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PREDICTIVE POWER MODEL OF A PHOTOVOLTAIC SYSTEM UNDER PARTIAL SHADING CONDITIONS USING NEURAL NETWORKS

Braulio José Cruz Jiménez
Universidad Americana de Europa (UNADE)
Quintana Roo, México

Rodrigo Cadena Martínez
Universidad Americana de Europa (UNADE)
Quintana Roo, México

Roberto Rico Camacho
Falco Electronics
Yucatán, México

Luis Josué Ricalde Castellanos
Universidad Autónoma de Yucatán
Yucatán, México

Mirtha Janeth Montañez Rufino
Universidad Autónoma de Yucatán
Yucatán, México

Abstract: Photovoltaic energy has emerged as an extremely attractive alternative for electricity generation, especially with advancements in control systems that facilitate its integration with electrical applications. However, despite careful planning in the placement and fixing of panels, shading is inevitable in various circumstances due to space limitations and obstacles such as clouds, buildings, trees, and snow. This article aims to anticipate the energy production of photovoltaic systems under partial shading conditions. Energy loss in such conditions is addressed using bypass diodes, and artificial neural networks are implemented to predict power output. Three key parameters are trained for this prediction, enabling a more accurate estimation of energy generation under shading conditions.
Keywords: photovoltaic systems, partial shading, power predicting, artificial neural network.

INTRODUCTION

Currently, the world is facing a high demand for energy due to the increasing population. Most of the energy used to supply the growing population comes from fossil fuels. However, this resource is depleting and causing atmospheric pollution, among other problems. To address these issues, renewable energy sources such as solar, wind, and fuel cells are being utilized. Among renewable energy sources, energy is predominantly being produced from photovoltaic solar systems due to the large amount of solar energy available to meet humanity's increasing energy needs. Energy production based on photovoltaic systems has gained popularity, and awareness of this is high among countries in general. As a result, governments provide grants aimed at technological developments to significantly reduce the cost per watt of photovoltaic systems [12].

Despite some technological improvements, there are still challenges in photovoltaic energy output, such as low conversion efficiency, depending on variable irradiation and temperature conditions. The main problems that disrupt energy generation in photovoltaic systems are losses due to divergence in the electrical characteristics of photovoltaic panels. Photovoltaic system mismatch results from the manufacturing systems employed, module aging, poor soldering links, and irregular irradiation conditions or partial shading. Of these, partial shading conditions have created detrimental consequences in terms of the photovoltaic system's performance efficiency [12].

Even though panels are placed and fixed after careful planning, shading is inevitable in many circumstances due to space constraints and issues such as clouds, buildings, trees, and snow. Additionally, inadequate maintenance can lead to dust accumulation on the panels, creating an irregular response to radiation. The electrical performance characteristics of shaded panels differ from those of unshaded panels, resulting in a lack of photovoltaic efficiency that increases with the intensity of the shade. Photovoltaic energy generation is reduced by this mismatch, and improving photovoltaic output in such circumstances is a critical task since the decrease in production is not only related to the shaded area but also depends on various other issues such as array formation, shade intensity, and the position of the shaded panel in the photovoltaic array [12].

Photovoltaic energy systems have become a very attractive option for generating electricity, especially with advancements in control systems used to integrate such systems with electrical applications. Additionally, the correlation between the loads of most energy systems and the energy generated from photovoltaics makes it an efficient option used to power larger loads during the day. Numerous developments in photovoltaic systems have been introduced to increase their efficiency and reduce the cost of generated energy by using new and modified materials or improving the performance of the power converter.

A condition where the complete modules of a photovoltaic array do not receive the same solar irradiance is known as a partial shading condition. Partial shading conditions are inevitable, especially in solar systems installed in urban areas and areas where low-moving clouds are common. If the control system cannot detect and react to this situation, the photovoltaic system will deviate from the optimal operating mode [7].

Photovoltaic systems comprise several photovoltaic modules connected in parallel or series to achieve the required output voltage and current supply capacity. The efficiency of the output can be negatively affected when these modules are subject to non-uniform irradiance, as in the case of partial shading of the photovoltaic system. The extent of the case depends on the system architecture, the implementation of the shading scheme, or the number of bypass diodes integrated into the photovoltaic modules. Partial shading occurs due to the occlusion of the sun by objects such as buildings, trees, and other elements. Under partial shading conditions, a photovoltaic module may receive different levels of solar irradiance compared to other in the array, resulting in a complex and multi-peak P-V output characteristic curve [13].

