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Maximum Power Point Tracking in PV System with Home Applications

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Abstract: The use of photovoltaic energy in modern transmission systems is increasingly preferred due to its environmentally friendly features. Modular photovoltaics show a nonlinear correlation between the generated power and the environmental conditions. This study presents a Maximum Power Point Tracker (MPPT) based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) to optimize solar power systems. The designed controller optimizes the output power of a DC-DC converter linked to a 250W solar array. The complete analysis of the model is done using MATLAB/SIMULINK, considering the key characteristics of the technical data. The controller behavior is evaluated under diverse weather conditions. The paper suggests that the controller is effective in tracking peak power of the panel.

KEY WORDS: PV system, Maximum Power Point Tracking, ANFIS Algorithm

INTRODUCTION

Fossil fuels are rapidly reaching their limit and their use for electricity generation is causing even faster environmental pollution. It is essential to develop commercially viable and sustainable alternatives for electricity production. Solar radiation is an amazing energy source. that can be used to generate electricity. Solar energy is a renewable and optimal alternative for electricity generation because it never runs out, is environmentally friendly and is freely available. Moreover, the radiant power of the sun shines down upon us, abundant and limitless, ready to be harnessed from every corner of the earth. The many advantages of solar energy have been recognized for various regions and have been summarized in a table in reference [1]. With the advancement of solar technology, the areas of application of solar energy have diversified, broadened and monetized [2]. Efficiency may be further diminished influenced by variables such as temperature of the solar module, the magnitude of solar radiation, and the load circumstances. The attributes of solar modules are variable, and their power production capabilities fluctuate consistently based on geographical location and meteorological circumstances [3]. The relationship between junction temperature and the electrical efficiency of photovoltaic modules, as well as the fluctuation of junction temperature in relation to ambient temperature and radiation intensity, is succinctly examined in [4]. A straightforward model is presented in [5] to forecast the performance of photovoltaic modules based on solar radiation intensity and temperature. A multitude of methodologies have been suggested in scientific literature to maximize power extraction from solar modules [6]. The proposed strategies may be categorized into constant parameters, measurement-and-comparison, mathematical computation, trial-and-error, and intelligent methods based on the tracking approach. In indirect approaches, the Maximum Power Point (MPP) is determined using basic assumptions without assessing the power output of the photovoltaic (PV) system. In direct approaches, factors like power, voltage, and current of photovoltaic systems are quantified using sensors, and the maximum power point is ascertained by processing these measured values.

Example for MPPT techniques: Constant Voltage (CV) method, perturbation and observation (P&O) approach, On-Line MPP Search (OLMPP), the incremental conductance (INC) method, Hill Climbing method, fractional open-circuit voltage (FOCV) and artificial intelligence (AI)-based methods, Grey Wolf Optimization (GWO) method and others. Although the P&O approach [7] is often used in MPPT applications, it exhibits many issues. The accuracy under stationary sunlight circumstances is diminished due to the process of disturbance, causing the power of the solar module to swing around the maximum power point, leading to energy loss. The oscillation frequency may be reduced by reducing the amount of disturbance step size; however, a lower perturbation size will lead to a reduction in MPPT speed. Furthermore, the P&O approach is likely incapable of attaining the maximum power point owing to sudden fluctuations in sunlight. The INC approach [8] is advised for enhancing tracking accuracy and dynamic performance in quickly changing ambient situations. The benefits of the incremental conductance (INC) approach relative to the P&O method were examined in [9]. The INC is predicated the gradient of the power curve of the photovoltaic module at MPP=0, positive to the left side, and negative to the right side. This basic assumption is the foundation of the INC methodology. They use the derivative method to ascertain the

