

RESEARCH ARTICLE

Maximum Power Point Tracking using Artificial Neural Networks

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ABSTRACT

The aim of this work is to optimize the operation of photovoltaic generators. Photovoltaic (PV) solar energy is produced through the direct conversion of solar radiation into electrical energy using photovoltaic cells. These cells are made of semiconductor materials that are sensitive to solar radiation wavelengths and temperature. By interconnecting several PV cells in series and/or parallel, a photovoltaic generator (PVG) is formed, characterized by a nonlinear current–voltage I(V) curve containing a maximum power point (MPP) under specific operating conditions.

This work focuses on maximum power point tracking (MPPT) using two techniques. The first technique is the classical Perturb and Observe (P&O) method, while the second is based on artificial intelligence (AI) using an artificial neural network (ANN).

Keywords

PV Panel;
MPPT;
P&O;
ANN

Article History

Received 12 May 2026
Revised 19 Jun 2026
Accepted 27 Jun 2026

I. INTRODUCTION

Photovoltaic (PV) technology has become an attractive alternative and complement to conventional electricity generation sources because of its numerous advantages: [1-3]

- It is a reliable technology that requires minimal maintenance.
- It produces electricity using the sun's free and renewable energy.
- It operates without the need for fuel.
- It is quiet, environmentally friendly, and non-polluting.
- It is flexible and can be adapted to different applications and energy needs.

The aim of this work is to improve the performance of photovoltaic systems in order to optimize the operation of photovoltaic generators. photovoltaic (PV) solar energy is generated through the direct conversion of solar radiation into electrical energy by means of photovoltaic cells. These cells are manufactured using semiconductor materials that are sensitive to the wavelengths of sunlight. By connecting several PV cells in series and/or parallel, a photovoltaic generator (PVG) is obtained, exhibiting a nonlinear current–voltage I(V) characteristic that includes a maximum power point (MPP).

This operating point is determined by the load connected to the generator and may therefore differ from the maximum power point, which corresponds to the optimal current and voltage values capable of delivering maximum power [1,2].

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Moreover, the output power of the photovoltaic generator is affected by several climatic parameters, mainly irradiance and temperature. For this reason, real-time tracking of the Maximum Power Point (MPP) is essential to ensure optimal operation and improve the overall efficiency of photovoltaic systems.

During this work, MATLAB was chosen as the testing and simulation tool, and the polycrystalline photovoltaic module was used. This module is available at the LMER laboratory

II. PERTURBATION AND OBSERVATION TECHNIQUE

The Perturb and Observe (P&O) algorithm is one of the most commonly used techniques for Maximum Power Point Tracking (MPPT). As implied by its name, the method operates by perturbing the system through either increasing or decreasing the reference voltage V_{ref} , or by directly modifying the duty cycle of the DC–DC converter, and then observing the resulting effect on the output power of the photovoltaic panel. If the measured power at the current instant $P(k)$ is greater than the previous power value $P(k-1)$, the perturbation continues in the same direction; otherwise, the perturbation direction is reversed [4].

The flowchart of this algorithm is presented in Figure 1.

