

# Maximum Power Point Tracking of PV System Using ANFIS Prediction and Fuzzy Logic Tracking

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*Abstract*— The maximum operating point of solar Photovoltaic (PV) panels changes with environmental conditions. Many methods have been proposed to locate and track the maximum power point (MPP) of PV cells. The difficulties that face these methods are the rapid changes in solar radiation and the variety in cell temperature which affects the MPP setting. External sensors are used in many approaches to measure solar irradiation and ambient temperature to estimate the MPP as a function of data measured. In this paper, linear correlation is proposed to analyze the experimental data to select the appropriate PV parameters that can recognize the MPP location. Short circuit current ( $I_{sc}$ ) and open circuit voltage ( $V_{oc}$ ) are selected as inputs factors instead of environmental influences. The paper demonstrates how these simple factors are necessary to locate accurate MPP under wide changes in environmental conditions. The statistical analysis is used to classify the data in appropriate fuzzy memberships. The proposed maximum power point tracking (MPPT) model depends on an Adaptive Neuro-Fuzzy Inference System (ANFIS) which is designed as a combination of the Sugeno fuzzy model and neural network. ANFIS of five layers with four fuzzy rules is used to acquire a high precision of locating  $V_{max}$  with few adaptation epochs. The fuzzy logic controller (FLC) utilizes the ANFIS output voltage to track the MPP. The MPPT controller is designed to acquire high efficiency with low fluctuation.

*Keywords:* Fuzzy control, Photovoltaic, Adaptive fuzzy.

## 1 Introduction

Renewable energy becomes an essential source for many applications in the last four decades. It is difficult to supply electrical energy to small applications in remote areas from the utility grid or from small generators. Stand alone photovoltaic (PV) systems are the best solutions in many small electrical energy demand applications such as communication systems, water pumping and low power appliances in rural area [1][2]. In general, the cost of

electricity from the solar array system is more expensive compared to electricity from the utility grid [3][4]. For that reason, it is necessary to study carefully the efficiency of the entire solar system to design an efficient system to cover the load demands with lower cost.

There are many external and internal influences which have an effect on the efficiency of the PV panel. The maximum power point (MPP) of a PV system depends on cell temperature and solar irradiation, so, it is necessary to continually track the MPP of the solar array [1]. Therefore, the tracking control of MPP is a complicated problem. Many tracking control strategies have been proposed to overcome this problem such as; perturb and observe, incremental conductance, parasitic capacitance, constant voltage, neural network and fuzzy logic control[5][6]. The drawbacks of these methods comes from its high cost, difficulty, complexity, and non-stability[7]. The main purpose of such controlling techniques is the way of adjustment the duty cycle of the shunt MOSFET transistor of maximum power point tracking (MPPT) converter. The MPPT converter is used to maintain the PV array's operating point at the MPP. MPPT controller does this by controlling the PV array's voltage or power independently of the load [1]. The fuzzy controller introduced in [5] uses  $dP/dI$  and its variations  $\Delta(dP/dI)$ , as the inputs and computes MPPT converter duty cycle. The adaptive fuzzy tracker of maximum power point considers variation of duty cycle, but it uses  $dP/dV$  and  $\Delta(dP/dI)$  to adapt duty cycle of the DC-DC converter [7]. The previous type of search is called on-line search algorithm which does not need reference MPP parameters. Therefore, it does not require measure of temperature and solar irradiation [7][8]. Fast and stable MPP tracking under a high environment changes need reference MPP parameters. A solar radiation is used in [9] and [1] to obtain a reference power and voltage. The maximum power point voltage ( $V_{max}$ ) is obtained as a reference voltage in [10] as a function of open circuit voltage ( $V_{oc}$ ). A neural network was also used to estimate the MPP in[11][12] using solar irradiation. The paper presents a method based on Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate the MPP using the data collected from several experiments performed in different environmental condi-

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tions. This paper utilizes statistical analysis methods to analyze the data of experiment that has been collected in different environmental conditions. The statistical analysis will confirm the necessity of using both Voc and short circuit current (Isc) as input data for ANFIS to estimate maximum power point voltage(Vmax). The data will be used to test the ANFIS output with deduced appropriate rules.