If a panel of a photovoltaic system is partially shaded, the shaded panel would consume the power produced by the other panels and dissipate heat. Under this condition, the current of the series-connected panel will be reduced to the same as the shaded panel's current. To address this issue, bypass diodes can be interconnected in parallel with each photovoltaic module; these diodes will be reverse biased with uniform solar radiation. In contrast, these diodes will be forward-biased and draw current from the solar panel under the shading effect. Although the shaded part of the panels will be protected from damage, the photovoltaic energy output is not optimal [11].

In typical situations, power-voltage (P-V) and current-voltage (I-V) graphs show a single maximum peak, but in cases of partial shading, the curve presents multiple peaks. Therefore, it is crucial for the designer to select the optimal value and employ maximum power point tracking (MPPT) to capture the maximum available power [11].

A photovoltaic array consists of multiple cells connected in series. By inserting a bypass diode, each string of cells transforms into individual substrings. These substrings are connected in parallel, creating a path that allows current to flow even in the presence of partial shading. In photovoltaic systems employing bypass diodes to enhance energy efficiency, artificial neural networks are used to accurately predict energy generation [8].

The ability of artificial neural networks to predict energy production in photovoltaic systems affected by partial shading has been a topic of intensive research in the past decade. This interest stems from the critical need to maximize the efficiency of these systems in urban and natural environments where physical obstacles are inevitable [9].

A study conducted by [5] used neural networks to predict the power output of photovoltaic systems under different weather conditions. The researchers trained neural network models using historical data that included variables such as solar intensity, temperature, and degree of shading. The results demonstrated that neural networks could accurately predict power fluctuations, outperforming other predictive models such as regression and support vector machines.

In [14] a study is presented on the use of artificial neural networks (ANN) to model the energy production of photovoltaic solar panels. It describes in detail the methodology used to develop and train the ANN model, which includes the collection and preprocessing of data on solar irradiation, ambient temperature, module temperature, wind speed, and relative humidity. The study evaluates the ANN model's performance by comparing it with other traditional approaches such as multiple linear regression models and power law models. The results indicate that Zeng's proposed ANN model offers greater accuracy in energy output predictions, with a coefficient of determination (R^2) and mean absolute error (MAE) that significantly surpass traditional methods. Additionally, the article highlights the ANN model's ability to capture the inherent non-linearity in solar energy production, contributing to better data adaptation and greater reliability in diverse scenarios. The work concludes that using ANN in modeling photovoltaic panel energy is not only viable but also highly effective, suggesting its implementation as a standard tool in solar energy system management and optimization.

On the other hand, [2] focused on developing a deep neural network to dynamically adjust the operating parameters of photovoltaic systems in response to real-time detected shading variations. Their research showed that adjusting system parameters based on neural network predictions could increase energy production by up to 15% compared to systems that did not use adaptive adjustments.

In [6], an artificial neural network was used to develop a highly accurate energy production prediction model for solar panels. This study used a self-developed feedforward neural network model employing the rectified linear unit activation function. Weather, climate, and solar irradiation data collected over the past year at a residential location were used to train the models. The model's performance was identified based on minimum mean absolute error, mean squared error, and maximum linear correlation coefficient. Additionally, the current self-developed ANN model was consistent with other experimental results and theoretical analyses of solar energy.

In the study [4], artificial neural networks (ANN) and regression models are used to predict the energy production of photovoltaic modules, analyzing the effects of climatic conditions and operating temperature on the estimated production. The models are based on six days of experimental data, creating a comprehensive dataset. After preprocessing the data, suitable attributes were selected as inputs, considering features such as solar irradiation, ambient and module temperature, wind speed, and relative humidity, while energy generation was used as the target. From this data, the impact of the training algorithm on the ANN model's predictive performance was investigated. The results indicate that solar irradiation, ambient and module temperature are crucial factors in predicting energy generation from photovoltaic modules, as they are strongly correlated with photovoltaic energy production. Additionally, it was found that the Levenberg-Marquardt algorithm was the most effective for training. The ANN model demonstrated superior accuracy compared to the developed multiple linear regression models.

