Adaptive fuzzy & Neuro-Fuzzy Inference controller based MPPT for photovoltaic systems

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Abstract: This paper grants a smart technique called Adaptive Neuro Fuzzy Inference controller (ANFIS) to optimize the performances of photovoltaic techniques. The method consists of a PV panel, a DC–DC booster converter, a maximum power point tracker controller and a resistive load. ANFIS methodology comprises of a hybrid system of fuzzy logic and neural network technique. The fuzzy logic takes into account the decision making based on the rules and uncertainty of the system that is being modeled while the neural network gives it a sense of adaptability. The important thing of the proposed strategy is the use of a ANFIS controller is trained to generate maximum power corresponding to the given solar irradiance level and temperature. The performances of the ANFIS are compared with those obtained using a conventional Adaptive fuzzy controllers with different gains and in each case, the proposed ANFIS controller outperforms its conventional counterpart.

Keywords:*PV panel, ANFIS, Output scaling factor, Fuzzy rules.*

1. INTRODUCTION

The ever-increasing utilization of energy, fossil fuels soaring costs and exhaustible nature, and worsening global environment have created a booming interest in renewable energy generation systems, one of which is photovoltaic. Such a system generates electricity by converting the Sun's energy directly into electricity. The Conventional sources of energy are rapidly decreasing. Moreover the cost of energy is increasing and therefore photovoltaic system is a promising alternative. They are scarce, pollution free, distributed throughout the earth and recyclable. The hindrance factor is it's high installation cost and low conversion efficiency. Therefore our aim is to increase the efficiency and power output of the system. It is also required that constant voltage be supplied to the load irrespective of the variation in solar irradiance and temperature. PV arrays consist of parallel and series combination of PV cells that are used to generate electrical power depending upon the atmospheric conditions (e. g solar irradiation and temperature). So it is necessary to couple the PV array with a boost converter. More over our system is designed in such a way that with variation in load, the change in input voltage and power fed into the converter follows the open circuit characteristics of the PV array. Our system can be used to supply constant stepped up voltage to the fuzzy logic controller to convert the given dc input to the respective ac output.The photovoltaic renewable energy generation is attracting a growing amount of political and commercial interest. The growth of photovoltaic (PV) systems has exceeded the most optimistic estimations because of the many merits they have such as providing a green renewable power by exploiting solar energy, autonomous operation without any noise generation. In addition their easy use make them suitable to both home energy applications and small-scale power generation applications.

Several methods have been proposed in the literature for tracking the MPP of PV systems. Among these methods, Hill climbing perturb and observe (P and O) algorithms were commonly used due to their straight forward and low cost implementation. An alternative approach that overcomes this effect is called the increment inductance method. However, all these listed methods did not respond correctly under rapidly changing atmospheric conditions. Recently MPPT methods based on artificial intelligence techniques such as neural networks, genetic algorithmsand fuzzy controllers have emerged. The use of Adaptive neuro fuzzy inference controller (ANFIS) is more suitable for MPPT compared with conventional controllers because they produce a better performance with changing atmospheric conditions

In this paper, an ANFS controller is used to track the MPP of a photovoltaic panel. The proposed fuzzy Inference controller is significantly different from others as it uses an adaptive output scaling factor which can provide a good performance for PV systems. The rest of the paper is organized in four sections. In Section 2, the mathematical model of the PV module is presented. The

structure of the adaptive fuzzy inference controller is described in detail in Section 3. Section 4 presents the simulation results. Finally, a general conclusion is given in Section 5.

2. Photovoltaic panel modelization

2.1. Mathematical model

The mathematical model explain as Fig. 1 suggests the equivalent circuit of a solar cell. This circuit consists of a image current supply I_{Ph}, a diode D_i , an identical parallel resistance R_{sh} and an identical sequence resistance R_s.

The Shockley diode equation which describes the $I(V)$ attribute is given by using

$$I_d = I_0 \left[exp\left(\frac{V_d}{n.V_T} \right) - 1 \right]$$

(1)

Where I_d is the forward diode current, I_0 is the reverse saturation current, V_d is the diode's direct voltage, n is the diode component (quite often between 1 and 2) and V_T is the thermal voltage which is expressed with the aid of the equation:

$$V_r = \frac{K.T}{q}$$

(2)

Where k is the Boltzmann consistent, T is the mobile's working temperature expressed in Kelvin and q is the electron's charge.