MPP. This approach necessitates augmented computational power in the controller because of a complex process of the decision-making involved in the differentiation process. Consequently, the INC technique necessitates enhanced computational capabilities and more storage capacity [10], potentially resulting in elevated system costs. Furthermore, the outcomes of the INC approach are inadequate at low irradiance due to the complexities involved in the differentiation process. The efficacy of several techniques for monitoring the maximum power level is evaluated in [11]. The predominant approaches documented in the literature exhibit poor stability and may induce variations in power production owing to the extremely nonlinear properties of the solar module. Moreover, traditional approaches do not facilitate the rapid attainment of maximum power points for energy produced by solar panels [12]. Artificial intelligence-based techniques guarantee elevated precision and adaptability in nonlinear systems. In scientific literature, artificial intelligence techniques have been suggested to enhance dynamic performance for maximizing power output from solar modules. The use of artificial intelligence emphasizes the nonlinear properties of solar modules and provides a rapid, nonetheless, computationally challenging resolution to this issue. The methodologies of artificial intelligence mostly rely on controllers and neural networks. Maximum power point detection and regulation using different kinds of fuzzy logic MPPT controllers is examined in [13,14]. Fuzzy logic controllers are distinguished by their resilience and relative simplicity, since they do not need information of the model state . The predominant approaches documented in the literature exhibit poor stability and may induce variations in power production owing to the extremely nonlinear properties of the solar module. Moreover, traditional approaches do not facilitate the rapid attainment of maximum power points for energy produced by solar panels [12]. Artificial intelligence-based techniques guarantee elevated precision and adaptability in nonlinear systems. In scientific literature, artificial intelligence techniques have been suggested to enhance dynamic performance for maximizing power output from solar modules. The use of artificial intelligence emphasizes the nonlinear properties of solar modules and provides a rapid, yet computationally demanding, solution to this issue. The recognition and regulation of the MPP using various designs of fuzzy logic (FL) MPPT controllers is discussed in [12,13,14]. An adaptive FL controller for grid-connected solar systems is introduced in [15]. Fuzzy logic controllers are characterized by their resilience and relative simplicity, since They do not need exact knowledge of the model [16]. Fuzzy logic controllers use domain information to establish inference rules. Formulating inference rules requires skill. The efficacy of fuzzy logic control for MPPT is heavily contingent upon the proficiency of the user or control engineer in determining the suitable error computation and formulating the rule basis table [16]. A further drawback of fuzzy logic control is the intricate algorithms, leading to elevated implementation costs [17]. Conversely, artificial neural network (NN) models are predicated on the brain's electrical neural architecture, enabling the identification of the greatest power point with fewer repetitions and fluctuations around that point. The use of neural networks as MPPT controllers in solar systems is covered in reference [18]. A neural network control functions as a black box model, requiring no comprehensive knowledge on the photovoltaic system. The neural network control can successfully monitor the MPPT in real-time after it understands the association between open circuit voltage (V_{OC}), irradiance levels, temperature, and maximum power point voltage(Vmpp). This research employs ANFIS, a hybrid model that combines neural networks with fuzzy logic, using the advantages of each to provide a highly successful artificial intelligence methodology. This study presents an ANFIS-based model implemented in Matlab/Simulink that uses different kinds of operational levels of temperature and levels of irradiance as inputs to optimize power extraction from a photovoltaic module.

Modeling of the solar panel Photovoltaic System Load Characteristics

Photovoltaic cells include P-type and N-type semiconductors. When the interface between P-type and N-type semiconductors is subjected to photon radiation, an electron flow is generated via the addition circuit, a process referred to as the photovoltaic effect. This phenomenon generates an electric current. Photovoltaic cells function as a power source. Figure 1 illustrates the electrical model of the solar cell.

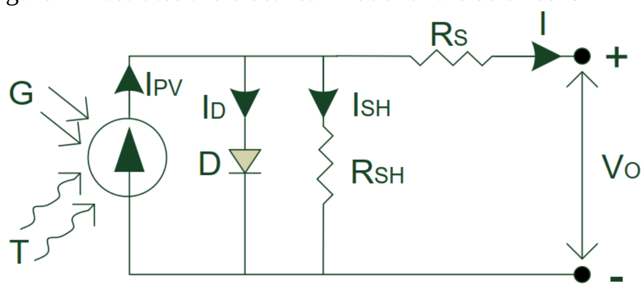

Figure 1. Single diode equivalent circuit model of a photovoltaic cell.