METHODOLOGY

Figure 1 illustrates the equivalent electrical circuit of a photovoltaic cell. In this diagram, a current source, denoted as I_{pv}, represents the current generated by solar radiation. Additionally, the presence of a diode is shown along with two resistors: R_s in series arrangement and R_{sh} in parallel configuration. R_s reflects the losses associated with contacts and connections, while R_{sh} represents the diode's leakage current [10].

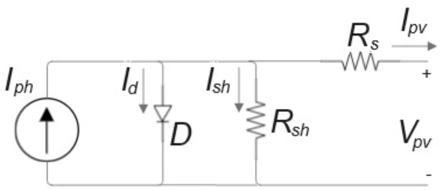

Figure 1. Model of a photovoltaic cell

By applying Kirchhoff's voltage and current law to the circuit depicted in Figure 2, we can derive the current generated (I_{pv}) by the solar panel, as expressed in equation (1) [3]:

$$I_{pv} = I_{ph} - I_d - I_{sh} \quad (1)$$

Given that I_{sh} represents the current losses in the parallel resistor, given by:

$$I_{sh} = \frac{V_{pv} + R_s I_{pv}}{R_{sh}} \quad (2)$$

The diode current I_d is given by equation 3:

$$I_d = I_o \left(e^{\left(\frac{q(V_{pv}+R_s I_{pv})}{K T_c A}\right)} - 1 \right) \quad (3)$$

Substituting equations (2) and (3) into (1) results in:

$$I_{pv} = I_{ph} - I_o \left(e^{\left(\frac{q(V_{pv}+R_s I_{pv})}{K T_c A}\right)} - 1 \right) - \left(\frac{V_{pv} + R_s I_{pv}}{R_p} \right) \quad (4)$$

where I_{ph} is the photogenerated current, Io is the diode's reverse saturation current, q is the electron charge (1.6 x 10^{-19} C), V_{pv} is the solar cell voltage, *K* is the Boltzmann constant (1.38 x 10^{-23} J/K), T_c is the operating temperature of the cell, and *A* is the diode ideality factor, which distinguishes the behavior between a silicon cell and a germanium cell, depending on the solar cell manufacturing technology.

The photogenerated current varies as a function of the solar radiation and the cell temperature present during measurement, as described in equation (5).

$$I_{ph} = \frac{R}{R_{ref}} \left[I_{ref} + U_{I_{sc}} \left(T_c - T_{c_{ref}} \right) \right] \quad (5)$$

where *R* is the solar radiation measured at the instant, R_{ref} is the solar radiation under standard conditions (1000 W/m²), I_{ref} is the photogenerated current under reference conditions taken as the short-circuit current ($I_{sc} = I_{ref}$), U_{Isc} is the short-circuit current temperature coefficient, and T_{cRef} is the operating temperature of the cell under standard conditions (298°K). The diode's reverse saturation current also depends on the temperature, which is described in equation (6).

$$I_o = I_{o_{ref}} \left(\frac{T_c}{T_{c_{ref}}} \right)^3 e^{\left[\frac{qEg\left(\frac{1}{T_{ref}} - \frac{1}{T_c}\right)}{KA} \right]} \quad (6)$$

where I_{oRef} is the reverse saturation current under reference conditions and E_g is the semiconductor's bandgap energy. This energy provides an idea of the ease with which an electron can move from the valence band to the conduction band. It is necessary for the photons incident on the junction to have an energy greater than the material's bandgap energy value to produce the photoelectric effect in the semiconductor material. The optimal value to maximize the absorption of the solar spectrum at sea level is around 1.5 eV. The current I_{oRef} is defined according to equation (7).

$$I_{o_{ref}} = \frac{I_{sc}}{e^{\left(\frac{V_{oc}}{K T_c A}\right) - 1}} \quad (7)$$

To obtain appropriate voltage and current for different applications, several solar cells are interconnected in series or parallel to form a photovoltaic module, which in turn can be interconnected with others to form what is known as a photovoltaic array. Therefore, the equation for a photovoltaic cell described in (4) is augmented with the coefficients N_p, which is the number of modules in parallel, and N_s, the number of cells in series, so that the current-voltage characteristic equation of a solar panel is denoted in equation (8) [1].

