



## Implementation and Evaluation of Maximum Power Point Tracking (MPPT) Based on Adaptive Neuro-Fuzzy Inference System for Photovoltaic PV System

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**Abstract** – The conversion of energy of sunlight into electricity is done using photovoltaic (PV) cells. This paper introduces, comparing, analyzing and evaluating the performance of the PV systems which are operating with MPPTs that work by adaptive neuro fuzzy inference system (ANFIS) technique with other MPPT algorithms such as Perturb and Observe (P&O) algorithm, Fuzzy Logic Control (FLC) algorithm and Artificial Neural Network (ANN) algorithm. These algorithms work to control the duty cycle (D) of the pulse signal that goes to the switch of the DC-DC converter for maximizing the power generated by the solar panel. The paper also introduces simulating and modeling a general PV panel with some adjustable parameters for modelling any real PV model using its electrical data sheet. In addition, the work tests the model for the influence of changing in operation solar irradiation and operation temperature on I-V and P-V curves. MPPT algorithms are implemented using boost DC-DC converter with constant resistive load. All systems are analyzed and simulated by using MATLAB-Simulink program. Simulation results show that the ANFIS and ANN based MPPT method gives faster response to archive the MPP and is more efficient than FLC MPPT and the P&O MPPT methods.

**Keywords** – Photovoltaic cell, maximum power point tracking, fuzzy logic control, artificial neural network, adaptive neuro-fuzzy inference system

### 1. Introduction

Renewable energy systems such as wind, sea waves and solar energy systems has been improving rapidly over the last few years and robust studies are maintained in this respect by researchers. Nowadays, solar energy is considered as one of the most reliable, daily available, free and environment friendly source of renewable energy when compared to other traditional energy sources such as coal, gas and nuclear oil which have negative effects on the environment that result in climate change [1,2]. Solar energy is one of the most common renewable energy sources that has been gaining increased world interest in recent years [3,4]. The conversion of solar radiation power to electrical power is done by a semiconductor device that is called Photovoltaic (PV) and the device produces electricity with direct electricity generation method. However, PV source is a non-linear source and the conversion efficiency is between 10% to 25% of the total power, moreover it is effected by the operation temperature ( $C^{\circ}$ ) and solar radiation ( $Kw/m^2$ ) [5]. Therefore, for maximum operating efficiency, it is necessary to use a maximum power point tracking (MPPT) algorithm to deliver possible available PV output power to the load at different operating points. MPPT is a power electronic device that contains DC-to-DC converter that includes controller work and one of MPPT algorithms. As seen in literature, various MPPT algorithms have been developed and many studies have been carried out to optimize these various MPPT techniques [6, 7].

With this technique, the system will force the PV cells to operate at its maximum power point (MPP). A MPPT such as the widely used Perturb and Observe algorithm (P&O) which is a conventional algorithm that tracks the MPP with constant step of duty cycle. The time response to reach the MPP depends on the value of the duty cycle; if the

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cycle is too small the time response will be large and vice versa. With intelligent control systems such as Fuzzy Logic Control (FLC), Artificial Neural Network (ANN) and the hybrid of the two of them as ANFIS, the performance of the system can be better than the conventional algorithm. ANFIS is an intelligent technique that can be used as intelligent maximum power point tracking control algorithms to optimize the performance of the PV system over the widest range of operating conditions.

The previous MPPT algorithms and ANFIS technique are used in this study for controlling duty cycle of the electronic switch of DC-DC boost converter. The PV system was operated under variable operation conditions to deliver the maximum power to the resistive load. All the simulations are done using MATLAB SIMULINK computer software.

## 2. Photovoltaic Cell

Electrical energy can be obtained directly from sunlight using photovoltaic (PV) devices (cells). The photovoltaic cells convert solar radiation power to electrical power under the photovoltaic effect [8, 9]. Photovoltaic (PV) cells are made from semiconductor materials. Usually the amount of the current for one cell is given in (mA) and the voltage is around 0.6 V. Cells are connected in series and parallel to obtain the desired voltage and power [3].

### 2.1. Equivalent circuit of PV cell

The equivalent circuit of a solar cell can be categorized as p-n semiconductor junction, when exposed by the light, the DC current is generated in the terminal of the cell [10]. The equivalent electrical circuit which can represent the complex physics of a PV cell, is shown in Figure 1.

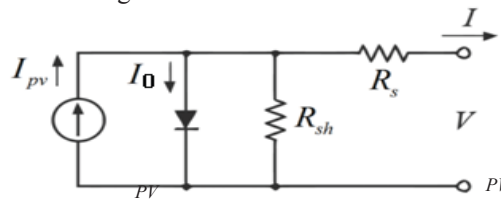


Figure 1. Equivalent circuit of PV cell

Output current characteristic is expressed with the following equations:

$$I_{pv} = I_{ph} - I_0 * \left[ e^{\left( \frac{V_{pv} + I_{pv} * R_s}{A * k * T_{ak}} \right)} - 1 \right] - \left( \frac{V_{pv} + I_{pv} * R_s}{R_{sh}} \right) \quad (1)$$

$$I_{ph} = I_{scr} + K_i * (T_{ak} - T_{rk}) * G \quad (2)$$

$$I_0 = I_{rs} * \left( \frac{T_{ak}}{T_{rk}} \right)^3 * e^{\left[ \left( \frac{q * E_g}{A * k} \right) + \left( \frac{1}{T_{ak}} - \frac{1}{T_{rk}} \right) \right]} \quad (3)$$

And for the large arrays modeling of  $N_s \times N_p$  series and parallel cells the equation becomes:

$$I_{pv} = I_{ph} * N_p - I_0 * N_p * \left( e^{\left( \frac{q(V_{pv} + I_{pv} * R_s)}{N_s * k * A * T_{ak}} \right)} - 1 \right) - \frac{V_{pv} * N_p + I_{pv} * R_s}{R_p} \quad (4)$$

where:

$T_{rk}$ : The reference temperature = 298 K.

$I_{ph}$ : The light generated current (A).

$A$ : Ideality factor = 1.6.

$q$ : Electron charge =  $1.6 \times 10^{-19}$  C.

- $I_{scr}$ : The PV module short-circuit current.
- $K_t$ : The short-circuit current temperature Coefficient.
- $E_g$ : The band gap for silicon = 1.1 eV.
- $V_{pv}$ : The open-circuit voltage or the output voltage (V).
- $I_{pv}$ : The output current of the PV module (A).
- $I_{rs}$ : The reverse saturation current (A) at  $T_{rk}$ .
- $k$ : Boltzmann constant =  $1.3805 \times 10^{-23}$  J/K.
- $R_s$ : The series resistance of the PV module.
- $R_p$ : The parallel resistance of PV module.
- $G$ : The PV module illumination ( $W/m^2$ ).
- $N_s$ : The number of cells connected in series.
- $N_p$ : The number of cells connected in parallel.
- $I_o$ : The PV module saturation current.
- $T_{ak}$ : Ambient temperature.

The relationship between the Current–Voltage and the Power–Voltage is used for describing the electrical characteristics of the PV cell and it is depicted as curve. The I-V and P-V curves of the PV cell has the shape shown in Figure 2, and power is obtained for a given radiation level [2].

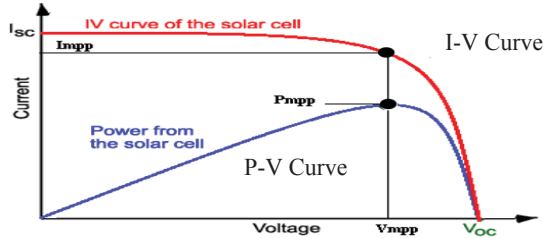


Figure 2. Power curves and maximum power point (MPP) of the PV cell

### 2.2 Temperature and solar radiation affection on PV output

Influence of changing on the operation solar radiation on the output power that when the amount of the radiation increases the short-circuit current (ISC) and open-circuit voltage (VOC) of the solar cell increase. As in the equation (2), the photon current is almost in a linear proportional relationship with irradiance. On the other hand, as the temperature increases, the open-circuit voltage decreases and the short-circuit current increases (Figure 3).