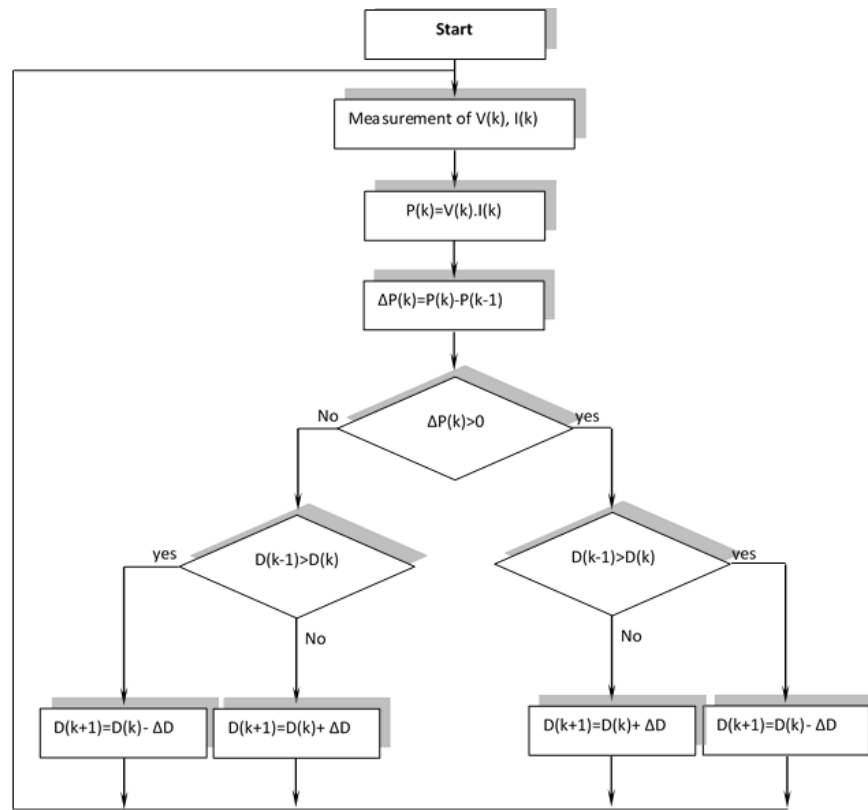


Figure 1. P&O organigram

In this approach, the operating voltage V is perturbed during each MPPT cycle. Once the maximum power point (MPP) is reached, the operating voltage oscillates around the optimal voltage V_{mp} . These oscillations generate power losses whose magnitude depends on the perturbation step size.

- A large perturbation step allows the MPPT algorithm to respond quickly to sudden variations in operating conditions; however, it also increases power losses under steady-state or slowly changing conditions;
- Conversely, a very small perturbation step minimizes power losses in stable conditions, but reduces the system's ability to track rapid changes in temperature and solar irradiance;

Therefore, the optimal perturbation step size ΔD depends on the characteristics of the system and is generally determined experimentally.

Figure 2 shows the variation of power as a function of voltage toward the maximum power point. The advantage of the P&O method lies in its simplicity. It can be observed that the maximum power point is accurately detected.

