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Implementing GA-ANFIS for Maximum Power Point Tracking in PV System

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Abstract

Nowadays, it has been a developing consideration towards utilization of photovoltaic (PV) system. This paper proposes the Adaptive Neuro-Fuzzy Inference System (ANFIS) and an integrated offline Genetic Algorithm (GA) to track the PV power based on different circumstances due to the various climate changes. Training data in ANFIS are optimized by GA. The proposed controller is accomplished and studied applying Matlab/Simulink software. The results show minimal error of Maximum Power Point (MPP), Optimal Voltage (V_{mpp}) and superior capability of the suggested method in MPP tracking.

Keywords: ANFIS, GA, MPPT, Photovoltaic System.

1. Introduction

For tracking the incessantly diverging the MPP of the solar array, MPPT control approach acts a significant part in the PV arrays[1-3].

The rifest methods are the perturbation and observation (P&O) algorithm[3,4], Incremental conductance (IC)[5,6] fuzzy logic controller (FLC)[7,8] and artificial networks (ANN)[9-11]. The P&O and IC methods are widely applied in the MPPT due to its simplicity and easy execution, one of the drawbacks of this technique that it is precision in steady-state condition is low since the perturbation operation would cause to oscillate the operating point of the PV module around the MPP that wastes the energy. When perturbation step size is minimized, variation can be decreased, but a smaller perturbation size decelerates the speed of MPPT. As well as, the rapid changing of weather condition affects the output power and this method fails to track easily the MPP[12,13].

In recent decade, FCL is employed for tracking the MPP of PV module since it can be considered robust, simple in design because they do not need knowleminimal necessity of the mathematical model dge of the accurate model and Nevertheless, the FLC depends on deliberate election of parameters, explanation of membership functions and fuzzy rules. The effectiveness of FLC technique requires specialist science and testing in choosing membership functions and parameters. Some other weakness of FLC is complex algorithms which lead in the high cost of implementation[14,15]. To overcome these weaknesses, new methods such as ANN have been applied. The application of ANN in different subjects has been increasing as it gives an advantage of doing on non-linear tasks. ANN is based on learning process and does not need to be reprogrammed[16,17].

Neural network with approximation of the MPP in photovoltaic module uses inputs such as environmental conditions, PV irradiance, wind velocity, temperature and time parameter which have been provided in[18]. Besides, this paper shows the number of neurons is kept as 5 in the hidden layer and the output estimates the maximum power. Maximum power prediction has been carried out by comparisons between neural network and multiple regressions. One of the problems in[18] is that the results of ANN are heavily dependent on preliminary selection of training data.

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The modeling and performance of the MPP in PV module based on RBFN have been provided in[16]. In comparison with traditional P&O method, RBFN is faster and also has less fluctuation in performance point.

ANN can be considered as a best method for mapping inputs-outputs of non-linear functions, but it lacks subjective sensations. In the other words, fuzzy logic approach has the capability to transform linguistic and mental data into numerical values. However, the determination of membership functions and FLC rules depends on the previous knowledge of the system. Neural networks can be integrated with fuzzy logic and through the combination of these two smart tools, a robust AI technique called ANFIS can be obtained[19-21].

In this study first, the 360 data of Temperature and irradiance as the inputs data are applied to GA and V_{mpp} corresponding to the MPP delivery from the photovoltaic system, afterward the optimum values are implemented for training the ANFIS.

The remnant of this article is formed as follows: structure of photovoltaic module has been presented in part 2. The GA method and ANFIS structure are explained in part 3. The simulation results have been presented in part 4. Finally, conclusion described in part 5.

2. Structure of PV System

In Figure 1, the PV cell equivalent circuit is depicted. Characteristic of one solar array is reported as following equations (1):

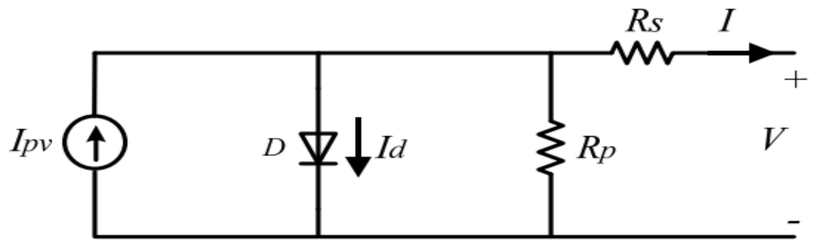


Figure 1. Structure of PV solar cell.

$$I = I_{pv} - I_0 \left[\exp\left(\frac{V + R_S I}{V_t n} \right) - 1 \right] - \frac{V + R_s I}{R_P} \qquad (1)$$

Where, I represents the photovoltaic current, V represents the photovoltaic voltage, Ipv is the light generated current, the ideality factor can be represented by n, Rsh and Rs are the parallel and series resistance. Vth is the thermal voltage of diodes. The name-plate details are reported in Table 1.