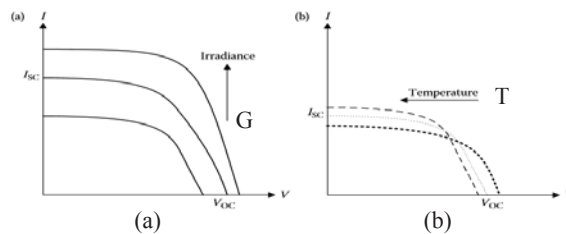


Figure 3. (a) Influence of the ambient irradiance and (b) Influence of the cell temperature on the cell I–V characteristics [3]

A general PV model is simulated in this paper using MATLAB Simulink to show the effects of varying temperature and solar radiation on the I-V and P-V curves. Scientists and researchers have been working to overcome these problems by adding intelligent power electronic systems connected to the PV system in order to force the PV system to run at its MPP.

### 3. Maximum Power Point Tracking

Maximum power point tracking (MPPT) is a technique used for maximizing power extraction from the available power in the PV module under all conditions. For maximizing the PV generated power, a DC-DC converter with MPPT algorithm is used by adjusting the duty cycle (D%) of the pulse signal that goes to the switch of the converter (Figure 4).

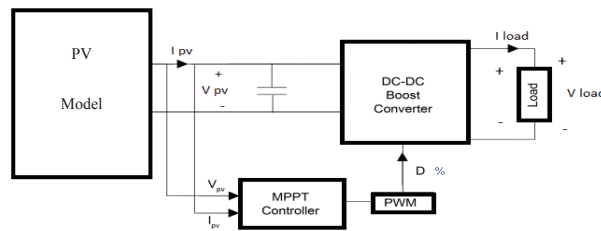


Figure 4. Block diagram of the MPPT with PV system

#### 3.1 MPPT algorithms

The literatures are rich with many type of MPPT techniques based on different algorithms and with varying complexity. Many methods have been developed by researchers to determine MPPT [11, 12, 13,14]. The most popular MPPT method is P&O algorithm which is mostly used for evaluating the performance of the PV system compared to other MPPT algorithms [15]. The algorithms that will be presented in this paper are:

1. Perturb and Observe MPPT algorithm.
2. Fuzzy Logic control based MPPT algorithm.
3. Artificial Neural Network based MPPT algorithm.
4. Neuro Fuzzy interferons system based MPPT algorithm.

##### 3.1.1. Perturb and observe method

The Perturb & Observe (P&O) technique is the most commonly used method of MPPT due to its ease of implementation and simple structures and it is highly competitive against other MPPT methods [13, 14, 16]. The main idea of this method is increasing the duty cycle with initial value ( $\Delta D$ ) mostly 0.01 and observing the power perturbation of the PV. If it is positive, then it runs in right direction and the operating point becomes closer to the MPP. As a result, new value is added to the current value of duty cycle in the same direction. And if the power perturbation of the PV is negative, that means the point of operation is moving away from the MPP. Therefore, the perturbation of the operating current should be reversed by the decrease in the duty cycle [17, 18].

Figure 5 presents the control flow chart of the P&O algorithm. The MPPT control system operates by incrementing or decrementing the solar array voltage periodically [19]. It measures the current and voltage of the PV at current iteration  $k$  and calculate  $P(k)$  as follows:

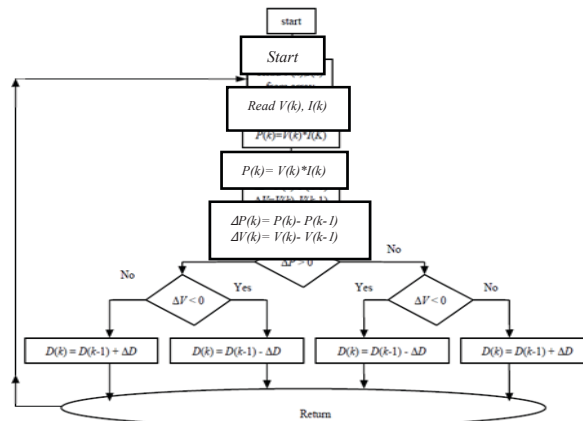


Figure 5. The flowchart of the P&O Algorithm

One of the disadvantages of this algorithm is that the time response depends on the step size of the  $\Delta D$ . if  $\Delta D$  is a large value, the time response becomes fast to reach MPP but the operation point is not actually at MPP due to large perturbation [16].

In addition, if the step size of  $\Delta D$  is a small value, the time response to reach MPP will be slow but the operation point can be very close to actual MPP with small perturbation; see Figure 6(a) which assumes the operation point at point 1 where incising the duty cycle with positive  $\Delta D$  voltage will increase and power the positive perturbation which will be at point 2, close to actual MPP, however, less than that. Therefore, the algorithm will increase the duty cycle with the same value of  $\Delta D$  which in turn will increase the voltage but the operation will move away from the actual MPP at point 3, see Figure 6(b) where the perturbation will be negative then the next step will be back to point 4 and then to point 5 and from point 5 to point 6 and so on. This makes the operation point increasing and decreasing around the actual MPP; see Figure 6(c) where the cycle is reputed while the system is running [20, 21].

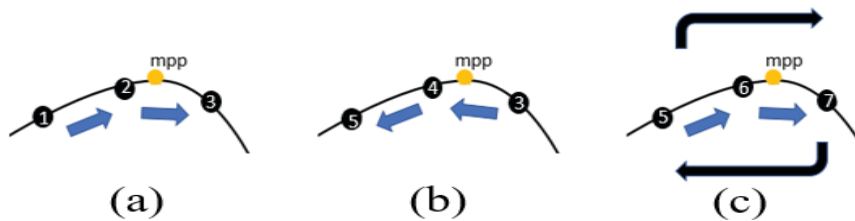


Figure 6. Perturbation of operation point (a) around actual MPP. Positive perturbation (b) Negative perturbation (c) Reputed cycle

### 3.1.2. Fuzzy logic control based MPPT

The Fuzzy Logic system was introduced by professor Lotfi A. Zadeh in 1965. Fuzzy logic is a form of logic used for expressing expert systems and has been applied in many fields from control theory to artificial intelligence applications. Fuzzy logic control system has faster and smoother response than conventional systems with a less control complexity [22]. Fuzzy logic includes a simple, rule-based IF X AND Y THEN Z approach for solving a control problem rather than attempting to model a system mathematically [21]. Fuzzy logic technique includes the following three steps:

1. **Fuzzification** – Convert classical data or crisp input into fuzzy data to Membership Functions (MFs) by using one of the fuzzy sets form mostly triangle fuzzy sets are used, see Figure 7.
2. **Fuzzy Inference Process (Rule)** – Combine membership functions with the control rules to derive the fuzzy output. This process is performed for determining a single MF among the group MFs by using operation on sets And, Or and Not this set has a membership degree. It is easy to build a rule base since it is closer to human languages; IF input high THEN output is low. Take air condition as an example; if it is hot than the fan is fast.

**3. Defuzzification** – After defining the set from rule base, the defined set or sets have membership degrees between 0 to 1 and by putting it in the output fuzzy sets that are defined from rules and by determining all the area under this degree (as seen in Figure 8, the MF degrees are a and b) after that will produce an area in one or two sets. These areas are fuzzy output as it is seen in Figure 8 and by calculating the centroid of the area or center of gravity that converts the fuzzy output to crisp output [23].

MPPT based fuzzy logic takes samples from the output of the PV system current (I) and voltage (V) at time (k) and calculate the result power P(k), with memories the measured previous sample at previous time (k-1) [26]. And it calculates the error E(k) and the change in error ΔE(k) :

$$P(k) = I(k) * V(k). \tag{5}$$

$$P(k-1) = I(k-1) * V(k-1). \tag{6}$$

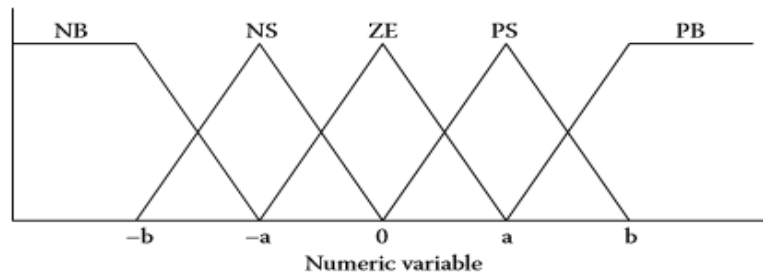
$$\Delta P = P(k) - P(k-1).$$

$$\Delta V = V(k) - V(k-1).$$

$$E(k) = \frac{\Delta P}{\Delta V} \tag{7}$$

$$\Delta E(k) = E(k) - E(k-1) \tag{8}$$

In the fuzzification process, the first step is the controller dose. This process converts the crisp input variables into linguistic variables using the membership functions. Five fuzzy sets with linguistic variable names of: NB (negative big), NS (negative small), ZE (zero), PS (positive small), and PB (positive big) as it is seen in Figure 7. The controller has two inputs and one output. The numeric variables are E(K) and ΔE(K) for inputs and D duty cycle for output. Each input has its membership functions and is same for the output. The value of a and b in the figure are selected by experience for acquiring the best performance [3, 17].



