Recurrent neural network-based electrical modeling and simulation of solar photovoltaic cell

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ABSTRACT

Photovoltaics (PV) are an important renewable energy (RE) source and a key component of solar power plants. Accurate modeling of their electrical output characteristics is crucial for efficient system design, such as the current-voltage (I-V) and power-voltage (P-V) curves. These characteristic curves depend on the photovoltaic cell (PVC) parameters such as short circuit current (I_{SC}), open circuit voltage (V_{OC}), and maximum power (P_{MAX}). Previous studies have explored the artificial neural network (ANN) in photovoltaics generation (PVG) systems to estimate the output power of the PVC. Nevertheless, most ANN-based approaches are limited to estimating output power only from the daily power generation data of the PVG system. In this paper, a PVC model was developed using a recurrent neural network (RNN) to increase the exactness estimation of electrical parameters. The proposed RNN-based PVC model employs solar irradiance (S), temperature (T), and series resistance (R_S) as input variables, whereas the output variables are the power and current of PVC. The contributions of the PVC model is evaluated through simulations under changing physical and environmental conditions. The simulation yield of the RNN-based PVC model successfully reproduces I–V and P–V curves and also fundamental parameters consistent with the behavior of real PVC.

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1. INTRODUCTION

Solar energy (SE) is a renewable energy (RE) whose availability is virtually inexhaustible. Through the use of photovoltaic (PV) technology, sunlight can be directly changed into electrical energy via photovoltaic panels (PVP). These PVPs can operate efficiently in any geographical location that receives sunlight and offer a clean and eco-friendly alternative to fossil fuels, as they do not generate greenhouse gases or air pollutants during operation [1]-[3].

The utilization of SE has great potential in Indonesia, which is a tropical country located along the equator and receives abundant solar radiation throughout the year. On average, the country benefits from 10 to 12 hours of sunlight daily, making it one of the extremely promising regions for solar energy utilization. The intensity of received solar radiation typically averages 4.5 kWh/m²/day, though this varies depending on weather conditions such as clear, cloudy, or rainy skies. However, solar energy has not been optimally utilized in daily activities as a source of electrical energy [4]-[6]. Therefore, the Indonesian government's target is to build 69.5 gigawatts (GW) of new power plants by 2034 [7]. This concrete step aims to achieve the energy self-sufficiency program and simultaneously support the net zero emission (NZE) target by 2060. A total of 52.9 GW (76%) of new power plants will come from renewable energy such as solar, hydro, wind, bioenergy, geothermal, and nuclear, equipped with energy storage systems such as pumped hydropower batteries. Meanwhile, 17.1 GW (24.6%) of RE comes from SE.

One of the challenges in utilizing solar energy is its unstable nature. The obtained energy of solar PV is extremely affected by the sunlight, the temperature, and the voltage generated in the photovoltaic cell (PVC). For this reason, PV system modeling is very necessary to estimate its desired output power, so that the power grid system can be managed accurately. Previous studies have explored artificial intelligence (AI) applications in photovoltaic generation (PVG) systems. The development of PVC models using self-constructing neural network (SCNN) techniques has been proposed to increase the accuracy of PV electrical characteristics under various physical and environmental conditions [8]. An efficient PVC model using an artificial neural network (ANN) has also been proposed to estimate the hourly output power in a given period of a PV system installed in the city of Agadir, Morocco [9]. Next, an ANN was designed to estimate the power output of PV modules and to investigate the influence of weather situations and temperature on the predicted power output. The models were built using a week of experimental data [10]. An output power estimation method using a recurrent neural network (RNN) has also been discussed to accurately estimate the output of a PVG system. The proposed estimation method is clarified by employing real PV energy in Lille, France [11]. In addition, a daily PV output power forecasting model using an RNN has been developed and implemented. Daily PV power estimation is crucial for grid managers to obtain PV output power data in advance [12]. However, previous researchers have shown that most AI methods employed to only predict solar power plant output are based on data acquired directly from the PVG system.

