ERURJ **2023**, *2*, 3, 385-398
Article

Efficient MPPT control for a photovoltaic system using artificial neural networks

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Received 13th April 2023, Revised 29h April 2023, Accepted 8th May 2023.

DOI: 10.21608/ERURJ.2023.301364

ABSTRACT

The photovoltaic (PV) system with maximum power point tracking (MPPT) is a frequently employed method for achieving an effective strategy under variable climatic conditions such as varying irradiance and temperature levels. This research investigates increasing the efficiency of a PV system via an artificial neural network (ANN). A feedforward neural network receives measured current and voltage as inputs and estimates the optimum duty cycle corresponding to maximum power as output. The ANN automatically detects the MPP of the PV module by using a preselected number of power measurements of the PV system. The PV system typically displays an I-V nonlinear feature curve with varying MPPs based on solar irradiance and temperature. The maximum power the PV module produces can be transferred to the load when the PV system operates at its MPP. This is achieved by matching the impedance between the PV system and the load through the DC-DC converter with an ANN that adjusts the converter's duty cycle. The results demonstrate that the proposed ANN is more effective and that oscillations around the MPP are significantly decreased during uniform irradiance levels, sudden changes in irradiance levels, and sudden changes in temperature levels.

Keywords **-** Photovoltaic system, MPPT control, DC-DC boost converter, Artificial Neural Networks.

1. Introduction

Concerns regarding the depletion of fossil fuels and the worsening state of the environment stimulate research into renewable energy sources. PV energy is particularly important among renewable energy sources. In addition to its minimal operating costs and decreased pollutants, the capability of direct transformation to electric power offers a solid foundation of benefits. Thus, the massive adoption of PV systems in the energy industry is unsurprising. Although PV systems have numerous benefits, their non-linear characteristics and dependence pose a significant barrier [1-3].

Tracking the highest power of the PV system is required to improve the system efficiency using several MPPT techniques. Traditional MPPT approaches, such as perturb and observe (P&O) and incremental conductance, provide modest performance with an acceptable level of implementation complication. Improved performance using artificial intelligence-based MPPT approaches such as artificial neural networks (ANNs) have been proposed for enhanced transient and steady-state performance, particularly in partial shade and quickly changing environmental circumstances. The advantages of ANNs include robust operation, quick tracking, non-linear system tolerance, and offline training. Thus, numerous ANN-based PV MPPT approaches have evolved recently. ANN-based PV MPPT approaches differ, including controller setup, training algorithms, required measurement signals, complexity, and robustness of implementation [3-6].

The ANN-based MPPT algorithms presented in previous literature are typically used to mitigate parameter variations in the PV system when identifying local MPPs [11–13]. The ANN-based MPPT method proposed in [14] estimates the GMPP using a single voltage and current measurement. Still, the study is limited to a few shading combinations, making it impractical for a generic PV system, followed by [15], which presented ANN continuously subjected to rapidly changing and non-uniform shading conditions. The novelty of this paper can be summarized as follows:

1. Developing and adapting the ANN-based MPPT controller to maximize the output power from a PV with a resistive load based on the module voltage and current measurements.
2. Tracking of the MPP under different operating conditions during uniform irradiance levels, sudden changes in irradiance levels, and sudden changes in temperature levels.

This paper will be structured as follows: Section 2 presents the overall system description, such as the PV system, converter, and MPPT-based ANN. Section 3 shows the simulation results, while Section 4 concludes the paper.

2. Standalone PV System Description

The solar system under consideration, seen in Figure 1, employs the PV system, whose electrical properties are listed in Table 1, a DC-DC boost converter, an MPPT controller based on a neural network, and a resistive load [3].

