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Optimal Maximum Power Point Tracking of PV Systems based Genetic-ANFIS Hybrid Algorithm

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Abstract—The maximum power point tracking (MPPT) technique in the photovoltaic (PV) system is used to achieve maximum power from the solar PV system. In this context, three MPPT techniques, artificial neural network (ANN), fuzzy logic control (FLC) and adaptive neuro-fuzzy inference system (ANFIS), are implemented and their performance is investigated in terms of efficiency and response. And they are developed in MATLAB/Simulink environment. This system is developed by combining the models of established solar module and DC-DC boost converter with the genetic algorithm for the three techniques. So this paper presents a new approach based on the genetic algorithm used to perform a constrained tuning technique for the PID parameters to optimize the power output of solar panel. The dynamic model is used to design the controller parameters of the conventional PID controller. The dynamics of the DC-DC converter is non linear. Therefore, it is hard to derive desirable performance. Hence, Genetic algorithm is used to optimize the control parameters of the boost converter. In order to obtain the fitness of an individual, Simulink model of the boost converter is designed and the genetic algorithm is programmed to search for the optimal control parameters by the MATLAB built ingatool. The system is simulated under different climate conditions and MPPT algorithms. According to the comparisons of the simulation results, it can be observed that the photovoltaic simulation system can track the maximum power accurately using the three MPPT algorithms discussed. Therefore, the interest is generated to design a more effective and efficient MPPT to achieve maximum power transfer to the load.

Index Terms— Adaptive neuro-fuzzy (ANFIS), Fuzzy logic (FLC), Genetic algorithm (GA- PID) controller, Maximum power point tracking (MPPT) of PV system,Neural network (NN).

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1 INTRODUCTION

Due to growing the global energy demand, the consumption of electrical energy is continuously increasing all over the world. The energy generation is mostly dependent on fossil fuels causing the increase of greenhouse emissions.So; RECENTLY, energy generated from clean, efficient, andenvironmentally friendly sources has become one of the majorchallenges forengineers and scientists. Renewable energy sources are wind turbine (WT), solar PV system, Bio fuel cell (FC), Biomass and mini hydro power generation etc. Now-a-days, renewable energy sources are more popular due to various advantages such as, pollution free, easy availability and economic [1]. Among all renewable energy sources, solar power systems attract more attention because they provide excellent opportunity to generate electricity as it is an everlasting, clean renewable energy source and has no potential damage to the environment. But the efficiency of solar cells depends on many factors such as temperature, insolation, spectral characteristics of sunlight, dirt, shadow, and so on. Changes in insolation on panels due to fast climatic changes such as cloudy weather and increase in ambient temperature can reduce the photovoltaic (PV) array output power. However, due to its low energy conversion efficiency, many researchers have been focusing to minimize these drawbacks and increase the PV system efficiency [2]. This method is commonly named as a maximum power point tracking (MPPT) technique. The main function of MPPT technique is to achieve maximum power from a PV system [3]. There is a large number of algorithms that are able to track MPP of a PV module have been proposed to solve the problem of efficiency. The most common methods are the perturb and observe (P&O) and the incremental conductance (InCond). The first method is popular due to its hardware simplicity [4]. The second InCond method has a great accuracy with good flexibility to rapidly varying climatic conditions. But both methods have drawbacks and need enhancements to be more accurate [5]. Nowadays, intelligent systems are progressively used such as neural network and fuzzy logic MPPT techniques [6]. Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC) and adaptive MPPT controllers-based neuro-fuzzy inference system (ANFIS) based techniques are implemented [7]. Comparative analysis is discussed among the three different advanced MPPT techniques. Genetic Algorithms (GA) are promising methods for solving difficult technological problems, and for machine learning. In this paper genetic algorithm is used to calculate the optimal control parameters of PID controller of the boost converter [8]. The proposed models show how the GA enhances the model performance when combined with the previous three advanced algorithms. The purpose of this paper is to study and compare advantages, shortcomings and execution efficiency for three power-feedback type MPPT methods, including (ANN), (FLC) and (ANFIS) methods without and with GA-PID controller. Matlab/Simulink is used in this paper to implement the modeling and simulations tasks, and to compare execution efficiency and accuracy for the selected MPPT methods.

