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# Maximum Power Point Tracking Control for Photovoltaic System Using Adaptive Neuro- Fuzzy "ANFIS"

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***Abstract*— Due to scarcity of fossil fuel and increasing demand of power supply, we are forced to utilize the renewable energy resources. Considering easy availability and vast potential, world has turned to solar photovoltaic energy to meet out its ever increasing energy demand. The mathematical modeling and simulation of the photovoltaic system is implemented in the MATLAB/Simulink environment and the same thing is tested and validated using Artificial Intelligent (AI) like ANFIS. This paper presents Maximum Power Point Tracking Control for Photovoltaic System Using Adaptive Neuro- Fuzzy "ANFIS". The PV array has an optimum operating point to generate maximum power at some particular point called maximum power point (MPP). To track this maximum power point and to draw maximum power from PV arrays, MPPT controller is required in a stand-alone PV system. Due to the nonlinearity in the output characteristics of PV array, it is very much essential to track the MPPT of the PV array for varying maximum power point due to the insolation variation. In order to track the MPPT conventional controller like Adaptive Neuro-Fuzzy "ANFIS" and fuzzy logic controller is proposed and simulated. The output of the controller, pulse generated from PWM can switch MOSFET to change the duty cycle of boost DC-DC converter. The result reveals that the maximum power point is tracked satisfactorily for varying insolation condition.**

***Keywords—Photovoltaic; Pulse Width Modulation; Proportional Integral Controller; boost DC-DC;ANFIS;fuzzy logic;MPPT.***

## I. INTRODUCTION

Today photovoltaic (PV) systems are becoming more and more popular with increase of energy demand and there is also a great environmental pollution around the world due to fossils and oxides. Solar energy which is free and abundant in most parts of world has proven to be economical source of energy in many applications [1]. The energy that the earth receives from the sun is so enormous and so lasting that the total energy consumed annually by the entire world is supplied in as short a time as half an hour. The sun is a clean and renewable energy source, which produces neither green house effect gas nor toxic waste through its utilization. It can withstand severe weather conditions, including cloudy weather. The watt peak price is decreased since the seventies, this leads to large scale promising areas. It does not have any moving parts and no materials consumed or emitted. Unfortunately,[3] this system has two major disadvantages, which the low conversion efficiency of electric power generation (9 to 16%), especially under low irradiation conditions and the amount of electric power generated by solar array changes continuously with the weather conditions like irradiation and temperature. To overcome this problem, maximum power point tracking (MPPT) technique will be used.

Fuzzy logic control "FLC" and adaptive neuro-fuzzy "ANFIS" control. The tracking algorithm integrated with a solar PV system has been simulated with boost DC-DC converter in stand - alone PV system. The proposed PV system with boost DC-DC converter is shown in Fig.1. The given model operates very fast in comparison on with available methods and has proper accuracy in maximum power point tracking (MPPT).

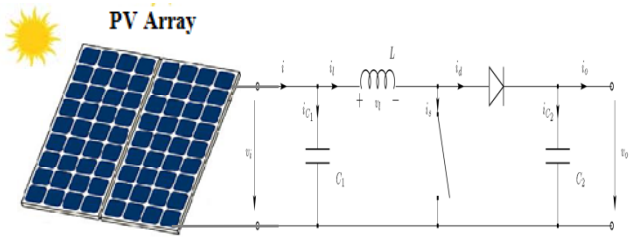



Fig.1. Photovoltaic module with DC-DC boost converter.