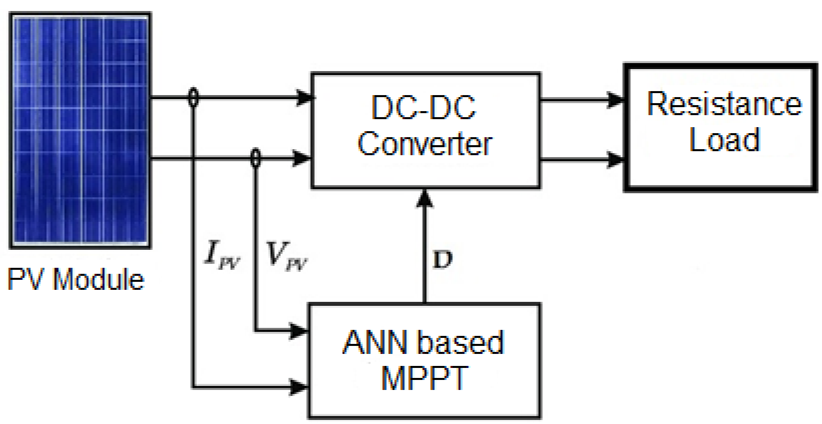


Figure 1 Schematic diagram of the proposed system.

Table 1 Parameters of PV module.

Module Characteristics	Values
P_{max}	245 W

V_{max}	30.2 V
I_{max}	8.06 A
I_{SC}	8.81 A
$sub - OCV_{OC}$	38.3V

A. Mathematical model of PV module

The single-diode model is a suitable compromise between simplicity and accuracy. A photocurrent source in parallel with a single nonlinear diode, a shunt resistor, and a series resistor are depicted in Figure 2. The photocurrent source is primarily determined by the amount of solar irradiation and the cell's operating temperature. These equations define the model of the PV cell [3,4]:

$$I = I_{ph} - I_D - I_{sh} \tag{1}$$

$$I = I_{ph} - I_S \left[exp(\frac{q(V+IR_s)}{K_C A}) - 1\right] - \frac{V+IR_s}{R_{sh}} \tag{2}$$

$$I_{ph} = [I_{SC} + K_1(T_C - T_r)]\lambda \tag{3}$$

Where I_{ph}: photocurrent current, I_D: diode current, I: output current from the cell, I_{Sh}: shunt resistor current, I_S: diode saturation current, K_1: Boltzmann constant, q: electron charge, T_c: actual cell temperature, R_{Sh}: shunt resistance, and I_{SC}: short-circuit current, T_r : reference temperature, λ: irradiance and R_{Sh}: series resistance, V and I are the output voltage and output current of the PV module respectively.

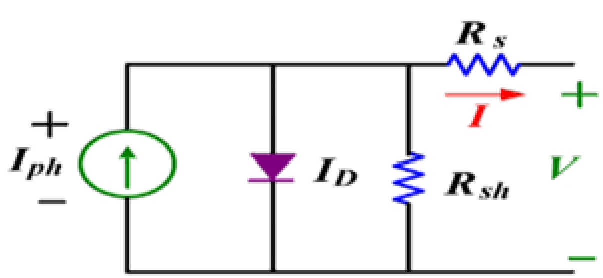


Figure 2 PV cell equivalent circuit.

B. Modeling of the boost converter

The maximum power transmission occurs in PV systems when the internal resistance of the system equals the load impedance. Typically, this is accomplished by fine-tuning the converter's duty cycle while positioned between the PV source and the load [7]. Figure 3 depicts the boost converter and the PV system's output voltage Vo can be stated as [8, 9]:

$$V_i = (1 - D)V_o \tag{4}$$

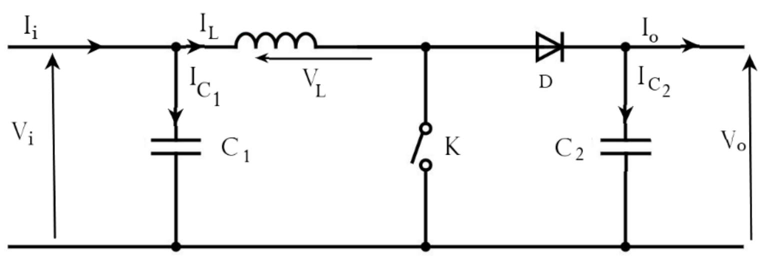


Figure 3 Circuit diagram of the converter.