This paper is organized as follows. Section(2) explains the effect of main environmental influences and load types on output PV parameters ,section(3) investigates in Buck-Boost DC-DC converter, the data collected is analyzed in section(4), section(5) introduces the ANFIS model, section(6) explain the fuzzy logic controller (FLC) proposed, the results are discussed in section(7) and fuzzy logic controller is, and section(8) is a conclusion.

## 2 Input/output parameters

Solar irradiation, ambient temperature and wind speed are the main environmental factors that affect PV systems. Isc, Voc, Vmax and MPP current (Imax) are the main characteristics that specify the I-V and PV curves of PV panels [13][14][3]. I-V curve characteristics and cell junction temperature of PV panels is adjusted due to any changes in environmental conditions.

MPP changes due to irradiance level and cell junction temperature. Ambient temperature with current flows in PV cell increase the cell junction temperature. The temperature of cell junction is the main factor that reduces the maximum power output of PV panel [14]. Figure 1 shows how the I-V curves and power curves change with PV cell junction temperature. Figure 2 shows how voltage and current those denote the MPP changes with irradiance changes.

The operating voltage on I-V curves depends on load type and load value, Figure 2 shows the operating point in I-V curve which denoted by intersection between different load curves and I-V curves of PV panels at different irradiance. This operating point mostly is not the MPP.

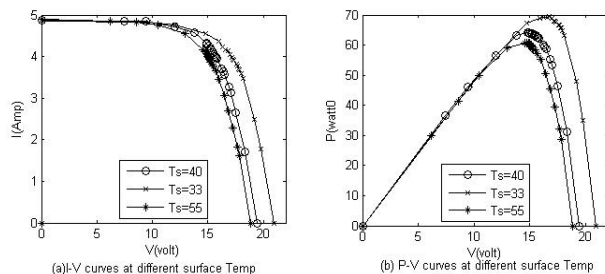


Figure 1: I-V and P-V curves at different surface temperature

The Isc of solar cell depends exclusively and linearly on

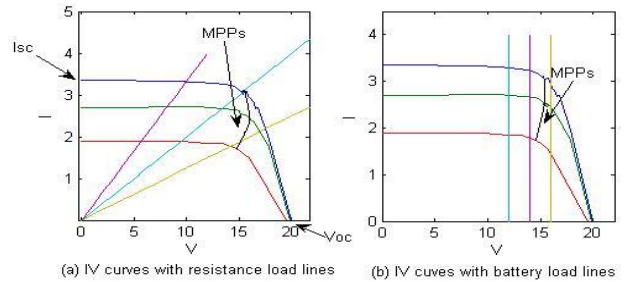


Figure 2: I-V curves at different loads and irradiance

the irradiance [4]. It is of the order of 30 mA /cm<sup>2</sup> for an irradiance of 1kW/m<sup>2</sup> for single-crystal silicon cell at 25 °C Photocurrent will increase 0.1% per °C) which is neglected at normal operating conditions [14]. The Voc increases slightly with solar irradiation. There is a strong linear dependence between Voc and cell junction temperature. The Voc would decrease by (-2.3mV / ° C) between 20° C and 100°C [14] [4]. Accordingly in this paper Isc and Voc are used as inputs to PV panels instead of solar irradiation and cell junction temperature. The reason for this substitution is the difficulty of cell junction temperature measuring. In addition the simplicity of Isc measurement solves the problem of solar irradiance external sensor. In addition at different load; voltage, current and power represent the output parameters of PV panels. When the load is directly coupled to the PV panel, this leads to a certain mismatch between the actual and the optimum operation voltage( Vmax) of the solar generator which lessens the generated power from PV panels . The mismatch can be defeated by introducing a matching DC-DC converter between the load and PV panels. A DC-DC converter such as buck-Boost converter decouples the characteristic curves of the PV panels and the load.

## 3 Buck- Boost converter:

Buck-Boost converter is used to step up/step down the voltage of PV system. To control the DC-DC converter we should control the duty cycle (D) of converter MOS-FET transistor. The duty cycle represents the ratio of time open of electronic switch using a square wave signal to open this switch. The relation between input and output voltage of Buck-Boost converter can be calculated from (1):

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

Vo is a load voltage on a converter output terminal.