The model seen in Figure 1 is known as the one diode design and is the most often used model. The present version of the photovoltaic cell fluctuates with solar irradiation (G) and cell temperature (T). Equation 1 calculates the output current of the solar cell electrical model. The current generated by the photovoltaic cell, influenced by solar irradiation and temperature, is defined by Equation 1 and 2.

$$I = I_{ph} - I_o \left[exp\left\{ \frac{q(V_{PV}+I_{PV}R_S)}{\alpha KT} \right\} - 1 \right] - \frac{V_{PV}+I_{PV}R_S}{R_{sh}} \quad (1)$$

$$I_{ph} = I_{sc} + K_i \left(T - T_{ref}\right) \frac{G}{G_{ref}} \quad (2)$$

Where I is the PV panel output current, Iph is the light-generated current, I_o is cell reverse saturation current, Isc is the cell short-circuit current at a 25 ºC and 1 kW/m², T_{ref} is reference temperature in Celcius, T is cell temperature in Celsius, K_i is the cell short-circuit current temperature coefficient, ,K is Boltzmann's constant (1.38 $\times 10^{-23}$ J/K), G_{ref} is reference solar radiation in W/m² ,q is the electron charge (1.6 $\times 10^{-19}$ C), G is solar radiation, R_{sh} is the shunt resistance; R_s is the series resistance.

The electrical data from the photovoltaic system was integrated into the modeling environment to provide representations that represent different solar radiation and temperature levels. The electrical parameters of the simulated PV system are shown in Table 1. The statistics presented in Table 1 were collected by the producer according to the information provided in the information sheets and were collected under the conditions of 1.0 kW/m2 and 25 °C. Figure 2 presents the current-voltage characteristic curve of the simulated panel based on the data provided in the study. The figure was made at a steady temperature of 25 °C, reflecting the change of solar radiation from 0.2 kW/m² to 1.0 kW/m². Figure 3 illustrates the variation in the current-voltage characteristics of a single photovoltaic panel under a constant solar radiation of 1.0 kW/m², with respect to differing temperature values. The temperature range shown in the graph is 25 to 45 °C.

Parameter	Value	Unit
Number of cells	60	Pieces
Open circuit voltage (Voc)	37.3	voltage
Short Circuit Current (Isc)	8.66	Amper
Maximum voltage of the panel (Vmpp)	30.7	voltage
Maximum Power Current (*Impp*)	8.15	Amper
Maximum Power	250	Watt

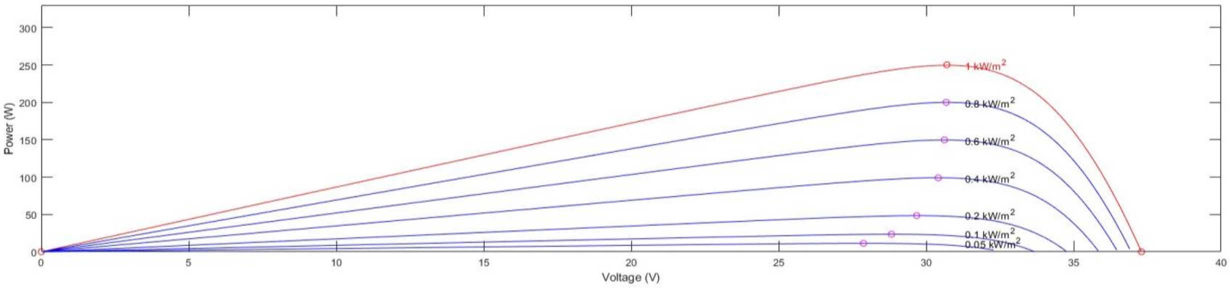

Figure 2. Output power and voltage of the photovoltaic panel at constant temperature with varying solar radiation.

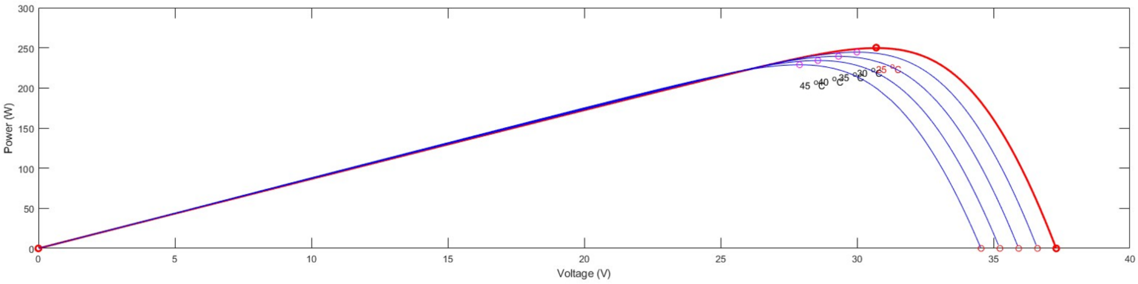

Figure 3. Output power and voltage of the panel during constant solar radiation and various temperatures.