$$I_{pv} = N_p I_{ph} - N_p I_o \left(e^{\left(\frac{q\left(\frac{V_{pv}}{N_s} + \frac{R_s I_{pv}}{N_p}\right)}{K T_c A} \right)} - 1 \right) - \left(\frac{V_{pv}\left(\frac{N_p}{N_s}\right) + R_s I_{pv}}{R_p} \right) \quad (8)$$

Equation (8) is simplified because the shunt resistance does not affect the efficiency of a solar cell, as the resistance tends to be very large or infinite, so it can be assumed that $R_{sh} = \infty$. However, the series resistance significantly affects the cell's behavior; therefore, the equation becomes:

$$I_{pv} = N_p I_{ph} - N_p I_o \left(e^{\left(\frac{q\left(\frac{V_{pv}}{N_s} + \frac{R_s I_{pv}}{N_p}\right)}{K T_c A} \right)} - 1 \right) \quad (9)$$

Equation (9) is a detailed representation of how a solar cell converts light energy into electrical current, considering both the intrinsic characteristics of the cell and the external conditions that affect it. The implementation will be carried out in Matlab's Simulink, as it allows for complex and dynamic simulations, especially in real-time, in addition to having an intuitive graphical interface and advanced analysis and visualization tools.

SIMULATION OF DATA FOR NEURAL NETWORK TRAINING

Partial shading occurs when only a portion of a solar panel or module is covered, while the rest remains exposed to direct sunlight. This phenomenon can be caused by objects such as trees or buildings casting shadows on the panel or due to installation at an angle that allows part of the panel to be obstructed by another. The effect of this shading on the solar panel's performance is significant, as the shaded section generates less electricity than the illuminated section. Since the solar cells in a panel are interconnected in series, even minimal shading can reduce the voltage across the entire panel and negatively impact its energy efficiency.

To better understand the potential impact on energy production, different partial shading conditions are simulated. For this, two photovoltaic panels connected in parallel, each with 60 cells, are considered. Different irradiances are applied to each section of the panels, as shown in Figure 2.

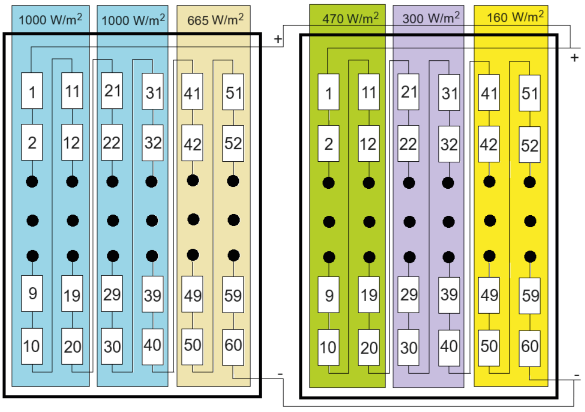

Figure 2. Schematic diagram of 120 PV array

To conduct the simulation for obtaining the voltage, current, and power data that will be used to train the neural network, the Simulink block model is utilized to represent each section of the solar panel. Each block can have adjustable parameters such as temperature, the number of solar cells, and irradiation conditions. In this model, partial shading is defined by adjusting the solar irradiation parameters for certain panels or sections of panels. Additionally, controlled switches are included to activate the bypass diodes when a drop in efficiency of certain sections of the panel due to shading is detected, as shown in Figure 3.

