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Fuzzy controllers and maximum power point tracking in PV systems

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CONTENT

1. Introduction

Any community, large or small, needs access to affordable, sustainable electricity to fulfil its social and economic needs. The vast sparsely populated highland areas of the Eastern Pamirs (Tajikistan) do not have hydrocarbon energy sources, and are also located far from existing large hydroelectric power plants. The most available source of energy in these areas is solar energy with good indicators on the number of sunny days throughout the year and high irradiation. In 2017, the first 200 kW PV plant was launched in Murghab village, and in 2023 a larger 600 kW plant with a 1.2 MWh energy storage system will be installed (Fig. 1a, 1b). However, all this is only the beginning in order to supply the population of settlements located at least 50 km away from each other. In addition, it is necessary to build at least 10 such power plants. The Murghab Power PV Station+ Accumulation System is located at an altitude of 3612 meters above sea level, with UTM W 84 coordinates of 414428.00 meters East and 421584.9 meters North, which corresponds to 37.176499° decimal latitude and 74.023007° decimal longitude. Solar panels for the Murghab Power PV Station were purchased from JinKO Solar (Tiger Neo n-Type 78HL4-(V) 519-615 Watt in the form of Mono-Facial Module), a Chinese company.

Figure 1a. Solar Power Station in Murghab (3600m above sea level, 700 kWt)

Figure 1b. Solar tracking System

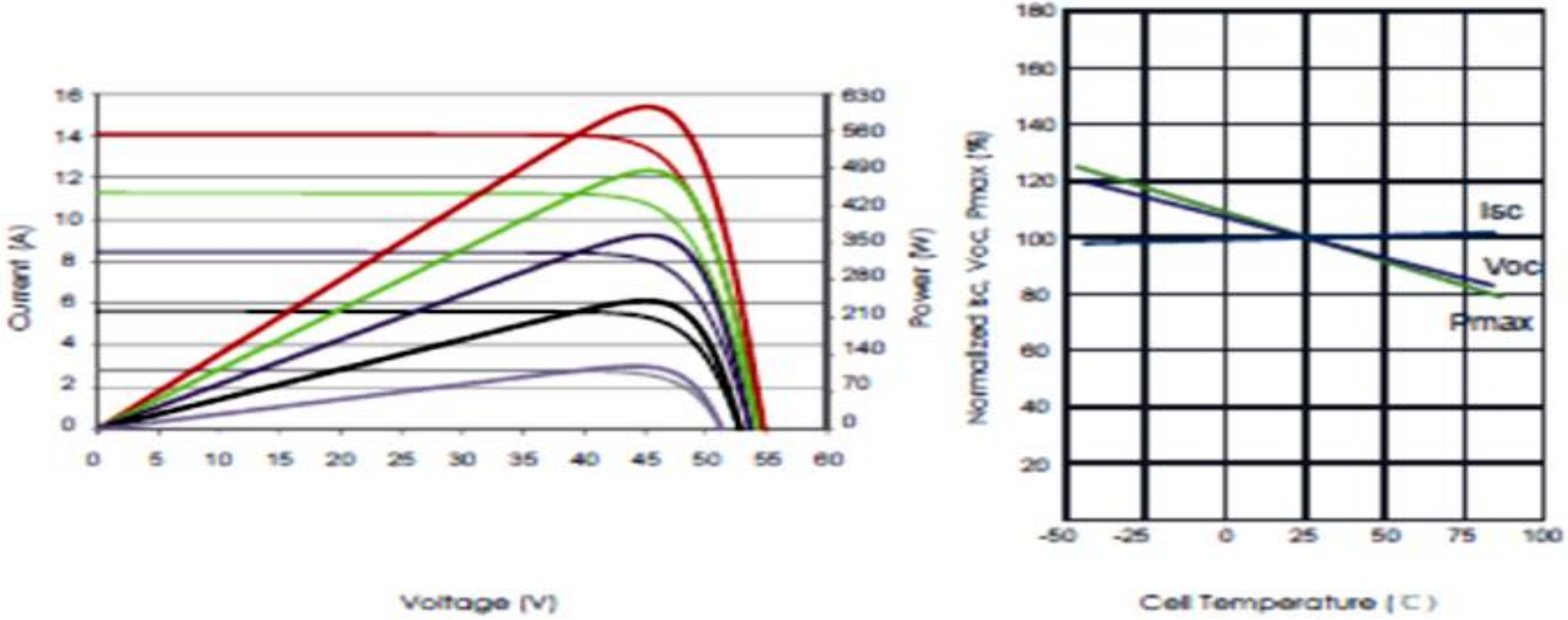

Figure 1c. Current Voltage & Power Voltage Curves (605 W), Temperature Dependence of Isc, Voc, Pmax.