In this paper, an electrical model of a PVC is developed using one of the AI techniques, namely RNN. The development process of the RNN-based PVC model begins with the creation of a PVC model referring to the PV module data sheet. The second stage involves developing a PVC model using the RNN method. The third stage, the RNN-based PVC model is trained using data generated from the solar PVC model. The final stage, the trained RNN-based PVC model can be directly used as a representation of the PVC model. The RNN-based approach increases the accuracy of predicting the electrical characteristics of the PVC. Next, the contribution of the submitted method is clarified by conducting simulations under varying solar irradiance, cell temperature, and series resistance conditions. This paper is structured as follows: Sections 1 and 2 describe the introduction and the modeling of solar PVC. Section 3 presents the principles of the RNN, followed by the design of the RNN-based PVC model in Section 4. The contributions of the proposed RNN technique are demonstrated using MATLAB/Simulink simulations in Section 5. Finally, the last section concludes the paper, and the references are provided at the end.

2. MODELING OF SOLAR PHOTOVOLTAIC CELL

PVC is typically built from silicon or germanium semiconductor materials. When sunlight hits a PVC, the energy from the photons activates electrons in the silicon atoms, causing them to be released. These free electrons flow through an external circuit, generating an electric current and thus producing electrical energy. PVC can be assembled in series to improve voltage or in parallel to increase current, allowing the system to generate the desired electrical output.

The performance of PVC is highly dependent on the amount of sunlight received. Climatic conditions also reduce the amount of solar energy reaching the PVC, thereby affecting its obtained output. A simple electrical circuit of a PVC is built by a current source installed in parallel with a diode. The PVC model includes a photocurrent source (I_{PC}), a diode (D), a series resistance (R_S), and a shunt resistance (R_{SH}) is presented in Figure 1 [13]-[18].

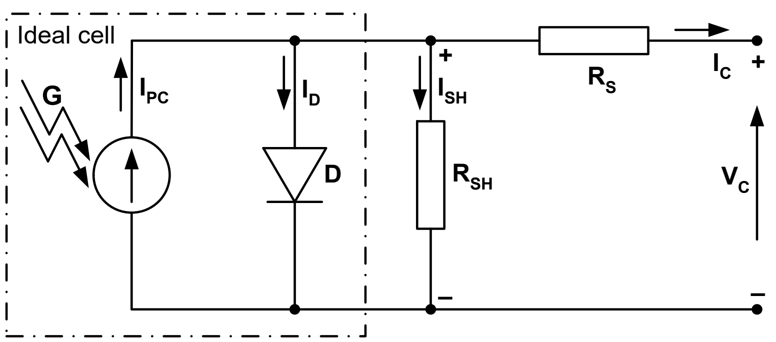


Figure 1. Electrical circuit of PVC

The diode plays a key role in determining I–V curve of a PV cell. The current source output is directly proportional to the incident sunlight on the PV cell. The open-circuit voltage improves exponentially, as described by the equation of the Shockley diode, which defines the relationship between current and voltage. The ideal model of PVC can be described using a sunlight-produced current source (I_{PC}) installed in parallel with a diode (D), as illustrated in Figure 1. The output current (I_C) is formulated in (1) [15]-[19].

$$I_C = I_{PC} - I_D = I_{PC} - I_0\left(e^{\frac{qV_C}{kT}} - 1\right) \tag{1}$$

Where I_D, I_0, q, V_C, k, and T are diode current, diode saturated current, electron charge (1.602×10^{-19} Coulomb), output voltage of PVC, and Boltzmann's constant, respectively.

In practice, the PVC model includes series resistance (R_S) and shunt resistance (R_{SH}). This causes the I-V curves of the PVC model to differ from the ideal PVC model in (1) and produces the characteristics shown in (2). The photocurrent (I_{PC}) is expressed in (3) [15]-[19].

$$I_C = I_{PC} - I_D - I_{SH} = I_{PC} - I_0\left(e^{\frac{qV_C}{kT}} - 1\right) - I_{SH} \tag{2}$$

$$I_{PC} = \left[I_{SC} + K_i(T_r - T_0)\left(\frac{S}{1000}\right)\right] \tag{3}$$

Where I_C, I_{SH}, I_{SC}, K_i, T_r, T_0, and S are the output current of PVC, shunt current, short-circuit current, short-circuit current temperature coefficient (A/Kelvin), reference temperature, operating temperature, and sunlight irradiance, respectively. From (2) and (3), it can be seen that the current of PVC is influenced by the solar irradiance and the cell's working temperature.

