANN) model for forecasting the output power of various PV types, to assess the voltage, current, and power characteristics of each module, and to compare the efficiencies of monocrystalline and polycrystalline panels.

II. THEORY OF PHOTOVOLTAIC (PV)

A. Overview Of PV

Photovoltaics refers to the process by which solar cells convert sunlight directly into electricity. While it is experiencing rapid growth as a renewable alternative to conventional fossil fuels, photovoltaics is relatively new compared to other electricity generation technologies, with initial practical demonstrations dating back to the 1950s [7]. Currently, photovoltaic systems are extensively deployed to support electricity supply to the power grid due to the cost competitiveness of solar cell electricity in numerous regions. The predominant material used in most solar cells available today is silicon, which enhances the efficiency of solar cell electricity conversion from sunlight while remaining affordable. These cells are often aggregated to create larger modules, which can be installed on rooftops of residential or commercial buildings in ceiling-mounted racks or assembled into massive utility-scale solar energy systems.

B. Photovoltaic Electrical Characteristics

The electrical performance of photovoltaic cells is tested in order to identify important parameters and conversion efficiency. The I-V curve illustrates the features of the PV, shown in Fig. 1 [8]. This graph depicts the relationship between current and voltage over the load spectrum, ranging from short circuit current (Isc) to open circuit voltage (V_{OC}). It demonstrates the performance of solar cells, modules, and arrays. Solar cells or modules are exposed to a specific degree of radiation in order to ensure optimal power generation while controlling cell temperature, load resistance, and output current. The circuit includes two endpoints: the open circuit voltage (Voc) and the short circuit current (Isc). Voc refers to the voltage across the positive and negative terminals when the circuit is open, resulting in zero electricity flow due to infinite load resistance. The power curve peaks at its maximum, known as PMP, which represents the operational position where the solar cell produces the most power production. The position, which is known as the maximum power point (M_{PP}), is defined by the voltage V_{MP} and the current IMP, also known as P_{MAX} or M_{PP}. Isc represents the current flowing between a cell or unit's positive and negative terminals, with zero voltage between the terminals due to the absence of load resistance. Solar cells and modules operate at various voltages and currents. It is challenging to ascertain the true efficiency of the PV cell or module solely based on the curve. Instead, the point at the maximum power point (Pm) is typically considered.

C. Equivalent Circuit Model

The current that results from the pair of electrons and positive holes which obstruct solar radiation is known as the source photonic current and is denoted by Iph. It is affected by the quantity of sunlight and ambient temperature at a certain hour of the day [8]. To maintain the appropriate forward bias voltage and residual current IL, a portion of the photonic current flows through the diode via an internal load resistance RL, as seen in Fig. 2. The voltage-current traits of the solar cell can be delineated as follows:

$$I = Iph - Io\ [exp\left(\frac{(qV+IR_S)}{AK_bT_K}\right) - 1] - \left(\frac{V+IR_S}{R_{sh}}\right) \quad (1)$$

Where,

I_o is diode current

I is output current

T_k is Operating temperature

K_b is Boltzmann's constant

$I_{ph} = I_{sc}$ is photon current

A is diode ideal factor

q is electron charge constant ($1.602 \times 10{-}19\ C$)

D. Type of PV

Solar cells are commonly referred to as "semiconductor cells," and their characteristics are crucial for efficient sunlight absorption. Cells designed for terrestrial applications absorb sunlight differently from those intended for space use. Solar cells can come in various physical designs, including single-junction solar cells, as well as multi-junction designs with different absorption mechanisms and charge separation systems. Solar cell technologies are categorized into first, second, and third generations. The main material used in commercial photovoltaic (PV) technology is crystalline silicon, which comprises polysilicon and monocrystalline silicon and is referred to as first-generation or conventional cells.