The maximum power point tracking (MPPT) method is important because the maximum power point (MPP) depends on environmental parameters such as surface temperature, solar irradiation and weather conditions. The algorithm for finding the MPPT should ideally improve the PV panel output power and power generation efficiency. The MRRT methods proposed in the literature can be categorized into two groups. The first group includes traditional methods such as trial and error, or (P&O) [1] and incremental conductivity [2, 3], which utilize the voltage-current characteristics of the panel. The mathematically based β - MPPT method [4], and curve fitting [5] use calculations associated with various equations to determine MPP. Note also, methods with constant parameters including fractional open circuit voltage [6] and short circuit current [7], which, require periodic open circuit voltage and short circuit current, respectively (Fig. 1c).

2. Modeling of Solar Photovoltaic System

Solar PV modules depend on irradiation and temperature for power generation. These two factors in part depends on atmospheric conditions such as weather, climate, seasonal phenomena. Other conditions such as partial shading of the modules due to clouds, nearby mountains and dust also have an impact on power generation [20, 21]. Thus, there is a need for power optimization in solar photovoltaic systems depending on the tracking of the maximum power point (Pm) and the location of the Sun. Traditional methods (e.g., perturb and obsurb method) allow a large number of recurrence oscillations and hence have a low level of accuracy [22-24]. Artificial Neural Network method uses learning-based behavioral and operational patterns that allow acting quickly and independently of the nature of the applications. ANN-based MPP tracking gives good performance under normal environmental conditions, but fails to establish MPP tracking under shading. In addition, ANN-based training for large systems becomes very expensive and exclusive. On the contrary, fuzzy analysis based tracking systems give better performance, which will be discussed in Section 3.

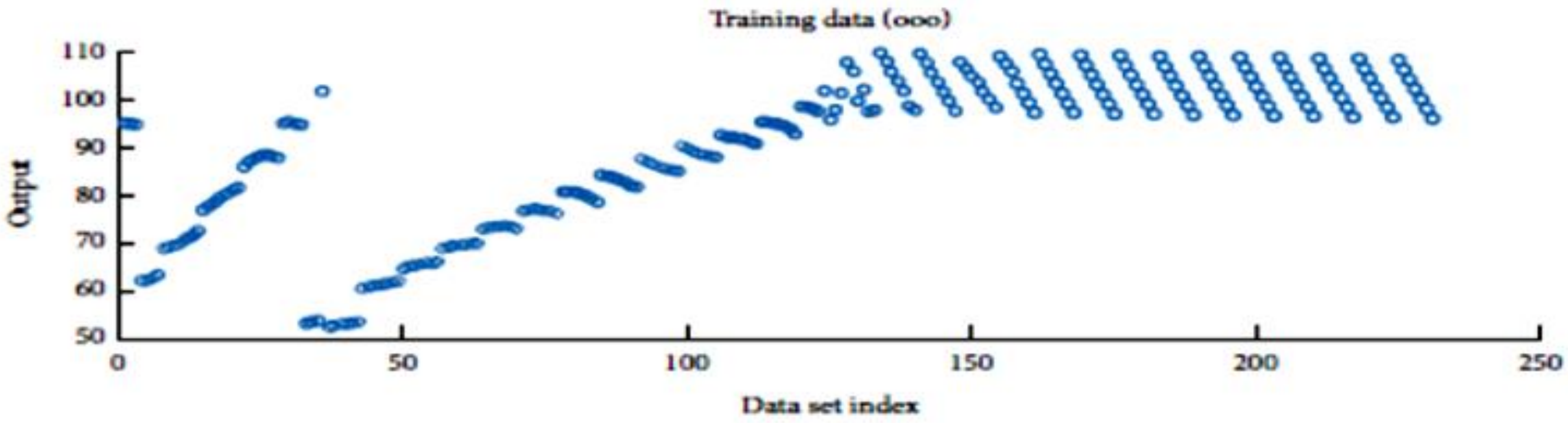

Figure 2. Training datasets.

Figure 3. Training output.