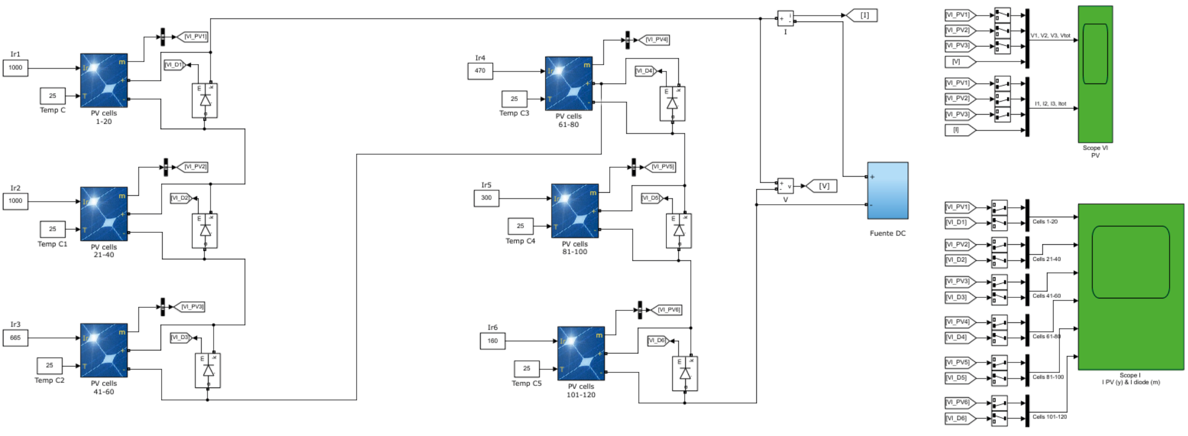

Figure 3. Simulink model of the photovoltaic system

DEVELOPMENT OF THE NEURAL NETWORK

An artificial neural network is a parallel distributed processor formed by simple processing units (neurons) that stores experiential knowledge and makes it available for use. Knowledge is acquired by the network through a learning process, and the connection weights between neurons, known as synaptic weights, are used to store this knowledge. The procedure used for the learning process is called the training algorithm, whose function is to modify the synaptic weights of the network in an orderly manner to achieve a desired design objective.

Multilayer Perceptron (MLP) are an extension of simple perceptron and are used to solve more complex problems that cannot be addressed by individual perceptron. These networks consist of multiple layers of neurons, each connected to the next layer, allowing for the representation and learning of non-linear functions. The structure of a multilayer neural network is described as follows:

1. Input Layer: This layer receives the input features or variables. Each node in the input layer represents a feature of the data.
2. Hidden Layers: Between the input layer and the output layer, there are one or more hidden layers. These layers are responsible for capturing non-linear relationships in the data. Each neuron in a hidden layer applies an activation function to a linear combination of the outputs from the previous layer.
3. Output Layer: This layer produces the final output of the network, which can represent a classification (in the case of classification problems) or a continuous value (in the case of regression problems).

The objective of training a neural network is to establish values for the weight vector so that the error made when evaluating the training examples is minimized. Once these weights are calculated, the network is ready to be tested with other test patterns that it has not been trained on. The goal of this new testing is to see how the network behaves when the inputs are different from those used for training.

When training a neural network with specific training examples and attempting to minimize the error to minimal levels, there is a risk of over-specializing the network, which will perform optimally with the examples it was trained on, but for examples it has not been trained on, considerable errors may occur. This leads to the conclusion that while it is necessary to minimize the error, overfitting should be avoided as it results in a loss of generalization.

The sigmoid function is used as the activation function, which is one of the most commonly used activation functions in artificial neural networks. It is a non-linear function that limits the input values to a range between 0 and 1. As the input increases, the output tends to 1, and for lower values, it approaches 0. This activation function is crucial for handling complex patterns and solving complicated problems in neural networks.

The sigmoid function is characterized by having a steeper slope around the input value of 0, which facilitates fast learning by allowing quick adjustments in the network's weights. However, it faces the challenge of the vanishing gradient problem when the output values are high, reducing the slope to almost zero and consequently slowing down the learning rate. This problem can limit the effectiveness of deep neural networks.

Additionally, the sigmoid function experiences saturation when the output values approach the extremes of 0 or 1, reducing the slope to nearly zero and minimizing weight updates during training. This phenomenon poses an obstacle in learning as the network deepens.

The use of non-linear functions is essential in artificial neural networks because linear functions are insufficient for solving highly complex problems. By employing non-linear activation functions such as the sigmoid, neural networks can effectively learn and model intricate patterns, enabling them to tackle a wide range of challenges.

In the output layer, a linear function is used, which causes the output to vary directly in proportion to the input. Since it is a linear transformation, even when connecting multiple linear layers, the relationship remains a single linear function. Therefore, successively using linear functions does not increase the expressive capacity of the neural network nor facilitate the learning of complex patterns effectively. Hence, including linear transfer functions in the hidden layers of structures like the multilayer perceptron does not add significant value. However, in situations where the predicted values are real numbers, such as in regression tasks, the linear transfer function can be appropriate and improve performance as an activation function.