The reverse saturation current I_0 varies with temperature as mentioned within the following:

$$I_0 = I_{rs} \left(\frac{T}{T_r} \right)^3 exp\left[q.E_g \left(\frac{1}{T_r} - \frac{1}{T} \right) \right]$$ (3)

Where T_r is the mobile reference temperature, Irs is the reverse saturation current at T_r and E_g is the band gap energy of the semiconductor used within the solar cell.

For the reason that the identical circuit in Fig. 1 with a parallel resistance R_{sh} just about limitless, the $I(V)$ characteristic of a sun telephone can be described by using the next equation:

$$I = I_{ph} - I_0 \left[exp\left(\frac{V+IR_s}{n.V_T} \right) - 1 \right]$$

(4)

V is the cell voltage which equals to PV panel voltage divided by the quantity of cells in series and R_s is the identical sequence resistance. Eq. (5) gives the cell's photocurrent I_{ph}. This final depends upon the irradiation $S(W/m^2)$ and the temperature $T(k)$:

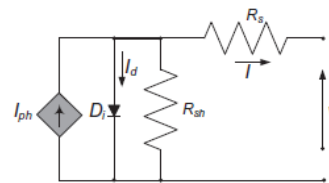$$I_{ph} = I_{sc}[1 + a.(T - T_r)]\frac{s}{100}$$ (5)

Fig. 1. One diode model of solar cell.

Where I_{sc} is the telephone's short circuit current at the reference temperature T_r and α is the cell's brief circuit present temperature coefficient.

2.2. Power versus voltage curves:

The extraordinary parameters of the PV model will also be determined by using examining the manufacturer's datasheets. Table 1 indicates the used knowledge in our simulations for a BP SX150S panel manufactured by means of BP solar company.

The PV module grants a nonlinear behavior which depends upon the temperature and sun radiation. Fig. 2 shows the 3D $I-V-P$ traits of the used PV panel below variable atmospheric conditions, in phrases of temperature and irradiance. The determine suggests that there are four elements on the curves, referred to as the maximum power points, at which the PV panel operates with a maximum effectively and produces highest output energy using distinctive irradiances and temperatures.
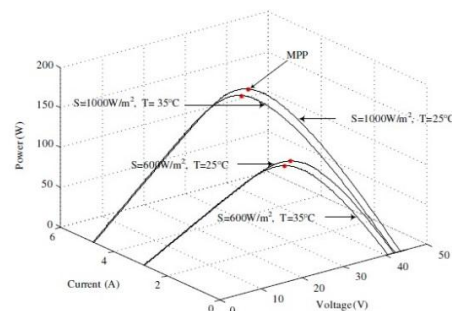

Fig. 2. PV panel 3D $I-V-P$ characteristic curves.

3. Proposed adaptive neuro fuzzy inference (ANFIS) controller:

The main objective of this paper is to adapt a new method for tracking the maximum power point using an adaptive neuro fuzzy inference system (ANFIS) controller which is described in detail in this section.

3.1. PV system structure:

An ordinary functional diagram of a PV energy conversion approach is depicted in Fig.3. The procedure contains a PV panel, a DC–DC enhance converter, a maximum vigor point tracker controller (MPPT) and a resistive load. The MPPT has the objective to attract as much vigor as viable from the PV panel underneath all running stipulations via adjusting continuously the obligation cycle D of the raise converter.

Fig.4. shows the fundamental accessories of the DC–DC boost converter in most cases utilized in PV programs. The energy change Sw modulates the energy transfer from the input source to the burden when managed via a various obligation cycle D. In our simulation we use the continuous current typical model of a boost converter which is controlled by varying duty cycle D.

$$\begin{cases} V_O = \frac{V_i}{1-D} \\ I_i = \frac{I_O}{1-D} \end{cases}$$

(6)

Where V_i and I_i are respectively the voltage and current on the input factor, V_0 and I_0 are respectively the voltage and present on the output factor.