**Figure 7.** Membership function for inputs and outputs of MPPT based FLC

Fuzzy logic controller output diction is ΔD that will be added to current operation; D% increases and decreases with variable step size based on defuzzification process. The rules of the base system of fuzzy logic controller is presented in this table 1 [3].

**Table 1.** Rule base of fuzzy logic controller based MPPT in Table1

$\Delta E(K) \backslash E(K)$	PB	PS	ZE	NS	NB
PB	ZE	ZE	NB	NB	NB
PS	ZE	ZE	NS	NS	NS
ZE	ZE	ZE	ZE	ZE	ZE
NS	PS	PS	PS	ZE	ZE
NB	PB	PB	PB	ZE	ZE

As an example, for a certain control rule from Table 1, if ΔE(K) is PB and E(K) is NS THEN ΔD is NB. This means that if the operating point is far from MPP towards right hand side and the change in E(K) is small, then the controller should decrease the duty ratio largely for reaching MPP. When both the ΔE(K) and E(K) are changing by a small value, it means that the system is close to MPP so a small value will be added to the current D [3].

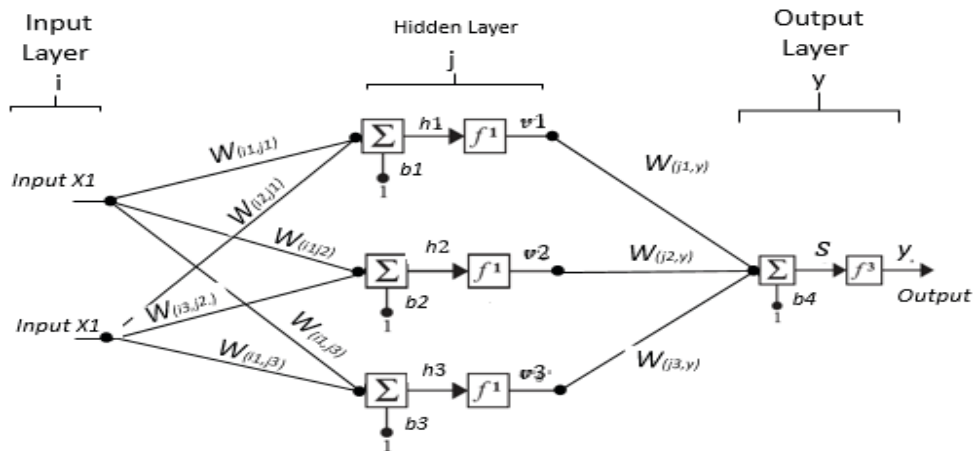
### 3.1.3. Neural networks based MPPT

Another intelligent MPPT control technique is the neural network (NN). Artificial Neural Network (ANN) is an artificial network that mimics the human biological neural system. Networks behavior is widely used in modeling complex relationships between inputs and outputs in linear and nonlinear systems and used for data mapping and function approximation [24, 3].

The network structure of the three layers:

- Input layer: it contains the input features represented by nodes; each node is connected to every single node in the hidden layer and each connection has its weightiness that will be adjusted in the training process.
- Hidden layer: first it takes summation of the multiplication of each input node with connected weights than the output of hidden node is calculated by applying the activation function.
- Output layer: repeats the same process in the hidden layer to get the output. Figure 10 shows these layers.

The structural type of neural network that is used in this paper for building MPPT controller is multi-layer feed forward networks. The inputs of the MPPT controller in the input layer are generally two nodes PV set parameters, such as radiation (G), temperature (T) and one single output node in the output layer which represents the output decision (D). ANN processes these inputs, and determines the adapter operation duty cycle D% as the output resolution. The network must be trained off-line before being used in the system. Figure 8 shows a network that has three-layers where input layer *i* contains two nodes that represent the two inputs ( $x_1, x_2$ ), the hidden layer *j* contains three nodes and one output layer, finally *y* contains one neuron connected to the previous neurons in the hidden layer [25].



**Figure 8.** Three layers of multi-layer feed forward network structure

According to the figure above, the output of the network can be calculated by:

$$h_j = \sum(W_{(i,j)} * x_i + b) \quad (9)$$

where  $W_{(i,j)}$ : the weight of connections between input node *i* and the hidden neuron *j*.

*b* : Bias parameters like the weights usually have constant of 1.

The output of neurons in the hidden layer calculates  $v_j$  by applying the activation function (*f*) sigmoid function is usually used as transfer function.

$$v_j = f(h_j) = \frac{1}{1+e^{-h_j}} \quad (10)$$



The calculation of the hidden neurons' output multiplication summation according to neuron weight by; according to their weights by:

$$S_o = \sum(W_{(j,y)} * v_j) + b_4 \quad (11)$$

Then the output of the network y can be calculated by applying the activation function on s.

$$y = f[v_1 * W_{(j_1,y)} + v_2 * W_{(j_2,y)} + v_3 * W_{(j_3,y)} + b_4] = f(s)$$

Where  $W_{(j,y)}$  weights of the connection between the hidden layer neuron j and the output neuron y

f: Transfer function, usually the sigmoid function is used and it takes the form of:

$$y = f[s_0] = \frac{1}{1+e^{-s_0}} \quad (12)$$

Throughout the training, the connection weights are modified until the best fit is attained for the input–output patterns from the training data set based on the minimum errors that are selected.

#### ❖ Backpropagation Learning Algorithm

Any neural network must learn the tasks first before putting it in the system [25, 26]. The type of learning that is used here is supervised learning algorithm which makes the network learn from examples in the training data. The teach way is by setting and adjusting weights between nodes. The initial weights are usually set at random numbers and then they are adjusted during NN training. Supervisor Backpropagation learning algorithm is used for training the multilayer feed-forward network, it works to decrease the error between the desired and computed unit values. That by propagating the error from the output layer to the input layer. A new set of weights which minimizes the error, is also determined during this process. The general learning procedure in the backpropagation algorithm is achieved by following the steps and equations below:

1. Calculate the summation of the node in the hidden layer of the feed-forward ANNs in the figure using Eqn (9).
2. Apply activation function to get output of the hidden neuron using Eqn (10).
3. Calculate Summation of the node in the output layer by using Eqn (11).
4. Apply activation function to get output y of the output neuron by using Eqn (11).
5. Then compute the cost function which is the mean square error in the output.

$$E = \frac{1}{2} \sum (y^d - y)^2 \quad (13)$$

Where  $y^d$ : is the Desired Output, and y is the Calculated Output.

E: the mean square error in the output.

6. Update the old weight  $W_{(j,y)}$  in iteration t by:

$$W_{(j,y)}(k+1) = W_{(j,y)}(k) + \eta * \frac{\partial E}{\partial W_{(j,y)}} \quad (14)$$

Where  $\eta$ : learning rate or correction factor constant effects on the step size of the minimizing the square error and it determines the speed of the learning, if it is small the network learns slow.

$W_{(i,j)}$ : the weight between node i and node j.