Table 1. Red sun 90w module

I_{MP} (Rated current)	4.94 A
V_{MP}(Rated voltage)	18.65V
P_{MAX} (Rated power)	90W
V_{OC} (Open circuit voltage)	22.32
I_{SC} (Short circuit current)	5.24
N_p(Parallel cells number)	1
N_S (Series cells number)	36

3. Genetic Algorithm Technic and ANFIS

3.1 Applying of GA

ANFIS and GA methods are used to follow the optimal point for MPP in environmental circumstances. Besides, genetic algorithm is implemented for optimal values. Then, these optimal values are applied for training ANFIS[22,23]. Implementing of GA is as follows[24]:

1. the objective function and recognizing the design parameters are determined,

2. the initial population is defined, 3. determining the size of population and applying objective function, 4. conducting convergence test.

Objective function of genetic algorithm is used for its optimization as following: detecting the optimum X= (X_1, X_2, X_3,..., X_n) to put the F(X) in the maximum value, that the design variable number is considered as 1. X is the design variable equal to array current and also, F(X) is the array output power which should be maximized[22]. The power should be arranged based on the array current (I_X) to elect the objective function. The GA parameters have been given in Table 2.

$$F_{(X)} = V_X * I_X \quad (2)$$

$$0 < I_X < I_{SC} \quad (3)$$

Table 2. The parameters of GA

Design Variable Number	1
Size of population	20
Crossover constant	80%
Mutation rate	10%
Maximum Generations	20

3.2 ANFIS Systems

An adaptive neural network has the advantages of learning ability, optimization and balancing. However, a FLC based on rules constructed by the knowledge of experts20,21. The good performance and effectiveness of FLC have been approved in nonlinear and complicated systems. ANFIS combines the advantages of using adaptive neural network and FLC. ANFIS makes use of Sugeno. Fuzzy inference system (FIS), a prevalent rule set is obtained with 2 fuzzy if-then rules by the following Equations. The fuzzy rules can typically reported as follows: Rule 1: If x is A1 and y is B1; afterward

$$f1 = p1x + q1y + r1 \quad (4)$$

Rule 2: If x is A2 and y is B2; afterward

$$f2 = p2x + q2y + r2 \quad (5)$$

Which x and y can be considered as the inputs and f is the output. [pi, qi, ri] are called the consequent parameters, i = 1, 2.. The ANFIS structure of the above statements is shown in Figure 2.

Layer 1: this layer consists of an adaptive node with a node function. We have:

$$Q_{1,i} = \mu A_i(x), \quad for\ i = 1,2 \quad ...(6)$$

$$Q_{1,i} = \mu B_{i-2}(y), \quad for\ i = 3,4 \quad ...(7)$$

Output of this layer is its membership value. Membership functions for A can be any proper parameterized membership function. Each parameter is regarded as a default parameter.

Layer 2: this layer has been called with an "n" and the output of each node is the product of multiplying all incoming signals for that node. These nodes perform the fuzzy AND operation, and we have:

$$Q_{2,i} = w_i = \mu A_i(x)\mu_{Bi}(y) \quad for \quad i = 1,2 \quad ...(8)$$

Layer 3: Each node in this layer has been labeled with an "N". Nodes calculate the normalized output of each rule. Then we have:

$$Q_{3,i} = \overline{w_i} = \frac{W_i}{W_1 + W_2} \quad i = 1,2 \quad (9)$$

Where, Wi is the firing strength of that rule.

Layer 4: Each node in this layer is associated with a node function. Then we have:

$$Q_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \quad (10)$$

Where, Wi represents the normalized firing strength of the third layer and {pi, qi, ri} are parameters sets of the node i.

Layer 5: The single existing node in this layer is labeled as Σ. It computes the sum of all its input signals and sends them to the output section.