3.2. Adaptive Fuzzy controller as an MPP tracker:

Before describing the new structure of the adaptive fuzzy controller, allow us to in short keep in mind the extraordinary accessories of a conventional fuzzy controller. Fig. 5 shows the principal components of conventional fuzzy controller.

Table 1
Parameters of BP SX150S panel.

Maximum power(P_{max})	150W
Voltage atP_{max} (V_{max})	34.5V
Current atP_{max} (V_{max})	4.35A

Open circuit voltage(V_{oc})	43.5V
Short circuit current(I_{sc})	4.75A
Temperature coefficient of I_{sc} 0.065%/°C	

In the fuzzification the input variables $e(k)$ and $\Delta e(k)$ can be converts to linguistic values equivalent constructive enormous and terrible big.
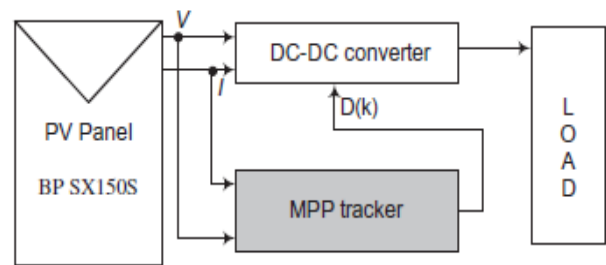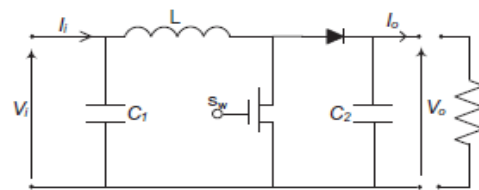

Fig. 3. Photovoltaic system.

Fig. 4. Basic circuit of the boost converter.

The two controller's inputs are defined by way of the following equations:

$$e(k) = \frac{P(k)-P(k-1)}{V(k)-V(k-1)} \quad (7)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (8)$$

Where $e(k)$ and $\Delta e(k)$ are respectively the error and the alternate of error, $P(k)$ the output power of PV panel at time okay and the $V(k)$ is the terminal voltage of PV panel. As illustrated in Fig. 5, the instantaneous value of $e(k)$ indicates if the weight operation vigor point on the immediate k is located on the right $(e(k) < 0)$ or in the left $(e(k) > 0)$ of the MPP, while the input $\Delta e(k)$ expresses the relocating path of this point.

A fuzzification example of the two inputs $(e, \Delta e)$ making use of five fuzzy sets denoted as NB, NS, ZE, PS and PB respectively for terrible tremendous, negative Small, Zero, positive Small and constructive gigantic, is

illustrated in Fig. 6.The defuzzification unit aggregates the outputs of all of the rules which have fired for the particular enter fuzzy units to provide a numerical crisp output. G_D is the output scaling component of the controller.

3.3.Structure of the adaptive fuzzy controller:

A fuzzy controller (FC) is adaptive if anyone of its tunable parameters (membership functions, fuzzy rules and output scaling factor) changes when the controller is being used, or else it is a non-adaptive or a traditional FC. Fig.7 shows the block diagram of the adaptive FC.
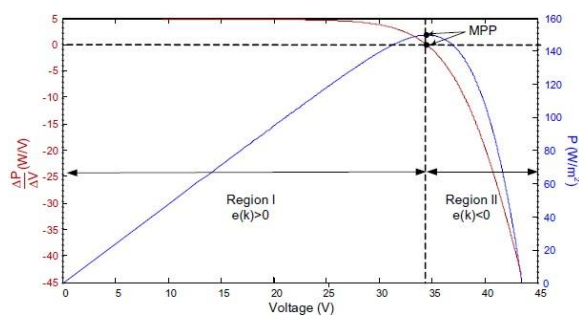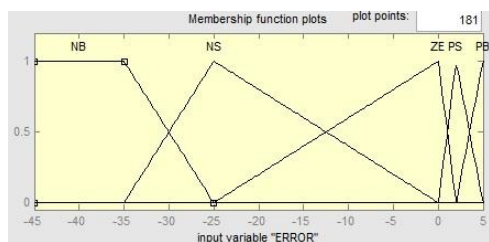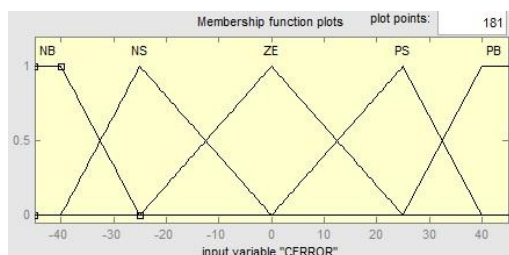

Fig. 5.P(V), $\frac{\Delta P}{\Delta V}(V)$ characteristic curves of PV panel.