The calculation of the propagation error ( $\frac{dE}{dw_{jy}}$ ) between hidden and output layers is done by finding the derivative of the error with respect to the weights. Solving the partial derivatives of the error can be derived by the chain rule after solving equation (14)

$$W_{(j,y)}(k + 1) = W_{(j,y)}(k) + \int * y * (1 - y) * v_j * - (y^d - y) \quad (15)$$

Update the old weight  $W_{(i,j)}$  in iteration  $k$  by:

$$W_{(i,j)}(k + 1) = W_{(i,j)}(k) + \int * \frac{\partial E}{\partial W_{(i,j)}} \quad (16)$$

The calculation of the propagation error ( $\frac{\partial E}{\partial W_{(i,j)}}$ ) is done by solving the partial derivatives of the error also by the chain rule. Finally find the new  $W_{(i,j)}$  using equation:

$$W_{(i,j)}(k + 1) = W_{(i,j)}(k) - \int * x_i * W_{(j,y)} * v_j * (1 - v_j) * (y^d - y) * y(y^d - y) \quad (17)$$

These basic steps should be done for one sample from the training data. First, all weights are selected randomly and the minimum error that is allowable is determined then the network is fed forward to calculate the actual output and if the result is not the same with the desired output, that means the mean square error is bigger than the allowable error [26]. It can be said that the algorithm learns through iterations. The number of iterations in typical network can be any number from ten to ten thousand. Therefore, training it is hard to be done manually, even for the very small amount of training data, therefore for large training data computers are used to train the network. **MATLAB** program has neural network tools which make it easy to build the network and train it using any training data.

A neural network will be built and trained in this study using the data that contains all possible operation temperature and solar radiation as inputs, and their best decision of duty cycle as output to work as MPPT controller. The performance of the ANN based MPPT controller depends on how well the network is trained.

### 3.1.4. Adaptive neuro-fuzzy inference system based MPPT

Another MPPT algorithm uses an artificial intelligence technique which is proposed to be called ANFIS and is an efficient algorithm for working with MPPT concept; it has also been applied and proved its efficiency [27, 28]. The Fuzzy logic system is a useful tool for building a system based on human thinking without modelling the system mathematically. The output decision of FLC is based on the written rules to make defuzzification on the output membership functions parameters. These parameters are designed by an expert or by the experiences and adjusted several times in order to improve the performance of the controller. The artificial neural network system has capabilities of learning from examples or learning from data as it is seen in the previous section.

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system has been introduced by Jang in [29] for constructing a fuzzy logic controller. ANFIS is a kind of artificial neural network that uses learning capabilities and hybrid learning of ANN to generate fuzzy IF-THEN rules and select the membership functions parameters of the Takagi–Sugeno fuzzy inference system, a set of input-output samples, from training data for mapping or approximating any nonlinear system. ANFIS architecture is shown in Figure 9 [30].

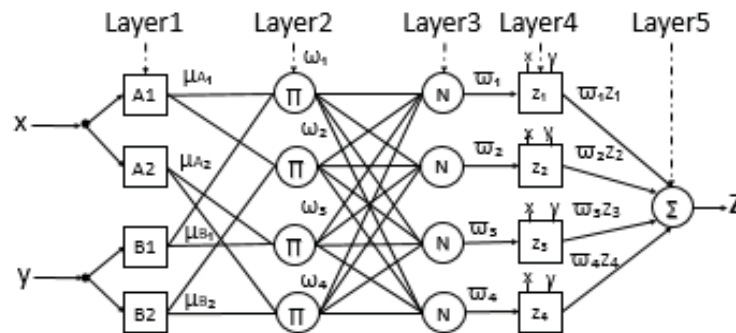


Figure 9. Architecture of ANFIS with four rules and two membership function for each input

ANFIS in Figure 12 has two inputs; x and y, and one output; z. For the first-order in Sugeno fuzzy model, a typical rule set with four fuzzy if-then rules can be expressed as:

Rule: If x is A and y is B, then z = (p\*x+ q\*y + r)

where Ai and Bi are the fuzzy sets in the antecedent, and pi, qi and ri are parameters which are determined during the training process.

ANFIS consists of five layers, and the nodes in each layer depend on the number of inputs, membership function and rules and mostly on a single output as it is seen in Figure 9:

❖ **Layer 1:** this layer consists of the number of nodes, and i represents inputs membership functions.

$$\begin{cases} O_{(1,i)} = \mu A_{i(x)}, & i = 1,2 \\ O_{(1,i)} = \mu B_{i(x)}, & i = 3,4 \end{cases} \quad (18)$$

where:  $\mu A_i(x)$  and  $\mu B_i(y)$  membership degrees can be obtained by the fuzzification process; for example Triangular membership function is mostly used with the equation below:

$$\text{Triangle}(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x \geq c \end{cases} \quad (19)$$

where {a,b,c} is the parameter set that change the shapes of the MFs, and the parameters in this layer are called premise parameters

❖ **Layer 2:** each node in this layer receives the linguistic variables with MF degrees and calculates the firing strength of a rule via multiplication and sends it to the next layer. T-norm operators can be used as AND function to rule the firing [18].

$$O_{(2,k)} = \omega_k = \mu A_{i(x)} \mu B_{j(x)}, \quad i=1,2, j=1,2; \quad k = 2(i-1) + j \quad (20)$$

Where k: represents the output number.

❖ **Layer 3:** The outputs are called normalized firing strengths that by calculate the ratio of firing strength rule in the i node that comes from previous node to the sum of all rule's firing strengths.

$$O_{(3,i)} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2 + \omega_3 + \omega_4}, \quad i=1,2,3,4 \quad (21)$$

❖ **Layer 4:** Output of each node in this layer has the following function:

$$O_{(4,i)} = \bar{\omega}_i z_i = \bar{\omega}_i (p_i x + q_i y + r_i), \quad i=1,2,3,4 \quad (22)$$

Where  $\bar{\omega}_i$ : is referred to as the normalized firing strength from layer 3

pi, qi and ri: is the parameter set of ith node. These are referred to as consequent parameter

❖ **Layer 5:** The output node in this layer computes the overall output as the summation of all incoming signals divided summation of all weights or all rule's firing strengths from layer 2. It can be expressed as:

$$O_5 = \frac{\omega_1 z_1 + \omega_2 z_2 + \omega_3 z_3 + \omega_4 z_4}{\omega_1 + \omega_2 + \omega_3 + \omega_4} = \sum_{i=1}^4 \bar{\omega}_i z_i = \sum_{i=1}^4 \bar{\omega}_i (p_i x + q_i y + r_i) \quad (23)$$

The structure of a neuro-fuzzy system is like a multi-layer neural network. The square nodes in Figure 9 have adjustable parameters and the circle nodes have fixed parameters. The basic learning algorithm to optimize ANFIS parameters are backpropagation gradient descent algorithm which has been used for training the multi-layer ANN (see section 3.1.3) [31]. During the learning process, in order to achieve a desired input-output mapping, the premise parameters ( $a, b, c$ ) in the layer 2 and the consequent parameter ( $p_i, q_i, r_i$ ) in the layer 4 are updated according to the given training data and are trained until the desired response in the output is achieved.

❖ *Basic ANFIS Learning Algorithm*

Firstly, the training data set should be available to feed the inputs in the ANFIS network that mostly has two inputs. Second thing is selecting the number of the fuzzy membership function for each input and defining the kind of functions. The triangular is selected in this paper which has parameter ( $a, b, c$ ), see equation (19); these parameters are named premise parameters. The number of rules can be determined by the multiplication of the number of MF sets of the input1 with the number of MF sets in the input2. Then, it calculates the final output and total square error by:

$$E = \frac{1}{2} \sum (O^d - O_a)^2 \tag{24}$$

Where  $O^d$  : desired output.  
 $O_a$ : actual output.

The general equation of backpropagation for updating both the premise and the consequent parameters is:

$$\alpha(k+1) = \alpha(k) + \eta * \frac{\partial E}{\partial \alpha} \tag{25}$$

Where  $\eta$ : learning rate.  
 $\alpha$  : is any updating wanted parameter.

The MATLAB program includes an ANFIS tool which is used for building the FLC controller utilizing the process of training the ANFIS, based on the training data that contains vector of the inputs representing the operation temperature and the operation solar irradiation and the vector that represents the best decision of duty cycle is given to the system to run at MPP. MPPT based ANFIS have been seen in the literatures [27, 32].

3.2. *Boost Dc-Dc convertor*

Dc-Dc converters are power electronic circuits that convert a dc voltage to a different dc voltage level. It basically consists of a voltage source, an inductor, a power electronic switch (usually a MOSFET or an IGBT) and a diode. It usually also has a filter capacitor to deliver the output voltage. Its function is to step up input DC voltage to bring it to a desired level in the output. Figure 10 shows functional circuit of a boost converter which operates by periodically opening and closing an electronic switch. It is called a boost converter because the output voltage is larger than the input [33].