## II. MATHEMATICAL MODELING OF PHOTOVOLTAIC CELL

A PV cell can be represented by an equivalent circuit [9] as shown in Fig. 2. The characteristics of this PV cell can be obtained using standard equation (01).

$$I = I_{pv} - I_0[e^{\left(\frac{V+R_s I}{V_t a}\right)} - 1] - \frac{V + R_s I}{R_p} \qquad (01)$$

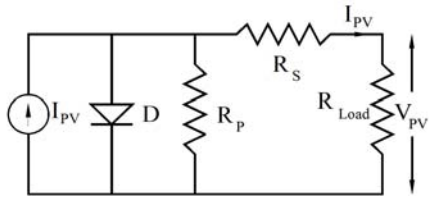



Fig. 2 Equivalent circuit of PV cell

$I_{PV}$ = photovoltaic current
$I_O$ = saturation current
$V_t = N_S\ k\ T/q$, thermal voltage of array
$N_s$ = cell connected in series
T = is the temperature of the p-n junction
k = Boltzmann constant
q = electron charge
$R_S$ = equivalent series resistance of the array
$R_P$ = equivalent parallel resistance of the array
a = diode ideality constant

Fig. 2 shows the single diode model. A single solar cell will produce only a limited power. Therefore it is usual practice in order to get desired power rating the solar cells are connected in parallel and series circuits which form a module. Such modules are again connected in parallel and series to form a solar array or panel to get required voltage and current. The equivalent series and parallel resistance of the array are denoted by the symbol $R_S$ and $R_P$ respectively in the equivalent circuit.

From the general I-V characteristic of the practical photovoltaic device one can observe that the series resistance $R_S$ value will dominate in the voltage source region and the parallel resistance $R_P$ value will dominate in the current source region of operation.

The general equation of a PV cell describes the relationship between current and voltage of the cell.

Since the value of shunt resistance $R_P$ is high compared to value of series resistance $R_S$ the current through the parallel resistance can be neglected. The light generated current of the photovoltaic cell depends linearly on the solar irradiation and is also influenced by the temperature [10] given by the equation (02)

$$I_{pv} = [I_{pv,n} + K_I \Delta_T] \frac{G}{G_n} \qquad (02)$$

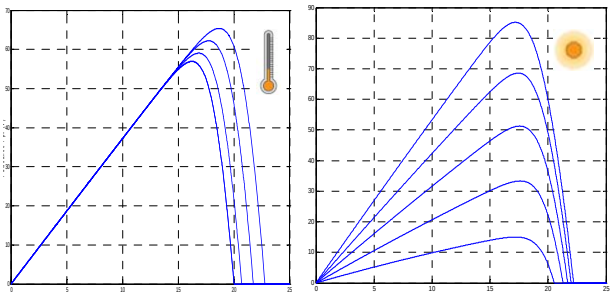
$I_{PV}$= is the light generated current at nominal condition ($25^0$C and 1000 W/ m2)
$\Delta T = T - Tn$
T = actual temperature [K]
$T_n$ = nominal temperature [K]
$K_I$ = current coefficients
G = irradiation on the device surface [W/m2]
$G_n$ = nominal irradiation

The current and voltage coefficients $K_V$ and $K_I$ are included as shown in equation (03) in order to take the saturation current $I_O$ which is strongly dependent on the temperature.

$$I_o = \frac{I_{sc,n} + K_I \Delta_T}{e^{\left(\frac{V_{oc,n} + K_V \Delta_T}{aV_t}\right)} - 1} \qquad (03)$$

$K_V$ = voltage coefficients
$K_I$ = current coefficients

Fig. 3(a) and Fig. 3(b) give the power voltage (P-V) characteristics of a PV module for different values of solar radiation and temperature. The short circuit current is clearly inverse dependence to the temperature; an increase in temperature causes a reduction of the open-circuit voltage (when sufficiently high) and also more maximum output power.



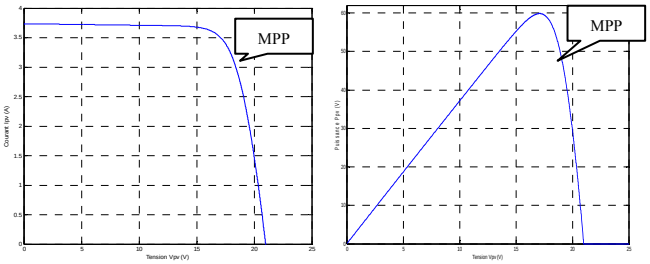
(a) (b)

Fig.3. Simulated waveforms showing the effect of
(a) Irradiation and (b) temperature on P-V characteristics.