$$Q_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (11)$$

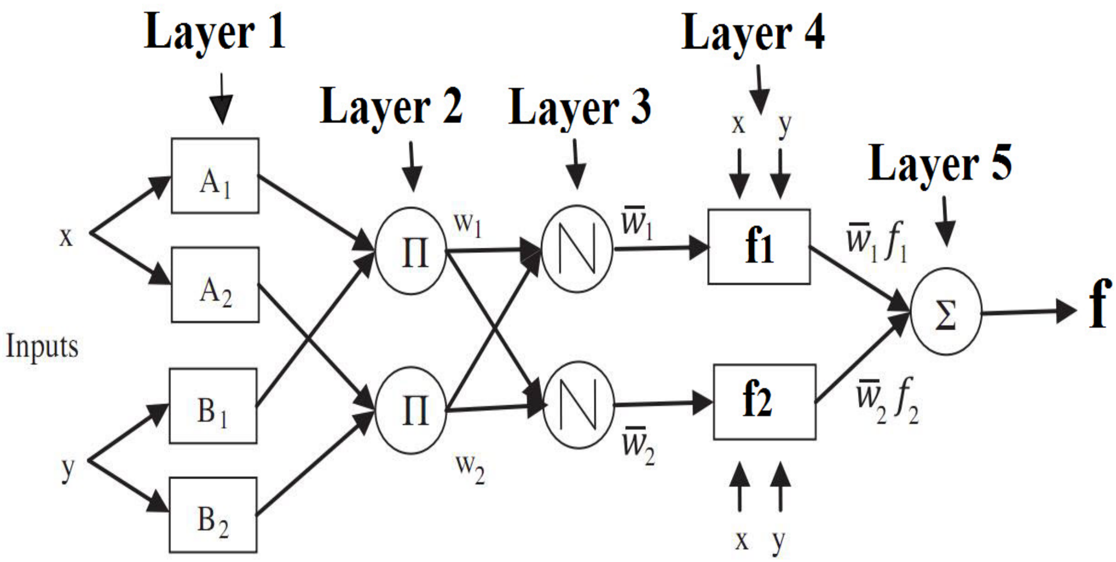


Figure 2. ANFIS architecture.

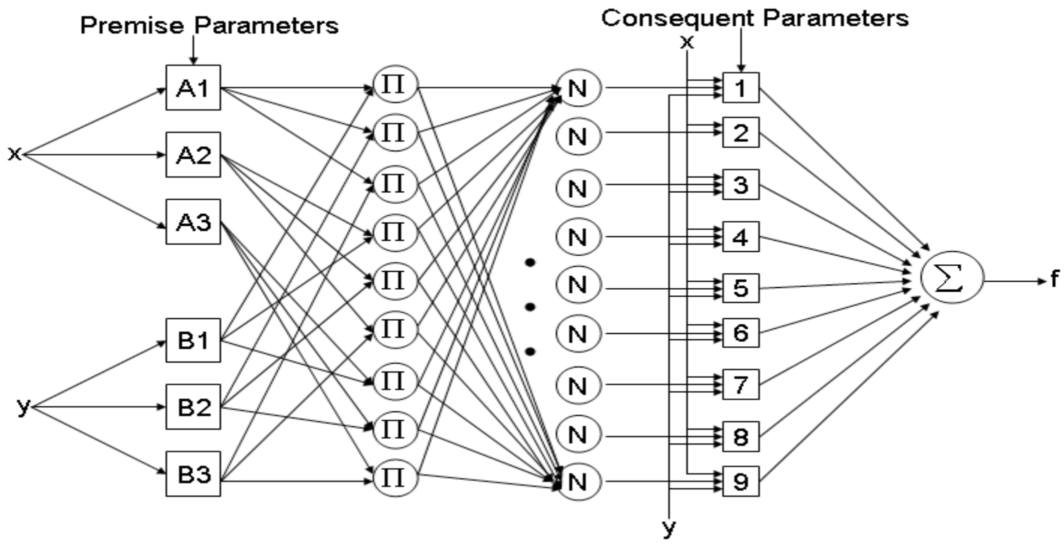


Figure 3. Typical ANFIS structure.

Where, Q_{5i} is the output of the node (i) in the fifth layer. For this reason, first, all existing rules will be established in the layer 1. For example, if we have two inputs, each of which has three membership functions, then we must form 9 rules.

That would be as follows in Figure 3.

4. Simulation Result

The mixture of least squares and gradient descent techniques are constructed the hybrid learning algorithm.

The input of the ANFIS can be considered irradiation and temperature and output is V_{mpp} corresponding to the MPP delivery from the PV system. Then, the output voltage of photovoltaic module with ANFIS output voltage was deducted to obtain the error signal. Then, through a PI controller, this error signal was given to a pulse width modulation (PWM) block. In Figure 4, the diagram of the presented MPPT is demonstrated. PV module was designed in order to obtain optimum values by genetic algorithm. A set of 360 data was put to temperature and irradiance as inputs shown in Figure 5(a) and the output was V_{mpp} corresponding to the MPP as depicted in Figure 5(b). Then these optimum values were utilized for training the ANFIS. By following Figure 5(a), all input were 360 data in which ANFIS model utilizes set of 330 data was for training and also, a set of 30 data is utilized to test the ANFIS. Input temperature ranged from 5 to 55°C in the steps of 5° C and irradiance varied from 50 to 1000 (W/m^2) in the steps of 32 (W/m^2).

V_{mpp} corresponding to MPP
sponding to MPP
MPP

ANFIS input structure is shown in Figure 6. It includes five layers. The two inputs represent irradiation and temperature; that have 3 membership functions. In Figure 7, the structure of the solar irradiance is shown and also, the structure of the temperature is illustrated as Figure 8.