The Levenberg-Marquardt algorithm is used to train artificial neural networks, being particularly useful in non-linear least squares optimization problems. This algorithm acts as a training function that updates the weights and bias values in neural networks through an optimization process. The MLP network consists of an input layer, two hidden layers, and an output layer. The output h_j of the *j-th* neuron in the hidden layer is calculated as follows:

$$h_1 = f\left(\sum_{i=1}^{10} w_{ij}x_i + b_1\right) \tag{10}$$

where w_{ij} are the weights from the input layer to the hidden layer, b_j is the bias of the hidden layer, and f is the activation function for each hidden layer. The output of the neural network is expressed as:

$$y_k = g\left(\sum_{j=1}^{m} v_{jk}h_j + c_k\right) \tag{11}$$

An MLP is structured such that the output of one hidden layer is fed as input to the next hidden layer or to the output layer. Therefore, each layer has its own bias value, as it is related to all the variables of the previous layer, and there are weightings for the variables between two consecutive layers. The structure of the artificial neural network used in the simulation is illustrated in Figure 4.

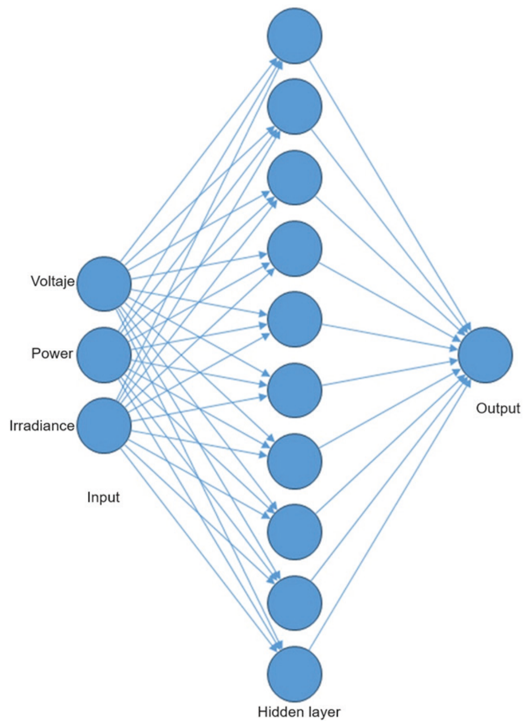

Figure 4. Structure of the neural network

RESULTS

Figure 5 presents a set of graphs showing the performance curves of solar panels under different shading conditions. These graphs represent the power output under various solar irradiation conditions. Each graph shows a clear pattern where power increases, reaches a peak, and then falls sharply, which is typical in partial or intermittent shading situations. As observed in Figure 5, the actual P-V curve is compared to the neural network prediction curve, showing the output power predictions generated by the neural network based on voltage, irradiance, and power inputs. It is important to note that the areas where the neural network predictions diverge from the actual values are not significantly large; if there are divergences, they may indicate issues with the model under certain input conditions or problems with the input data itself. A separate validation set is used to evaluate the model's performance before applying it to the test set. This helped to better generalize and avoid overfitting.

The interpretation of regression analysis results can be facilitated using scatter plots, as shown in Figure 6. These plots graph the relationship between the actual and predicted values, allowing for a visual assessment of how close the data points are to the regression line. If the points cluster around this line, it indicates that the model effectively predicts the relationship between the observed and estimated values. The regression line in the graph, whose slope can indicate the predictive accuracy of the model through correlation, reflects the relationship between the actual and predicted values. A slope close to 1 suggests a highly accurate model, where there is a high match between the actual and predicted values. The clustering of points around the line is also a desirable indicator of accuracy.

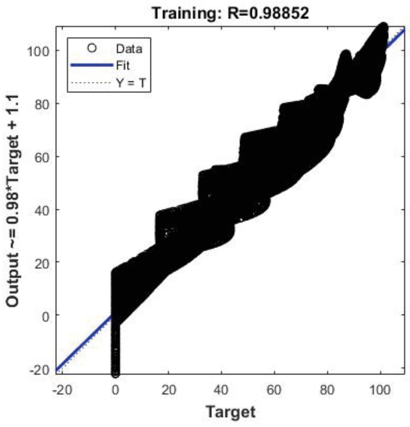

Figure 6. Scatter Plot of Training Data Fit

The Mean Squared Error (MSE) is a metric that calculates the average of the squares of the errors, i.e., the average of the squared differences between the values predicted by the model and the actual values, as illustrated in Figure 7. In the context of training a neural network, the MSE functions as a loss function that the network attempts to minimize by adjusting its parameters (weights and biases). Analyzing the MSE, a consistent decrease is observed, indicating that the network is effectively learning from the training data and adjusting its parameters to reduce the error.