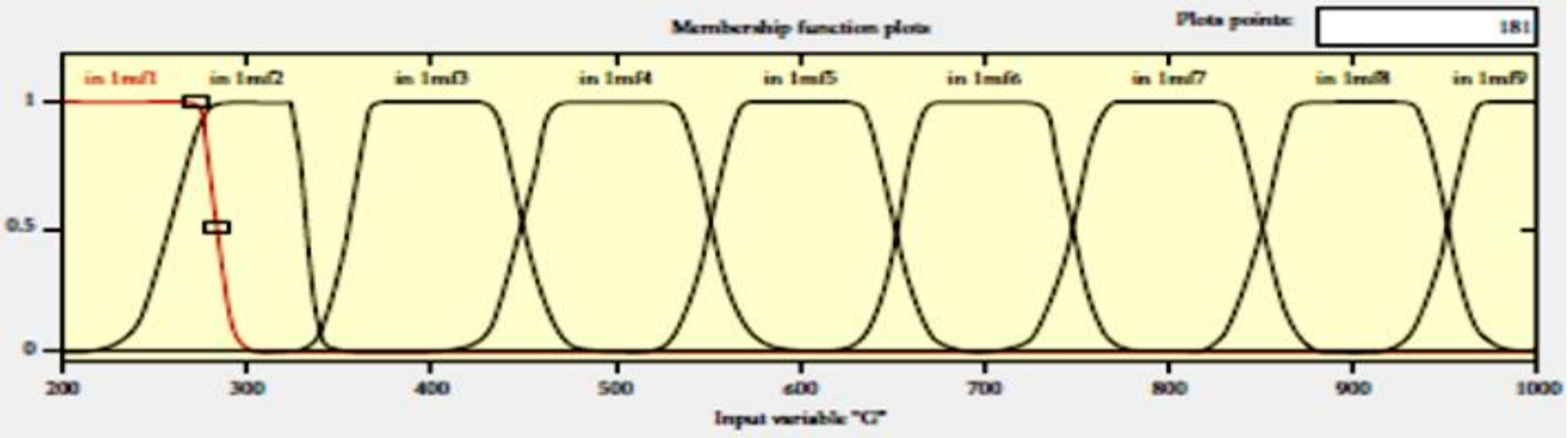

Figure 4. Membership function of irradiance (G).

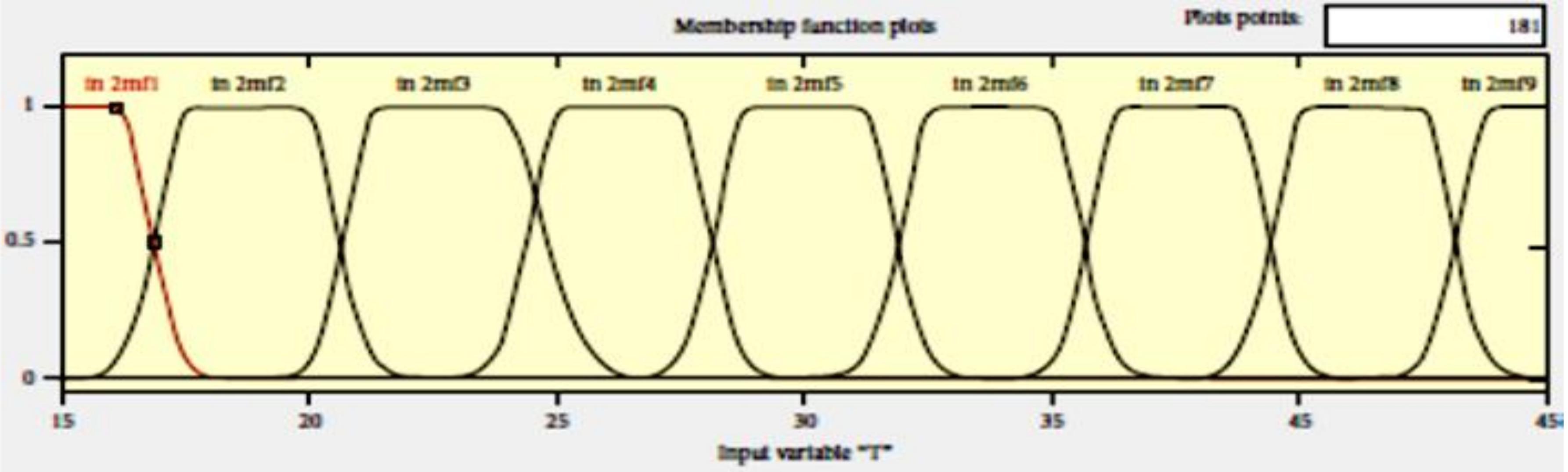

Figure 5. Membership function of temperature (T).