The reverse saturated current (I_{RS}) at the reference temperature and the diode saturated current (I_0) are described in (4) and (5). The (5) shows that the diode saturation current is affected by temperature.

$$I_{RS} = \frac{I_{SC}}{\left[exp\left(\frac{qV_{OC}}{N_S A k T_0}\right) - 1\right]} \tag{4}$$

$$I_0 = I_{RS}\left(\frac{T_0}{T_r}\right)^3 exp\left[\frac{qE_{go}}{Ak}\left(\frac{1}{T_r} - \frac{1}{T_0}\right)\right] \tag{5}$$

Where V_{OC}, N_S, and E_{go} are open-circuit voltage, cells connected in series, and band gap for silicon, respectively.

Due to an increase in the power generation capacity of PV systems, solar cells are usually implemented in shunt and series combinations. If N_P represents cells installed in parallel and N_S represents cells assembled in series, the connection between output voltage and current is described in (6) and (7).

$$I_{PV} = N_P x I_{PC} - N_P x I_0\left[exp\left(\frac{qV_{PV}}{N_S A k T}\right) - 1\right] - I_{SH} \tag{6}$$

$$I_{SH} = \frac{V_{PV} x^{N_P}/_{N_S} + I_{PV} R_S}{R_{SH}} \tag{7}$$

Where I_{PV} and V_{PV} are respectively the output current and voltage of a PV module.

3. PRINCIPLE OF RECURRENT NEURAL NETWORK

The structure of RNN is structurally identical to feedforward neural network (FNN). Nevertheless, unlike FNN, the RNN structure incorporates tapped delays (D), as illustrated in Figure 2. These delays allow the networks to capture temporal dependencies by storing information from previous inputs, which allows RNN to represent dynamic input–output mappings. Due to this ability to store and process sequential information, RNNs are more suitable for modeling dynamic systems compared to FNN [20]-[24].

In addition, the input layer (I_m) may include recurrent or context neurons that bring the activation of the hidden layer (H_{nn}) from the previous time step through a unit delay operator (D). The learning process in an artificial neural network involves adjusting the connection weights (W_{nn}) between nodes using a specific method, so that the network gradually acquires the desired weights. This adjustment process is essential to ensure that the network output (O) matches the desired target. If the initial weights cannot produce the desired output, they are updated through repeated training until the difference between network's output and target becomes minimal. Over time, the weight composition improves, resulting in better performance [22]-[24].

Neural network learning techniques usually consist of two types, such as supervised and unsupervised, respectively. One of the most widely used supervised learning methods is back-propagation, which iteratively reduces the error between the target and actual outputs. Once the neural network has been trained, it can be validated and deployed. Validation is considered successful if the network can correctly map new inputs to outputs that align with the expected targets [24], [25].

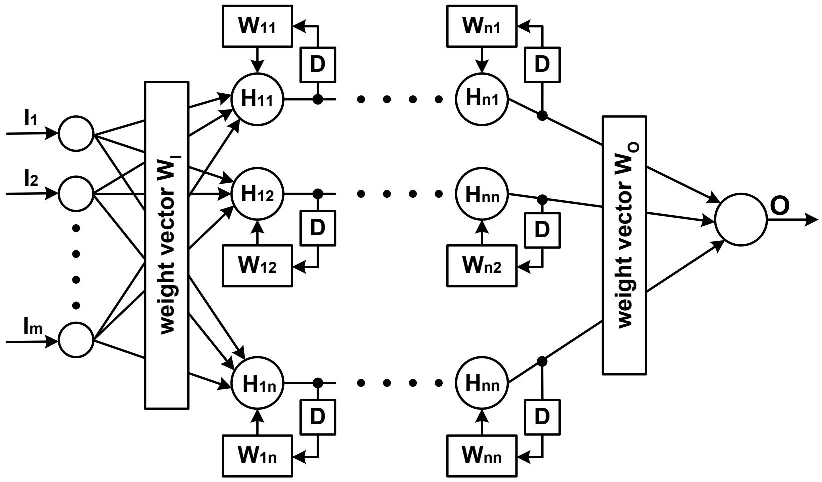


Figure 2. Architecture of a recurrent neural network (RNN)

4. MODELING OF RNN PHOTOVOLTAIC CELL

The RNN-based PVC model is illustrated in Figure 3. The RNN-based PVC model is built to estimate the electrical characteristics of a PVC. The RNN-based PVC model only requires 3 inputs and 2 outputs, such as temperature (T), solar irradiance (S), series resistor (Rs), current (I_{PV}), and power (P_{PV}). The RNN-based PVC model is influenced by the dynamic input and output signals of the electrical model of a PVC.