In this case, the incremental change in controller output ΔD is given by

$$\Delta D(k) = \{\alpha(k) * G_D\} * \Delta D_N(k) \qquad (9)$$

(a)

(b)

Fig. 6. Membership functions of e(a) and Δe(b).

Table 2

Rule base for computation of ΔD_N.

$\Delta \boldsymbol{D}_N(\Delta \boldsymbol{e})$ $\boldsymbol{e}$	NB	NS	ZE	PS	PB
NB	ZE	ZE	PB	PB	PB
NS	ZE	ZE	PS	PS	PS
ZE	PS	ZE	ZE	ZE	NS
PS	NS	NS	NS	ZE	ZE
PB	NB	NB	NB	ZE	ZE

The above Eq. (10), it is the effective gain of the adaptive controller is $\{\alpha(k) * G_D\}$.

3.3.1. Fuzzy rules:

The normalized incremental change in controller output ΔD_N for a PI fuzzy controller depends on the following fuzzy rules:

R_D: If e is PB and Δe is ZE then ΔD_N is NB   (10)
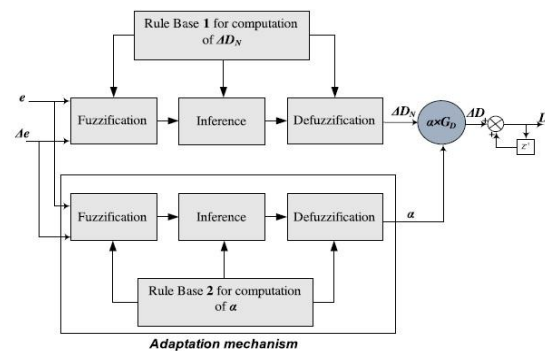

Fig. 7. Block diagram of the adaptive fuzzy controller.

All the fuzzy rules computing ΔD_N are shown in table 2. This table is probably used in literature commonly base template for fuzzy controllers built-in in MPPT methods.

The gain updating factor α is calculated using the following fuzzy rules:

R_α: If e is NB and Δe is PB then α is VB   (11)

Table 3

Rule base for computation of α

$\alpha(\Delta e)$	NB	NS	ZE	PS	PB
e					
NB	ZE	ZE	MB	B	VB
NS	ZE	ZE	VB	VS	SB
ZE	S	ZE	ZE	ZE	S
PS	S	SB	VS	ZE	ZE
PB	VB	VS	SB	ZE	ZE

In this paper, to achieve atracking of the MPP, the rule base depicted in desk three is designed and used to calculate the gain updating factor α.
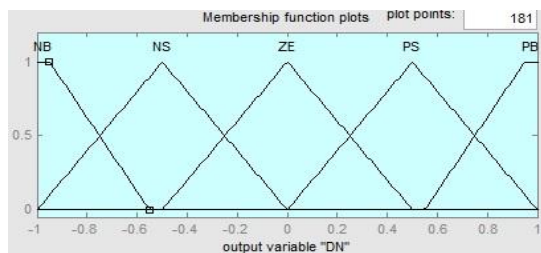

Fig. 8. Membership functions of ΔD_N.
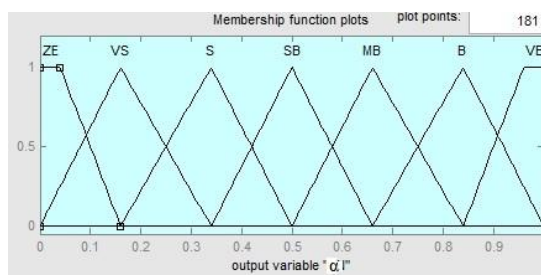

Fig. 9. Membership functions of α.