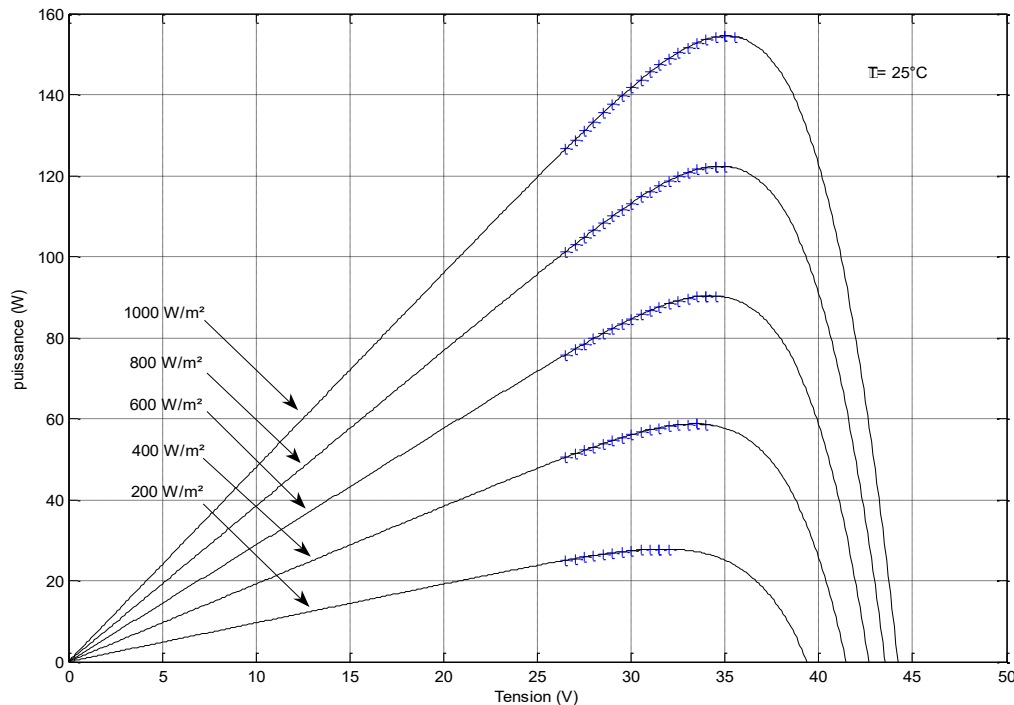


Figure 2. MPPT with using P&O

A limitation of the P&O method, highlighted by Hussein et al. [5], appears when a sudden increase in solar irradiance occurs. In this case, the panel power rises abruptly, and the algorithm incorrectly interprets this increase as the result of the previous perturbation. Consequently, it continues perturbing in the same direction, even though this direction may be incorrect, causing the operating point to move away from the true maximum power point. The algorithm eventually returns to the actual MPP once the irradiance becomes stable again.

III. PRINCIPAL OF THE NEURONAL NETWORK ARTIFICIAL (ANN)

Artificial neural networks (ANNs) are among the most important tools of artificial intelligence. Their structure is generally composed of three types of layers:

- The input layer: it consists of units responsible for receiving external signals and transmitting them to the next layer. This layer does not perform any processing operation, but simply acts as an interface between the input variables and the network. The input variables may represent the parameters of a photovoltaic generator (PVG), such as the open-circuit voltage V_{oc} and the short-circuit current I_{sc} , as well as meteorological data such as irradiance and temperature, or a combination of these parameters.
- The output layer: it provides the final response of the network according to the input signals.
- The hidden layers: located between the input and output layers, they perform the processing and analysis of the input data in order to extract the nonlinear relationships between the variables figure 3. They are called "hidden" because they do not communicate directly with the external environment.

The development of the $I(V)$ and $P(V)$ model mainly depends on the algorithm used in the hidden layers as well as on the type of learning adopted by the neural network. The different connections between neurons are associated with synaptic weights $W_{i,j}$, linking nodes i and j . These weights play an essential role in accurately identifying the current and power values of the PV generator.

The weights $W_{i,j}$ are determined during the training phase, during which the photovoltaic generator is tested over a long period in order to record the relationships between the input data and the network outputs.

Since photovoltaic generators exhibit different characteristics, each ANN must be specifically trained for the PV generator in which it will be used. Furthermore, the characteristics of a PV generator evolve over time due to aging and operating conditions. Consequently, neural networks require periodic retraining to maintain a minimal error between experimental and simulated values [6-9].

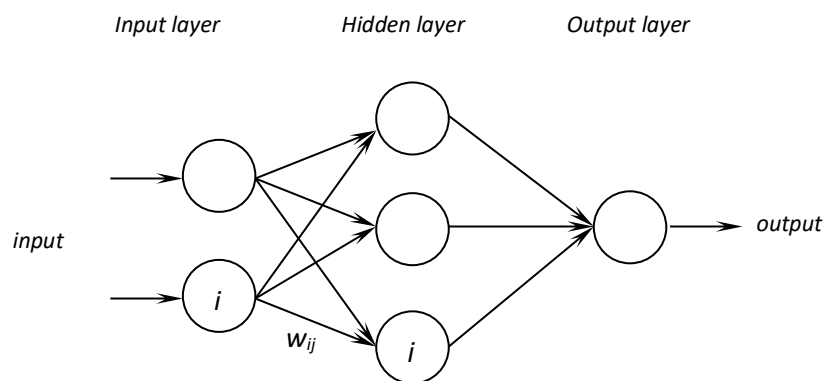


Figure 3. Example of ANN

1. The RNA modelling

The neural model adopted in this study is a feedforward (non-recurrent) neural network composed of:

- An input layer containing three neurons corresponding to irradiance, temperature, and voltage. The variation ranges of these input variables are:
- The input layer uses a sigmoid activation function.
- The network includes two hidden layers: the first with 20 neurons and the second with 30 neurons.
- The output layer consists of a single neuron corresponding to the target value used for estimating the output current.

Neural network training:

two tests stop are used in training algorithm

- Error = 10-10. If the norm is less than the specific error
- Max number of iterations = 1000.