This RNN-based solar PVC model should be learned before it is operated as a solar PVC model. The learning process of the RNN technique can be seen in Figure 4. The learning algorithm of the RNN-based PVC model uses back-propagation. Data learning of RNN is obtained from an electrical model of a PVC. In this way, the RNN-based solar PVC model can imitate the current and power of the PVC.

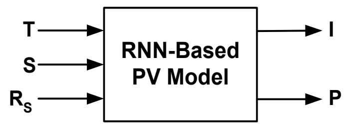


Figure 3. Recurrent neural network PV model

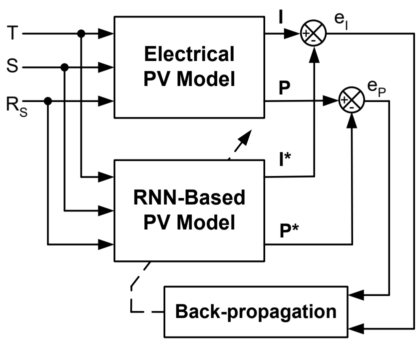


Figure 4. Learning process for recurrent neural network

5. RESULTS AND DISCUSSION

The contributions of the submitted RNN-based PVC model is evaluated by using Simulink/MATLAB software. The RNN-based solar PVC model is investigated with the conventional electrical PVC model under varying operating conditions, including solar irradiance (*S*), temperature (*T*), and series resistance (R_S). Table 1 presents the fundamental parameters of the solar photovoltaic (PV) modules used in this study. The PV modules are SOLANA MONO-12V-100, and the parameters are specified under standard test conditions (STC) [26].

Whereas, the RNN-based solar PVC model begins with the composing of an RNN structure, which considers complexity, such as the amount of hidden layers, the amount of neurons in hidden layers, learning rate, the maximum error, and the maximum epochs. The learning algorithm uses a back-propagation method. Table 2 describes the parameters of the RNN.

The RNN-based PVC model should be learned before being applied as a solar PVC model. The learning process determines the optimal connection weights (W_{nn}) between nodes until the training error is according to the desired error. The structure and hidden layer configuration of the RNN-based PVC model are presented in Figures 5 and 6. The hidden layers receive input from both the output of the previous process and its own output, reflecting the recurrent structure of the network. Figure 7 shows the training performance of the RNN-based solar PVC model for both I–V and P–V curves. The training process converged after 62 epochs, achieving a mean squared error (MSE) of 9.30×10^{-5}, which indicates strong convergence and satisfactory training performance.

Table 1. Parameters of the PV module

Parameters	Values
Maximum power (P_{MAX}), W	100
Voltage at maximum power (V_{MP}), V	18.30
Current at maximum power (I_{MP}), A	5.47
Open-circuit voltage (V_{OC}), V	22.10
Short-circuit current (I_{SC}), A	5.81
Number of cells	33

Table 2. Parameters of RNN

Parameters	Values
Amount of hidden layers	2
Amount of neurons in hidden layer	10
Maximum mean squered error (MSE)	1×10^{-4}
Maximum epoch	500

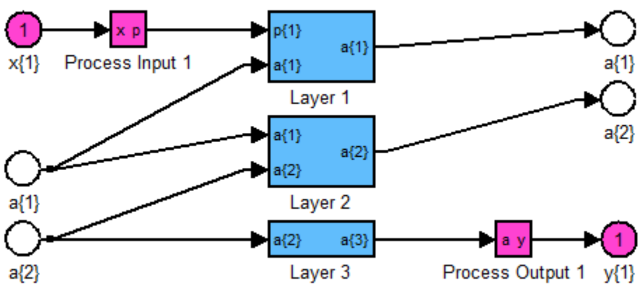
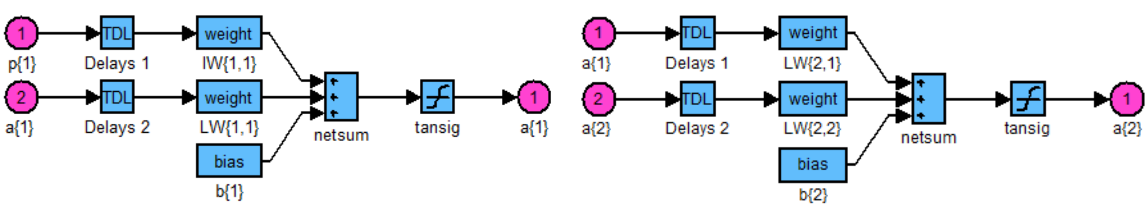