The manufacturer's data at standard conditions are given as $P_{max}$ = 80W, $I_{max}$ = 4.515 A and $V_{max}$ = 21.6V. The simulation results obtained were: $P_{max}$ = 78.51W, $I_{max}$ = 4.35 A and $V_{max}$ = 18.2 V. [4-8]

Simulated I-V, P-V characteristics for the maximum power point tracking (MPPT) is shown in Fig.4.

At this Maximum Power Point (MPP), the solar array is matched to its load and when operated at this point the array will yield the maximum power output. From Fig. 4 (a) & (b), it is observed that the power output has an almost linear relationship with array voltage unit, hence the MPP is attained. Any further increase in voltage results in power reduction. [5]




*(a)* *(b)*

Fig.4. PV array simulated curves
I-V curve (25°C) and (b) P-V curve (1000w/m2).

## III. DC – DC BOOST CONVERTER

A dual stage power electronic system comprising a boost type dc-dc converter and an inverter is used to feed the power generated by the PV array to the load. To maintain the load voltage constant a DC-DC step up converter is introduced between the PV array and the inverter. The block schematic of the proposed scheme is shown in Fig.5.

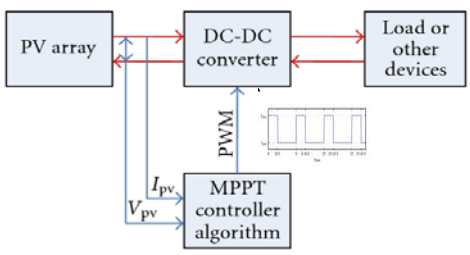



Fig. 5 A MPPT Controllers in a PV System

In this scheme a PV array feeds DC-DC converter used in step-up configuration.. For a dc-dc boost converter, by using the averaging concept, the input–output voltage relationship for continuous conduction mode is given by

$$\frac{V_o}{V_{in}} = \frac{1}{(1-D)} \tag{04}$$

Where, D = duty cycle. Since the duty ratio "D" is between 0 and 1 the output voltage must be higher than the input voltage in magnitude. [2-3]

## IV. Adaptive Neuro-Fuzzy MPPT Controller

### A. *Adaptive neuro-fuzzy principle*

A typical architecture of an ANFIS is shown in Fig. 6, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we consider two inputs x, y and one output z. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules can be expressed as:

Rule 1: if x is $A_1$ and y is $B_1$; then $z_1 = p_1 x + q_1 y + r_1$

Rule 2: if x is $A_2$ and y is $B_2$; then $z_2 = p_2 x + q_2 y + r_2$

Where Ai and Bi are the fuzzy sets in the antecedent, and pi, qi and ri are the design parameters that are determined during the training process. As in Fig. 6, the ANFIS consists of five layers:

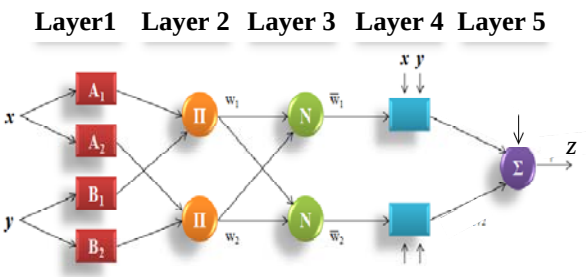



Fig. 6 Architecture of ANFIS.

**Layer 1:** Every node *i* in the first layer employ a node function given by:

$$\begin{cases} O_i^1 = \mu_{A_i}(x), & \text{i=1,2} \\ O_i^1 = \mu_{B_{i=2}}(x), & \text{i=3,4} \end{cases} \tag{05}$$

Where $\mu_{A_i}$ and $\mu_{B_{i=2}}$ can adopt any fuzzy membership function (MF) [15].