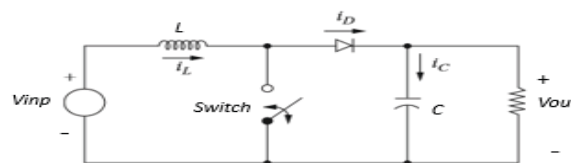


Figure 10. The boost converter circuit

The output voltage level is controlled by adjusting the ratio duty cycle (D%), on/off time of the switch. When the switch is in the **ON** state (closed), the diode is reverse biased and the whole circuit will be divided into two loops; one at the output side and another at the input side. Applying a dc voltage across an inductor for a period (usually in the 20 kHz to 5 MHz range) which causes starts to charge the inductor. On the other hand, when the switch is in the **OFF** state (open), the diode becomes forward-biased and there will be a closed loop consisting of power source, inductor and RC load. The energy stored in the inductor during the **ON** state (closed switch) is discharged to the RC load circuit through the closed diode.

The relation between input and output voltage is given by this equation:

$$V_{out} = \frac{V_{inp}}{(1-D)} \quad (26)$$

Where D: DC-DC converter's duty cycle.

For designing the minimum inductance for continuous current in the boost converter is given by :

$$L_{min} = \frac{D*(1-D)^2*R}{2f} \quad (27)$$

Designing boost converter for continuous-current operation will have an inductor value greater than:  $L_{min}$ . [22] and capacitor value is given by :

$$C_{min} = \frac{D*V_{out}}{R*\Delta V\%*f} \quad (28)$$

Where  $f$ : is the switching frequency. Alternatively, expressing the capacitance in terms of the output voltage ripple yields:

$\Delta V$  :Output voltage rippel.

For designing boost converter, usually C is selected greater than C mine.

The tracking efficiency of the MPPT algorithm is given by:

$$\eta\text{-MPPT} = \frac{P_{out}}{P_{mpp\text{-loss}}} \quad (29)$$

$P_{mpp}$  is the possible (theoretical) achievable power.

$P_{out}$  is the power extracted from the PV array by the MPPT algorithm that is used; it depends upon the ability of the MPPT to be as close as possible to the MPP [34].  $\eta$ -MPPT is not concerned with the physical efficiency of the converter (for example, switching loss). The next chapter will implement all the MPPT algorithms presented in this chapter using MATLAB program and run each algorithm with PV system in Simulink environment for analyzing the performance of each case.

#### 4. PV Model and Simulations of Case Studies

This section shows all the simulations of all the systems; the Photovoltaic PV model, boost converter and MPPT controller based on the purposed MPPT algorithms. All the simulations are done using MATLAB/SIMULINK software. This chapter discusses all the case studies and simulation results for the whole system. The next section contains modeling a general PV panel and shows some results regarding the effects of temperature and solar radiation on PV output power and MPP operation.

##### 4.1 PV model simulation

Among the objectives of this paper are simulating a PV model and estimating the I-V characteristic curves of the PV under different operation temperature and solar irradiation and use this simulated model for testing the dynamic performance of MPPT later. The simulation is done by MATLAB Simulink which models the equations (1,2,3,4) using subsystem blocks for building a general system that can model any PV system that contains one or more than one model as array. The simulated equations of the subsystems are shortened in one block, as shown in Figure 11 (a) and as shown in Figure 11 (b) by using mask parameter property there are some parameters designed to be adjustable. In addition, the PV model in Figure 11 (a) contains temperature (T) and solar irradiance (G) input which will be used as adjustable values for testing and analyzing the performance of the PV model [35]. A PPS130W AS8118 PV module characteristic data (Product available on Alibaba wibsid Solar Panel [250812]) which is shown in Table 2, was taken as the reference for simulation and analyzing temperature and solar irradiance affections on the output power.

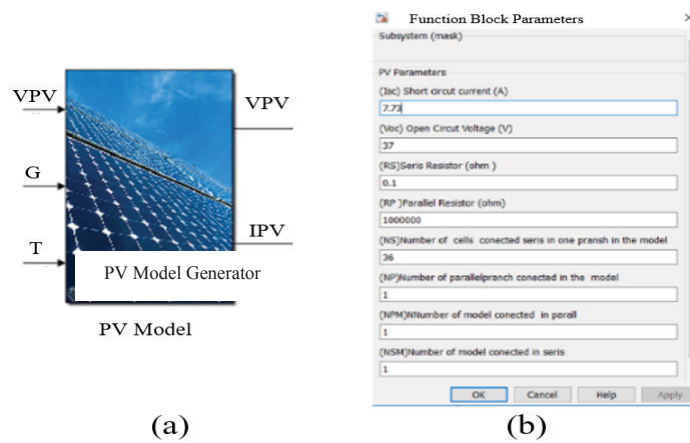


Figure 11. The main model of the PV (a) PV model block (b) Subsystem mask parameters

Table 2. Electrical Data of PPS130W AS8118 PV Module

Electrical Data Under STC	Value
Maximum Power (Pmax)	130W
Maximum power voltage (Vmpp)	18V
Maximum Power current (Impp)	7.23A
Open Circuit Voltage (Voc)	22.5V
Number of Cells	36 pcs

The simulation model is tested by connecting the model with a variable resistor load which is controlled to start from short circuit to open circuit and then plotting the relationship between the current and the voltage which represent I-V curve as well as the power and the voltage which represent P-V. Figure 17 shows the simulation circuit. The first test was done by applying constant operation solar radiation 1000 kw/m<sup>2</sup> with a changing temperature from 5 C° to 35 C° with step of 5 C°. On the other hand, the second simulation test was done by applying constant operation under the temperature of 25° with a changing solar radiation from 600 kw/m<sup>2</sup> to 1000 kw/m<sup>2</sup> and an increasing step of 100 kw/m<sup>2</sup>. Figure 12 shows the simulation circuit.