Figure 5. Structure of RNNs



(a) (b)

Figure 6. Details of the RNN hidden layers: (a) first hidden layer and (b) second hidden layer

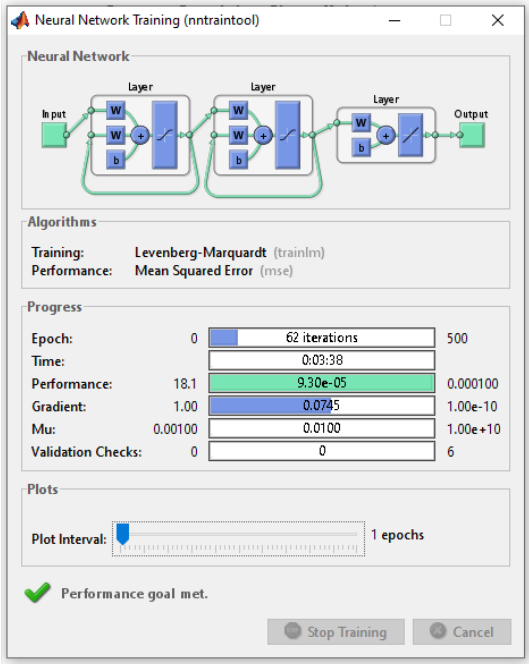


Figure 7. Training performance of RNN

5.1. The effect of solar irradiance variations

This simulation was conducted to find out the effect of solar irradiance variations on I–V and P–V curves of a solar PVM. The solar irradiance levels considered were 0.2 kW/m², 0.4 kW/m², 0.6 kW/m², 0.8 kW/m², and 1.0 kW/m², while other parameters were maintained constant, including a cell temperature of 25 deg. C and a series resistance of 0.005 Ω. Figure 8 shows the resulting I–V curves under these irradiance conditions. The simulation yields obtained using the proposed RNN model are represented by circular markers (○), whereas the conventional electrical model of the PVC is presented by a solid line. As observed in Figure 8, both the I_{SC} and V_{OC} of the PVC increase with increasing solar irradiance.

Figure 9 describes the P–V curves under varying solar irradiance levels. The simulation yields obtained from the proposed RNN model are represented by circular markers (○), while the results of the electrical model of the solar PVC are presented as a solid line. As observed in Figure 9, both the P_{MAX} and the V_{OC} of the photovoltaic cell increase as the solar irradiance increases. The simulation results of the irradiance changes yield the fundamental parameters of the PVC model, as illustrated in Table 3. As described in Table 3, higher irradiance levels result in a consistent increase across all fundamental parameters of the solar PV module.