Thin-film solar cells like amorphous silicon, CdTe cells, and CIGS are part of the second generation of solar cells. They are utilized in power plants, integrated photovoltaics, and small standalone power systems. Third-generation solar cells encompass various emerging thin-film technologies, which include organic materials such as organometallic and inorganic compounds. However, these technologies are still in the research and development phase and have not yet been commercialized [9]. In this project the focus will be on monocrystalline and polycrystalline cells.

1) Monocrystalline Silicon: The main and long-standing technique comprises using single crystal solar cells manufactured of pure silicon on thin silicon wafers. Each atom in single-crystal silicon is neatly structured into evenly

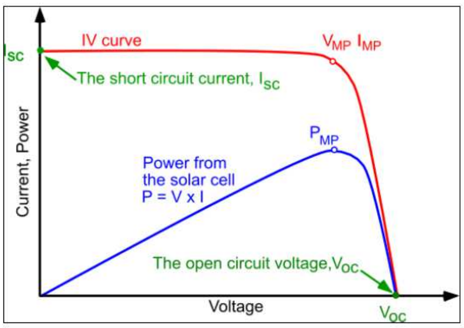


Fig. 1. I-V Curve [8].

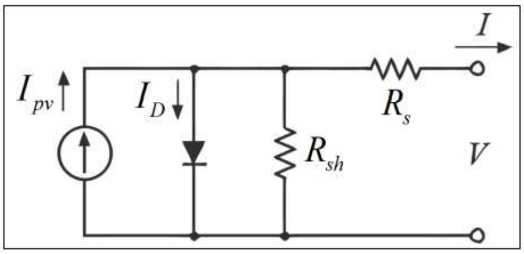
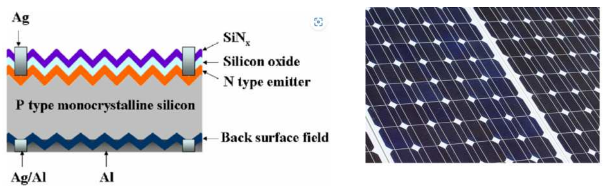


Fig. 2. Cell Equivalent Circuit [8].

dispersed crystal layers. This type of c-Si module is widely utilized in solar energy production and is predicted to stay popular for several decades. These modules are now widely accessible and provide substantial benefits, especially due to their inexpensive cost. [10][11]. P-doped wafers with p-n junctions are used to make c-Si modules. The production process begins with the manufacture of c-Si sheets, which are subsequently cut into wafers less than 0.3mm in diameter from this material. Under ideal illumination conditions, the complete solar cell assembly could produce 35mA of electricity and 0.55 volts. It is typical for these modules to exhibit a pyramid-like texture on their surface. The solar cells are combined into a solar cell module using the appropriate voltage and current. Fig. 3 depicts the schematic diagram and monocrystalline silicon solar panel.

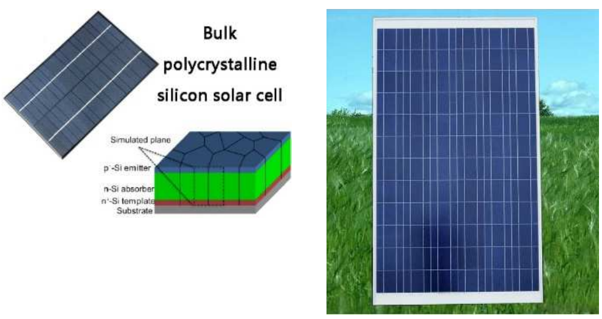
2) Polycrystalline Silicon: In the 1980s, polycrystalline silicon solar cells emerged as a cost-effective alternative to traditional silicon solar cell production, utilizing silicon waste from the electronics industry. However, despite advancements, the conversion efficiency of laboratory cells ($2cm^2$) for polysilicon solar cells remained relatively low, hovering around 13%, leading to limited support for the technology [11]. Poly c-Si represents another variation of c-Si photovoltaic technology, although it holds a slightly smaller market share compared to mono c-Si. Poly c-Si cells were devised to tackle the challenges related to metal contamination often encountered in mono c-Si cells. Similar to mono c-Si, poly c-Si utilizes parallel and series combinations of cells to assemble modules for practical use. Various crystal shapes can be engineered in laboratory settings to develop these cells. Fig. 4 provides a depiction of the cross-section and structure of a polycrystalline silicon solar panel.