**Layer 2:** Every node in this layer calculates the firing strength of a rule via multiplication

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(x), \qquad \text{i=1,2} \tag{06}$$

**Layer 3:** The *i*-th node in this layer calculates the ratio of the *i*-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \qquad \text{i= 1 ,2} \tag{07}$$

Where $\overline{\omega}_i$ is referred to as the normalized firing strengths.

**Layer 4:** In this layer, every node i has the following function:

$$O_i^4 = \overline{\omega}_i z_i = \overline{\omega}_i (p_i x + q_i y + r_i), \qquad \text{i= 1 ,2} \tag{08}$$

Where $\overline{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. The parameters in this layer are referred to as the consequent parameters[14-16].

**Layer 5:** The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_i^5 = \sum_{i=1}^{2} \overline{\omega}_i z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2}, \qquad \text{i= 1 ,2} \tag{09}$$

The output z in Fig. 3 can be rewritten as [7- 9]:

$$z = (\overline{\omega}_1 x) p_1 + (\overline{\omega}_1 y) q_1 + (\overline{\omega}_1) r_1 + (\overline{\omega}_2 x) p_2 + (\overline{\omega}_2 y) q_2 + (\overline{\omega}_2) r_2. \tag{10}$$

### B. *Adaptive neuro-fuzzy controller*

The ANFIS controller generates change in the duty cycle D, based on speed error ( e ) and derivate in the speed error ( de ) defined as:

$$\begin{cases} e = \Delta P \\ de = \dfrac{d\Delta P}{dt} \end{cases}$$

Where ΔP is changes in power

In this study first order Sugeno type fuzzy inference was used for ANFIS and the typical fuzzy rule is:

if e is $A_i$ and de is $B_i$; then $z_1 = f(e, de)$

Where A and B are fuzzy sets in the antecedent and z = f (e,de) is a crisp function in the consequent[13].

The significances of ANFIS structure are:

**Layer 1:** Each adaptive node in this layer generates the membership grades for the input vectors $A_i$ , i =1,…,5. In this paper, the node function is a triangular membership function:

$$O_i^1 = \mu_{A_i}(e), \quad \begin{cases} 0, & e \le a_i \\ \dfrac{e - a_i}{b_i - a_i}, & a_i \le e \le b_i \\ \dfrac{c - e}{c_i - b_i}, & b_i \le e \le c_i \\ 0, & c_i \le e \end{cases}$$

**Layer 2**: The total number of rule is 25 in this layer. Each node output represents the activation level of a rule:

$$O_i^2 = \omega_i = \min\left(\mu_{A_i}(e)\mu_{B_i}(de)\right), \quad \text{i=1,...,5.}$$

**Layer 3:** Fixed node i in this layer calculate the ratio of the i-th rule's activation level to the total of all activation level:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\sum_{j=1}^{n} \omega_j}$$

**Layer 4:** Adaptive node i in this layer calculate the contribution of i-th rule towards the overall output, with the following node function:

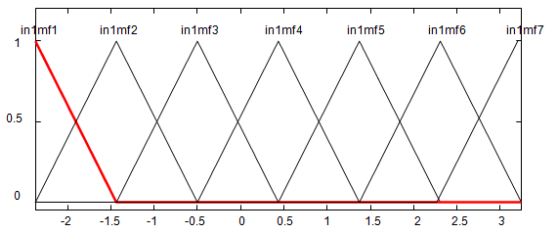
$$O_i^4 = \overline{\omega}_i z_i = \overline{\omega}_i \left( p_i e + q_i de + r_i \right).$$

**Layer 5:** The single fixed node in this layer computes the overall output as the summation of contribution from each rule:

$$O_i^5 = \sum_{i=1}^{2} \overline{\omega}_i z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2},$$

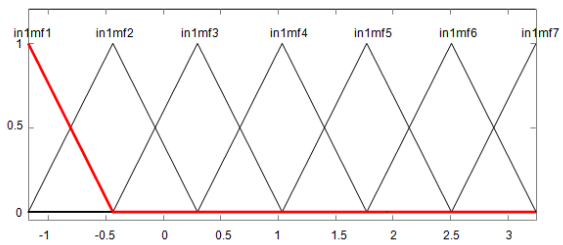
The parameters to be trained are ($a_i$, $b_i$ , and $c_i$ ) of the premise parameters and ($p_i$, $q_i$, and $r_i$ )of the consequent parameters. Training algorithm requires a training set defined between inputs and output [11 - 12]. Although, the input and output pattern set have 150 rows. Fig.7 shows optimized membership function for e and de.