The impedance of the load (R_L) to the PV source can be matched by fine-tuning the duty cycle. Alternately, optimal matching is achieved when the PV's I_{pv} and V_{pv} are equal to I_{opt} and V_{opt} corresponding to the optimal impedance (R_{opt}) which can be calculated in terms of duty cycle and load resistance as

$$R_{opt} = \frac{V_{opt}}{I_{opt}} = (1 - D^2)\frac{V_o}{Io} = (1 - D^2)R_L \tag{5}$$

C. Artificial neural network

It is well known that ANNs are highly effective at treating complex problems with nonlinearities. An ANN is a system that mimics the functions of a biological NN. It is composed primarily of interconnected neurons analogous to brain cells. Also, it typically consists of one input layer, one output layer, and one or more concealed layers. As depicted in Figure 4, every layer is connected to adjacent layers via interconnection weights w_{ij}. The ANN must be correctly trained to precisely perform the planned task. The neural inputs could consist of the parameters of the PV system, such as V_{oc} and I_{sc}, the temperature and irradiance, or any combination of these. In general, the neural output is the input duty cycle used by the converter to operate around the MPP point [7-8].

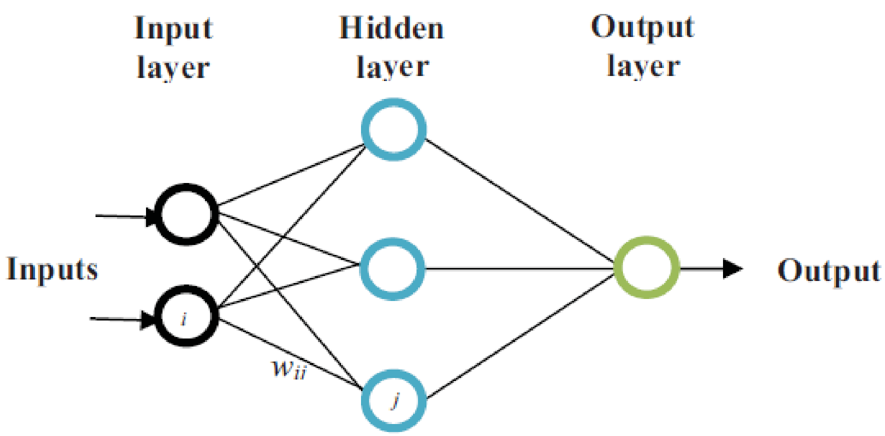


Figure 4. The construction of the neural network

The structure of the NN in this study, depicted in Figure 5, consists of two inputs, the voltage and current of the PV module, two hidden layers comprised of 10 and 8 neurons, and a single output neuron that represents duty cycle D. Tansig is the activation function for both the input and concealed layers, whereas logsig is used for the output layer. Levenberg-Marquardt backpropagation optimization is used to accomplish the training procedure. The training data collection for the 245W PV module includes 270 different I-V curves for varying irradiance values between 200 W/m^2 and 1000 W/m^2 and temperature values between [15-45°C]. From each I-V curve, the values of V_{mp} and Imp, representing the PV module voltage and current at MPP, are projected to calculate the optimal impedance $R_{opt} = V_{mp} / I_{mp}$. Using equation (5), the duty cycle is calculated as follows [8-10]:

$$D = 1 - \sqrt{\frac{R_{opt}}{R_L}} \tag{6}$$

Thus, a dataset containing 270 distinct values of temperature, irradiance, and duty cycle is obtained, with 75% of the values used for training the neural network and the remainder for testing.