The process involves melting and solidifying silicon to produce crystals with a single orientation, which are then fashioned into thin blocks, and eventually wafers, before



(a) (b)

Fig. 3. (a) schematic diagram (b) monocrystalline silicon solar panel [12].



(a) (b)

Fig. 4. (a) cross-section of poli-silicon (b) polycrystalline silicon solar panel [13].

undergoing cooling. These solar cells exhibit various random patterns on their surfaces and include an additional layer to minimize light reflection. Furthermore, the photovoltaic industry manufactures high-grade silicon minerals using metallurgical methods instead of chemical refining, which is more environmentally sustainable. The contamination level in polysilicon created for the photovoltaic sector is typically less than one billionth of a part per billion, although silicon derived from solar polysilicon may have lower purity levels [14].

In this paper the parameters of PV panels 250W monocrystalline and 110W polycrystalline which are used in constructing the ANN model [14][15]is shown in Table I.

The calculation of cell temperature incorporates ambient temperature, relative humidity, wind speed, and global irradiance, as indicated in (2). Similarly, equations are provided to derive the short-circuit current and open-circuit voltage, as shown in (3) and (4), respectively [15]. Furthermore, the current and voltage produced by the PV panel can be determined using (5) and (6), respectively, while the output power is obtained by multiplying the current and voltage together, as shown in (7) [15].

$$T_c = 0.954T_a + 0.3G - 1.629W_s + 0.088R_h + 3.9 \quad (2)$$

$$I_{SC} = I_{SC.ref}\left(\frac{G}{G_{ref}}\right) + \mu I_{SC}(T_C - T_{ref}) \quad (3)$$

$$V_{OC} = V_{OC} + \mu V_{OC}(T_C - T_{ref}) \quad (4)$$

$$I_m = I_{SC}(1 - a - b) \quad (5)$$

$$V_m = V_{OC}(1 - \left(\frac{b}{U_{OC}}\right) In\ a - R_S(1 - a - b)) \quad (6)$$

Where

T_C is cell temperature C.

I_{SC} is short circuit current A.

V_{OC} is open circuit voltage V

T_a is air temperature C.

G is global radiation W/m2.

TABLE I. SPECIFICATIONS OF MONOCRYSTALLINE AND POLYCRYSTALLINE SILICON PV MODEL

Parameters	Monocrystalline	Polycrystalline
Maximum Power, P_{max}	250 W	110 W
Maximum Voltage, V_{mpp}	30.2 V	17.1 V
Maximum Current, *Impp*	8.28 A	6.43 A
Open circuit voltage, V_{OC}	37.4 V	21.2 V
Short circuit current, I_{SC}	8.80 A	7.16 Ab)
Voc thermal coefficient,μV_{OC}	-0.350 %/C	-0.346 %/C
I_{sc} thermal coefficient,μI_{sc}	0.056 %/C	0.056 %/C

R_h	is relative humidity.
W_S	is wind speed m/s.
μV_{OC}	is Voc thermal coefficient.
μI_{SC}	is Isc thermal coefficient.

III. Artificial Neutral Network (ANN) Technique

Network design and development requires determining several network parameters, such as the number of neurons in hidden layers, transfer functions, and training and bias functions. In this project, the input data consist of air temperature (Ta), relative humidity (Rh), wind speed (Ws), maximum temperature (Tmax), minimum temperature (Tmin), cell temperature (Tc), and solar radiation (G), as depicted in Fig. 5. The voltage and current generated by the artificial neural network (ANN) in response to these inputs are trained and evaluated inside the established ANN model.