(a)




Membership Functions of the 1st Input Variable 1st (E)

(b)




Membership Functions of the 2nd Input Variable 2nd (ΔE)

Fig. 7 Optimized membership
E
ΔE

The number of epochs was 500 for training. The number of MFs for the input variables e and de is 7 and 7, respectively. The number of rules is then
49 (7*7 = 49).The triangular MF is used for two input variables. It is clear from (15) that the triangular MF is specified by two parameters.
Therefore, the ANFIS used here contains a total of 95 fitting parameters, of which 28 (7* 2 + 7*2 = 28) are the premise parameters and 147 (3* 49 = 147) are the consequent parameters. The training and testing root mean square (RMS) errors obtained from the ANFIS are 4*7 .$10^{-6}$ and 5*3.$10^{-6}$ respectively.

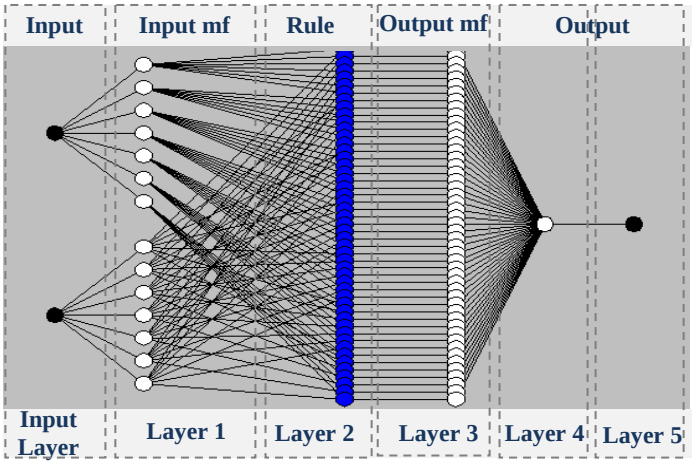


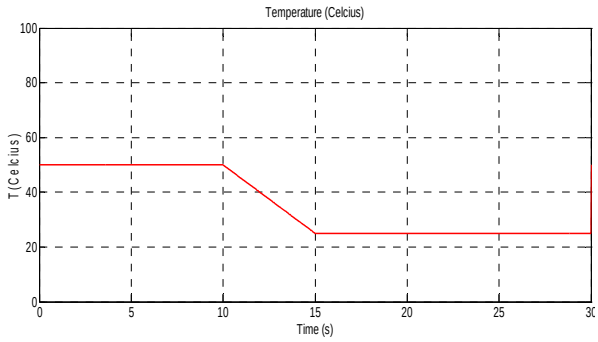

Fig. 8 The graphical representation of ANFIS system two input and one output variable

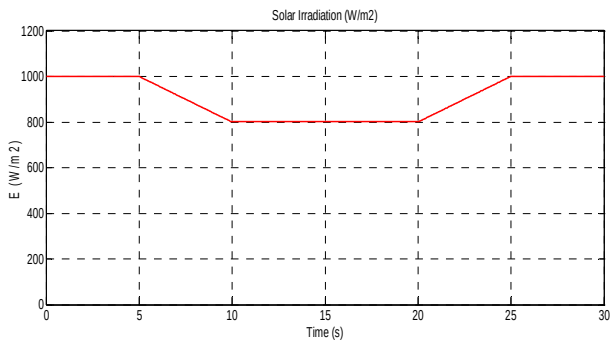
## RESULTS AND DISCUSSION

Simulation of neural fuzzy algorithm as MPPT on PV system is done by providing interference in the form of solar irradiation and temperature changes because these two variables affect PV output voltage and current.