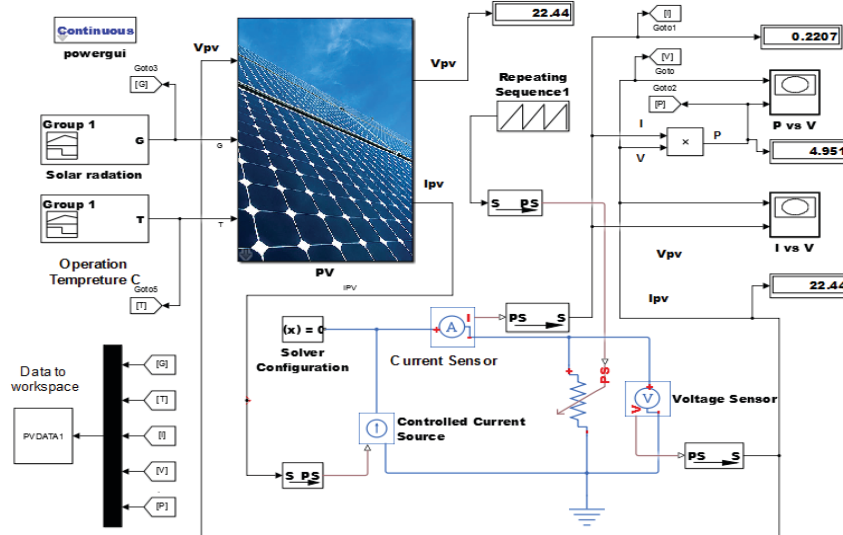
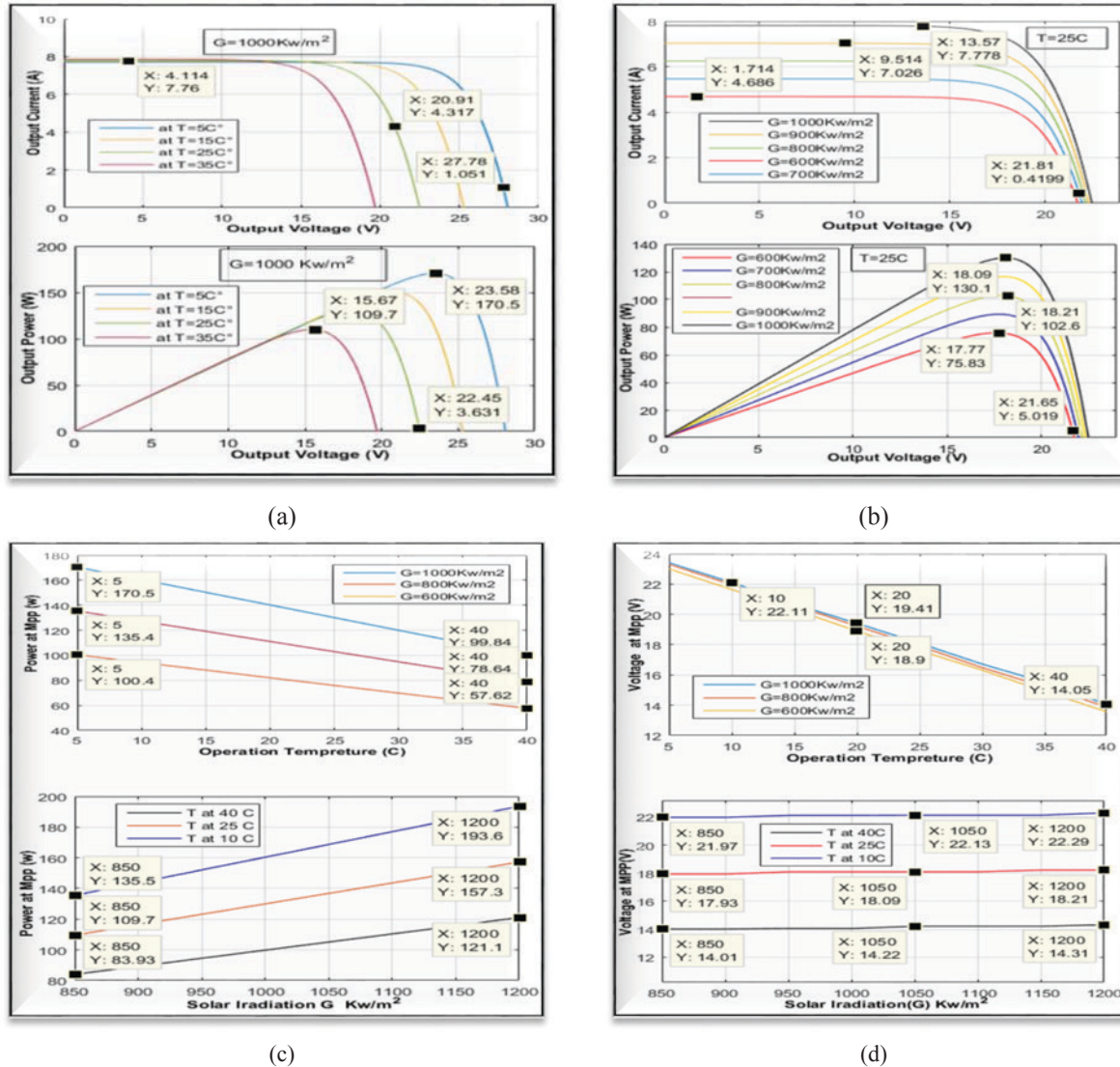


Figure 12. MATLAB simulation circuit for testing the PV simulation model



The result in Figure 13 (a) is seen in the plot. We have concluded that whenever the temperature increases the voltage and solar radiation, short operation current and the power output increase as well. The contrary happens with a small change in voltage. The power output decreases and vice versa, as seen in Figure 13 (b).



**Figure 13.** Influences of T and G (a), Influence of T on  $V$ - $I$  and  $P$ - $V$  curves (b), Influence of the G on  $V$ - $I$  and  $P$ - $V$  curve (c), Influence of G and T on MPP (d), Influence of G and temperature on  $V_{mp}$

Regarding the result seen in Figure 13 (c), we have concluded that MPP operation increases when the radiation increases and the vice versa happens with the temperature increase. Figure 13 (d) shows how the  $V_{MPP}$  increases when the temperature decreases and is approximately at constant when the radiation changes. These results prove that the operation point and maximum power point are the  $V$ - $I$  curve and  $P$ - $V$  curve and they are changing with any change in solar irradiation and temperature, according to the situation and the seasons of the year. A DC-DC converter controlled with MPPT technique is used for maximizing the PV power and delivering it to the load. The next section shows the simulation circuit for boost DC-DC converter which is used for analyzing the performance of the proposed MPPM algorithm in this paper.

4.2. Boost convertor model simulation

The parameters for the DC-DC boost converter are shown in table 3. The switching frequency ( $f_s$ ) is selected as 200KHz and the inductor value ( $L_1$ ) was selected greater than  $L_{min}$  in equation (3.6) and the capacitor values ( $C_1, C_2$ ) were chosen in order to obtain a fast response for the MPPT algorithms. The simulation circuit of the convertor is shown in Figure 4.11.

Table 3. Boost DC-DC convertor simulation parameters

Parameter	Value
Inductance $L_1$	(c) 1mH
Capacitor $C_1$	1 $\mu$ F
Capacitor $C_2$	200 $\mu$ F
Load resistor R	10 $\Omega$
Switching Frequency $F_s$	200kHz

4.3 Perturb and observe MPPT controller

The first system contains the PV system and is controlled based on P&O MPPT method. P&O is implemented using MATLAB function and programmed using MATLAB M-file based on the flowchart given in Figure 5. The initial value of  $\Delta D$  is selected as 0.001 and the time sample of given decathlon is selected as 0.02 ms.

4.4 Fuzzy logic controller model

Fuzzy controller based MPPT is designed using MATLAB Fuzzy logic designer tool. The controller has two inputs; the first one represents the calculated input error  $E(k)$  value and the second input represents the delay of error  $E(k)$  and the single output represents the  $\Delta D$  decision, last but not least the MFs were selected as shown in Figure 14 (a,b,c) below.

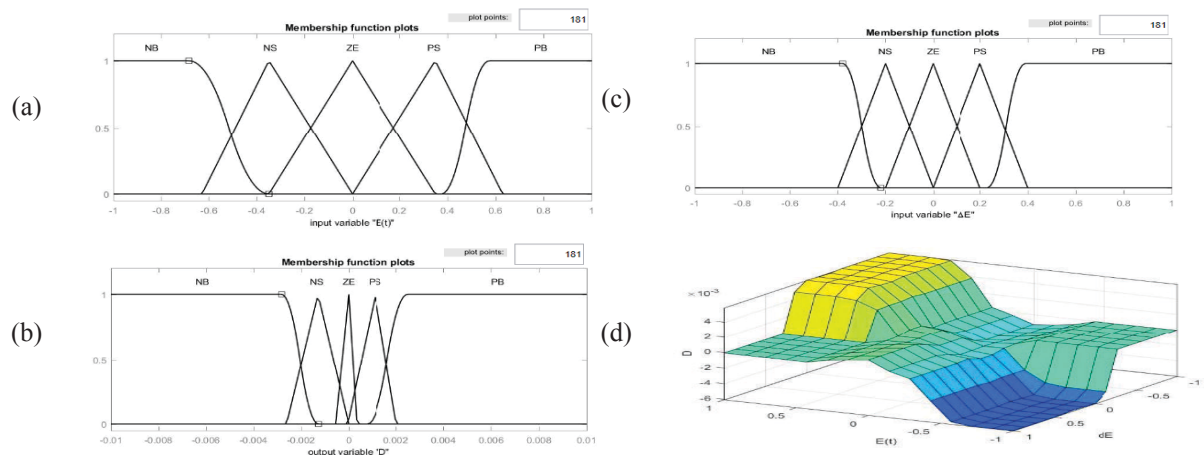


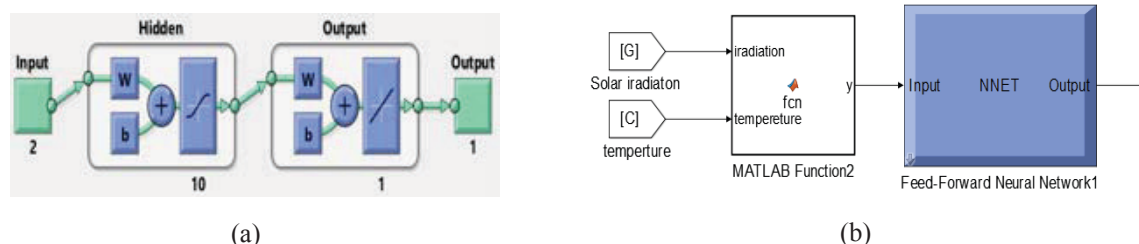
Figure 14. Membership functions of FLC based MPPT : (a) MFs of input error  $E(k)$  (b), MFs of input delta  $E(k)$  (c), MFs of output decision (c), Inference rule base surface of FLC based MPPT



The designed fuzzy logic controller should be imported to work space for use in simulink with the fuzzy controller block, where the controller can take samples of the calculated  $E(k)$  and  $E(k-1)$ . The time sample of the given decision is selected as 0.08 ms for obtaining an efficient performance.