Adaptive Network Fuzzy Inference System (ANFIS) for Maximum Power Point Tracking (MPPT)

The adaptive network-based fuzzy inference system (ANFIS) integrates neural networks and fuzzy logic [17]. Fuzzy rules are generated from the given input data, establishing the initial fuzzy model, after which a neural network is employed to enhance the rules of the proposed first fuzzy model.

A. ANFIS architecture

Figure 3 illustrates the ANFIS diagram.

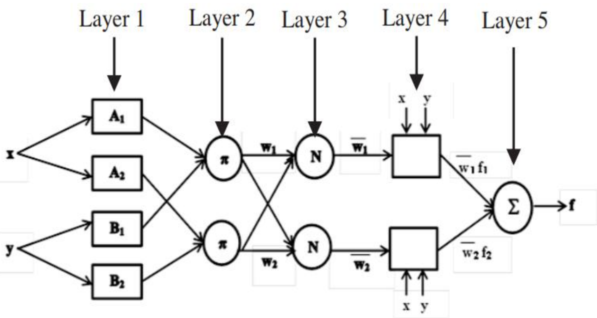

Figure 3. ANFIS architecture.

The ANFIS block comprises Two sources of input and one output. The rules are established based on the if-then framework suggested by Takagi and Sugeno [19]. In a first-order equations two-rule Sugeno fuzzy inference system, both rules may be expressed as follows according to [20]:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$.

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$.

The delineation of ANFIS layers is provided below.

Layer 1: Each node in this layer is adaptable, and the output is determined by:

$$\theta_i^1 = \mu_{Ai}(x) \quad (2)$$

In this context, the input of node i is denoted as X, the corresponding linguistic variable is represented by Ai, and μ_{Ai} signifies the membership function of Ai. μ_{Ai} (x) is presented below:

$$\mu_{Ai}(x) = \exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\} \quad (3)$$

Layer 2: The nodes are identified as fixed nodes, denoted as Π, as seen in Figure 3. The outcome of this layer may be expressed as,

$$\theta_i^2 = \omega_i = \mu_{Ai}(x) \times \mu_{Bi}(y), i = 1,2 \quad (4)$$

Layer 3: The nodes are very static. They are classified with N, signifying their function in normalizing the firing strengths from the prior layer. The output from the i^{th} node is the standardized firing strength represented by:

$$\theta_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}$$

Nodes in Layer 4 are adaptable. A first-order polynomial and the normalized firing strength are multiplied by each node in this layer to get the output. As a result, the criteria for defining the outputs of this layer are:

$$\theta_i^4 = \overline{\omega_i}\, f_i = \overline{\omega_i}\,(p_i x + q_i y + r_i) \quad (5)$$

Layer 5: It consists of a singular fixed node denoted by Σ. This node does the summing of all incoming signals. Consequently, the model's overall output is expressed as follows:

$$\theta_i^5 = overall - output = \sum \overline{\omega_i}\, f_i = \frac{\sum_i \omega_i f_i}{\omega_i} \quad (6)$$

Training and Evaluation Data

The paper used the Adaptive Neuro-Fuzzy Interface System (ANFIS) to predict the generated power of a 250 W PV system. ANFIS is a data analytics method designed to obtain specific results from input data by leveraging multiple artificial neural networks. Therefore, it is used in many applications worldwide. Within this framework, historical solar panel data was used for ANFIS, resulting in the training and creation of the FIS file. Figure 4 illustrates the rule relationship network and the layers of this FIS file. Actual temperature, radiation and power data from a real panel were used for the training technique. The irradiance was taken from 0 to 1000 w/m^2 and by taking a temperature from 15 to 45 c°

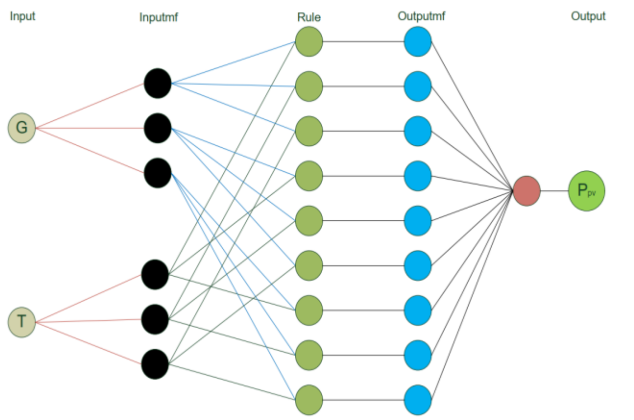

Figure 4. Graph that depicting the layers and connections of the FIS file generated throughout the research.