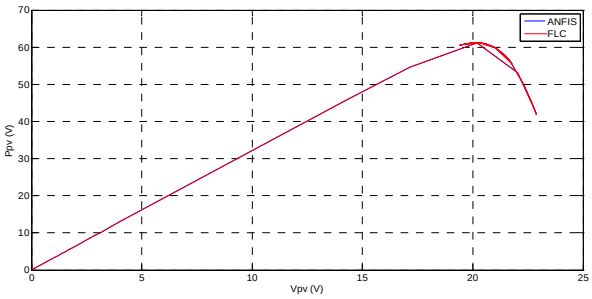
### *A. Solar irradiation and temperature Fixe*

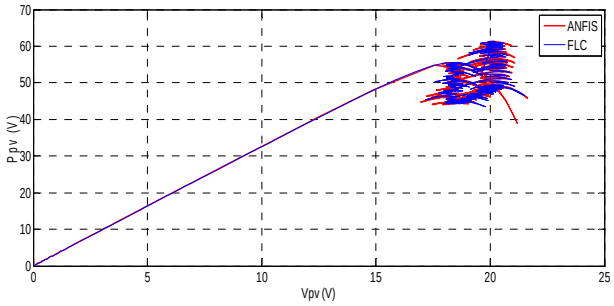
Les figures 10a, 11b, 12c, 13d shows the simulation results of the PV system with a PV Power of 112 W without disturbance at irradiation of 1000W/m2 and temperature of 25°C.
The responce of the system when we use ANFIS control is better than FLC control but with an overshooting in the dynamic response. In the both system of controls produce a maximum power point voltage of 20.17V as shown in Fig. 10a and Fig. 11b corresponding to characteristic P-V and I-V. The outputs of FLC and ANFIS regulators are connected to the boost converter, so they produce a duty cycle as shown in Fig. 13d. At steady state conditions output power reached the value of 112 W.



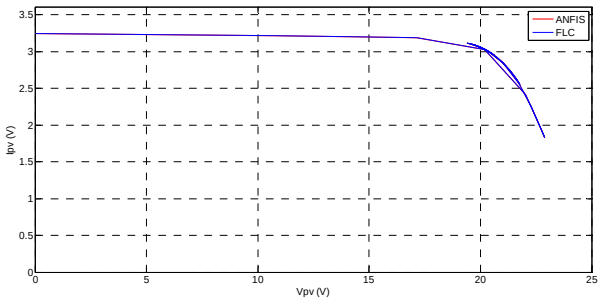



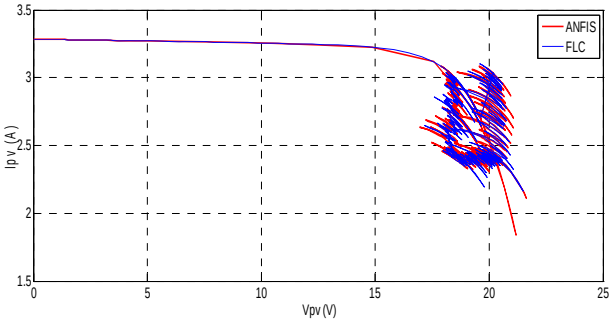

a) Fig.9 Solar irradiation and temperature change e)