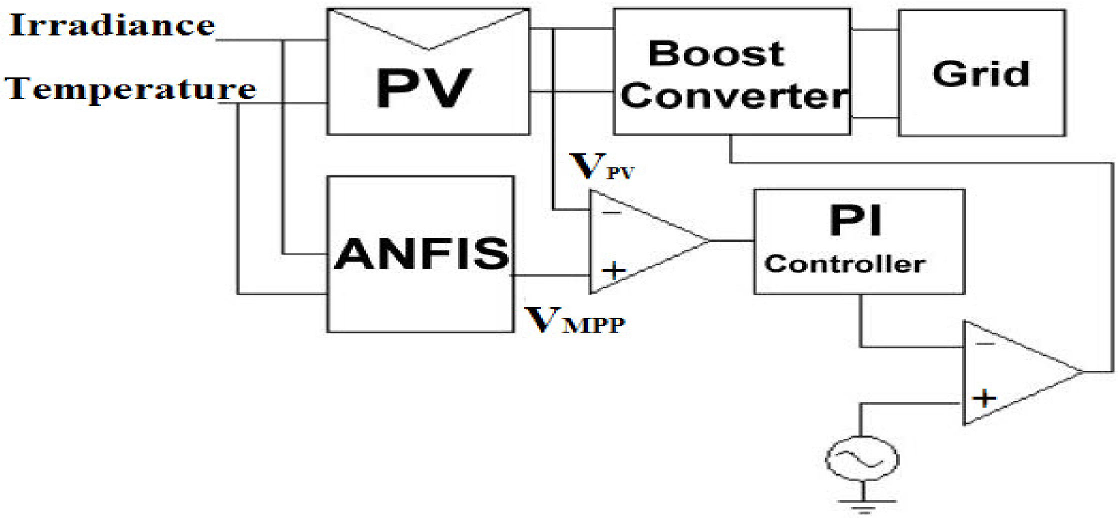
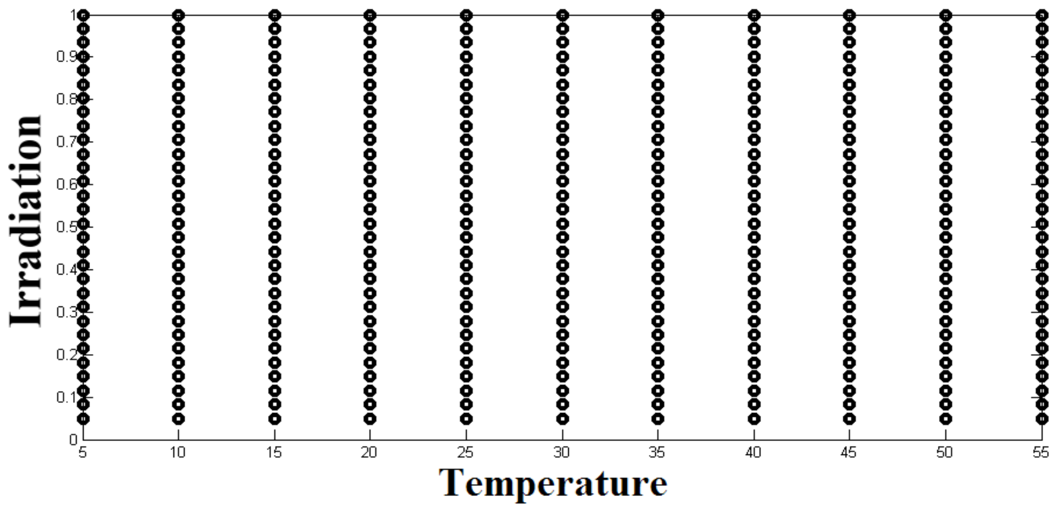


Figure 4. Proposed MPPT scheme.

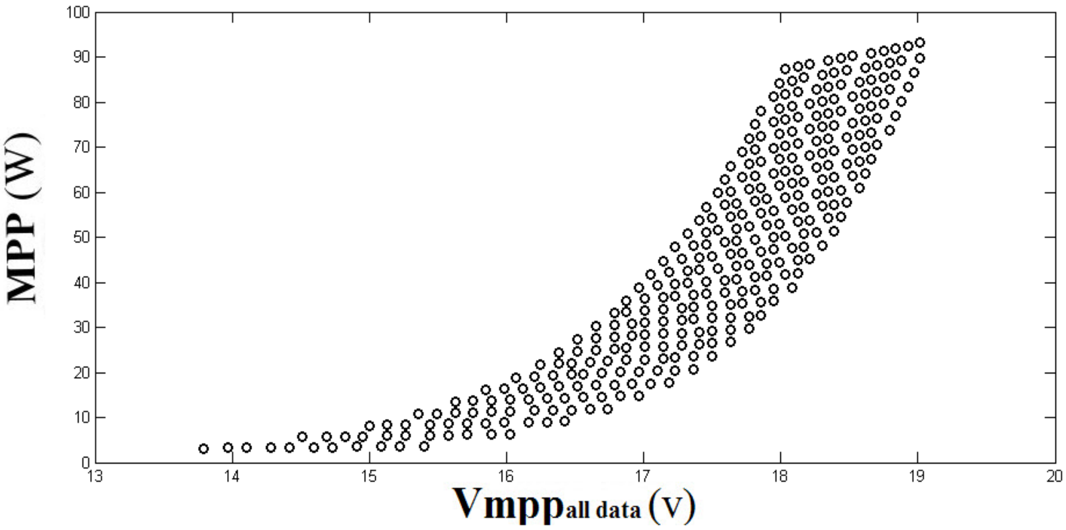


(a)