Validation:

The percentage errors between the desired outputs calculated by the photovoltaic cell model and the outputs of the ANN The absolute error in current is less than 0.3%, while the error in power remains below 1%. [10]

Thus, a very good agreement is obtained between the photovoltaic cell model and the neural network approach.

2. MPPT Based on the ANN Method

In this section, we proceed to the implementation of an MPPT technique based on ANNs. The proposed ANN-based approach consists of three stages, as presented previously, and is designed to predict the maximum power (P_{max}), along with the corresponding current and voltage values, under varying irradiance and temperature conditions. This method enables continuous and accurate tracking of the maximum power point while ensuring a fast and efficient dynamic response of the photovoltaic system.

a. First Neural Network for Estimating the Maximum Current

Selection of the Neural Network Structure

The neural model used in this study is a feedforward (non-recurrent) neural network composed of:

An input layer with two neurons corresponding to irradiance and temperature (the variation ranges of these input variables are described in equation (01)), a sigmoid activation function applied to the input layer, and one hidden layer containing 35 neurons.

$$\begin{cases} 0,2 \leq G \leq 1000 \\ 0 \leq T \leq 75 \end{cases} \quad (01)$$

An output layer with one neuron representing the target output used to estimate the maximum current I_{max} corresponding to the maximum power point P_{max}

Training

Two stopping criteria are applied during the training algorithm: Error = 10⁻¹⁰

the training process stops when the distance (according to a given norm) becomes lower than the specified error.

Maximum number of iterations = 1000.

b. Second Neural Network for Estimating the Maximum Voltage

Selection of the Neural Network Structure

This neural model is also based on a feedforward (non-recurrent) neural network composed of:

An input layer with two neurons corresponding to irradiance and temperature (the variation ranges of these input variables are described in equation (02)), a sigmoid activation function applied to the input layer, and one hidden layer containing 35 neurons.

$$\begin{cases} 200 \leq G \leq 1000 \\ 0 \leq T \leq 75 \end{cases} \quad (02)$$

An output layer with one neuron representing the target output used to estimate the maximum voltage V_{max} corresponding to the maximum power point P_{max}

Training

Two stopping criteria are used in the training algorithm:

Error = 10⁻¹⁰ the training stops when the distance (according to a given norm) becomes lower than the specified error.

Maximum number of iterations = 1000.

c. Third Neural Network for Estimating the Maximum Power

Selection of the Neural Network Structure

This neural model is based on a feedforward (non-recurrent) neural network composed of:

An input layer with two neurons corresponding to irradiance and temperature (the variation ranges of these input variables are described in equation (03)), a sigmoid activation function applied to the input layer, and two hidden layers, the first containing 30 neurons and the second containing 35 neurons.

$$\begin{cases} 200 \leq G \leq 1000 \\ 0 \leq T \leq 75 \end{cases} \quad (03)$$

An output layer with one neuron representing the target output used to estimate the maximum power Pmax.

Training

Two stopping criteria are applied during the training process:

Error = 10^{-10} the training process stops when the distance (according to a given norm) becomes lower than the specified error.

Maximum number of iterations = 1000.

IV. RESULTS AND DISCUSSION

As previously mentioned, this stage is used to verify that the three neural networks, after training, are capable of accurately predicting the desired outputs for input data that were not used during the training phase. The predicted outputs of the neural networks must always be compared with those obtained from the photovoltaic cell model, which remains the reference model for all comparisons.

The MPP trajectory and the I–V and P–V characteristic curves are illustrated in Figures 4 and 6, respectively.

The relative error percentages between the desired outputs calculated by the photovoltaic cell model and those predicted by the ANN models are presented in Figures 5 and 7.