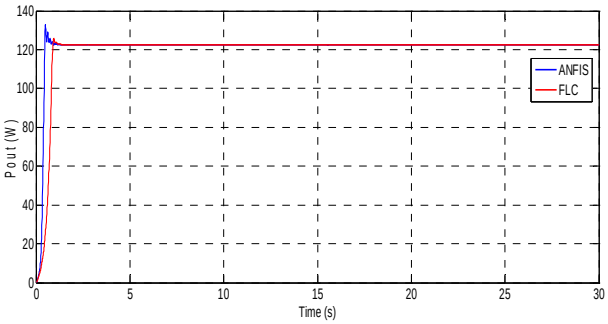



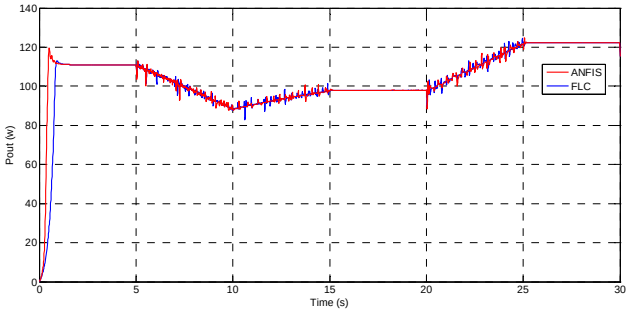

b) Fig.10 MPPT characteristic P-V f)



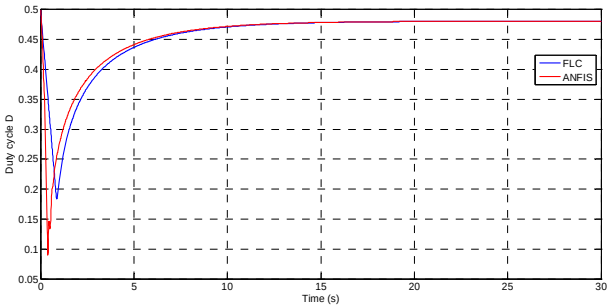




c) Fig.11 MPPT characteristic I-V g)




d) Fig.12 Power (W) output of the boost. h)



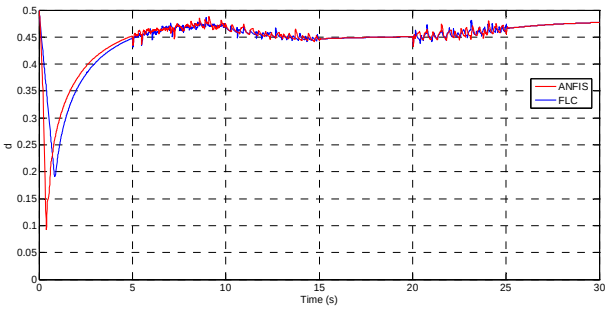




Fig.13 Duty cyle (d)

### B. *Solar irradiation and temperature change*

In this condition the output voltage transient response of buck converter shows the simulation results by giving solar irradiation disturbance. At the initial conditions for solar irradiation of 1000 W/m2 and changes until 800W/m$^2$ in t=5s and in t=25 increased to its initial conditions.

At the initial conditions, the PV temperature of 50$^o$C then decreased at a temperature 25$^o$C with different value of solar irradiation.

From t=5s to t=10s the fixed temperature 50$^o$C and solar irradiation decreased from 1000 W/m$^2$ to 800 W/m$^2$, PV output power of 112 W and will decreases to low value which causes by the decrease of the current in the output of the boost. This suggests that changes in solar irradiation will lead to changes in the PV output current. The two MPPT's controller produces changes in d, as shown in Fig 13h.

From t=10s to t=15s the fixed solar irradiation 800 W/m$^2$ and temperature decreased from 50$^o$C to 25$^o$C, PV output power of 88 W and will increases to high value which causes by the decrease of the current in the output of the boost as shown in Fig 10e,caused by the changing of the value of the duty as shown in Fig 13h . This suggests that a change in PV temperature is inversely proportional to changes in the PV output current.

From t=20s to t=25s the fixed temperature 25$^o$C and solar irradiation increased from 800 W/m$^2$ to 1000 W/m$^2$, PV output power of 98 W and will increases to high value as shown in Fig 12f,,which causes by the increase of the current in the output of the boost as shown in Fig 12g.

The change the value of D is very small as well as the environmental parameters change. This change of D value will affect the converter output voltage that reaches steady at 20.5 V. Because the D value changes only very little then the converter output voltage change is also small as shown in Fig 10a.