This paper is organized as follows. Section 1 is the introduction which includes the background of renewable energy and the purpose of this paper. Section 2 views the propsed system configuration. Sections 3 and 4 illustrate basic operation principles, advantages and shortcomings for ANN, FLC, Anfis and GA methods respectively. Section 5 is the simulation, analysis and conclusion discussion for the three MPPT algorithms without and with GA-PID. The summary and conclusion are given in Section 6.

2 System Description

The proposed system is divided into four major parts (a) The Solar PV system (b) Power electronics DC-DC boost converter (c) MPPT techniques (i) Artificial neural network (ii) Fuzzy logic controller (iii) adaptive neuro-fuzzy inference system. (d) Genetic Algorithm based PID controller. The schematic diagram of the complete system is shown in Fig.1.

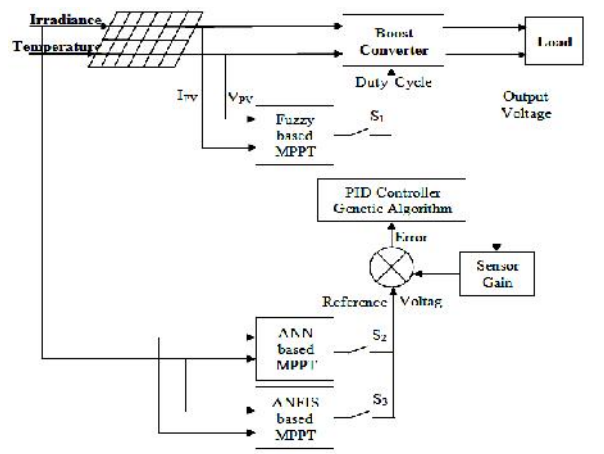

Fig. 1. System configuration diagram.

2.1 Photovoltaic Cell Modeling

An ideal solar cell can be modeled as a current source as the solar cell produces current proportional to the solar irradiation falling on it. The practical behavior of a cell is deviated from ideal due to the optical and the electrical losses, so appropriate components should be added with ideal current source. The electrical circuit representing a solar cell is shown in Fig.2. The optical loss is represented by the current source itself, where thegenerated current I is proportional to the light input. The recombination losses are represented by the diode connected parallel to the current source, but in the reverse direction. The ohmic losses in the cell occur due to the series and shunt resistance denoted by Rs and Rsh respectively [1]. The voltage-current characteristic equation of a solar cell is given in (1).

$$I = I_{ph} - I_s \exp((V + IR_s)/(KT_c A)) - (V + IR_s)/R_{sh} \qquad (1)$$

Where I_{ph} is a light-generated current or photocurrent, I_s is the cell saturation of dark current, q= ($1.6*10^{-19}$C) is an electron charge, k= ($1.38*10^{-23}$ J/k) is a Boltzmann's constant, Tc is the cell's working temperature, A is an ideality factor, R_{sh} is a shunt resistance, and R_s is a series resistance.

2.2 Boost Converter Design

The maximum power point tracking is basically a load matching problem. In order to change the input resistance of the panel to match the load resistance, a DC-DC converter is required (by varying its duty cycle). The boost converter is capable of producing a dc output voltage (Vo) greater in magnitude than the dc input voltage (Vs). The circuit topology for a boost converter is as shown in Fig.3. The conversion ratio is given in (2).

$$V_o/V_{pv} = I_{pv}/I_o = 1/(1-d) \qquad (2)$$

Where I_{pv} is the input current of the converter, duty cycle d = Ton /T and T=Ton+Toff , with its range $(0 \le d \le 1)$. Knowing the V_{pv} and I_{pv}, we can find the input resistance $R_{in}$of the converter. This is given by (3).

$$R_{in} = V_{pv}/I_{pv} = R_o\,(1-d)^2 \qquad (3)$$

Here, R_{in} varies from R_o to 0 and d varies from 0 to 1. The location of the MPP in the I-V curve of PV module is not known beforehand and always changes dynamically depending on irradiance and temperature. Therefore, the MPP needs to be located by tracking algorithm, which is the heart of MPPT controller. The goal of the MPPT is to match the load resistance R_L to the optimal output resistance of PV module R_{opt} defined as in (4).

$$R_{opt} = V_{m,pv}/I_{m,pv} \qquad (4)$$

When R_L matches with that of Ropt (R_{in}= R_{opt}), the maximum power transfer from PV to the load will occur. The MPPT method used in this work, which accommodate the duty cycle of the converter, is done by three main techniques discussed in details in the following sections.