3.3.2. Membership Functions of the Controller's Variables

The membership functions of the two input variables error and change of error are defined respectively on the intervals $[e_{min}, e_{max}]$ and $[\Delta e_{min}, \Delta e_{max}]$. The limits of these intervals are determined based on the characteristic curves of the studied PV system and are fine tuned through trial and error to achieve good performances. For example, in Fig $5\left(\text{see } \frac{\Delta P}{\Delta V} \text{ curve}\right)$, it is clear that the variable error e takes its possible values in the interval $[-45, 5]$. Therefore, it is logic to define all the associated membership functions in the interval $[-45, 5]$ as it is illustrated in Fig 6(a).

Unlike the input variables, the membership functions of the control's normalized output ΔN and the gain updating factor α are defined independently from the PV panel characteristics. ΔN is normalized on interval $[-1, 1]$ and α is normalized on interval $[0, 1]$. Their respective associated membership functions are shown in Fig 8 and 9 respectively.

3.4. Structure of ANFS controller:

If $f(e, \Delta e)$ is taken to be a first order polynomial a first order Sugeno fuzzy model is formed. For a first order two rule Sugeno fuzzy inference system, the two rules may be stated as:

R_{D1}: If e is NB and Δe is PB then $D = p_1 e + q_1 \Delta e + r_1$

R_{D2}: If e is NB and Δe is PS then $D = p_2 e + q_2 \Delta e + r_2$

Here type-3 fuzzy inference system proposed by Takagi and Sugeno is used. In this inference system the output of each rule is a linear
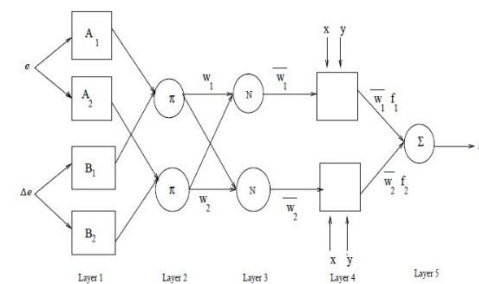

Fig. 10. ANFIS Structure.

combination of the input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in Fig. 10.

The individual layers of this ANFIS structure are described below :

Layer 1: Every node iin this layer is adaptive with a node function

$$O_i^1 = \mu_{A_i}(e) \quad (12)$$

where, e is the input to node i, A_i is the linguistic variable associated with this node function and μ_{A_i} is the membership function of A_i. Usually $\mu_{A_i}(e)$ is chosen as

$$\mu_{A_i}(e) = \frac{1}{1+\left[\left(\frac{e-c_i}{a_i}\right)^2\right]^{b_i}}$$

(13)

where e is the input and $\{a_i, b_i, c_i\}$ is the premise parameter set.

Layer 2: Each node in this layer is a fixed node which calculates the firing strength w_i of a rule. The output of each node is the product of all the incoming signals to it and is given by,

$$O_2^1 = w_i = \mu_{A_i}(e) \times \mu_{B_i}(\Delta e), \ i = 1,2,3..$$ (14)

Layer 3: Every node in this layer is a fixed node. Each ith node calculates the ratio of the ith rule's firing strength to the sum of firing strengths of all the rules. The output from the ith node is the normalized firing strength given by,

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2}, \ i = 1,2,3..$$ (15)

Layer 4: Every node in this layer is an adaptive node with a node function given by

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(p_i e + q_i \Delta e + r_i), \ i = 1,2,3.$$ (16)

Where $\overline{w_i}$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.

Layer 5: This layer comprises of only one fixed node that calculates the overall output as the summation of all incoming signals, i.e.

$$O_i^5 = overall\ output = \sum_i \overline{w_i}f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$ (17)

3.5.Learning Algorithm of ANFS controller:

In the ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output f in Fig. 10 can be written as

$$D = \frac{w_1}{w_1+w_2}f_1 + \frac{w_2}{w_1+w_2}f_2$$

$$= \overline{w_1}f_1 + \overline{w_2}f_2$$

$$=$$
$$(\overline{w_1}e)p_1 + (\overline{w_1}\Delta e)q_1 + (\overline{w_1})r_1 + \qquad (\overline{w_2}e)p_2 + (\overline{w_2}\Delta e)q_2 + (\overline{w_1})r_2$$
(18)

where D is linear in the consequent parameters $(p_1, q_1, r_1, p_2, q_2, r_2)$.