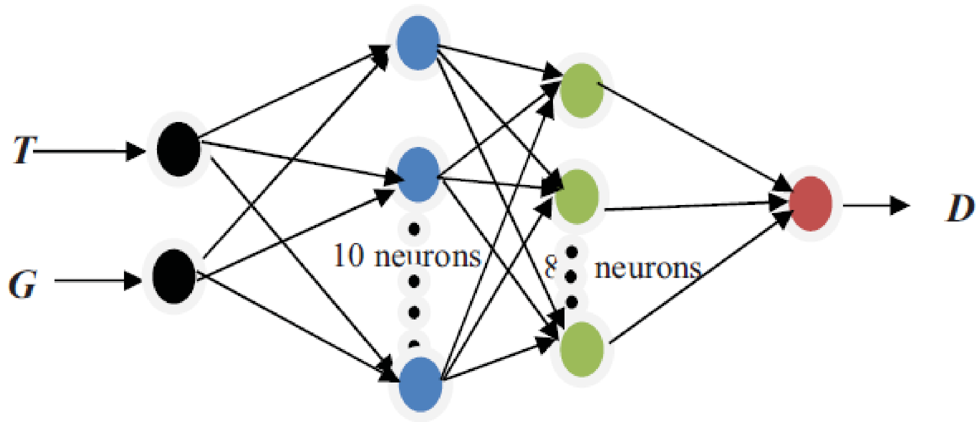


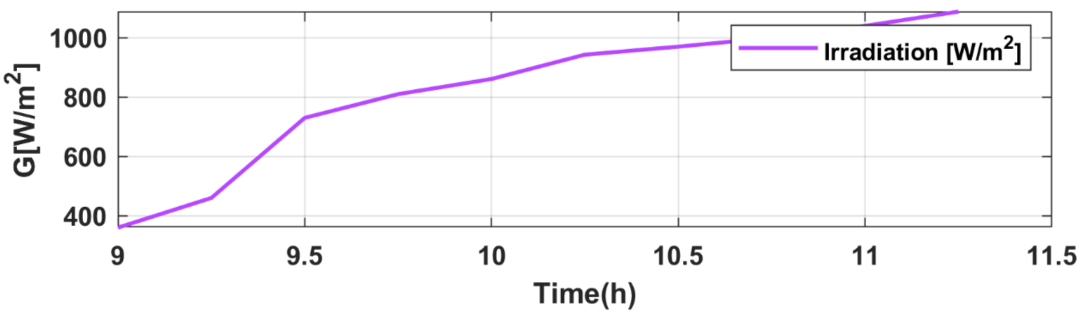
Figure 5 Proposed feedforward NN structure.

3. Validation work

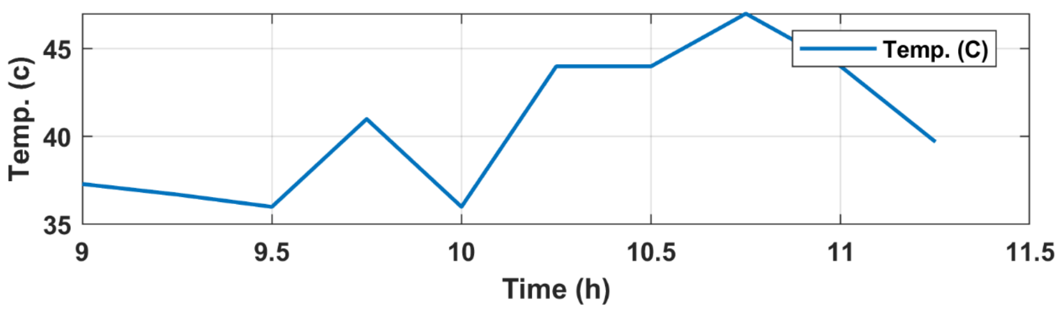
Before proceeding with the proposed algorithm, the ANN was validated using the previously published data of Salah et al. [13]. The model was represented by a PV module, a resistance load, and an MPPT control system represented by a boost converter and a feedforward neural network-based MPPT control. The PV module investigated by Salah et al. [13] consists of two parallel Siemens SM50-H PV modules. The electrical parameters of this module are listed in Table 2, and a variable resistor was considered in the simulation. According to the two inputs, irradiations, and temperature, depicted in Figure 6, used by Salah et al. [13], a comparison study can be implemented of the output power using the ANN of Salah et al. and the ANN of the present work, as shown in Figure 7. The main difference between the proposed ANN and that proposed by Salah et al. is that the proposed ANN requires only the measurement of PV voltages and currents, thus avoiding additional sensors providing information about the environmental operating conditions and temperature of PV modules like Salah et al., which need to measure the irradiance and temperature as two neural inputs.

Table 2 Parameters of PV module of Salah et. al [13].

Module Characteristics	Values
P_{max}	50 W
V_{max}	15.9 V
I_{max}	3.15 A
I_{SC}	3.35 A
$sub - OCV_{OC}$	19.8 V



(a)



(b)

Figure 6 Reference inputs to the PV module. (a) Irradiation. (b) Temperature.