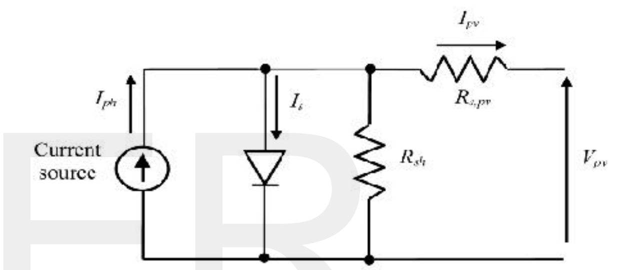

Fig. 2. Equivalent circuit of photovoltaic cell.

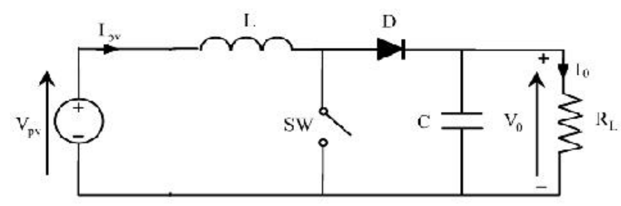

Fig. 3. Boost Converter.

3 MPPT Control Strategies

As mentioned earlier, the maximum power point of the system varies with changing conditions. Therefore, the use of MPPT techniques is mainly essential to extract maximum power of the PV system. In recent years, intelligent methods are adopted because of their reasoning, flexibility and ability to deal with the non-linear and complex system [7]. Hence, in present application artificial neural network, fuzzy logic and adaptive neuro-fuzzy inference system based MPPT techniques are proposed and discussed.

3.1 Neural Network based MPPT Controller

Artificial Neural Network (ANN) is an artificial network that mimics the human biological neural networks behavior, widely used in modeling complex relationships between inputs and outputs in nonlinear systems. ANN can be defined as parallel distributed information processing structure consisting of inputs, and at least one hidden layer and one output layer. These layers have processing elements called neurons interconnected together.

An ANN is developed, such that the current solar irradiance and temperature are its inputs and the voltage, which corresponds to maximum power, output of the array. The detailed ANN structure and data are as follows;

1. **Collecting Data:** The first step in designing an ANN is to collect historical data on the problem that is being solved using the network. In case of MPPT lots of array solar irradiances and temperatures and their corresponding maximum power point voltages are required to in order to train the network.
2. **Selecting Network Structure:** The developed ANN in this thesis is two inputs (solar irradiance and Temperature) with two layers (one hidden layer and one output layer).
3. **Training the Network:** The collected training points are passed into the designed network in order to teach it how to perform when different points than the training points are inserted to it using Matlab.
4. **Testing The Network:** Some of the test points will be applied in order to find out how accurate the developed network is.

At the output stage a reference voltage Vmpp is generated to be used in generating the duty cycle control signal for a DC-DC boost converter which drives the PV voltage to optimal voltage [9].

3.2 Fuzzy Logic based MPPT Controller

Fuzzy logic controllers have the advantages of working with imprecise inputs, no need to have accurate mathematical model, and it can handle the nonlinearity. It consists of two inputs and one output. The two FLC input variables are the error (E), change of error (CE) and output variable is duty cycle (D).

The main parts of a fuzzy logic controller are fuzzification, inference, rule base and defuzzification, are shown in Fig.4.

$$E(k) = (P_{PV}(k) - P_{PV}(k-1))/(V_{PV}(k) - V_{PV}(k-1)) \quad (5)$$

$$CE(k) = E(k) - E(k-1) \quad (6)$$

Where, P_{PV} is the instantaneous power of PV array fuzzy inference is processed using Mamdani's method. Defuzzification uses the center of gravity to process output which is the duty cycle.

$$D = \left(\sum_{j=1}^{n} \text{«}(D_j) - D_j\right) / \sum_{j=1}^{n} \text{«}(D_j) \quad (7)$$

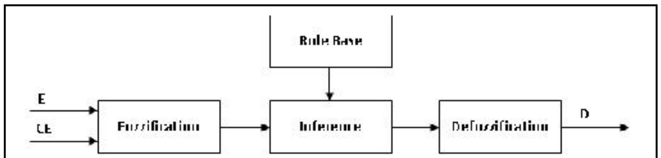

Fig. 4. Block diagram of Fuzzy Controller.