Vin is a PV operating voltage on converter input terminal.

D is the duty cycle of electronic switch.

Refer to equation(1) the rate of change of duty cycle in term of  $V_{in}$  can expressed in (2):

$$\frac{\partial D}{\partial V_{in}} = \frac{-V_o}{(V_o + V_{in})^2} \quad (2)$$

Curves in Figure 3 show how duty cycle changes with respect to  $V_{in}$  when  $V_o$  changes steeply from 1V to 22V. When the Buck-Boost converter operates at 12V input voltage the rate of change of duty cycle increases roughly 50% comparing with 18V operating as seen in Figure 4. Also it is observed from Figure 3. The output voltage has insignificant effect  $\Delta D$  when  $V_o$  changes from 6-20 Volt.

The load drives the output voltage of converter consequently from equation(1) it affects the value of input voltage of converter. Also  $V_{in}$  changes due to change in environment conditions as explained in section (2) . Duty cycle of converter has to adjust to track maximum power point voltage at different load values and with a huge change on environment conditions. The paper presents a method based on ANFIS to estimate  $V_{max}$  using field data collected as seen in next section.

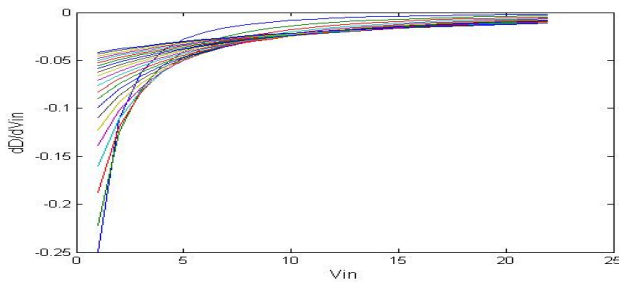


Figure 3: Rate of change of D with respect to  $V_{in}$  with wide change of VO

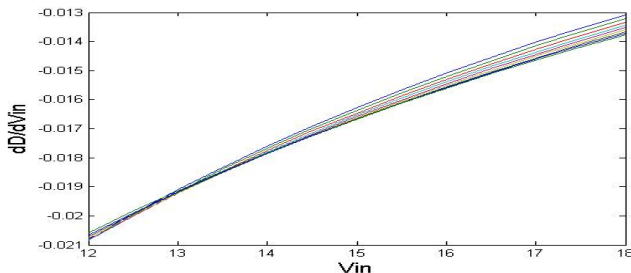


Figure 4: Rate of change of D with respect to  $V_{in}$  with finite change of VO

## 4 Data collection and analysis

The proposed ANFIS system is designed to simulate the result obtained from Field data. These data are based on climatic data of more than one year at different seasons

in four different climate regions in Yemen. Single crystal panel and Polycrystalline PV panels were tested to obtain this data. The characteristics under standard test conditions of two panels are shown in Table 1.

Table 1: solar panel characteristics under standard test conditions

| 85W single crystal panel |        | 51W polycrystalline panel |        |
|--------------------------|--------|---------------------------|--------|
| Voc                      | 22 v   | Voc                       | 21.2 v |
| Isc                      | 5.5 A  | Isc                       | 3.25 A |
| Imax                     | 4.91A  | Imax                      | 3.02 A |
| Vmax                     | 17.4V  | Vmax                      | 16.9 v |
| Pmax                     | 85.5 w | Pmax                      | 51 w   |

### 4.1 Core data of two types of PV panels

Maximum power point; power ( $P_{max}$ ) and voltage ( $V_{max}$ ) extracted from the experiment I-V curves and voltage power (V-P) curves using polynomial curve fitting in Matlab toolbox. The polynomial fitting acquired a high precision compare with Microsoft Excel fitting. Table 2 demonstrates all possibilities of acquisition data assumption that was enfolded. The proposed system is designed to simulate the data that is collected at the above situation to acquire a sufficient knowledge at different environment conditions.