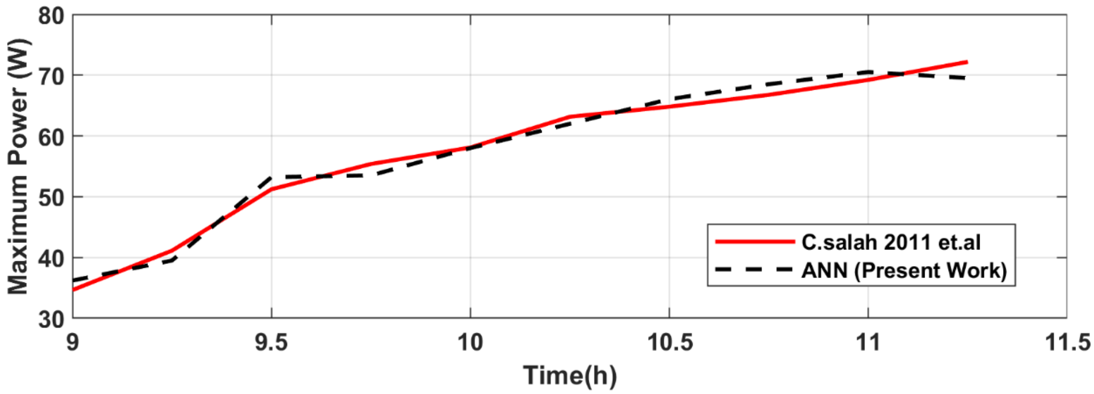


Figure 7 Comparison study of different MPPT controllers.

4. Results and discussions

Figure 8 illustrates the PV module characteristics at varied irradiations and constant temperatures (T= 25 ℃). Figure 9 depicts the PV module characteristics at various temperatures and constant irradiance levels (1 kW/m^2). The figures demonstrate the effect of increasing the irradiance levels to increase the PV output power while increasing the temperature will decrease the PV output power.

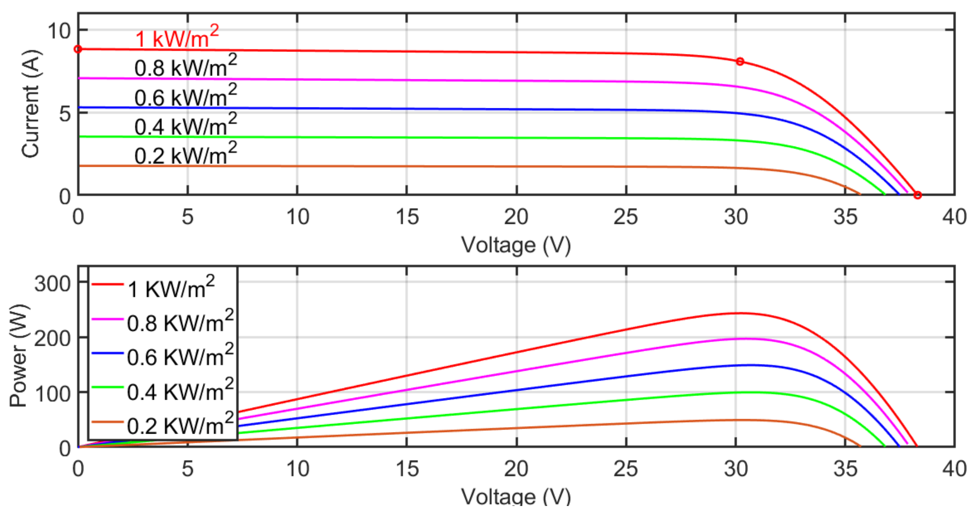


Figure 8 PV module characteristics at constant temperature and varying irradiance levels.