Table 4
Rules for ANFIS:

e	Δe	D
NE	NE	NE
NE	NE	ZE
NE	PS	PS
NE	NE	NE
ZE	NE	ZE
ZE	PS	PS
PS	NE	NE
PS	ZE	ZE
PS	PS	PS

In the forward pass of the learning algorithm, consequent parameters are identified by the least squaresestimate. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm

3.6. Optimization of the initial fuzzy model

The ANFIS structure of the system which is being modeled is considered as the final model for which the RMSE is the minimum. The consequent parameters of the initial fuzzy model are updated by using the Least squares estimation (LSE) algorithm.

Similarly, the rules which are obtained from the clustering or the grid partition based method are updated by neural network which uses back propagation learning method with gradient descent algorithm. This updation leads to the optimization of the premise parameters of the fuzzy membership functions to give the final fuzzy model

4. Results:

In order to demonstrate the effectiveness of the proposed approach, the designed controller is used to track the MPP under constant and varying atmospheric conditions. For each atmospheric conditions case, a comparative study between the proposed adaptive fuzzy inference controller and a conventional fuzzy controller is performed.
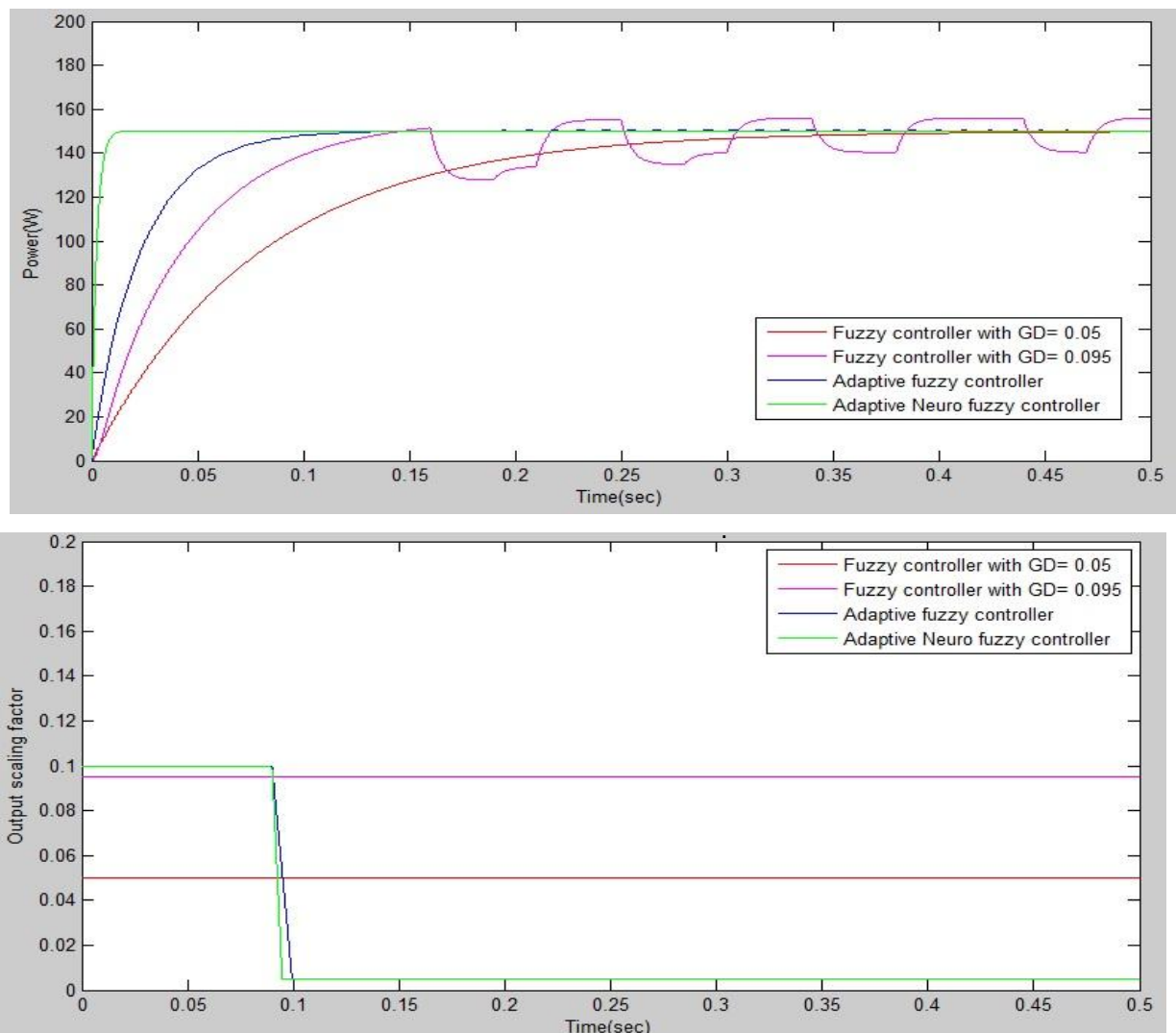