Table 2: assumption of field data collected

| G      | Ta     | Tc     | influences        | Regions  |
|--------|--------|--------|-------------------|----------|
| High   | High   | High   | No                | Desert   |
| Medium | Medium | Medium | No                | General  |
| Low    | Low    | Low    | No                | Genral   |
| High   | High   | Miduim | Wind              | General  |
| High   | Medium | Medium | Wind and altitude | Mountain |
| High   | Medium | Low    | Wind and altitude | Mountain |
| Medium | Low    | Low    | Wind and altitude | Mountain |
| Low    | Medium | Miduim | High humidity     | Coast    |
| Medium | Medium | High   | High humidity     | Coast    |

### 4.2 Correlation analysis of MPP parameters

To investigate on a relation between different parameters of field data of PV panels a correlation coefficient (CC) between these parameters is obtained using linear correlation. We can observe from Table 3 the correlation coefficient between different output characteristics of two panels. The CC between Isc and Pmax for 85W and 51W PV panels are 0.98 and 0.97 respectively, which imply a

high CC between input irradiance and Pmax, in spite of PV panels worked on different surface temperature in four regions. The slight decrease in linear relation between Isc and the Pmax values refer to temperature effect. To operate the PV panels at Pmax, the panels has to operate at Vmax. There is a poor CC between Isc and Vmax appears in Table 3. Moreover, the CC between Voc and Vmax is more than 0.88 of both PV solar panels, but these values are not sufficient to set up a logical relation between inputs and outputs of PV panels. Within small range of Isc, we can decrease the effect of logarithm relation between Voc and solar radiation. Therefore, the linear relation of cell temperature becomes more effective with Voc thus, with Vmax of PV panels. Generally, when a mutual effect between inputs is reduced, the individual relation between input and outputs becomes more comprehensible. Hence a relation between Voc and Vmax becomes more apparent when Isc varies in a small range. With small change in Isc a CC between Voc and Vmax will improve. The above assumptions can be confirmed by classify the input data of PV panels and recognize the amounts of increasing on CC at different clusters. Studying the CC in different appropriate cluster is essential to initiate an outstanding control method to locate and track the MPP of PV panels.

Table 3: Correlation coefficient between panel parameters

| 85W single crystal panel |       |       | 51W polycrystalline panel |       |      |
|--------------------------|-------|-------|---------------------------|-------|------|
| Character                | Vmax  | Pmax  | Character                 | Vmax  | Pmax |
| <b>Isc</b>               | -0.24 | 0.988 | <b>Isc</b>                | -0.33 | 0.97 |
| <b>Ts</b>                | -0.89 | 0.273 | <b>Ts</b>                 | -0.98 | 0.11 |
| <b>Voc</b>               | 0.88  | 0.29  | <b>Voc</b>                | 0.93  | 0.25 |

### 4.3 Input data clustering

Clustering of numerical data forms the basis of many classification and system modeling algorithms. Cluster analysis can help in creating "balanced" treatment and control groups for a designed study [15]. K-means clustering is used to clustering the input data of two types of PV panels. K-means is suitable for core data because it partitions the observations in data in to k mutually exclusive [15].

Table 4 demonstrates the values of CC in different groups that obtained from K-means function in matlab toolbox. Row one in Table 4 signifies the CC between Voc and Vmax without data clustering. It can be observed in remaining rows the CC in different clustered that was obtained after using K-means clustering function. The CC for 85W panel is more than 0.975 in all clusters, and more than 0.985 for 51W panel. The CC in small groups is very high comparing with the CC of over-all data. Further-

more the CC at high Isc (high irradiance level) is close to unity.

Table 4: Correlation coefficient in different clusters

| CC between Voc and Vmax for 85 W panel |         | CC between Voc and Vmax for 51W panel |        |
|--|---------|---------------------------------------|--------|
| Range of Isc                           | CC      | Range of Isc                          | CC     |
| 0 - 6.85                               | 0.8824  | 0 -4.19                               | 0.92   |
| 0 - 1.67                               | 0.9756  | 0 -1.27                               | 0.9856 |
| 1.82 - 2.78                            | 0.9835  | 1.42 -1.9                             | 0.9907 |
| 2.95 - 3.8                             | 0.979   | 2.08 - 2.46                           | 0.9886 |
| 4.22 - 4.95                            | 0.9909  | 2.63 - 2.98                           | 0.9959 |
| 5.13 - 5.56                            | 0.9934  | 3.05 - 3.4                            | 0.9954 |
| 5.9 - 6.85                             | -0.9869 | 3.95 - 4.19                           | 1      |

## 5 Locating MPP using ANFIS model

ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems [16]. It applies a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership functions(MFs) parameters to estimate a given training data set.