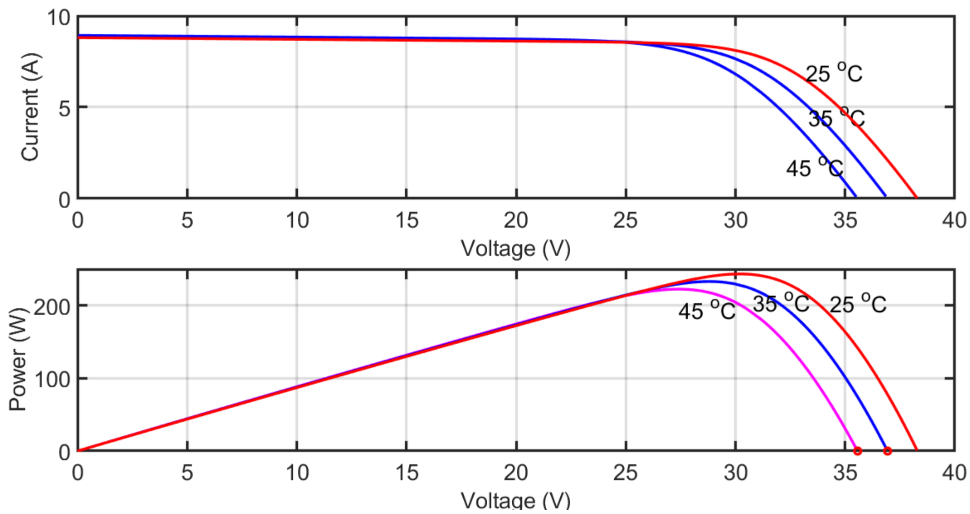


Figure 9 PV module characteristics at varying temperatures and constant irradiance levels

Figure 10. illustrates the PV output power with the ANN under constant atmospheric conditions (T = 25°C, G = 1000W/m2). Under a resistive load, the time required for the ANN to attain a steady state was 0.05 seconds. Figure 11 and Figure 12 show the output voltage and current from the PV system using the ANN controller. It shows that the ANN can reach the maximum voltage and current at an irradiance level of 1000W/m^2.

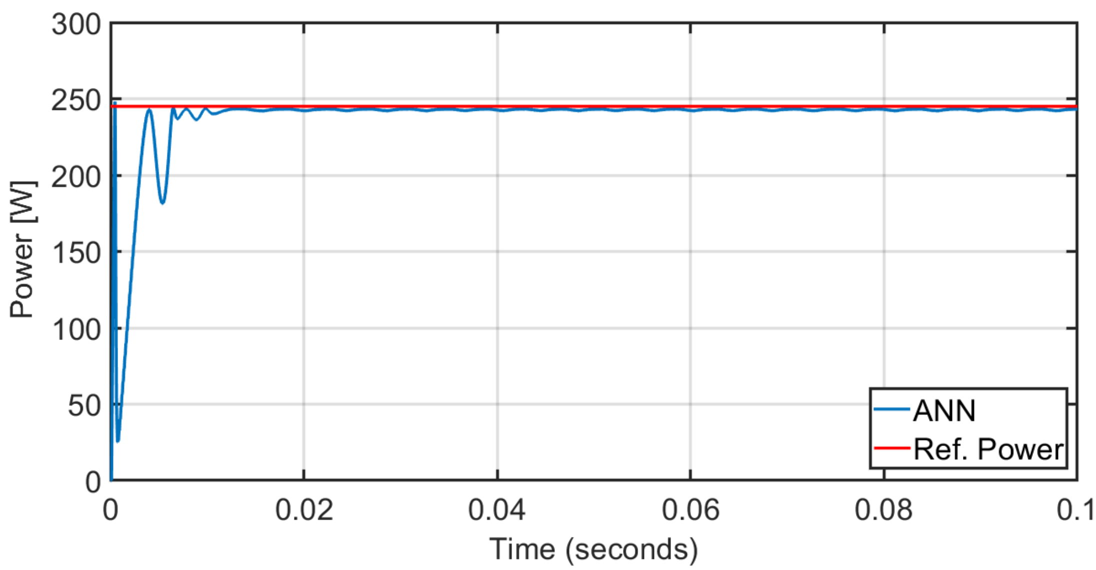


Figure 10 Output power from the PV system under constant atmospheric conditions.