Application That Can Be Powered by The PV System

High-quality polycrystalline solar panel, 250W, suitable for residential rooftop and ground installations. To decrease your house electricity expenses or enhance your residence's sustainability, solar energy is a very cost-effective power alternative. By using the panel that we used in this paper, different kinds of applications can be run together or individually. In Table 2, there are some sorts that can be worked with this model.

Appliance name	Minimum power	Maximum power
42 Inch LED TV	58 W	60 W
Air Cooler	65 W	80 W
American-Style Fridge Freezer	40 W	80 W
Aquarium Pump	20 W	50 W
Ceiling Fan	60 W	70 W
Curling Iron	25 W	35 W
Fridge	100 W	220 W
Water Filter and Cooler	70 W	100 W

SIMULATION RESULTS

To validate the efficacy of the devised MPPT algorithm for controlling the PV panel, a numerical simulation was conducted using MATLAB/SIMULINK as shown in figure 5.

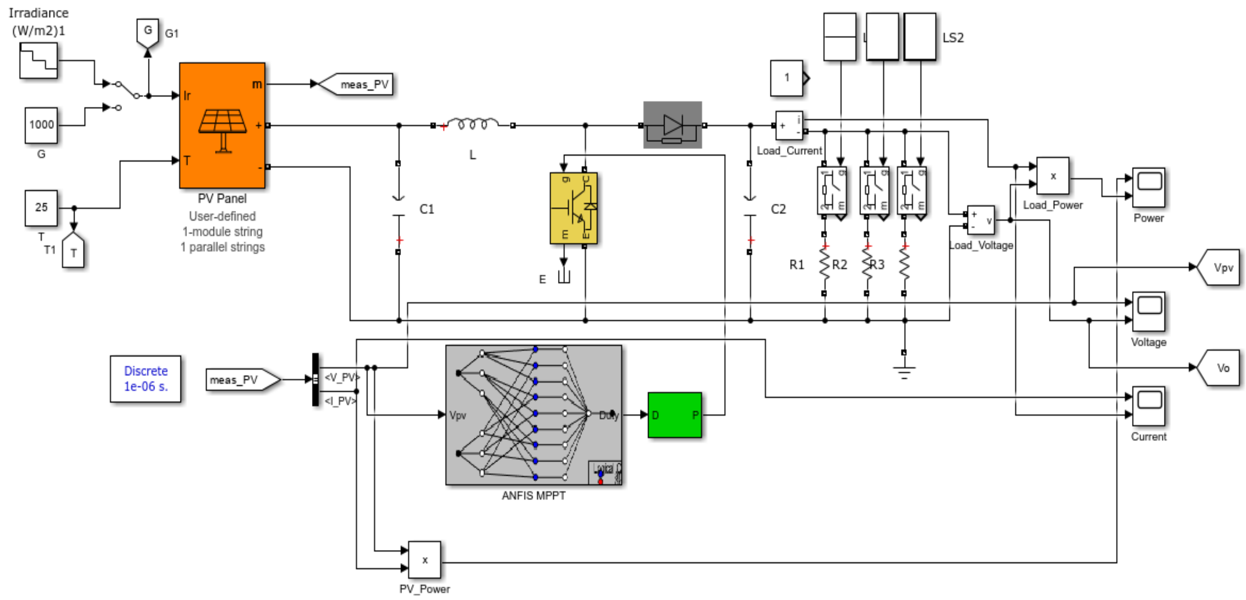

Figure 5. ANFIS modeling system

When utilized domestically, the photovoltaic panel links to multiple loads, each representing an individual application that activates and deactivates in 0.3 and 0.6 seconds. During the initial test, we fixed the irradiance and temperature at 1000 w/m^2 and 25°C, respectively. The results indicate that the power remained constant at a rate of 250 watts even with a change of the load as shown in figure 6.