The forty nine fuzzy rule base used in this paper [10], is given in Table.1.

TABLE 1
FUZZY RULE BASE

E/CE	NB	NM	NS	ZE	PS	PM	PB
NB	ZE	ZE	ZE	NB	NB	NB	NM
NM	ZE	ZE	ZE	NS	NM	NM	NM
NS	NS	ZE	ZE	ZE	NS	NS	NS
ZE	NM	NS	ZE	ZE	ZE	PS	PM
PS	PS	PM	PM	PS	ZE	ZE	ZE
PM	PM	PM	PM	ZE	ZE	ZE	ZE
PB	PB	PB	PB	ZE	ZE	ZE	ZE

3.3 ANFIS based MPPT Controller

3.3.1 Adaptive neuro-fuzzy principle:

ANFIS is the hybrid system which combines two methods between neural network and FL. Among many FIS models, the Sugeno fuzzy model is the most widely applied one. 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 $z_2 = p_2 x + q_2 y + r_2$
The ANFIS consists of five layers:

1. **Layer 1:** Every node i in the first layer employ a node function given by (8).

$$\begin{cases} O_i^1 = \text{«}_{A_i}(x), \ldots i = 1,2 \\ O_i^1 = \text{«}_{B_{i=2}}(x), \ldots i = 3,4 \end{cases} \quad (8)$$

Where «_{A_i} and $\text{«}_{B_{i=2}}$ can adopt any fuzzy membership function (MF) [11].

2. **Layer 2:** The function of node is multiplied with every input. The output layer declares degree every fuzzy rule (firing strength μ_i). Equation in the second layer is as follows;

$$O_i^2 = \mu_i = \text{«}_{A_i}(x)\text{«}_{B_i}(x), \qquad i = 1,2 \quad (9)$$

3. **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 (normalized firing strengths $\bar{\omega}_i$).

$$O_i^3 = \overline{\mu_i} = \mu_1/(\mu_1 + \mu_2), \qquad i = 1,2 \quad (10)$$

4. **Layer 4:** In this layer, every node is adaptive node. Every node is multiplied with p, q, r parameter (Consequentparameters(p_i, q_i, r_i) [11].

$$O_i^4 = \overline{\mu_i} z_i = \overline{\mu_i}(p_i x + q_i y + r_i) \quad (11)$$

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

$$O_i^5 = \sum_{i=1}^{2} \overline{\mu_i} z_i = \sum \mu_i z_i / \sum \mu_i \quad (12)$$

The output z in Fig. 5 can be rewritten as:

$$z = \overline{(\mu_1 x)}\, p_1 + \overline{(\mu_1 y)}\, q_1 + \overline{(\mu_1)}\, r_1 + \overline{(\mu_2 x)}\, p_2 + \overline{(\mu_2 y)}\, q_2 + \overline{(\mu_2)}\, r_2 \qquad (13)$$

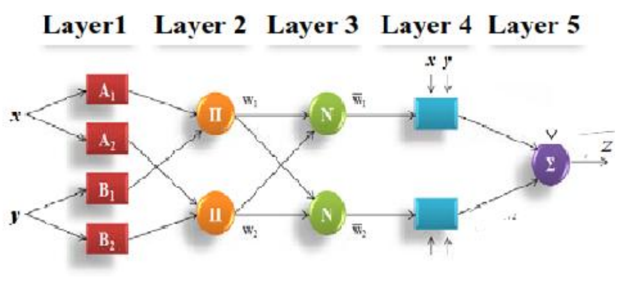

Fig. 5. Architecture of ANFIS.

3.3.2 Adaptive neuro-fuzzy controller:

Design of MPPT control using ANFIS, to obtain MPP can be achieved with modification of duty cycle based on changing E(k) and CE(k) in (5) and (6). FL with 2 input and 1 output, algorithm is trained by ANFIS to track a fuzzy rule. A typical rule in ANFIS is given as follows

Rule i: if E(k) is U_{i1} and CE(k) is U_{i2} then $D_i=y_{i1}u_1+y_{i2}u_2+y_{i3}$

Where,

Di is duty cycle changing

Uij is membership function

4 GA BASED PID CONTROLLER

4.1 Genetic algorithm concept:

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that use a performance criterion for evaluation and a population of possible solutions tothe search for a global optimum.The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. We can apply the genetic algorithm to solve a variety of difficult optimization problems.