#### 4.5 Neural Network Controller Model

The ANN controller based MPPT is designed using MATLAB M-file code [36] and trained using backpropagation learning algorithm with 126 training sample which is obtained by operating the two PV systems. The first one works with P&O MPPT and a smaller constant value, just to determine the range of the duty cycle. Later, copied to the second PV system that running with the adjustable duty cycle for increasing and decreasing the duty cycle for obtaining an accurate and reliable result. The ANN which is shown in Figure 15 (a), is designed with ten hidden layers, two inputs and one output.



**Figure 15.** (a) Neural network structure based MPPT, (b) Simulation circuit of ANN controller based MPPT

In Figure 15 (b), ANN controller has two inputs (solar irradiance and temperature) and one output which is the duty cycle that operates at maximum power point. The MATLAB function which is used for arranging the values of  $G$  and  $T$  as vectors, is located between the network and the inputs.

#### 4.6 Neuro-Fuzzy controller model

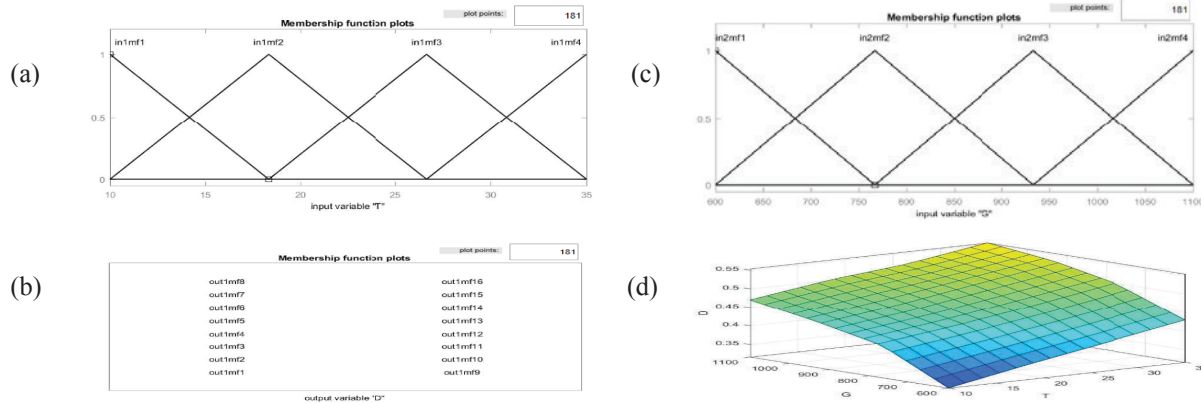
MATLAB Neuro-Fuzzy designer tool is used for training the ANFIS with the same training data that the ANN controller is trained. Backpropagation training algorithm is used for optimizing the FLC parameters and generating the system, as shown in Figure 16 below.



**Figure 16.** The structure of the generated FLC system after the ANFIS training

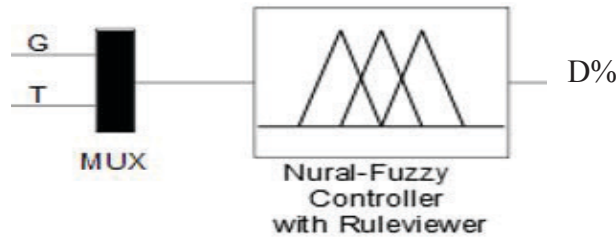
MFs are selected for each input and their parameters are optimized during the training process. The output is the optimized MFs as constant samples during the training process.

MFs membership functions are given below:



**Figure 17.** Generated membership functions (a), MFs of temperature (b), MFs of solar irradiation (c), Output samples of the Sugeno FLC system (d), Inference rule surface of FLC generated by ANFIS

The inference rule base is optimized during the ANFIS training process, as shown in Figure 17 (b) whereas the rule surface is demonstrated in Figure 17(c). The previous generated FLC should be imported in MATLAB work space in order to be used as a controller in Simulink environment.



**Figure 18.** Purposed FLC controller based MPPT whose parameters are generated by ANFIS training

## 5. Simulation Circuit of Proposed PV Systems

The complete system is simulated using the MATLAB/SIMULINK (See Figure 19) where each block in the simulation represents a kind of PV system. The simulation is done by operating the five PV systems where each system has the same PV model and boost converter parameters but a different MPPT mechanism.

For controlling the duty cycle with each system:

- 1) The first PV system which is shown in block 1 in Figure 23, operates without any controlling for tracking the MPP and the duty is selected as 0.503 to operate PV system at its MPP only case of solar irradiation equals 1000 Kw/m<sup>2</sup> with the temperate of 25 C°. Note that D is constant and does not change depending on the variations in the values of G and T.
- 2) Second PV system which is shown in block 2 in the figure, works with MPPT of P&O algorithm for guiding the PV system to the possible MPP operation.
- 3) Third PV system which is shown in block 3 in the Figure, works with FLC controller based MPPT.
- 4) Fourth PV system which is shown in block 4 in the Figure, works with ANN controller based MPPT.
- 5) Fifth PV system which is shown in block 5 in the Figure, works with FLC controller that is designed by the ANFIS training based MPPT.

Each system will be running with variation in temperature and solar irradiation in order for the researchers to observe the effects on the output power of each system for analyzing the performance of each MPPT controller and thus see what happens to the output power of the PV system work without an MPPT controlling algorithm. The simulation result and the conclusion are presented in the next and the last section which offers a conclusion together with a comparison regarding the performances of all the PV systems summarizing how the performance of each PV system differs from one another.