### 5.1 Motivation for using ANFIS

An antecedent clustering with correlation analysis clarifies the CC improvement between Voc and Vmax when the input data clustered regarding Isc. Takagi and Sugeno's fuzzy if-then rules are used when the output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output[16]. This method is effective according to the high CC between inputs and Vmax in different clusters. Also ANFIS has the ability to divide the data in groups and adapt these groups to arrange a best MFs that clustering the data and deducing the output desired with minimum epochs.

### 5.2 Proposed ANFIS model analysis

To generate a Sugeno-type fuzzy inference system (FIS) structure Genfis1(Generate an FIS structure from data without data clustering) is used in Matlab toolbox to produce an FIS structure for the experiment data of two solar panels based on different proposed Gauss membership functions. The ANFIS model programmed in MATLAB is used to predict Vmax using Isc as a first input of ANFIS model and Voc as a second input. According to either reach to error criterion or the number off epochs setting in ANFIS function the input MFs parameters and output linear MFs of a Sugeno-type FIS structure is modified to reach best MFs that clustering input output data with minimum root mean square error(RMSE). Five models with a small number of rules achieved minimum RMSE from many models have been tested as seen in Figure

5 and Figure 6. RMSE between experiment Vmax outputs and ANFIS outputs changes after 100 epochs applying different groups of inputs gauss MFs. The number of rules have been generated depends on the number of MFs, which equal number of MFs of input1 times MFs of input2. Hence optimizing with minimum numbers of rules is very important in control system designed. Minimum error setting is associated with the system precision requirements.

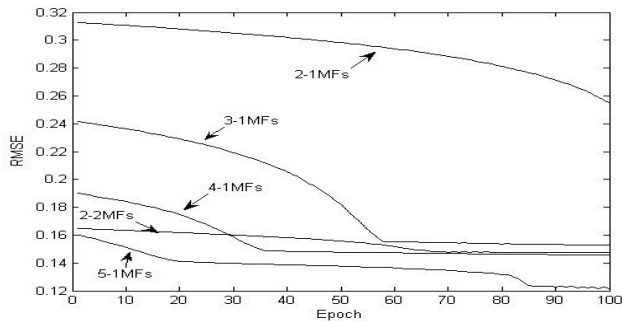


Figure 5: RMSE of of 85 PV panel at different MFs

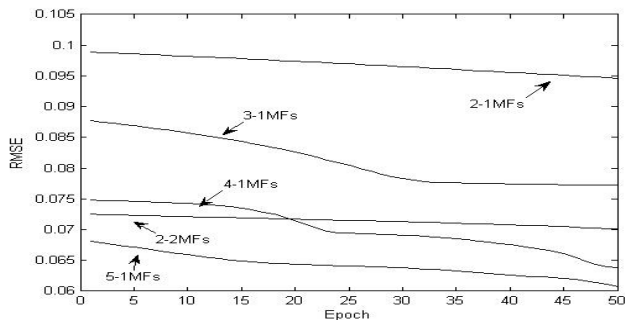


Figure 6: RMSE of of 51 PV panel at different MFs

## 6 MPPT using FLC

At a certain Isc and Voc the ANFIS model will estimate the Vmax, this reference voltage with Isc are used as a crisp inputs on FLC to adjust the duty cycle of electronics switch of Buck-Boost converter to match between load voltage and Vmax of PV panels. The reference voltage changes if either Voc or Isc has ample changes.

Referring to preceding operation the FLC can face three main problems. These problems can be expressed as follow:

- Instability caused by great and fast changes in weather condition
- High changes in output voltages of Buck-Boost converter due to load types.

- Nonliterary between duty cycle of Buck-Boost converter and input voltage.