The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

Selection. This operator selects the individuals, called parents, which contribute to the population at the next generation. The fitter the individual, the more times it is likely to be selected to reproduce.

Crossover. This operator randomly combines two parents to form children for the next generation.

Mutation. This operator randomly applies changes to individual parents to form children.

The process of GA follows this pattern [8].

1. Create an initial population (usually randomly generated string).
2. Evaluate all of the individuals (apply some function or formula to the individuals).
3. Select a new population from the old population based on the fitness of the individuals as given by the evaluation function.
4. Apply some genetic operators (mutation & crossover) to members of the population to create new solutions.
5. Evaluate these newly created individuals.
6. Repeat steps 3,4,5 and 6 (one generation) until the termination criteria has been satisfied (usually perform for a certain fixed number of generations).

The concept of implementation sequence is the survival of the fittest. The reproductive success of a solution is directly tied to the fitness value, which is assign during evaluation. The least fit solution may not reproduce at all. The major advantage of GA lies in their computational simplicity, and their powerful search ability to obtain the global optimum. The further attraction of GA is that they are extremely robust with respect to complexity of the problem.A simple GA flow chart is shown in Fig.6.

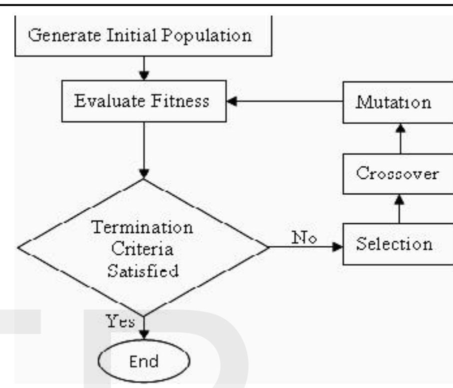

Fig. 6. Flow chart of Genetic algorithm.

4.2 Genetic algorithm concept:

Fitness functions used in genetic PID controllers are basically depending on the error between the actual and reference predicted solutions. However, better solutions are achieved according to decreasing the error signal.

The goal is to solve some optimization problem where we search for an optimal solution in terms of the variables of the problem (Kp, Ki and Kd). To minimize F is equivalent to getting a minimum fitness value in the error signal. A suitable fitness function for each set of individuals, in this case, and used in the proposed model expressed by (14).

$$f(t) = \frac{1}{T}\int_0^t e^2(t)\,dt \qquad (14)$$

The GA parameters' values used in Matlab/simulink gatool,are as in the following Table 2.

TABLE 2

GENETIC ALGORITHM PARAMETERS

GA Property	*Value/Method*
Population size	20
Maximum number of generations	20
Fitness Function	MSE
Selection method	Roulette
Crossover method	Arithmetic
Crossover propability	80%
Mutation method	Add/Sub
Mutation propability	0.1%

5 Simulation Results And Discussion

The proposed system was simulated in the MATLAB/Simulink program. The parameters of the developed photovoltaic array are shown in Table 3

TABLE 3

PV Array Parameters at ($T=25^{o}C$ and $R=1kW/m^{2}$)

Description	Parameter
Maximum Power	P_{max}= 40.9081 W
Voltage at Maximum Power	V_{mp}= 17.16 V
Current at Maximum Power	I_{mp}=2.3839 A
Short Circuit Current	I_{SC}= 2.55 A
Open Circuit Voltage	V_{OC}=21.24 V

The output power of the solar PV system depends on solar irradiation and temperature. The typical P-V and V-I characteristics at different irradiation (R) and temperature (T) are shown in Figs. 7(a),7b),7(c) and 7(d).

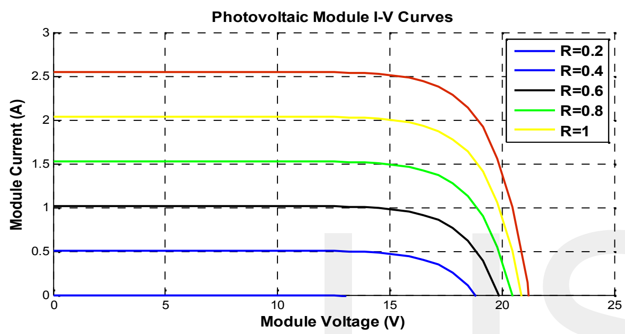

Fig. 7(a). I-V module curves under various radiations and Tac = $25^{o}C$.