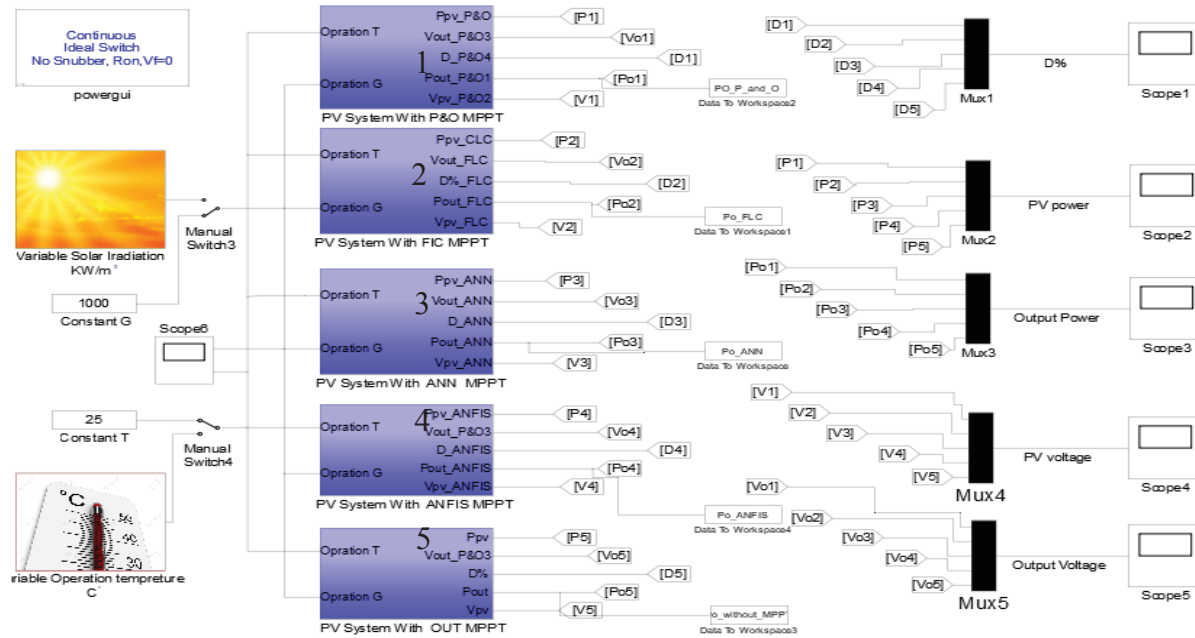
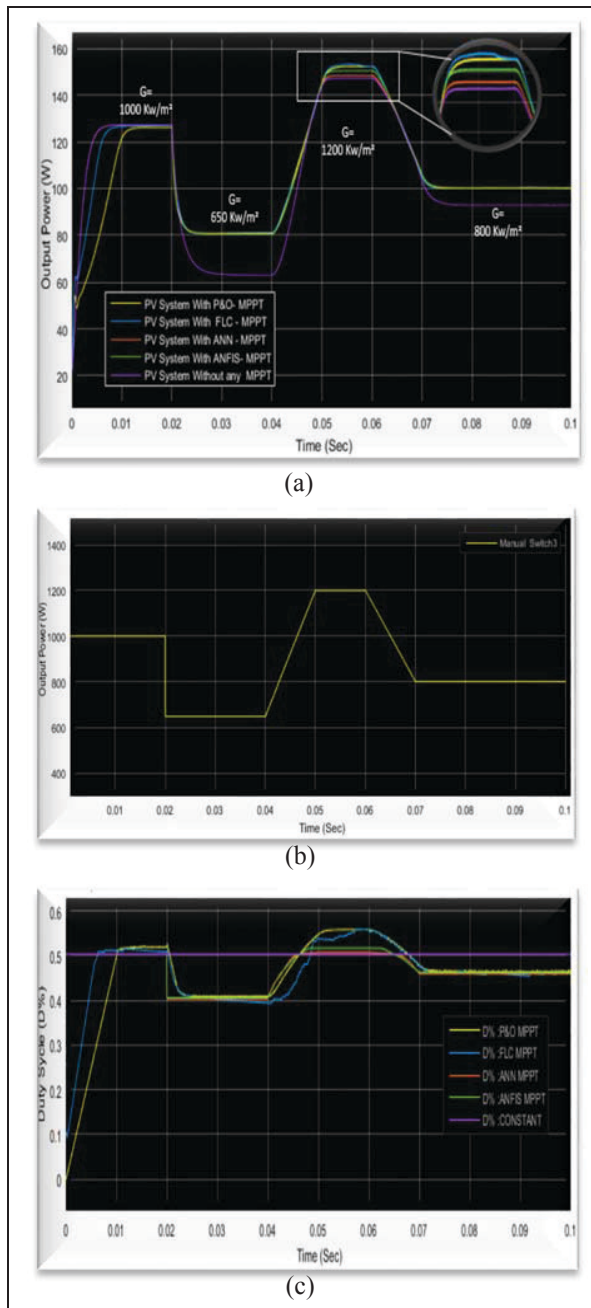


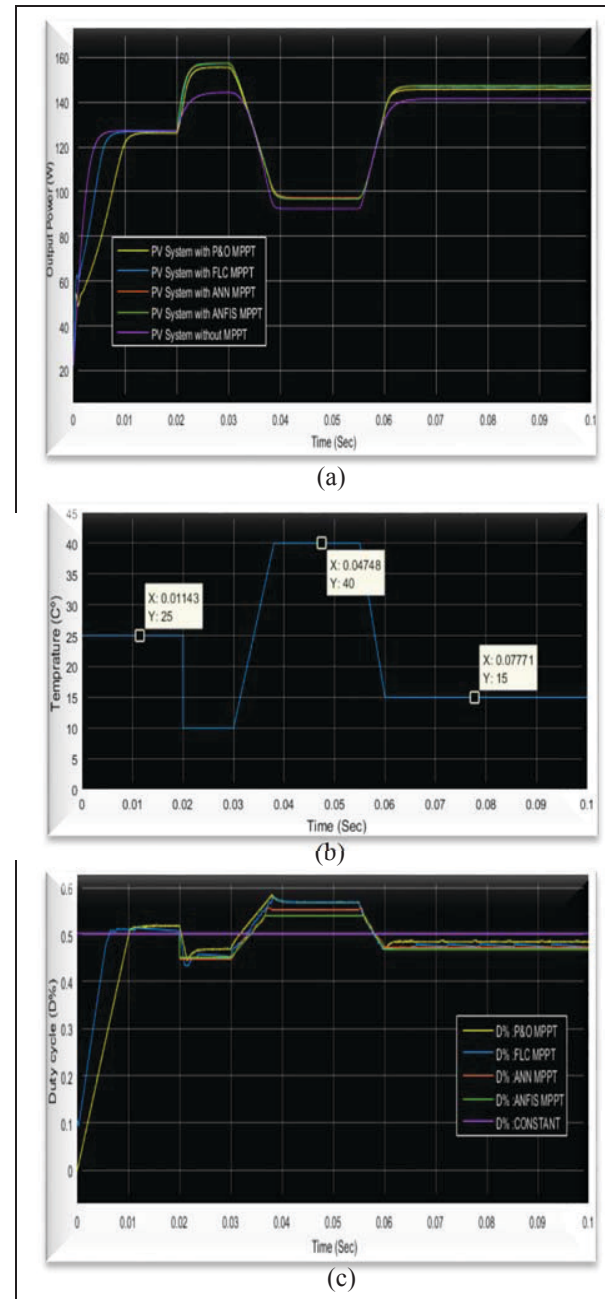
Figure 19. The simulation circuit of all PV systems for evaluating the performance of each MPPT

### 5.1 Simulation results

The simulation results are given in Figure 20 for the case varying in operation solar radiation value and in Figure 21 for the case varying in operation temperature value.



**Figure 20.** Simulations results for variation in G. (a) Output power of PV systems, (b) Solar irradiation variation signal, (c) Duty cycle decisions.



**Figure 21.** Simulations results for variation in T. (a) Output power of PV systems, (b) Solar irradiation variation signal, (c) Duty cycle decisions.

## 6. Conclusion

As it is also seen in literatures and our simulation results, we conclude that the output power of the PV system which does not operate with MPPT, is less than the output power of the other PV systems which work with MPPT technique. Approximately 25% of the expected power is lost. For the system which works with the conventional P&O MPPT, we conclude that the time response for tracking MPP is slow and the MPP operation has less efficiency than the other systems. For the system which operates with MPPT based FLC, the time response for tracking the MPP is faster than P&O MPPT method and also more efficient for tracing MPP. For the MPPT based ANN and ANFIS; these techniques have the fastest time response for tracking the MPP and have a high efficiency for delivering the maximum power to the load.

See Table 4; summarizing the performances of the five different PV systems.

**Table 4.** Comparing the results of the purposed MPPT algorithms

Type of PV System	System Classification type	Control Sensors	MPPT Complexity	Time Response	Efficiency
Without MPPT	Without MPPT	NON	NON	Normal	75.6%
With P&O MPPT	Direct MPPT	I- PV AND V PV	Simple	Slow ,0.0142 Sec	97.43%
With FLC MPPT	Direct MPPT	I-PV AND V-PV	Average	Fast ,0.0094 Sec	98%
With ANN MPPT	Indirect MPPT	T and G	Complex	Fast,0.008 Sec	98.28%
With ANFIS MPPT	Indirect MPPT	T and G	Complex	Fast ,0.007 Sec	98.88%

Notes: From Figure 20 (a) note that the output power time is between 0.05 Sec and 0.06 Sec where the solar radiation is equal to 1200 Kw/m<sup>2</sup> ; the efficient MPPT, as it is seen is the MPPT based FLC, then comes the P&O MPPT, then comes the MPPT based ANFIS and then MPPT based ANN. However, in Figure 21 (a) note that the output power time is between 0.4 Sec and 0.05 Sec where the operation temperature is 40 C° and all the results are equal.

The reasons which make the MPPT based ANN and MPPT based ANFIS are not efficient in this position; those two methods are indirect MPPT algorithms which make the decision of duty cycle based on the given values of G and T. ANN and ANFIS have been learning from the data that contains the situation of the system that operates in the range of G between 600 Kw/m<sup>2</sup> to 1100 Kw/m<sup>2</sup> and T from 10 to 30. So, the ANN and ANFIS do not give the right decision for a situation that they have not learned before the training process hence they give decisions that is close to the right decision. Therefore, the training process must be repeated with the training data that contains the new situation samples of G and T.

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