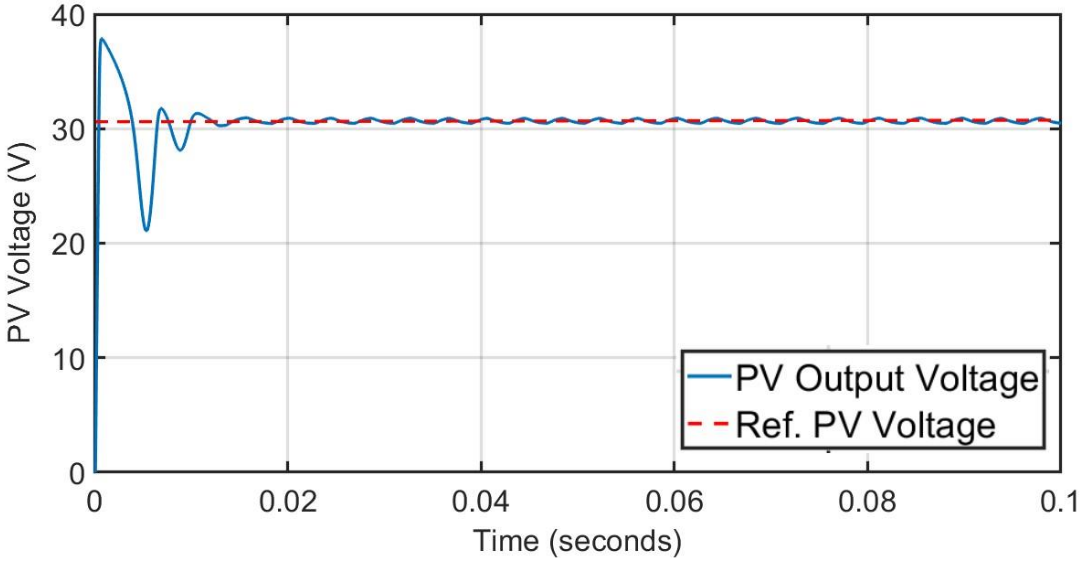


Figure 11 Output voltage from the PV system under constant atmospheric conditions.

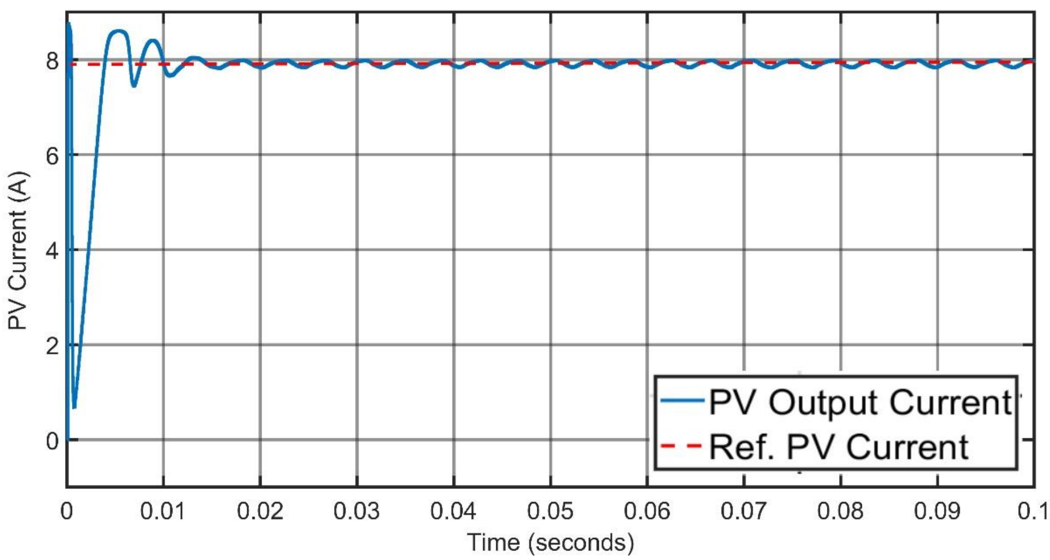


Figure 12 Output current from the PV system under constant atmospheric conditions.

Figure 13 depicts the PV output power under an abrupt change in the irradiance levels from 1000 W/m^2 to 600 W/m^2, then to 400 W/m^2, and back to 800 W/m^2 for the ANN. The ANN can track the MPP with a more stable response under varying irradiance levels.