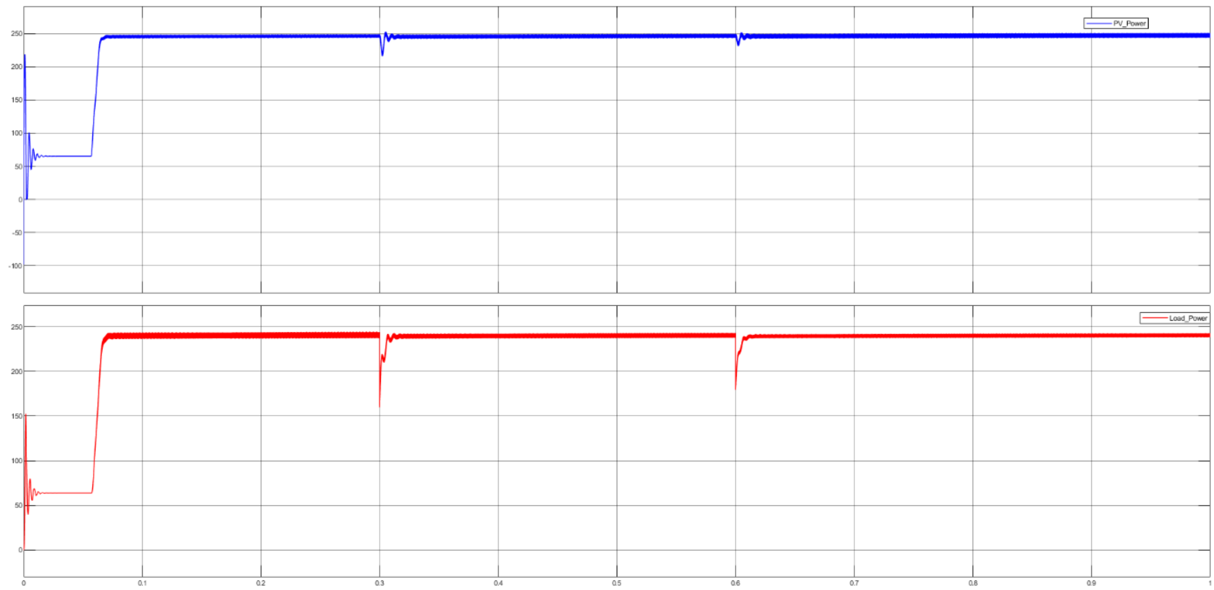

Figure 6. The output PV POWER under constant irradiance and temperature.

Another test is done by using different irradiance level (1000,800,600,400,200 W/m².). As we can see from the figure 7, when the irradiance level increases, the power will increase too.