During the training phase, modifications to parameters such as the number of training epochs, learning rate, and the number of hidden layers can be adjusted if the performance of the ANN deteriorates. The proposed ANN model is illustrated in Fig. 5. Prior to developing the model, the normalized data is divided into three categories: 70% for training, 15% for testing, and 15% for validation.. In this study, a multilayer perceptron (MLP) network was employed to train the input data using Levenberg-Marquardt (LM) backpropagation due to its superior accuracy in predicting and forecasting output compared to other networks.

When designing the optimal network, various factors such as numerous neurons, multiple epochs, and learning rates were carefully considered. The number of neurons ranges from 1 to 10, the learning rate varies between 0.001 and 1.0, and the number of epochs spans from 10 to 1000. With a correlation coefficient (R) close to 1, this network can be deemed the most suitable choice. Lower MSE values indicate effective training of the network. Three error statistics were utilized to evaluate the suggested ANN model in this project: mean squared error (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). The MSE quantifies the discrepancy between the actual and predicted outputs, while the MAPE serves as an accuracy indicator for the neural network.

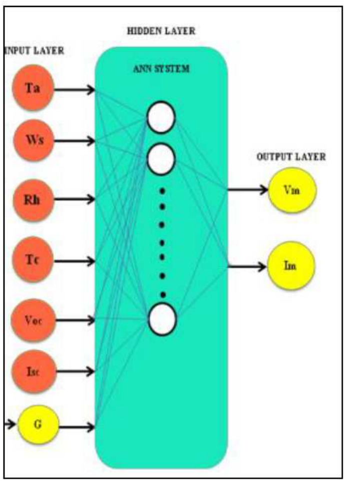


Fig. 5. The Proposed ANN Model [15].

IV. Results and Discussion

This section will cover the presentation of the results and the evaluation of the performance of PV panels. It will also discuss the development of the model and analyze the errors, as well as compare the outputs of the model.

A. Results from Mathematical Equation

In this study, calculations were carried out to extract and emphasize the required input from the data. To train the ANN models effectively, obtaining the cell temperature is crucial. In this project, (2) was utilized to predict the cell temperature. Another significant input parameter to consider in this calculation process is the predicted short-circuit current, determined by (3). This equation incorporates electrical parameters from the solar panel, including the short-circuit current, along with meteorological factors such as global solar radiation and temperature. Nevertheless, the predicted short-circuit current values for both monocrystalline and polycrystalline panels tend to be elevated. This phenomenon arises due to the impact of temperature and relative humidity on the cell, as evidenced by previous studies [16]. On the other hand, the open-circuit voltage value, predicted using (4), exhibits disparities between the two types of solar panels, with some instances showing significantly larger values. These current and voltage values serve as the targets for the ANN models to predict the model's output. The efficiency of a PV system is widely acknowledged as the primary metric for assessing the performance of a solar PV system, as noted in previous literature [17]. The short-circuit current, along with meteorological factors like global solar radiation and temperature, are key parameters derived from the solar panel. However, it's observed that the predicted short-circuit current values for both monocrystalline and polycrystalline panels tend to be elevated. This phenomenon is attributed to the influence of temperature and relative humidity on the cell, supported by [16]. Conversely, the open-circuit voltage value, determined by (4), exhibits variations between the two types of solar panels, with some instances showing notably higher values. The results of voltage, current, and power obtained through mathematical equations are compiled in Table II.