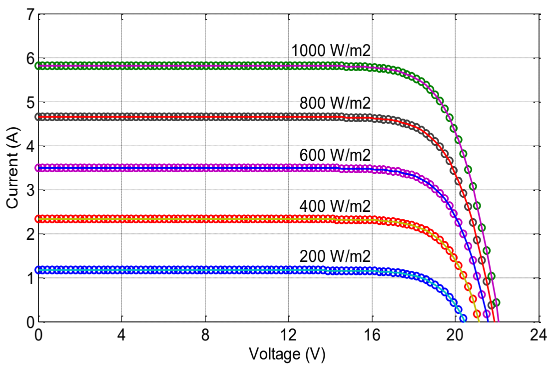


Figure 8. I-V curves for solar irradiance variations

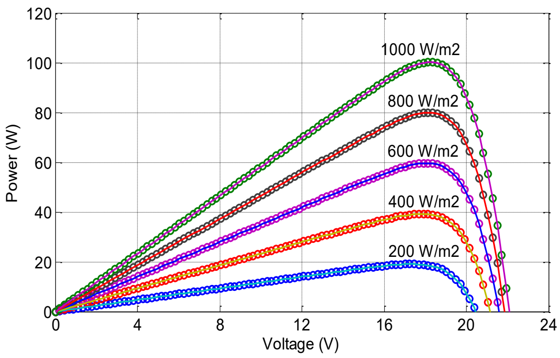


Figure 9. P-V curves for solar irradiance variations

5.2. The effect of module temperature variations

This simulation was carried out to know the effects of module temperature variations on I–V and P–V curves of a PV module. The temperatures considered were 0 deg. C, 25 deg. C, 50 deg. C, 75 deg. C, and

100 deg. C, while other parameters were kept constant, including an irradiance level of 1.0 kW/m² and a series resistance of 0.005 Ω. Figure 10 illustrates the resulting I–V curves under these temperature conditions. The simulation yields obtained using the proposed RNN model are represented by circular markers (○), whereas the electrical model of the solar PVC is depicted by a solid line. As the cell temperature improves, the I_{SC} slightly increases, while the V_{OC} decreases significantly.

Figure 11 presents the P–V curves of the PVC at different cell temperatures. The result of simulations obtained from the submitted RNN model is indicated by circular markers (o), while the results from the electrical model are shown as a solid line. As the cell temperature improves, both the P_{MAX} and V_{OC} of the PVC decrease. The simulation results of temperature changes produced the fundamental parameters of the PV panel model, as presented in Table 4. Table 4 shows that increasing the surface temperature of the PV module leads to an increase in the short-circuit current, while the other fundamental parameters decrease.

Table 3. PV parameters for solar irradiance variations

Parameters	Solar irradiances (W/m^2)				
	200	400	600	800	1000
Short-circuit current (I_{SC}), A	1.16	2.32	3.49	4.65	5.82
Open-circuit voltage (V_{OC}), V	20.46	21.16	21.58	21.87	22.12
Power maximum (P_{MAX}), W	19.02	39.20	59.57	79.92	100.11
Voltage at maximum power, V	17.25	17.92	18.14	18.19	18.28
Current at maximum power, A	1.10	2.19	3.28	4.40	5.48

Table 4. PV parameters for cell temperature variations

PV parameters	Temperatures (ºC)				
	0	25	50	75	100
Short-circuit current (I_{SC}), A	5.77	5.82	5.85	5.88	5.92
Open-circuit voltage (V_{OC}), V	23.54	22.12	20.64	19.16	17.68
Power maximum (P_{MAX}), W	108.87	100.11	91.39	82.62	73.84
Voltage at maximum power, V	19.75	18.28	16.80	15.20	13.80
Current at maximum power, A	5.51	5.48	5.44	5.44	5.35