## V. CONCLUSION

This paper has presented neural fuzzy for controlling PV system output voltage to operate at maximum power point although happened temperature and irradiation changes. Applications of neural fuzzy controller on MPPT of PV showed a good performance. The system was analyzed and designed, and performance was studied by simulation with Simulink/Matlab. PV system can operate at maximum power point although occur temperature and sun irradiation change that can shift maximum power point.

## REFERENCES


[1] Bimal K. Bose, "Global Warming Energy: Environmental Pollution and the Impact of Power Electronics", IEEE Industrial Electronics Magazine, pp.1-17, March 2010.

[2] M. Masoum, "Design, Construction and Testing of a Voltage-based Maximum Power Point Tracker (VMPPT) for Small Satellite Power Supply", 13th Annual AIAA/USU Conference on Small Satellite.

[3] Cong L. Hou, "Application of Adaptive of Solar Cell Battery Charger", IEEE DRPT2004.

[4] Adedamola Omole, "Analysis, Modelling and Simulation of Optimal Power Tracking of Multiple-Modules of Paralleled Solar Cell Systems", Master of Science Thesis, The Florida State University College of Engineering, 2006.

[5] V. Di Dio, D. La Cascia, R. Miceli, "A Mathematical Model to Determine the Electrical Energy Production in Photovoltaic Fields under Mismatch Effect", Proceedings of the 978(1) IEEE, pp.46-51, August 2009.

[6] Geoff Walker, "Evaluating of MPPT Converter Topologies Using a MATLAB PV Model", the University of Queensland.

[7] A. Saadi and A. Moussi, "Optimation of Buck Boost Converter By MPPT Technique With A Variable Reference Voltage Applied to Photovoltaic Water Pumping System Under Variable Weather Conditions," Asian Journal of Information Technology 6, 2007.

[8] A. Mellit, "An ANFIS-Based Prediction for Monthly Clearness Index and Daily Solar Radiation: Application for sizing of a Stand-Alone Photovoltaic System", Journal of Physical Science, Vol. 18(2), pp.15–35, 2007.

[9] N. Patcharaprakiti and S. Premrudeepreechacharn, "Maximum PowerPoint Tracking Using Adaptive Fuzzy Logic Control for Grid connected Photovoltaic System", PESW2002, volume 1, PP:372-377, 002.

[10] Marcelo Gradella Villalva, Jonas Rafael Gazoli, and Ernesto Ruppert Filho , "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays", IEEE Transactions on Power Electronics, vol 24, no. 5, 2009, pp 1198-1208.

[11] N. Femia, "Optimizing Duty-cycle Perturbation of P&O MPPT Technique", 2004 35th Annual IEEE Power Electronics Specialists Conference.

[12] Jain, S.K.; Agrawal, P.; Gupta, H.O.; "Fuzzy logic controlled shunt active power filter for power quality improvement" IEE Proceedings- Electric Power Applications, Volume 149, Issue5, Sept.2002 Page(s):317 -328.

[13] Fabio Lima, Walter Kaiser, Ivan Nunes da Silvay, Azauri Albano de Oliveira Juniory; "speed neuro-fuzzy estimator for indirect flux oriented induction motor control" XVIII Congresso Brasileiro de Automática / 12 a 16-setembro-2010, Bonito-MS.

[14] Kalika S., L. Rajaji, Subhash Gupta Gupta, H.O.; "Intelligent Technique Based Modeling for PVPS" International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 6, December 2012.

[15] T.R. Sumithira, A. Nirmal Kumar, R. Ramesh Kumar "An adaptive neuro-fuzzy inference system (ANFIS) based Prediction of Solar Radiation:A Case study" Journal of Applied Sciences Research, 8(1): 346-351, 2012 ISSN 1819-544X.

[16] Samira DIB, Brahim FERDI, Chellali BENACHAIBA "Adaptive Neuro-Fuzzy Inference System based DVR Controller Design" Leonardo Electronic Journal of Practices and Technologies ISSN 1583-1078 , Issue 18, January-June 2011.