Fig 11: Comparison between ANFS and Adaptive fuzzy study under constant atmospheric conditions

4.1.Simulation under constant atmospheric conditions

Simulation results $(P(k)$ effective gain $\{0.15 * \alpha(k), D(k))$, under constant atmospheric conditions, temperature $25°C$ and irradiance $1000 \ W/m^2$. Fig11 shows the evolution of the effective gain which reaches large values at the beginning of transient state and small values at steady state.

Therefore, the duty cycle of the boost converter is optimally adjusted. By comparing various results i.e. ANFS with those obtained using two conventional Adaptive fuzzy controllers (FC_1) and (FC_2) under the same irradiance level and the same temperature $(25°C, S = 1000 \ W/m^2)$. (FC_1) has a low output gain $G_D = 0.05$GD, whereas (FC_2) has a high output gain $G_D = 0.095$. It can be seen that the proposed Adaptive Neuro Fuzzy Syatem outperforms in transient state and in steady state.
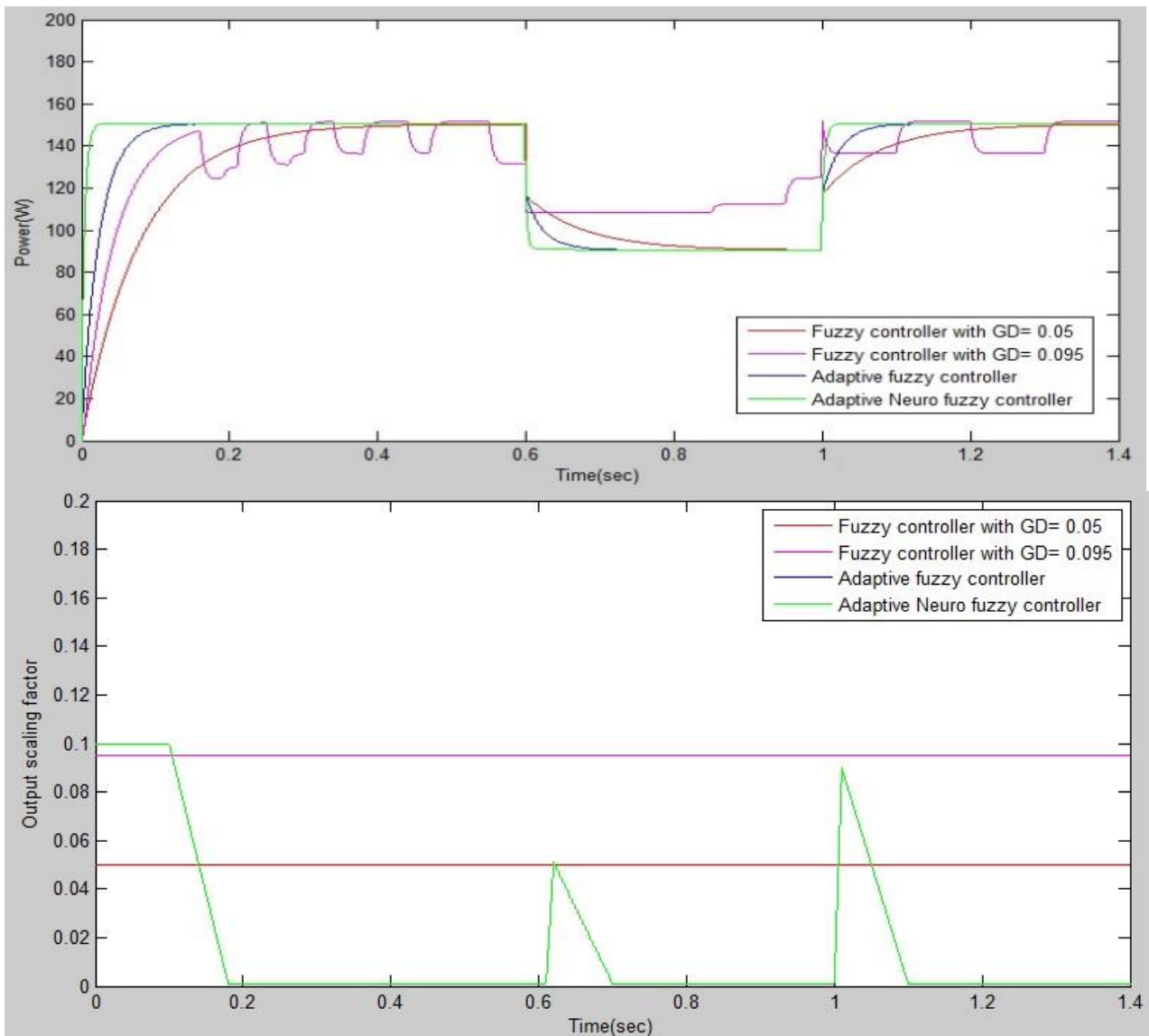