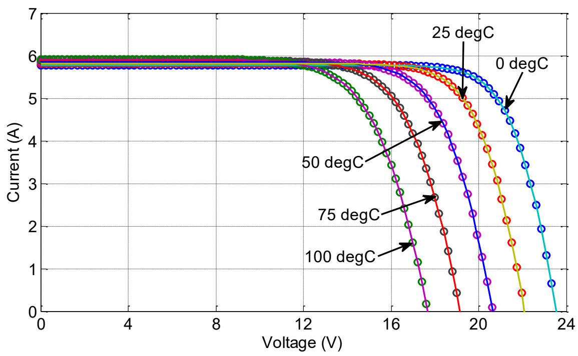


Figure 10. I-V curves for temperature variations

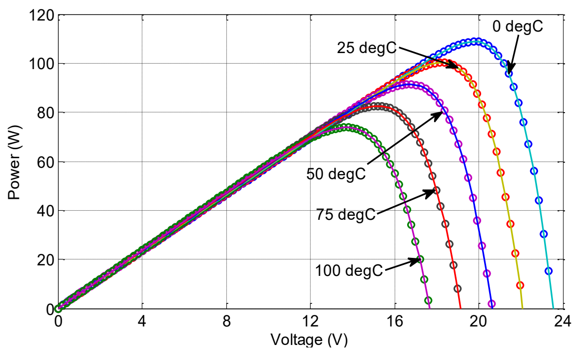


Figure 11. P-V curves for temperature variations

5.3. The effect of series resistance variations

This simulation was conducted to investigate the effect of series resistance variations on I–V and P–V curves of solar PV modules. The series resistance was varied at 0 Ω, 0.005 Ω, 0.010 Ω, 0.015 Ω, and 0.02 Ω, while all other parameters were kept constant, including an irradiance level of 1.0 kW/m² and a cell temperature of 25 deg. C. Figure 12 describes I–V curves according to different R_S values. The results obtained from the proposed RNN model are denoted by circular markers (○), whereas the mathematical model of the solar PVC is represented by a solid line. The I_{SC} and V_{OC} remain unchanged despite variations in series resistance. However, an increase in series resistance significantly affects the slope of I–V curve near the P_{MAX} point and in the high-voltage region, indicating increased internal power losses within the PV module.

Figure 13 presents the P–V curves of the solar PVC for varying series resistance. An increase in R_S leads to a subtraction in the P_{MAX} output. In contrast, the V_{OC} of the PVC remains nearly constant. From the series resistance changes simulation, the fundamental parameters of the PV model were determined, as summarized in Table 5. Increasing the series resistance value does not cause changes in the I_{SC} and V_{OC}, while other fundamental parameters decrease.

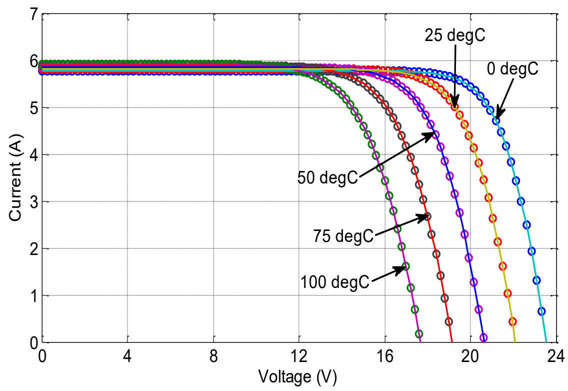


Figure 12. I-V curves for R_S variations

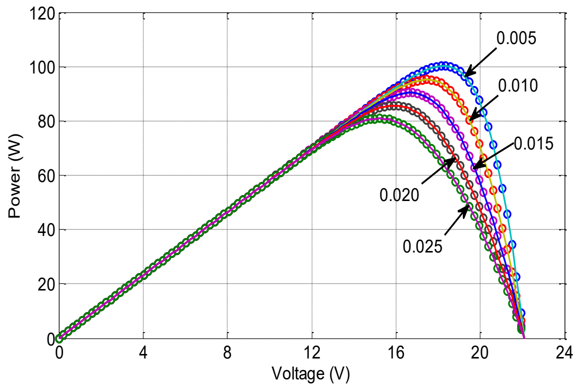


Figure 13. P-V curves for R_S variations

Table 5. PV parameters for R_S variations

Parameters	Series resistances (Ω)				
	0.005	0.010	0.015	0.020	0.025
Short-circuit current (I_{SC}), A	5.82	5.82	5.82	5.82	5.82
Open-circuit voltage (V_{OC}), V	22.12	22.12	22.12	22.12	22.12
Power maximum (P_{MAX}), W	100.11	95.22	90.32	85.54	80.83
Voltage at maximum power, V	18.28	17.47	16.68	15.90	15.23
Current at maximum power, A	5.48	5.45	5.42	5.38	5.31

6. CONCLUSION

The RNN based on a PVC model for producing the electrical characteristics has been modeled, simulated, and discussed. The RNN method is employed to increase the exactness of modeling the electrical characteristics of the solar PVC. The contributions of the RNN approach are investigated through simulations and compared with the conventional electrical PVC model. The simulations of the RNN-based PVC model are performed under varying operating conditions, including changes in solar irradiance (S), cell temperature (T), and series resistance (Rs). The results of simulations demonstrate that the RNN-based PVC model can successfully reproduce I–V and P–V curves and also fundamental parameters refer to the actual behavior of the solar PVC model. In addition, further research will focus on developing PVC models using the other AI methods and applying the findings to solar power plant design.

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AUTHOR CONTRIBUTIONS STATEMENT

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Saidah	✓	✓				✓	✓		✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this research are available from the corresponding author, [BP], upon reasonable request.

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