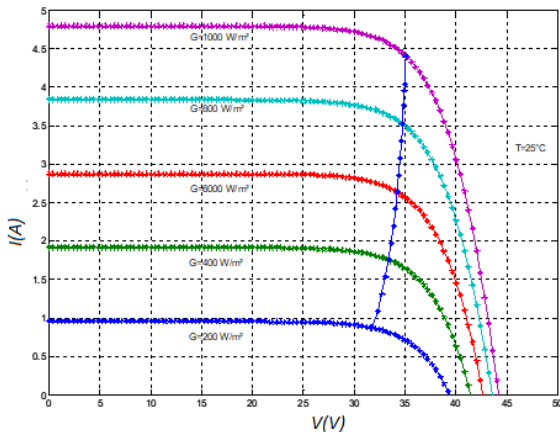


Figure 4. MPPT on the I(V) characteristic

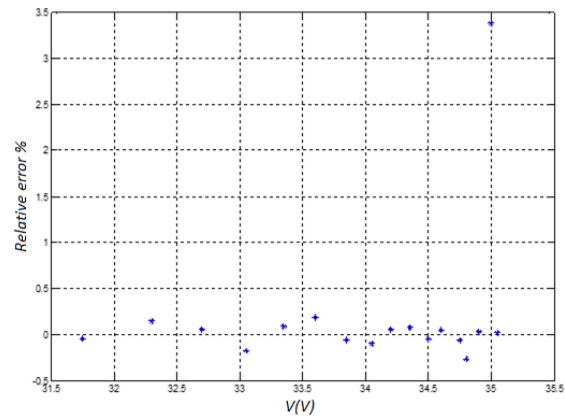


Figure 5. Relative error of the I(V)

The absolute value of the relative error percentage of the MPPT trajectory in the I–V characteristic is less than 3.382%, while the corresponding error in the P–V characteristic is less than 3.592% [10].

Furthermore, a very good agreement is obtained between the photovoltaic cell model and the neural network approach.

A major advantage of artificial neural networks (ANNs) lies in their capability to perform real-time maximum power point tracking (MPPT) under rapidly changing irradiance conditions. This feature is especially beneficial for mobile photovoltaic systems operating in dynamic environments, such as during vehicle turns or when moving through partially shaded areas, where solar irradiance may fluctuate abruptly. Consequently, ANN-based MPPT techniques ensure fast adaptation, improved tracking accuracy, and enhanced energy extraction efficiency

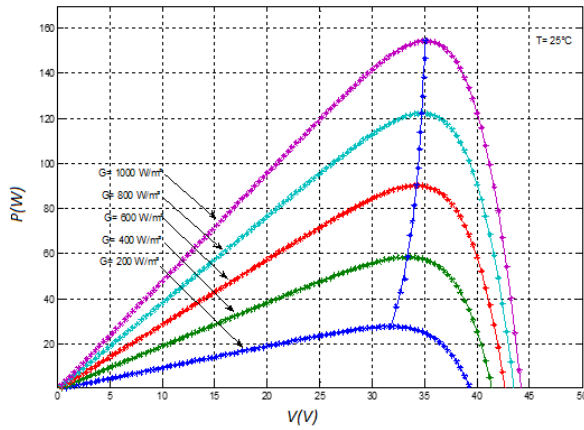


Figure 6. MPPT on the P(V) characteristic

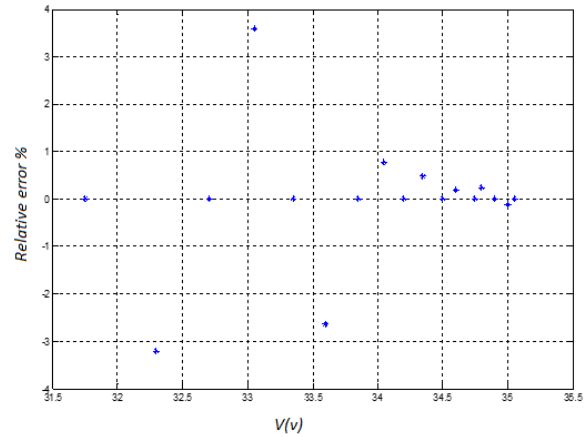


Figure 7. Relative error of the P(V)

V. CONCLUSION

In this work, a polycrystalline photovoltaic (PV) panel was modeled using two maximum power point tracking (MPPT) approaches. The first method is based on the Perturbation and Observation (P&O) technique, while the second relies on an artificial neural network (ANN) approach from artificial intelligence.

The performance of the PV panel was evaluated under outdoor conditions. The results obtained highlight the effectiveness of the ANN-based method in MPPT tracking, as it provides improved accuracy and lower simulation errors compared to the conventional technique.

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