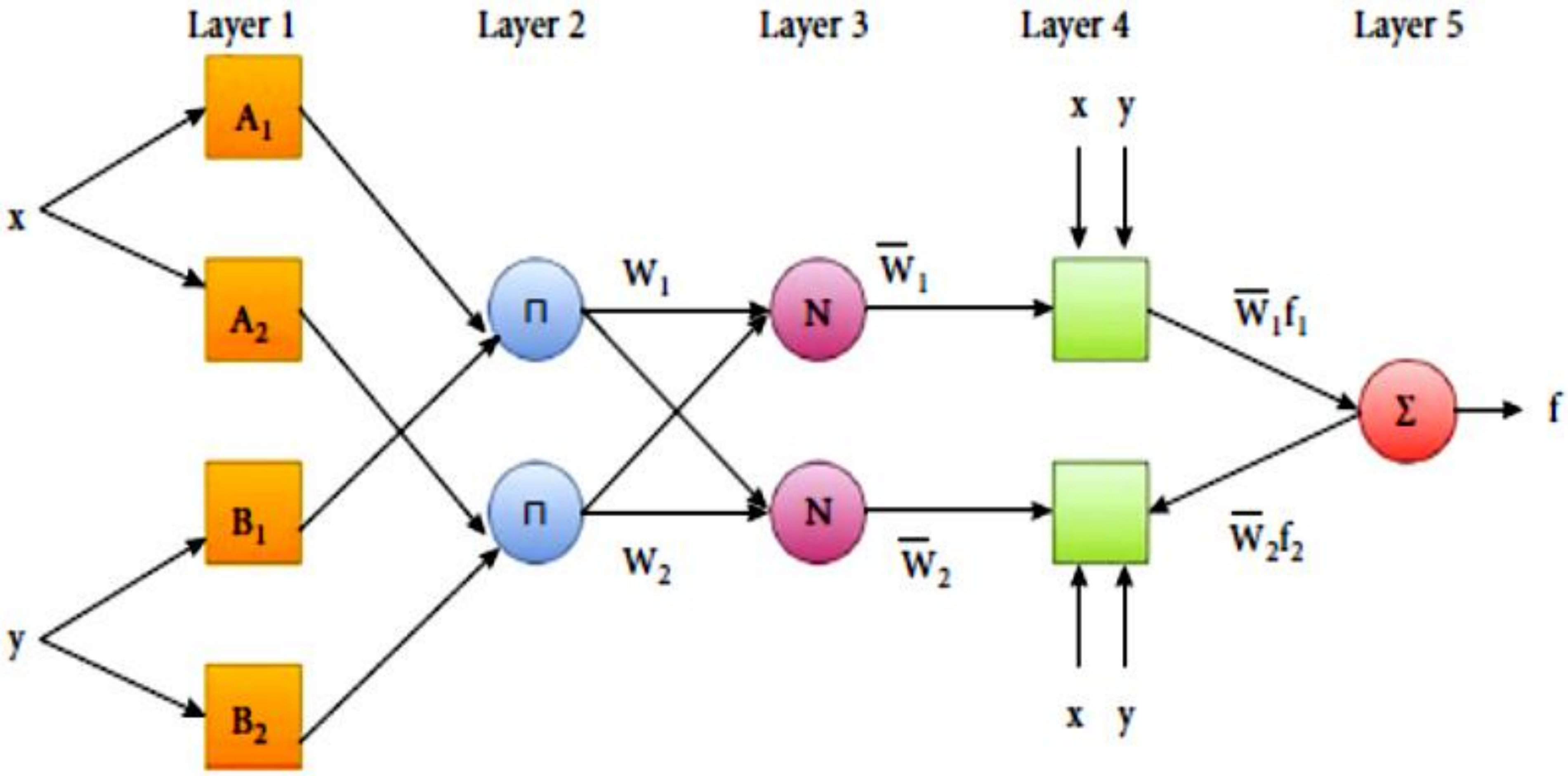

Figure 6. Architecture of the ANFIS

3. MPPT based on ANFIS

Adaptive neuro-fuzzy inference system ropes in functionalities of ANN and fuzzy logic.

Layer 1. All nodes are generally adaptive. The output of node i in this layer $O_{1,i}$ depends on the input of the membership functions of the corresponding node i

$$O_{1,i} = \mu_{A_i}(x), i = 1,2,$$

$$O_{1,i} = \mu_{B_i}(x), i = 3,4.$$

Here, x and y inputs and A_i and B_i are fuzzy sets in parametric form associated with nodes i. In our work, the membership functions are Gaussian.

Layer 2. The nodes are fixed and the output of node i is the result in ω, is called the neutral layer of the network

$$O_{2,i} = \omega_i = \mu_{A_i}(x) * \mu_{B_i}(y), \qquad i = 1,2.$$

Layer 3. All nodes are fixed and characterized using M. At the output of layer 3, $O_{3,i}$ is called standardized firing strengths since it is the sum of the firing strengths rules from the previous layer

$$O_{3,i} = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1,2.$$

Layer 4. The characteristics of the nodes are adaptable and the parameters are consistent. This is a fuzzy logic node with a set of parameters

$$(p_i, q_i, r_i).$$

The output of the node is shown in the following equation

$$O_{4,i} = \overline{\omega_i}\, f_i = \overline{\omega_i}(p_i, +q_i, +r_i), i = 1,2.$$

Layer 5. In this layer, only one node is fixed and its output is the sum of all incoming signals. The output function of this node is shown in equation

$$O_{5,i} = \sum_i \overline{\omega_i}\ \overline{f_i} = \frac{\sum_i \overline{\omega_i}\ \overline{f_i}}{\sum_i \overline{\omega_i}}\ , i = 1,2.$$

Adaptive neuro-fuzzy inference system integrates adaptive neural networks ANN through fuzzy logic. A fuzzy Sugeno controller can be trained through ANN to control crisp membership functions for variables based on their relationships [14, 15]. The included weight nodes can also be manipulated to create a complete rule base. Solar irradiation and ambient temperature or voltage and current of PV modules can also be used as model inputs. ANN helps to easily tune the membership functions and rule table [16. 17]. ANFIS controller output system fits a set of fuzzy rulebooks with fitness learning to optimize nonlinear functions. A set of fuzzy rulebooks can be specified for Fuzzy logic controllers (FLC) with two inputs (x, y) and one output (z) as follows:

The first rule is that if x is A_1 and y is B_1, then

$$f_1 = p_1 x + q_1 y + r_1.$$

The second rule is that if x is A_2 and y is B_2, then

$$f_2 = p_2 x + q_2 y + r_2\ .$$

And the output function will be given by the equation

$$F = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} = \overline{\omega_1} f_1 + \overline{\omega_2} f_2\ .$$

The ANFIS architecture is not a one-piece design: different layers can be combined as required in the application. The ANFIS learning algorithm tunes the alterable parameters in the adaptive layers (layer 1 – A_i, B_i, layer 4 - p_i, q_i, r_i) to verify the output. The architecture of the proposed ANFIS is shown in Fig. 6. ANFIS generates a load reference value from which a load signal is generated to control the output signal of the gain controller. The ANFIS maximum power point tracking device is simulated in MATLAB/Simulink environment for models in series with the boost converter to optimize the output power. The Simulink design is shown in *Figure* 7.

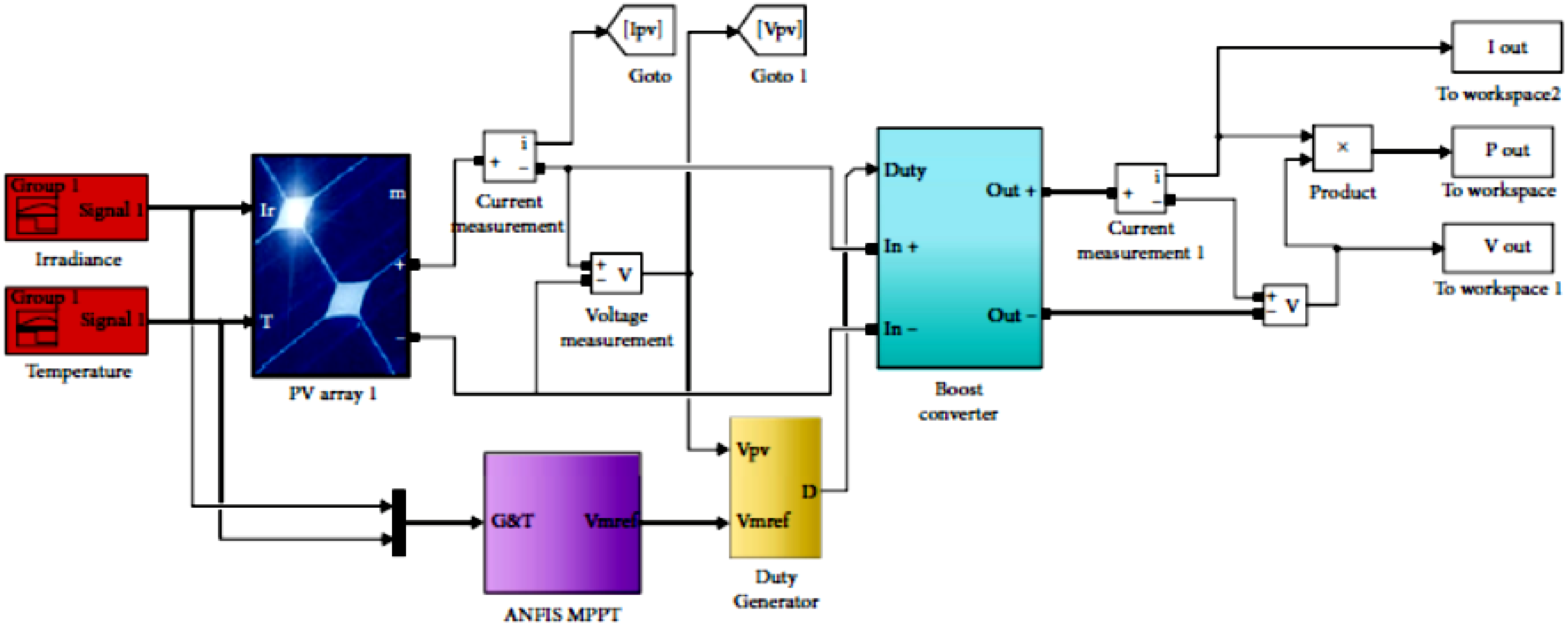

Figure 7. Simulink model of the power optimizer with ANFIS MPPT [20].