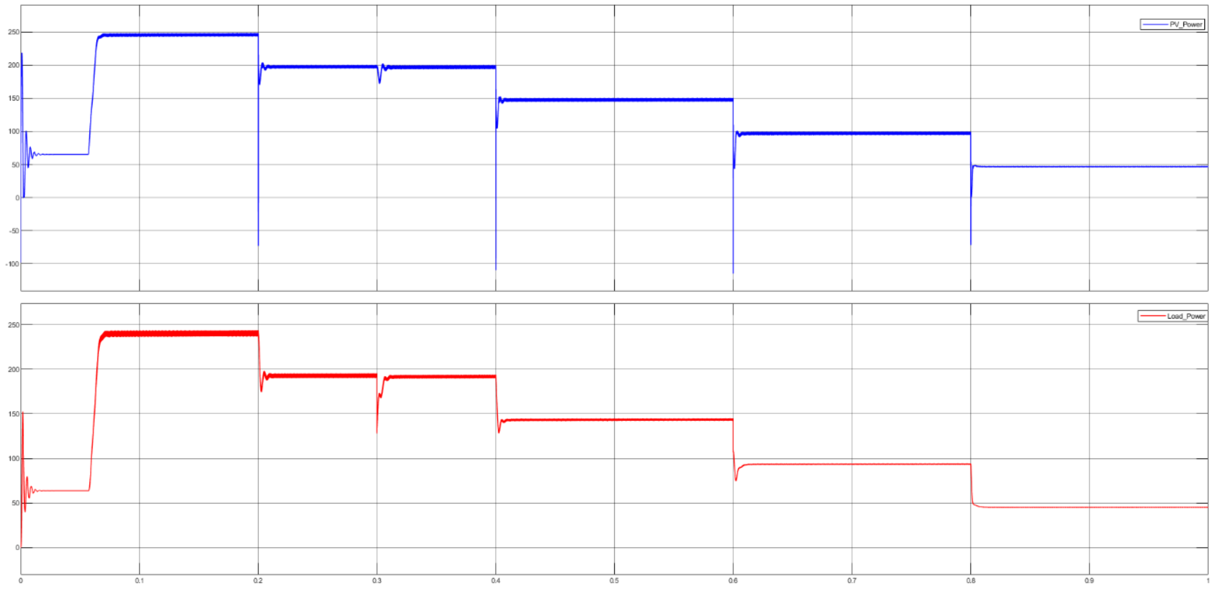

Figure 7. The output PV POWER under constant temperature and variable irradiance level.

Also, a test has been made in a constant irradiance (1000 W/m²) and different temperature rates (25°C and 45°C) and as we can see from the results in figure 8, when the temperature increases the power will decrease in the PV panel.

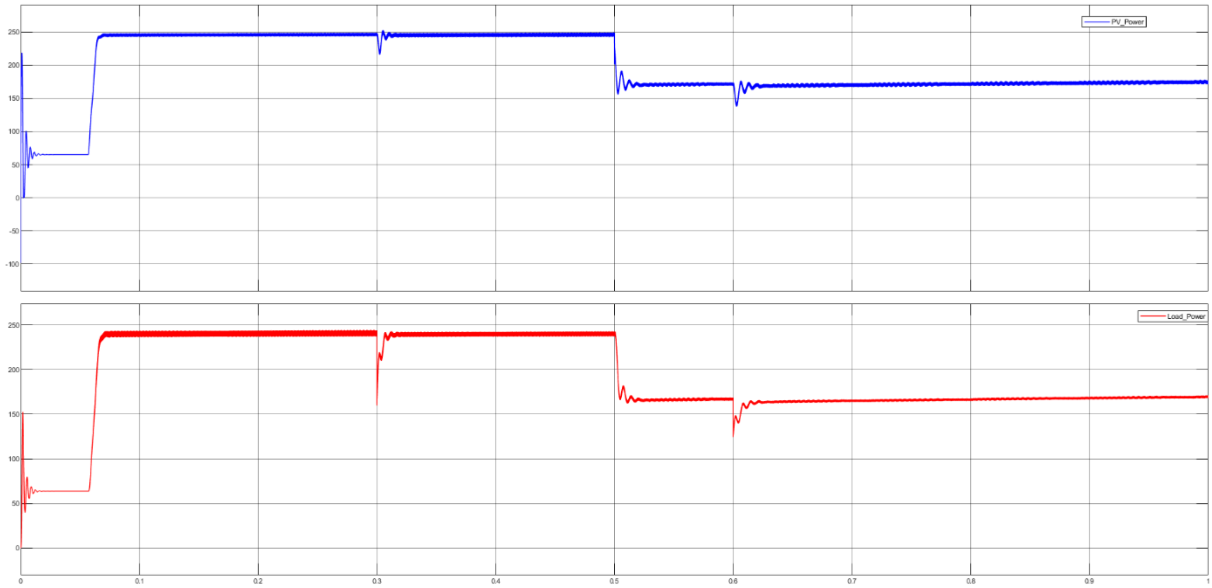

Figure 8. The output PV POWER under constant irradiance and variable temperature level.

CONCLUSION

This research presents a controller for a solar PV module that is based on an adaptive neuro-fuzzy inference system that can monitor the maximum power for 250 W photovoltaic panel. The functionality of the ANFIS-based MPPT controller is examined under fluctuating weather conditions. The simulations used Matlab/Simulink software, including two PI controllers to enhance system efficiency and minimize energy losses. The simulation findings indicate that the ANFIS-MPPT is the most efficient method for monitoring the maximum power of the photovoltaic panel, hence influencing the system's performance. Consequently, the ANFIS algorithm serves as an efficient instrument for mitigating oscillations.

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