Fig 12: Comparison between ANFS and Adaptive fuzzy study under variableatmospheric conditions

4.2.Simulation under variable atmospheric conditions

In this part, by applying controller to the PV system under the following conditions: constant temperature $(T = 25°C)$ and rapid changes in solar radiation (a change from $(25°C, S = 1000 \ W/m^2$ to $600 \ W/m^2)$ at t = 0.6 s and a change back to 1000 W/m2 at t = 1 s). The obtained results are presented in Figs. 12. The effective gain output presents highly nonlinear variations, especially at instants of change in irradiance level

Conclusion

In this paper, an adaptive neuro fuzzy inference controller is used to track the maximum power from the PV arrays. This method is updated by neural network which uses back propagation learning method with gradient descent algorithm. Simulation results show that the proposed controller can track the maximum power point with higher performances when compared to its adaptive fuzzy logic controller. For that reason the introducing of an adaptive neuro fuzzy to fulfill the requirement of needs of whole system.

References:

1] Xiao W, Dunford WG. A modified adaptive hill climbing MPPT method for photovoltaic power systems. In: 35th Annual IEEE Power Electronics, Specialists Conference, Aachen, Germany; 2004. p. 1957–63.

[2] Femia N, Petrone G, Spagnuolo G, Vitelli M. Optimization of perturb and observe maximum power point tracking method. IEEE Trans Power Electron 2004; 20(4):16–9.

[3] Kuo YC, Liang TJ, Chen JF. Novel maximum power point tracking controller for photovoltaic energy conversion system. IEEE Trans Ind Electron 2001; 48(3):594–601photovoltaic energy conversion system. IEEE Trans Ind Electron 2001; 48(3):554-601.

[4] Liao CC. Genetic k-means Algorithm based RBF network for photovoltaic MPP prediction. Energy 2010;35: 529-36.

[5] Hadji S, Krimand F, Gaubert JP. Development of an algorithm of maximum power point tracking for photovoltaic systems using genetic algorithms. In: 7th International Workshop on Systems, Signal Processing and their Applications (WOSSPA); 2011. p. 43–6.

[6] Boutalis YS, Karlis AD. New maximum power point tracker for PV arrays using fuzzy controller in close cooperation with fuzzy cognitive networks. IEEE Trans Energy Convers 2006;21(3):793–803.