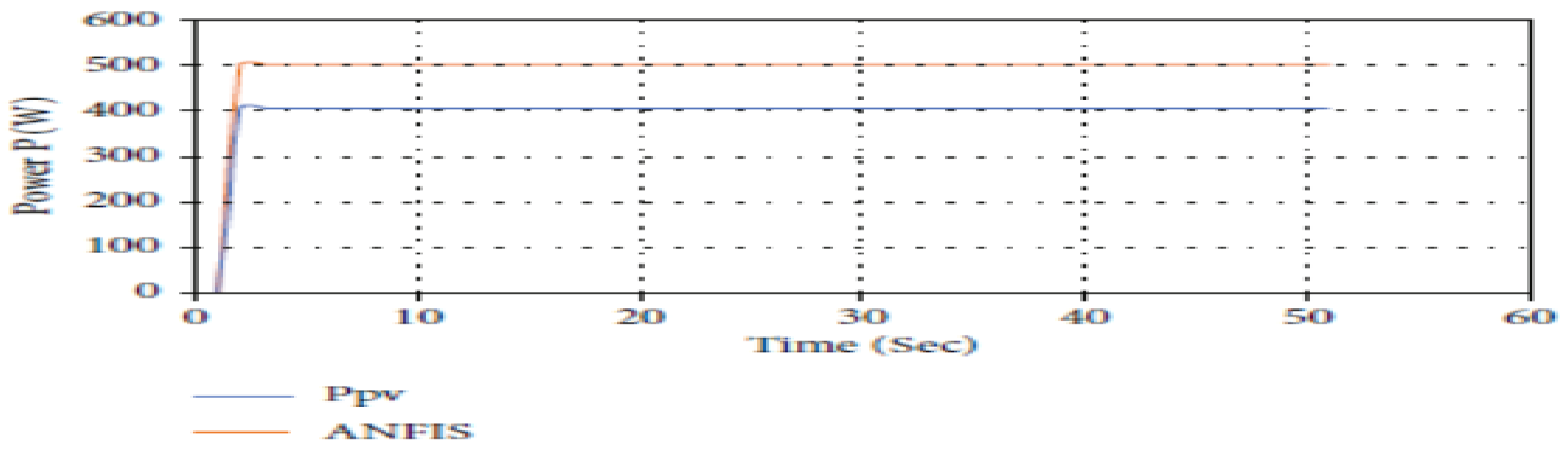

Figure 8. Output power of the optimizer with ANFIS MPPT at STC

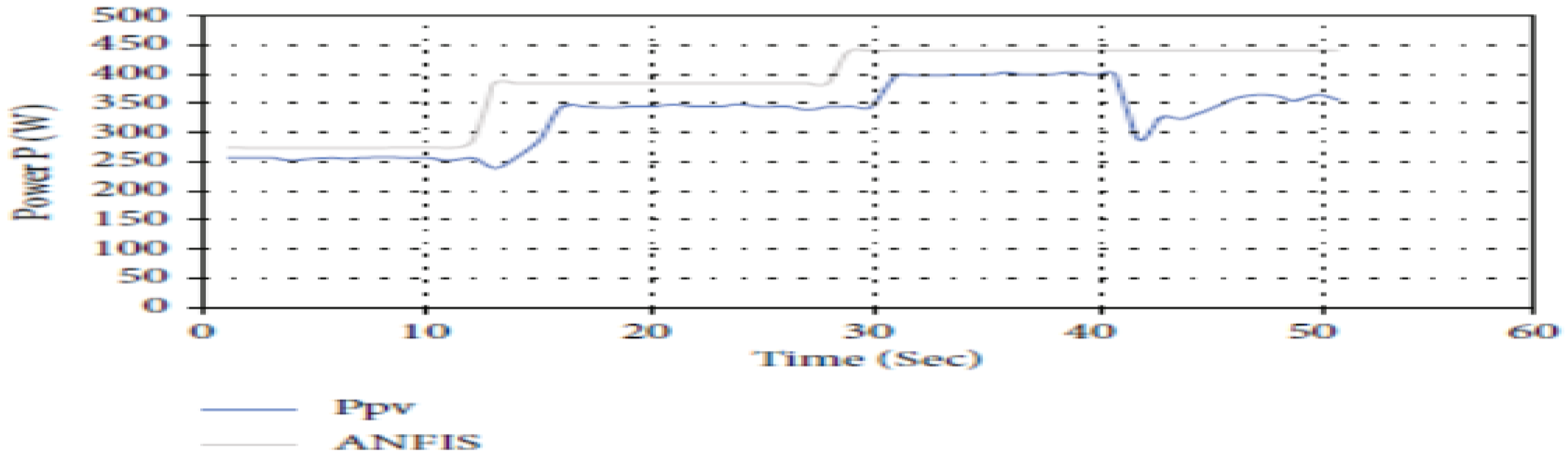

Figure 9. Output power of the optimizer with ANFIS MPPT at VWC

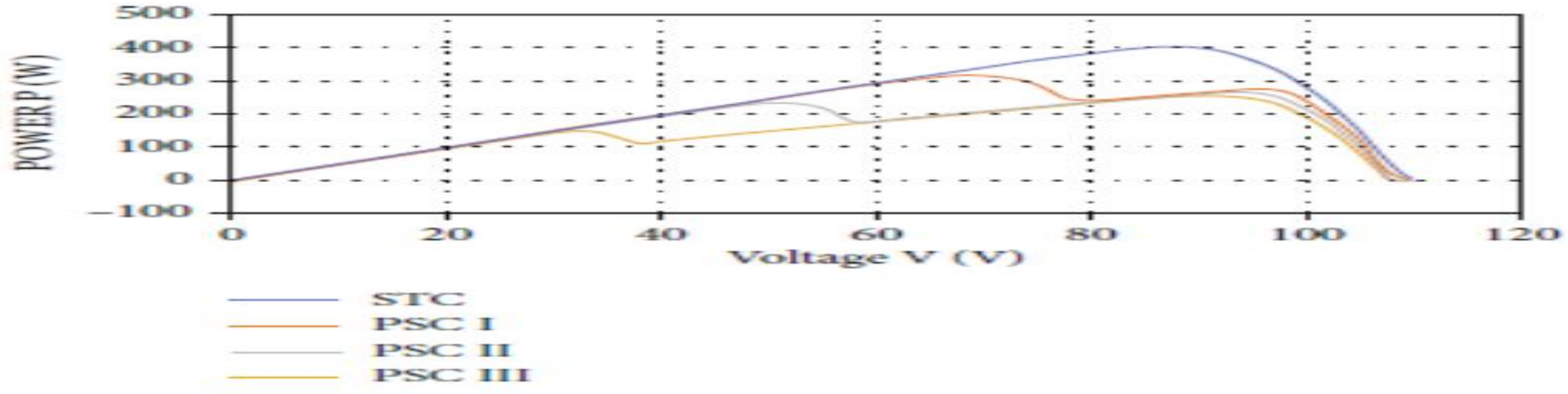

Figure 10. PV curve under PSCs

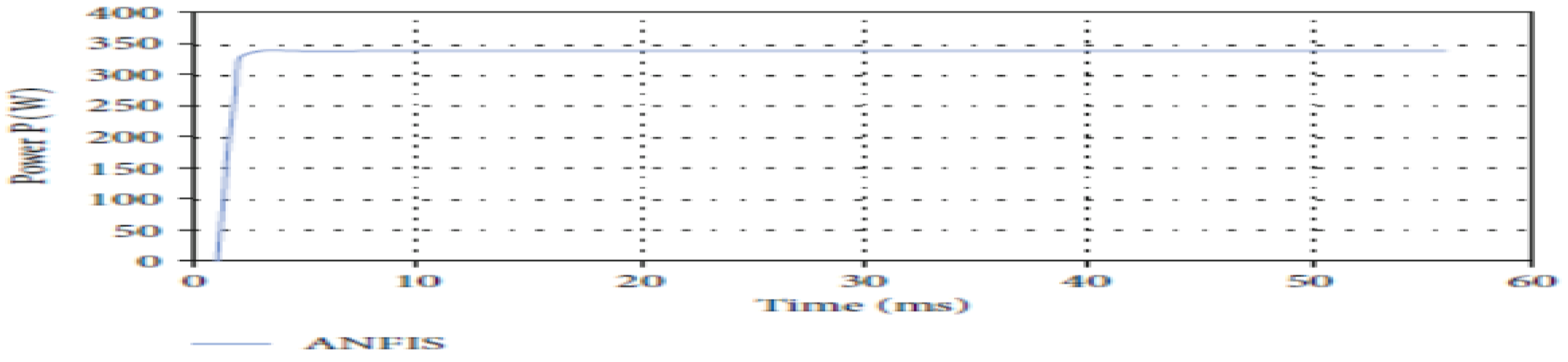

Figure 11. Output power of the ANFIS MPPT at PSC I

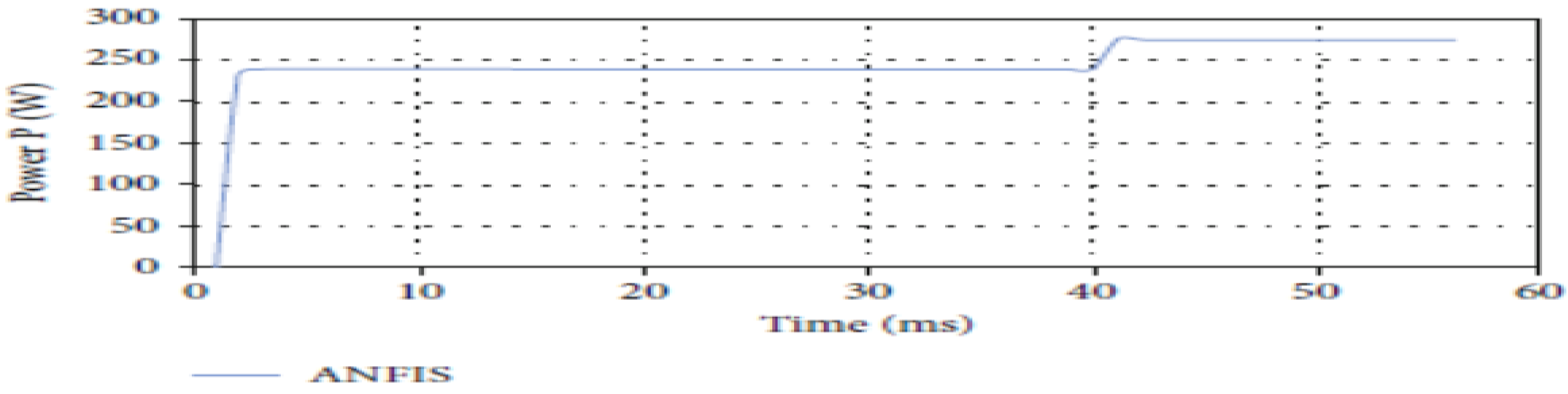

Figure 12. Output power of the ANFIS MPPT at PSC II

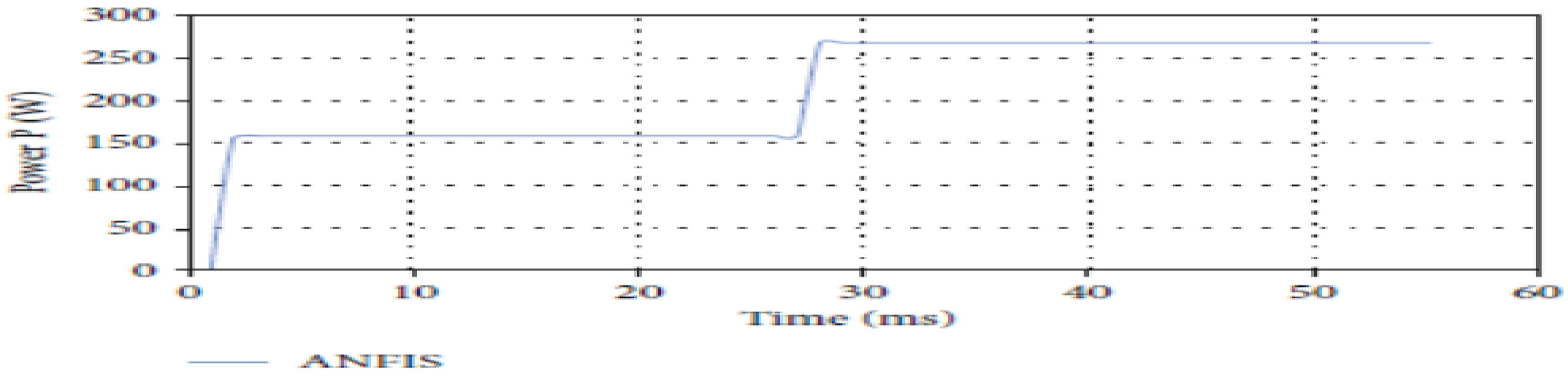

Figure 13. Output power of the ANFIS MPPT at PSC III

The proposed optimizer is tested under different conditions as presented as follows.

1. Standard Test Condition. The standard test conditions indicate that the SPV array works using an irradiance of 1000W/m2 and temperature of 25°C. The controller boosts the input voltage level to match the load voltage; hence, the values are higher. The output power of various maximum power point techniques at STC is compared with the output power of the PV array and it is shown in Figure 8.