B. Results from ANN Technique

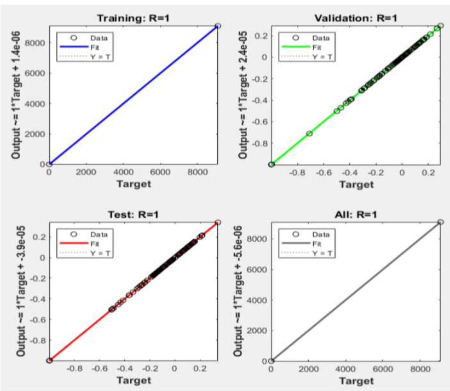
Table III presents the percentage of mean squared error (MSE) for both training and testing, along with the value of the correlation coefficient (R), across various numbers of neurons and training epochs. Notably, the MSE test values for the final three neurons were found to be the lowest, indicating the best fit for testing, while the correlation coefficient approached 1, suggesting a strong positive linear relationship. This suggests that the optimal number of neurons lies within the last three neurons, while an inadequate number of neurons may lead to overestimation or overtraining of the network. Furthermore, it is essential for the MSE value of the training data to be smaller than that of the testing data. Fig. 5 and 6 depict the best curve fit achieved by the ANN model for predicting voltage and current in both monocrystalline and polycrystalline solar panels. The consistency between the MSE values of the training, testing, and validation data indicates that the model has effectively learned from the training data. A correlation coefficient (R) value of 1 further confirms the strong fit of the model to the data. Fig. 6 (a) and (b) show the best curve fit for mono- and poly-crystalline Panel using ANN technique respectively.

TABLE II. RESULTS OF VOLTAGE, CURRENT AND POWER

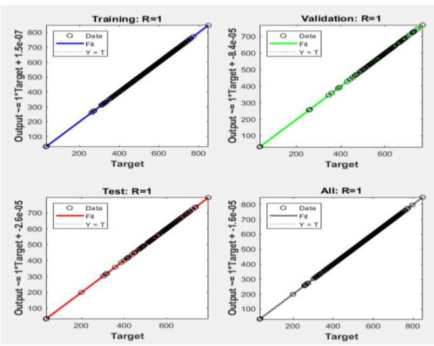
Parameter	Type of Photovolatic	
	Monocrystalline	*Polycrystalline*
Short Circuit Current, Isc	0.655A	0.559A
Open Circuit Voltage, Voc	35.648V	19.468V
Output Voltage	32.979V	19.52V
Output Current	572.305A	277.59A

TABLE III. MSE FOR DIFFERENT NUMBER OF HIDDEN LAYERS

Number of hidden layers	MSE Training	MSE Test	R Value
1	0.0134	0.0110	0.9671
2	0.0120	0.0189	0.9679
3	0.0158	0.0134	0.9735
4	0.0139	0.0161	0.9738
5	0.00123	0.0016	0.9999
6	0.0013	0.0098	0.9999
7	0.0066	0.012	0.9999
8	0.000	0.000	1.000
9	0.000	0.0000	1.000
10	0.000	0.0000	1.000



(a)



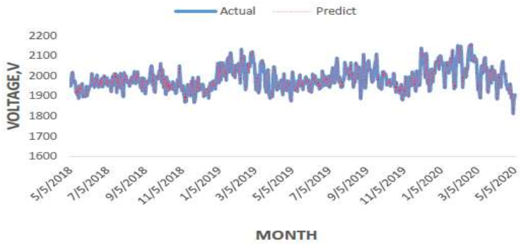
(b)

Fig. 6. Best Curve Fit for Polycrystalline Panel ANN Model.

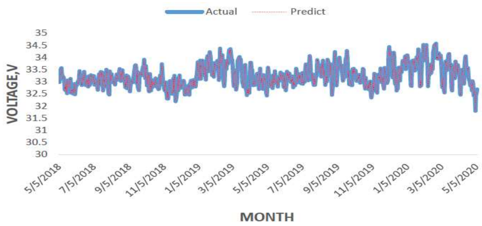
C. Voltage, Current and Power Performance

Fig. 7 and 8 illustrate the comparison between the actual and estimated data for the voltage of the solar panels over a span of three years from 2018 to 2020. From the figures, it is evident that the voltage initially starts at 2kV for polycrystalline PV panels, exhibiting a higher voltage compared to monocrystalline panels, which start at a lower voltage of 33.5V. Subsequently, the voltage gradually increases until reaching its peak in May 2019 for monocrystalline panels, and then fluctuates until reaching another peak in May 2020. The highest voltage values recorded are 2.1kV for polycrystalline panels and 34.5V for monocrystalline PV panels. It's noteworthy that there is a minor discrepancy between the estimated and actual values.