uts data of irradiation and temperature, (b) Vmpp corresponding to MPP
irradiation and temperature, (b) V_{mpp} corresponding to MPP
n and temperature, (b) Vmpp corresponding to MPP
rature, (b) Vmpp corresponding to MPP

They have 9 fuzzy rules in total as shown in Figure 9; these rules have a unique output for each input.

The network is trained for 10,000 epochs. After the training process, output data should be very close to the target outputs as shown in Figure 10.



(b)

Figure 5. Data: (a) Inputs data of irradiation and temperature, (b) Vmpp corresponding to MPP.

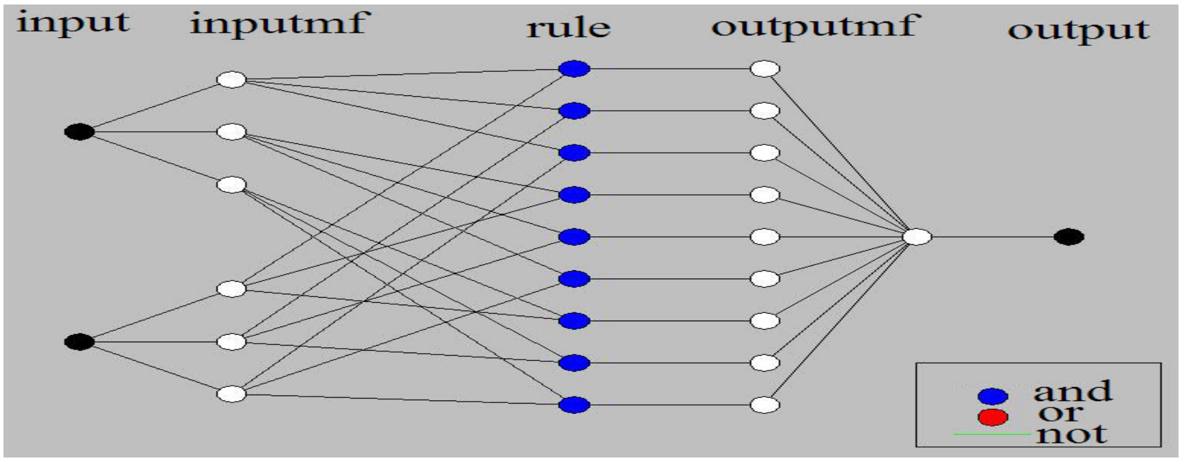


Figure 6. ANFIS controller structure.

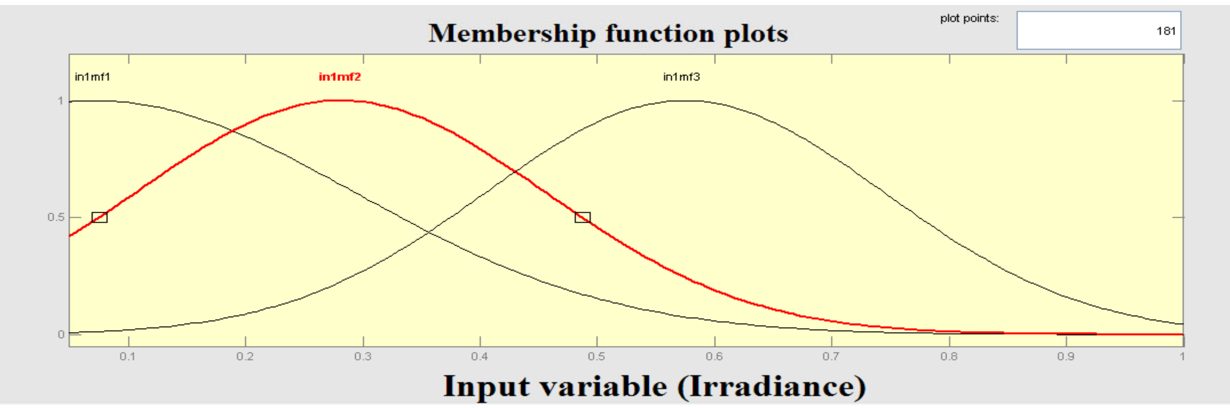


Figure 7. Solar irradiance membership function.