2. Under Rapidly Varying Weather Conditions. The PV array was tested for rapidly varying atmospheric conditions, which was achieved by varying the irradiance and temperature pattern. The inlet signals of the SPV array for varying weather condition VWC is given in Figure 9.

3. Partial Shading Conditions. The partial shading condition I is influenced in the PV array by reducing the irradiance input of one module by half (500 W/m2). In this condition, two modules out of the five in the PV array are partially shaded with irradiance values of 400W/m2 and 500W/m2. In this condition, three modules out of the five in the PV array are partially shaded with irradiance values of 400W/m2, 500W/m2, and 600W/m2. Figure 10 describes the effect of partial shading condition III on power-voltage characteristics of the array. Figures 11–13 represent the output power of the ANFIS MPPT at PSC I, PSC II, and PSC III, respectively. The ANFIS controller responds faster at all PSCs and shows no power fluctuations. The fuzzy controller converges at the same speed as the ANFIS controller in PSC I and II but shows a remarkable response delay under PSC III. Moreover, the fuzzy controller exhibits a little fluctuation under PSC I.

Efficiency is calculated using the equation

$$\eta = \frac{P_{max}}{GA} \times 100,$$

where P_{max} – maximum power (W), G – irradiance (W/m^2) and A – total area $A = 1.6864\, m^2$ as shown in table 1.

Table 1. *Output values*

Evaluation parameters	**P_{max} (kW)**	**Tr (m^2)**	**n (%)**	**Oscillations**	**Sensors**
ANFIS	0.502	3	30.33	No	G,T

4. Conclusion

ANFIS refers to such approaches as soft computing, which are convenient when analyzing nonlinear phenomena. Depending on the type of nonlinearity, the applied technologies have certain disadvantages. ANFIS technology shows better convergence and efficiency compared to other fuzzy logic based technologies. However, the performance of ANFIS controller depends on the quality of training data sets. There are still many unsolved issues here and hence further improvement of the method is relevant.

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