The input and output of FLC have been selected carefully to give a sufficient and simple information for FLC. In addition, the fuzzy logic rules and MFs are assembled to solve the problem mentioned previously. Firstly, ANFIS predicts Vmax with Great changes in weather conditions. The maximum power point voltage predicted from ANFIS is used to calculate the first input of FLC as follow:

$$\Delta V = V_{in} - V_{max} \quad (3)$$

The second input is Isc value, which represents the level of irradiance. The power losses at high irradiance level is more than that at low irradiance level due to Vmax deviation. Therefore, a high precision is required at high Isc, however, at low Isc a high precision is not essential to attain more stability on the controlling system. To prevent instability due to small changes in Vmax which make insignificant effect in generated power. Fuzzy rules in Table 5, and MFs in Figure ?? are set to accept a percentage deflection in Vmax to a void a system fluctuation. Also, the rules discriminate the level of Isc to prevent the oscillation in cloudy time.

Type of load affects strongly on MFs design. Figure 4 is drown to determine the rate and limit of duty cycle at different value of Vin to help on designing the rules and MFs that control the Buck-Boost converter with battery load. Battery has a constant voltage load which varies in small range. The MFs in Figure 7 is designed to refer to the values obtained from Figure 4. Resistive load drives the PV panel to operate in wide interval on I-V curves, thus the duty cycle is designed according to values obtained from Figure 3. Extending the MFs of FLC that control Buck-Boost converter with resistive load such as DC pumps is necessary to obtain a successful and fast tracking.

Table 5: FLC rules

| .....ΔV<br>Isc | NB | NM | NS | z | PS | PM | PB |
|----------------|----|----|----|---|----|----|----|
| B              | NB | NM | NS | z | PS | PS | PM |
| M              | NB | NM | NS | z | PS | PM | PM |
| S              | NB | NM | Z  | z | Z  | PM | PB |

Figure 8 gives a view about MPPT system parts, starting with method of selecting the appropriate ANFIS model and the connectives between PV system and the all parts of MPPT system.

## 7 Results

At certain Isc and Voc the ANFIS model will estimate Vmax. ΔV in equation (3) with Isc will be used as two

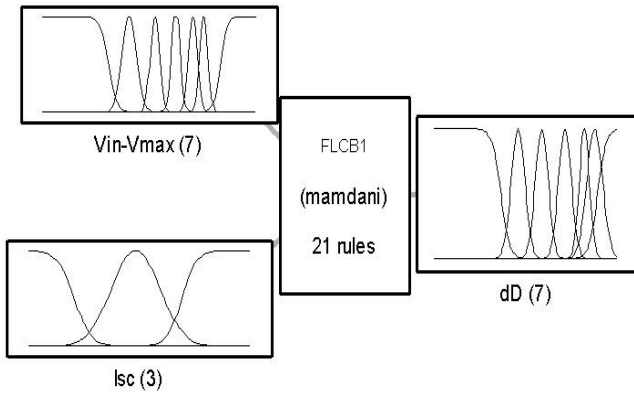


Figure 7: FLC system that control the duty cycle of Buck-Boost converter with battery load

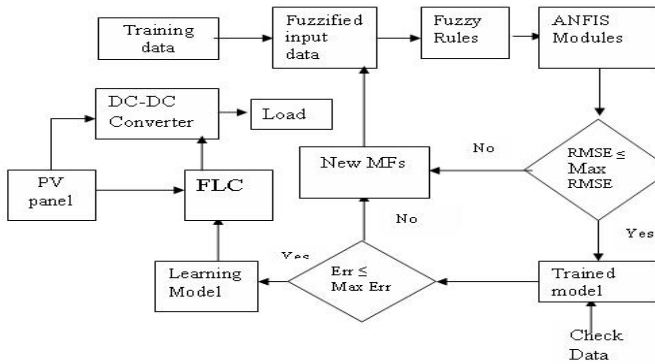


Figure 8: Connectives between PV system and the all parts of MPPT system

inputs for FLC to adjust the duty cycle of electronics switch of Buck-Boost converter to match between load voltage and  $V_{max}$  of PV panels.

### 7.1 ANFIS results

A test data was used applying ANFIS Models to predict  $V_{max}$ . The output of different ANFIS proposed models was compared with the real field output of PV panels. Three models are selected to estimate  $V_{max}$  regarding to a low percentage deviation error.  $4 \times 1$  MFs,  $5 \times 1$  MFs and  $2 \times 2$  model achieved a high precision with less than 2% absolute error between estimated voltage and real measured data as seen in Figure 9 and Figure 10.