Fig. 8 (a) and (b) depict the actual and predicted current, showcasing a notable similarity in trends with minimal margin error and differences between the actual and predicted values. Notably, the current exhibited a descending trend in May

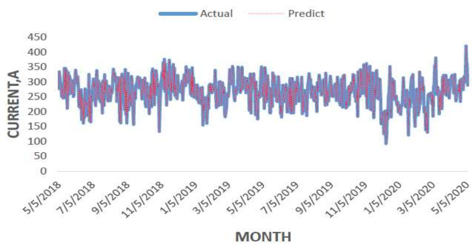


(a)

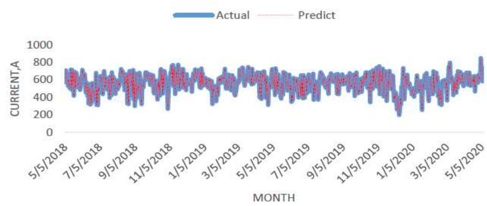


(b)

Fig. 7. The results of voltage (a) polycrystalline PV and (b) Monocrytalline Silicon PV Model.



(a)



(b)

Fig. 8. The results of current (a) polycrystalline PV and (b) Monocrytalline Silicon PV Model.

2018, followed by a relatively stable value in May 2019. Conversely, there was a downward trend in current observed in May 2020, attributed to the dry season spanning from May to July.

The average real and estimated values from the ANN output are shown in Table IV and Table V for both PV panels. It can be seen from the table that there was a small difference between the actual and predicted value and in some cases the differences are negligible. Polycrystalline produces a substantially higher voltage than monocrystalline. In contrast, monocrystalline PV panels tend to have a higher current value compared to polycrystalline PV panels. As a result, the efficiency of the PV module has a significant impact on the overall efficiency of the PV system. The efficiency of this component is mostly determined by the temperature of the surrounding environment and the solar radiation received. Efficiency of a PV module is defined as the ratio of the power output of the module itself to the power that is emitted by the sun during its operation.

V. CONCLUSION

This paper represents the design of ANN model that predicts the voltage and current of the photovoltaic for monocrystalline and polycrystalline. Furthermore, the calculation has been performed and highlight the input and output, were the calculated ambient temperature, cell temperature, short circuit current and open circuit voltage are obtained to be set as input for the model with other meteorological parameters such as relative humidity, wind speed, and global solar radiation. Furthermore, the ANN model results indicate the percentage of MSE testing and training for varied number of neurons. As a result of that, the last three neurons tend to be low. Meanwhile, MSE training for this model was equivalent to MSE testing and validation. It means the data of model have been learning very well during training and zero means that it has an overestimate the prediction of the network. In addition, the average real and estimated values from the ANN model shows that there was a small difference between the actual and predicted value. Nonetheless, voltage produced by polycrystalline panel is much larger than monocrystalline panel. In contrast, monocrystalline panels have a higher current value than polycrystalline. The overall power output and efficiency presented in this project shows that polycrystalline panels have a better performance than monocrystalline. Hence, the model perfectly predicts the output.

TABLE IV. RESULTS OF VOLTAGE, CURRENT AND POWER

Parameter	**Monocrystalline**	
	Math. Equ.	***ANN***
Voltage $_{Avg}$	33.369V	33.364V
Current $_{Avg}$	7.65kA	7.64kA
Power $_{Avg}$	950.192kW	950.390kW
Eff.	0.997%	

TABLE V. RESULTS OF VOLTAGE, CURRENT AND POWER

Parameter	***Polycrystalline***	
	Math. Equ.	***ANN***
Voltage $_{Avg}$	2.94kV	2.93kV
Current Avg	3.39kA	3.38kA
Power Avg	2.2GW	2.1GW
Eff.	0.999%	

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