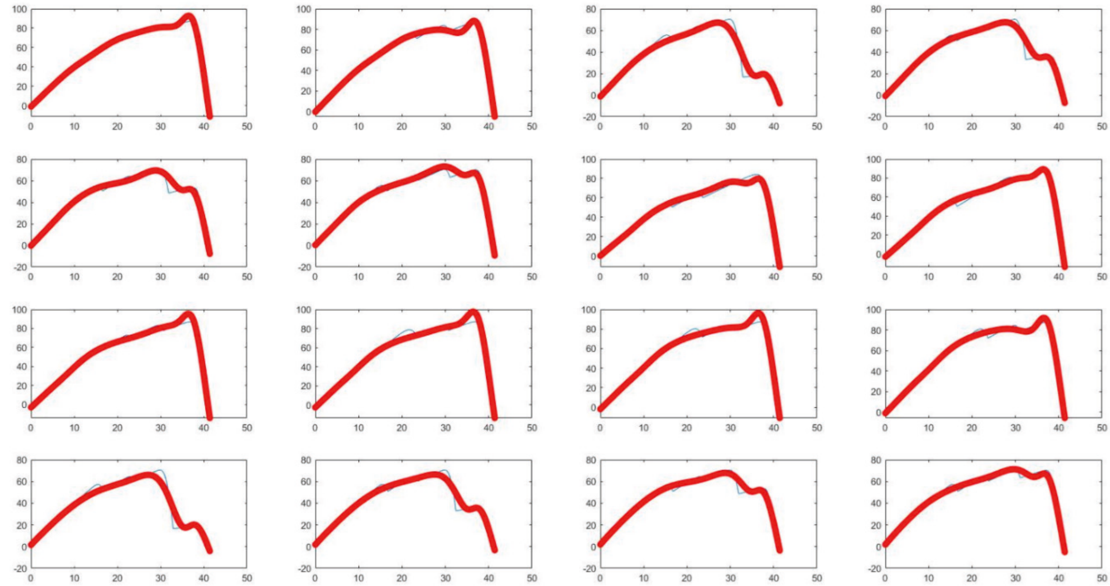

Figure 5. Actual P-V curves vs. neural network generated P-V curves

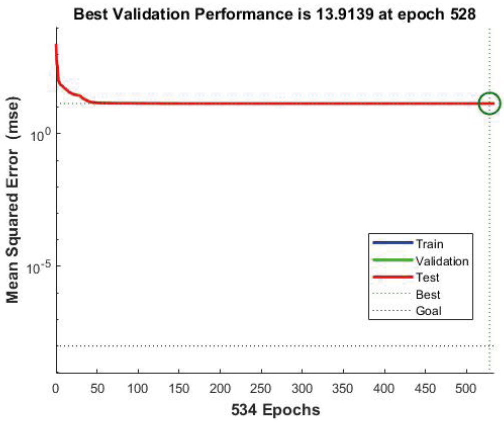

Figure 7. MSE of the Predictive Model

CONCLUSIONS

Using neural networks for power prediction in photovoltaic systems with partial shading has several significant advantages. First, these networks can dynamically adjust to changes in shading conditions and continue to provide accurate predictions. Second, compared to traditional prediction methods, neural networks are often more effective in handling nonlinear and complex data, such as those present in systems with partial shading.

As observed in the figures, this behavior is desirable in most model training scenarios because it suggests that the model will generalize well when faced with new, unseen data (assuming no overfitting and that the data are representative). This indicates that the network is effectively learning from the training data. As more examples are processed during iterations (epochs), the network adjusts its internal parameters to better align predictions with actual values.

The implementation of neural networks in the management of photovoltaic systems not only improves accuracy in power prediction but also aids in optimizing energy consumption and reducing operational costs. Moreover, businesses and households can enhance their energy planning and reduce the risk of equipment damage through better management of load variations caused by shading.

The ability to accurately predict photovoltaic energy production allows grid operators and energy planners to make more informed decisions regarding the integration of renewable energy into the energy matrix. This has direct implications for long-term planning and policies aimed at increasing the share of renewable energy in the market.

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