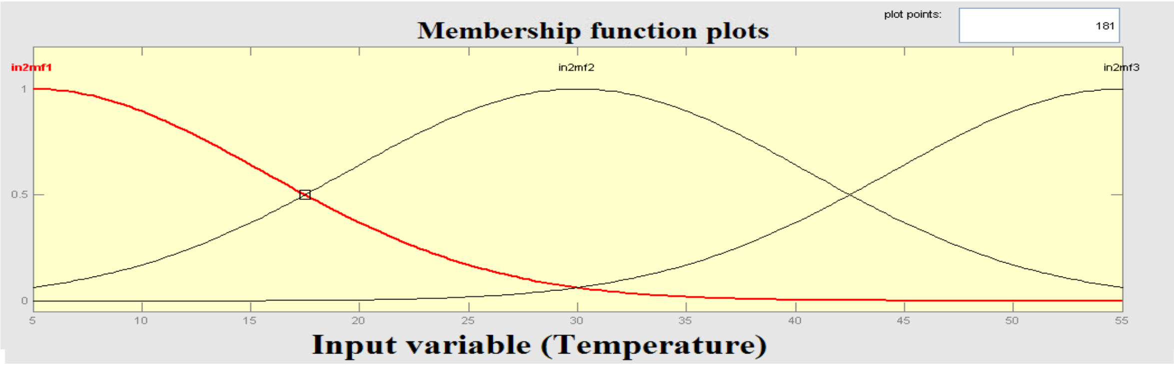


Figure 8. Temperature membership functions.

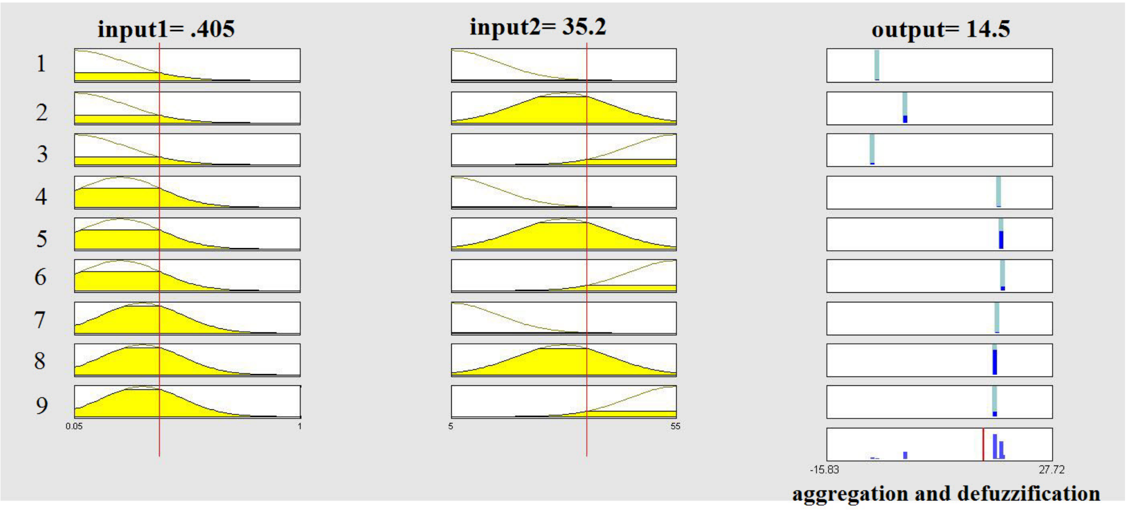


Figure 9. Fuzzy rules.