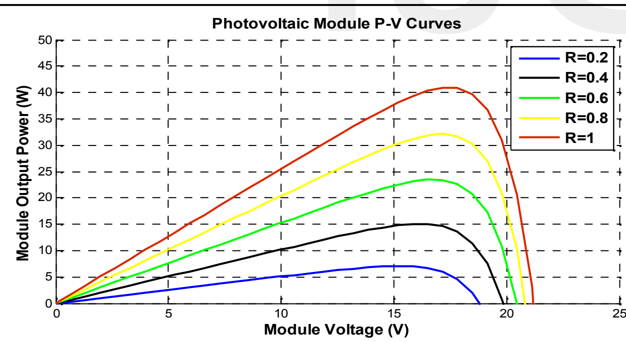

Fig. 7(b). P-V module curves under various radiations and Tac = $25^{o}C$.

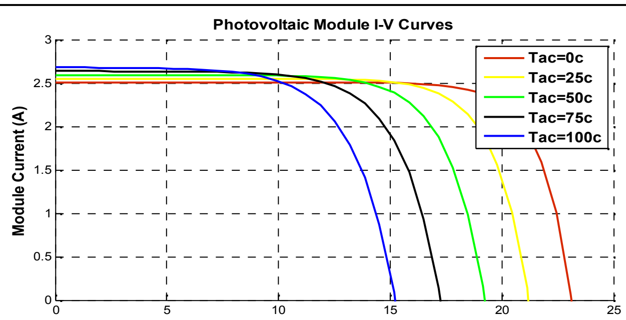

Fig. 7(c). I-V module curves under various temperatures and R =1 kW/m^{2}.

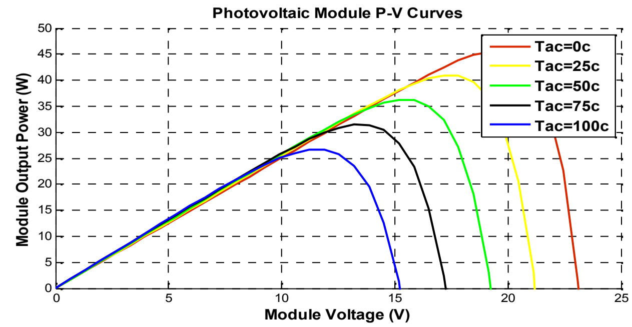

Fig. 7(d). P-V module curves under various temperatures and R =1 kW/m^{2}.

5.1 Neural Network based MPPT Controller

In design procedure of ANN based MPPT controller, solar radiation (R) and ambient temperature (T) are considered as inputs. A data set is provided for training of the network using NNET tool box in Matlab using (trainlm) as training function, (tansig) function transfer for the hidden layer and (purelin) transfer function for the output layer. Once a neural network is trained, then it can be used to accurately measure optimal voltage for the system at any random set of data which is not used for training.

5.2 Fuzzy Logic based MPPT Controller

For the fuzzy logic controller designing, the inputs are error (E) and change of error (CE) in parameters (voltage and current) of the solar PV system and output is the duty cycle. This generated duty cycle (D) targets the DC-DC converter to the optimal voltage. The membership functions for both inputs and output are shown in Figs. 8(a), 8(b) and 8(c).

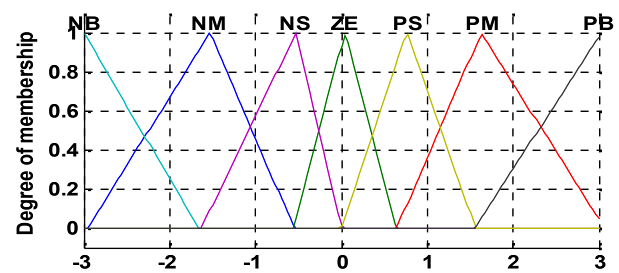

Fig. 8(a). Input 1(change in error)