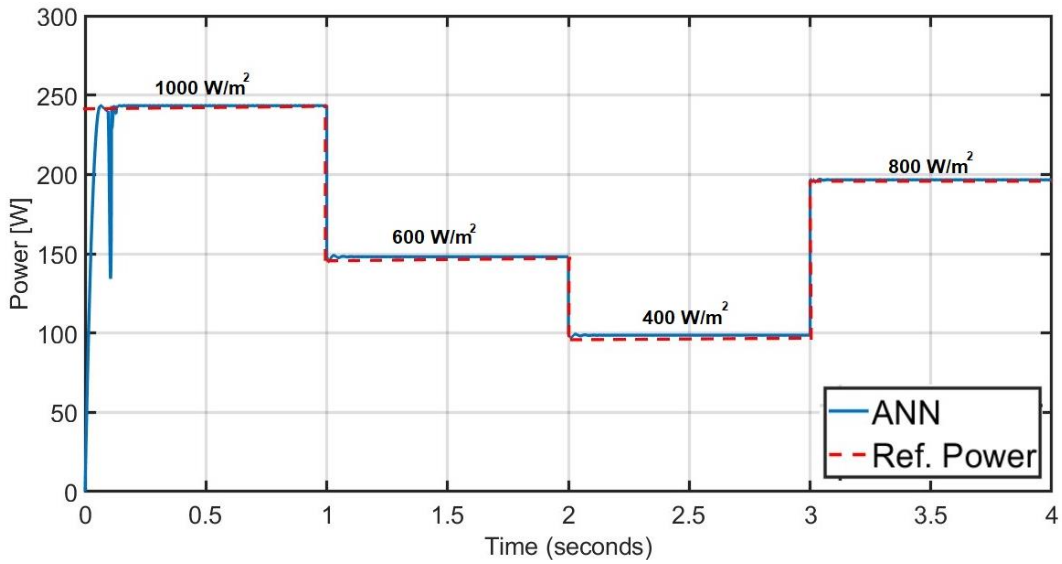


Figure 13 PV module output power at varying irradiance levels and constant temperature.

Figure 14 displays the PV power under abrupt temperature levels and uniform in the irradiance levels of 1000 W/m^2 with ANN. The temperature varied from 25C to 30C then 35C next 40C and back to 25C. The ANN can track the MPP under varying temperature levels.

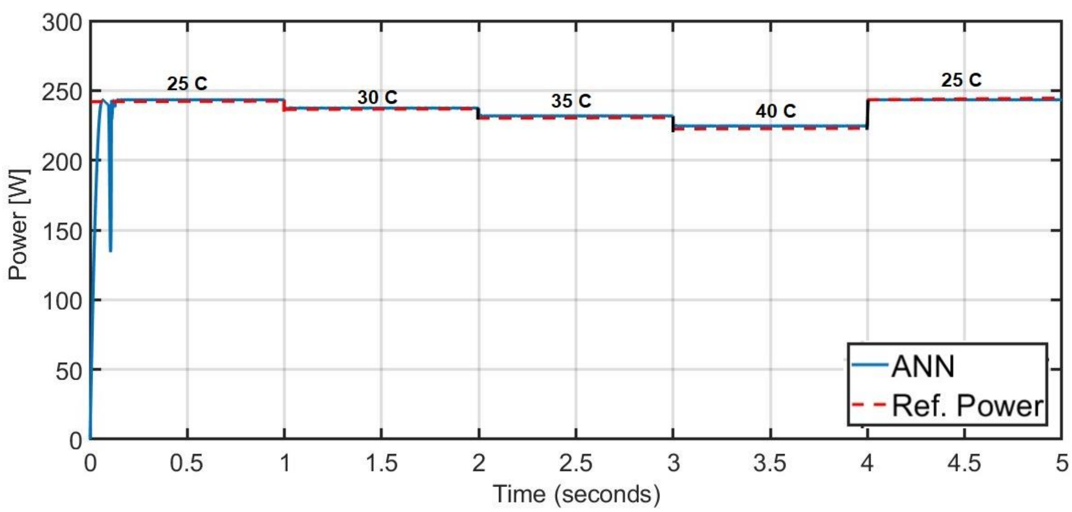


Figure 14 PV module output power at varying temperature levels and constant irradiation.

5. Conclusion

This paper examines the MPPT control based on artificial neural networks. The trained NN generates a tailored duty cycle fed into a boost converter that guarantees impedance matching between the photovoltaic system and the load resistance to ensure maximum power transfer. To evaluate the efficiency of the MPPT scheme under consideration, several scenarios were examined, including uniform irradiance levels, abrupt changes in irradiance levels, and sudden changes in temperature levels. The ANN demonstrates excellent monitoring performance. However, the ANN-MPPT method exhibits minimal oscillations surrounding the MPP, making it more effective.

- **Acknowledgment**

The authors are thankful for the kind support from the Egyptian Russian University to carry out the research work.

- **Conflict of Interest**

A declaration of conflict of interest.

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