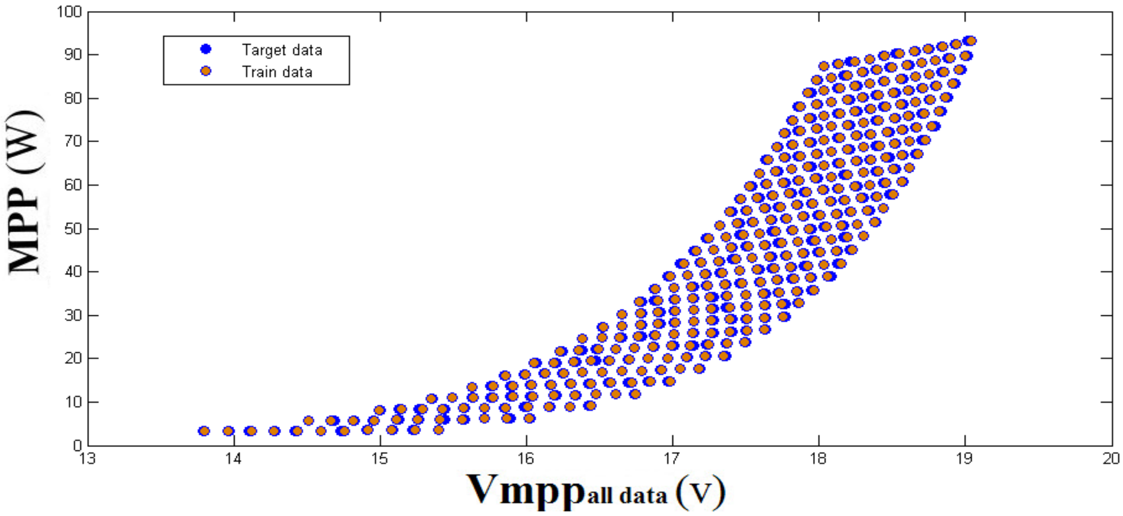


Figure 10. The output of the ANFIS with the value of target data

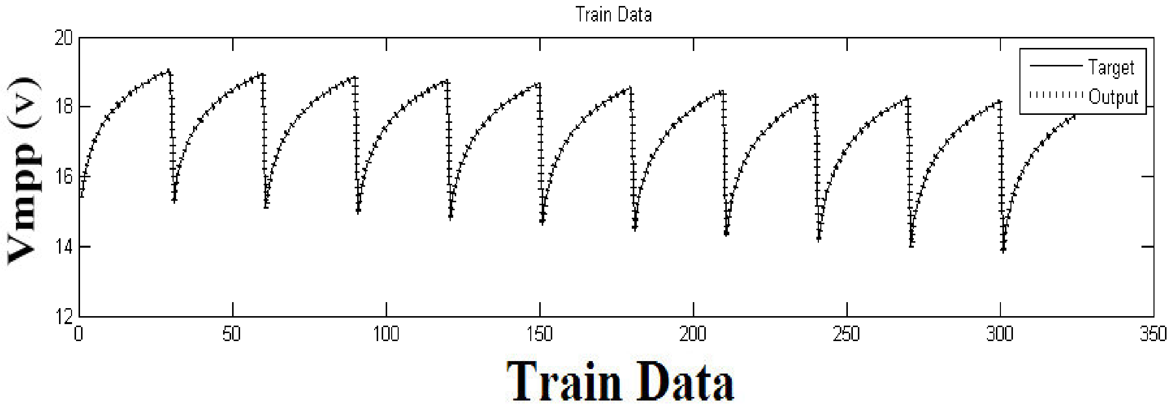


Figure 11. ANFIS output with the value of target data

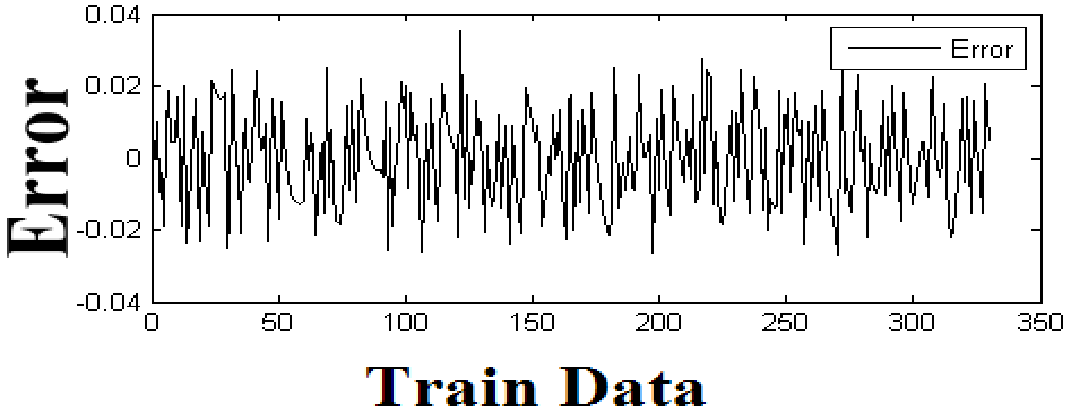


Figure 12. V_{mpp} error percentage.