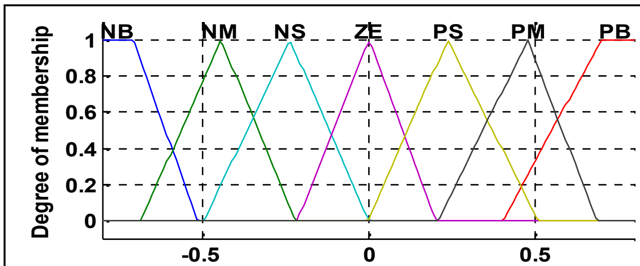

Fig. 8(b). Input 2(error)

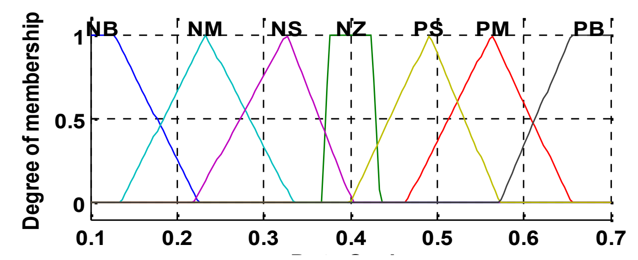

Fig. 8(c). Output (duty cycle)

5.3 ANFIS based MPPT Controller

Using the Simulink model of PV module, the operating solar irradiances is varied from 10 W/m² to 1100 W/m² and temperature varied from 10ºC to 74ºC, to get the training data sets for ANFIS. Totally 363 training data sets are used to the training data and the checking data. The ANFIS constructs a FL whose membership function parameters are tuned using hybrid method. The structure of ANFIS consists of a five layers. There are two inputs (temperature and irradiance), one output and three membership function which are learned by ANFIS.

In order to study the dynamic response of ANN, FLC and ANFIS, the designed MPPT techniques, the predefined varying irradiation and fixed ambient temperature (25°C) are considered as input to the PV array. As seen in Fig. 9 (a), the solar irradiation varies in the range of 500 W/m² to 1000 W/m². The comparison of output voltage and power of the three MPPT techniques are shown in Figs.9 (b) and 9(c). The obtained results show that the performance and efficiency of the ANN and ANFIS are better in comparison of FLC based MPPT techniques.Also ANFIS and ANN appeared to be identical but there is different which cleared by calculations. The tracking efficiency of each method is calculated in Table 4.

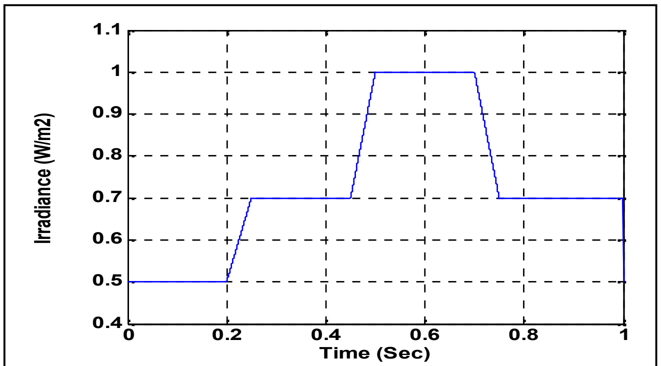

Fig.9(a). The system input.