Looking in data point by point  $4 \times 1$  memberships and  $5 \times 1$  memberships achieve a very low error in both type of PV panels, however  $2 \times 2$  memberships is necessary to face the extending changes in cell junction temperature which

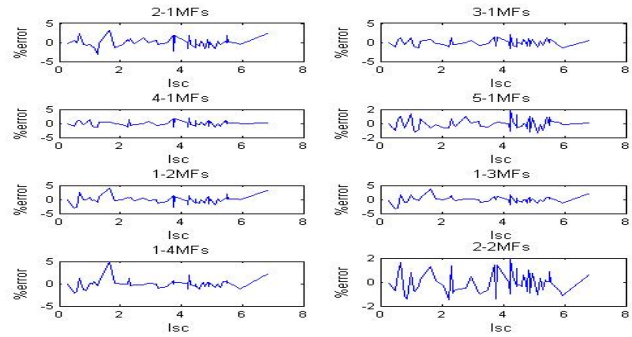


Figure 9: Error between Experiment  $V_{max}$  and ANFIS output for 85W PV panel

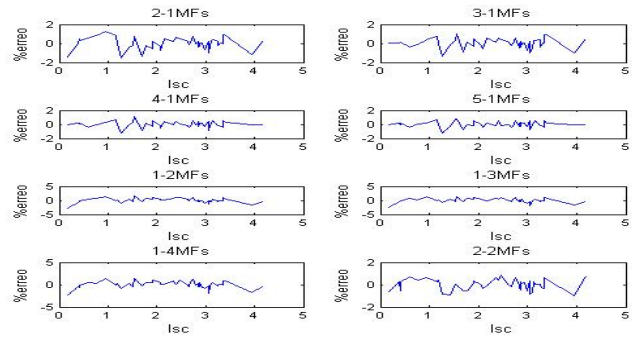


Figure 10: Error between Experiment  $V_{max}$  and ANFIS output for 51W PV panel

affects  $V_{oc}$  values especially with irregular open circuit voltage points at a high or a low ambient temperature regions.

Hence with a high precision on output voltage of ANFIS model, the outputs voltage will utilize as a reference voltage for FLC as a final stage of MPPT controller. The reference voltage  $V_{max}$  changes if either  $V_{oc}$  or  $I_{sc}$  has ample changes.

### 7.2 Fuzzy logic controller results

The duty cycle of Buck-Boost converter is adjusted using FLC in Matlab editor. Mamdanis method is used in FLC with max-min composition. After the rules have been applied, the center of area as a defuzzification method is used to find the change in duty cycle as crisp output.

The FLC that controlled the duty cycle of DC-DC Buck-Boost is simulated in MATLAB to track maximum power point voltage that predict by ANFIS model. The system is implemented with positive and negative values of  $\Delta V$  and several values of short circuit current. Figure 11 and Figure 12 show how MPPT system track  $V_{max}$  after a few number of epochs.

Figure 11 and Figure 12 demonstrate how MFs and rules are designed to acquire less than 1 volt in each step to



prevent an induced harmonics due to high  $dV/dt$ . Also, the MFs is designed to decrease the voltage steps when the MPPT system approaches from  $V_{max}$  to prevent system overshooting that can generate unstable system.

The FLC is designed to prevent the system oscillation on cloudy time. Figure 13 shows the performance of MPPT system at cloudy time and very low irradiance level. The input voltage of converter remains constant in Figure 13.