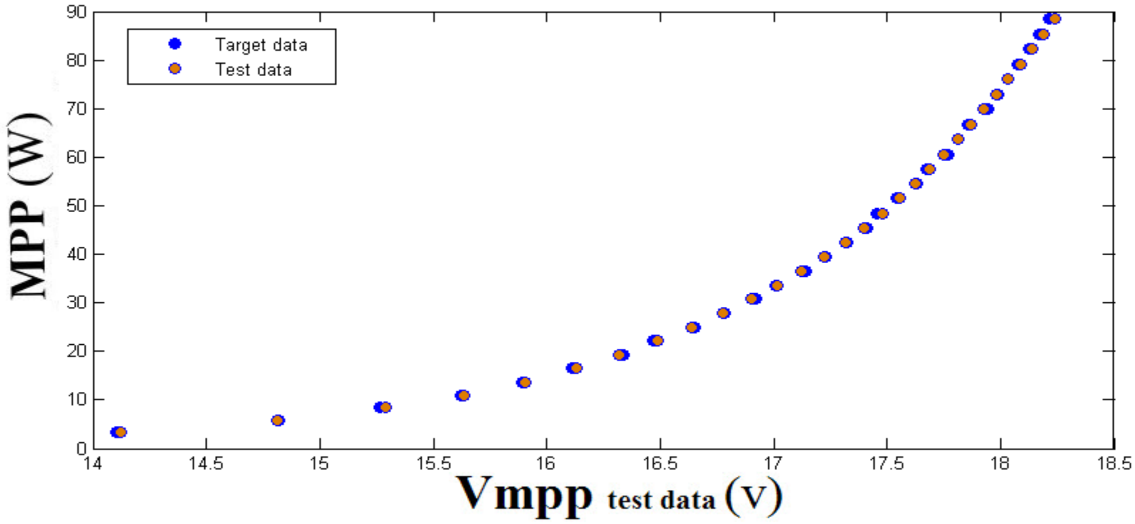


Figure 13. ANFIS test output with the value of target data Data.

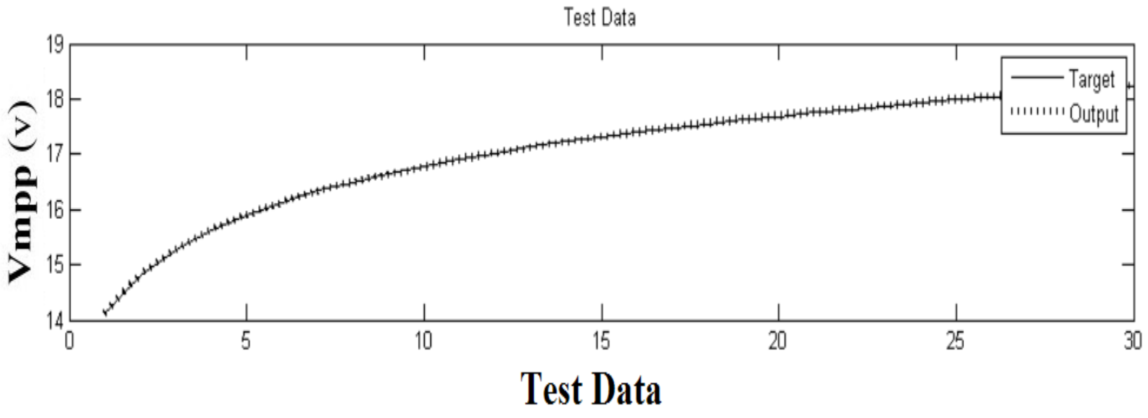


Figure 14. The output of the ANFIS test Vmpp with the value of target data.

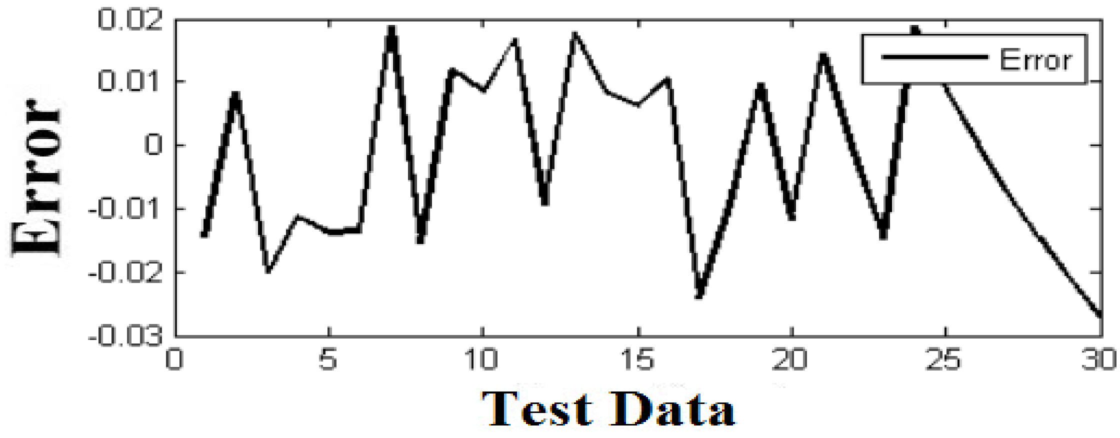


Figure 15. Test data error percentage.

According to Figures 11 and 12, Vmpp was compared with the target values and in Figures 13-15 the output of ANFIS test was compared with the target values, depicting a negligible training error of about 1.4%. The ANFIS based temperature and irradiation show best outcomes with minimum error and the output power is optimized with the assist of the GA method.

5. Conclusion

To track MPP of PV system GA-ANFIS method was applied. With the assist of this technique, the PV module was able to increase the production of the output power at an optimal solution under various circumstances. The GA was implemented to supply the optimal voltage corresponding to the MPP for each environmental circumstances. Then; optimized values were used for training the ANFIS. For various conditions the proposed method was verified and found that the error percentage of Vmpp between 0.05% to 1.46%. Incrementing the number of the training data could be diminished Error of ANFIS.

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