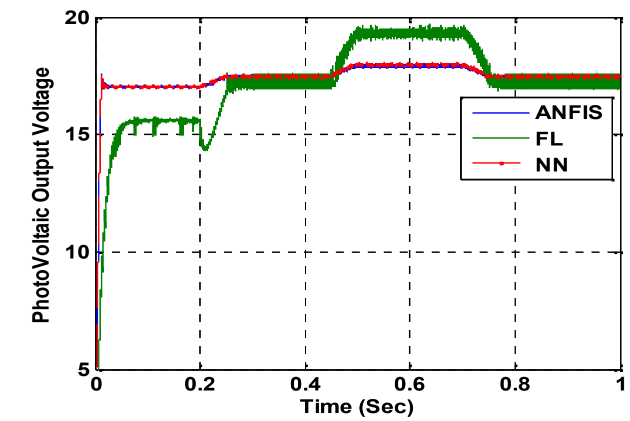

Fig. 9(b). The PhotoVoltaic Output Voltage

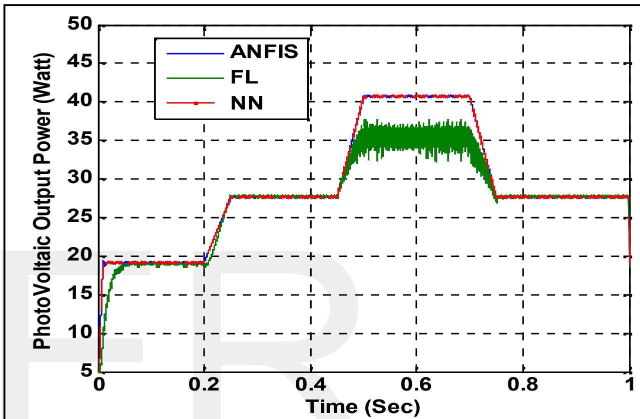

Fig. 9(c). The PhotoVoltaic Output Power

5.4 ANFIS based MPPT Controller withGA based PID controller

The output voltage and power resulted after GA based PID controller has included in the proposed model, are shown in Figs.10(a), 10(b). The obtained results show that the performance and efficiency of the ANFIS is much better after using GA in determining the PID variables shown in Table 5.Also tracking efficiency of the combined ANFIS with GA based PID controller, is tabulated in Table 4.

TABLE 4

TRACKING EFFICIENCY OF MPPTS

Irradiation (W/m^2)		500 W/m^2	700 W/m^2	1000 W/m^2
P_{max}		19.29	27.79	40.91
NN	P_{avg}	19.07	27.54	40.59
	η_{pv}(%)	98.86%	99.10%	99.22%
FL	P_{avg}	18.74	27.53	35.49
	η_{pv}(%)	97.15%	99.06%	86.75%
ANFIS	P_{avg}	19.18	27.62	40.72
	η_{pv}(%)	99.43%	99.39%	99.34%
ANFIS + GA	P_{avg}	19.28	27.78	40.90
	η_{pv}(%)	99.99%	99.99%	99.99%

TABLE 5

PID VARIABLES DETERMINED BY GA

K_P	K_I	K_D
0.815	0.913	0.278

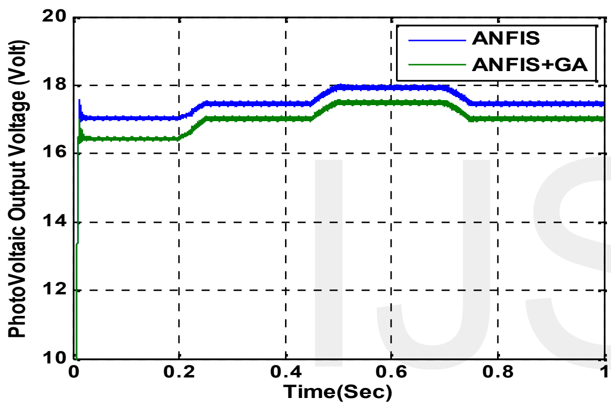

Fig. 10(a) ThePhotoVoltaic Output Voltage (ANFIS+GA)

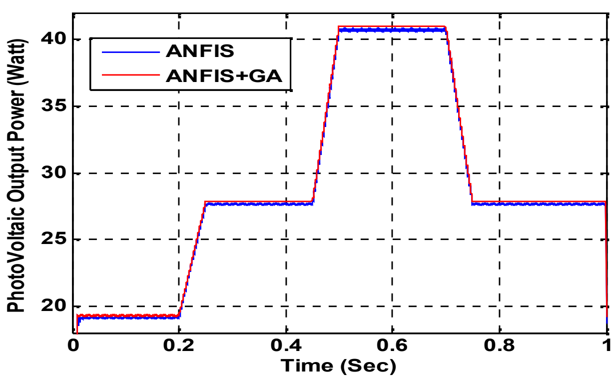

Fig. 10(b) ThePhotoVoltaic Output Power (ANFIS+GA)

6 CONCLUSION

In this paper, an adaptive neuro-fuzzy inference system ispro-posed for the maximum power point tracking under varying irradiance and temperature conditions. The results are obtained from ANFIS based MPPT method shows better performances and robustness compared to FL and ANN under varying irradiance conditions. The ANFIS combined with PID controller improvesthe tracking almost to ideality 100%. GA is very effective tool that solve difficult and nonlinear problems in very easy and simple way. PID parameters determined so faster, easier and more accurate than the conventional methods.

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