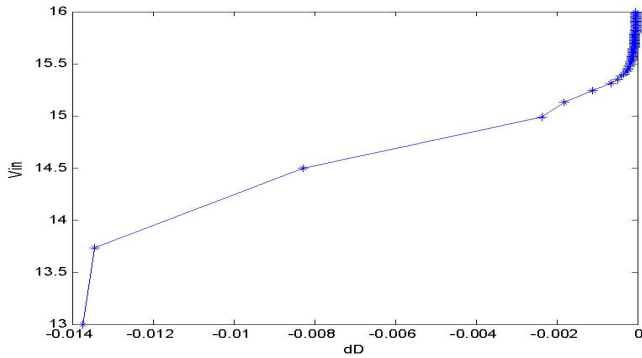


Figure 11: Tracking  $V_{max}$  with  $-3V \Delta V$  and  $550W/m^2$  irradiance

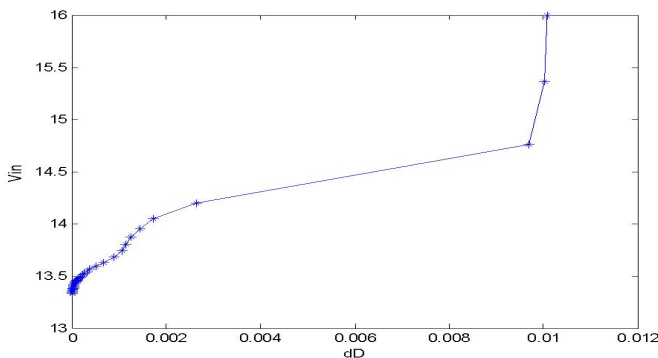


Figure 12: Tracking  $V_{max}$  with  $3V \Delta V$  and  $550W/m^2$  irradiance

Battery with  $13V$  is used to load Buck-Boost converter. The MPPT system tracking  $V_{max}$  with approximate 99% accuracy compared with ANFIS output voltage. The MPPT including FLC that proposed saves more than 10% in output generated power of  $85W$  PV panels compared with direct coupled battery system. Figure 14 shows the differences on power generated with high panel surface temperature at different irradiance level. And Figure 15 shows the differences on power generated with low panel surface temperature at different irradiance level. Moreover, the losses in power generated increase when the PV panels operate at low surface temperature owing to a high voltage deviation from  $V_{max}$ .

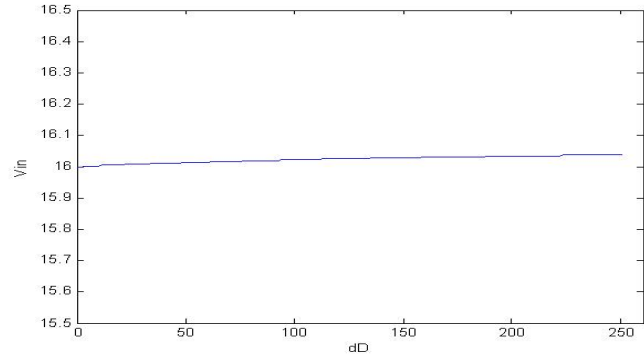


Figure 13: Stable MPPT system with  $0.5V \Delta V$  in cloudy time

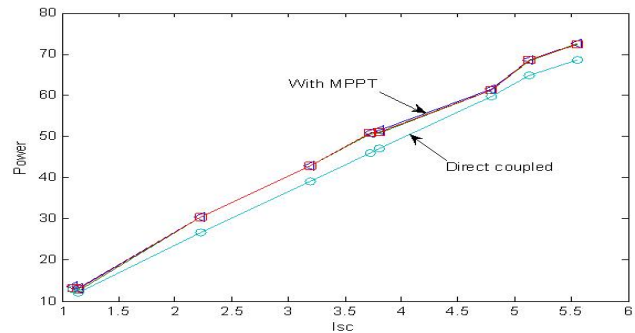


Figure 14: Differences in generated power of  $85W$  PV with and without MPPT at high temp

## 8 Conclusion

Studying the PV system's surrounding conditions is very important on designing PV systems, avoiding a descent in power generated from PV system due to alteration in environment conditions. .

The  $I_{sc}$  and  $V_{oc}$  of PV panels are used to stand for the external influences (solar irradiation and cell temperature) to simplify the system measurement.

The field data is analyzed using correlation analysis and data clustering. These two statistical analyses help on studying PV parameters associations. A high correlation between  $V_{oc}$  and  $V_{max}$  is observed when the effect of irradiance level on  $V_{oc}$  is decreased by clustering the input data and it helps on initiate ANFIS MFs and rules designing.

The estimated error in  $V_{max}$  from the ANFIS model is less than 2% with  $4 \times 1$  MS and  $5 \times 1$  MS. Also  $2 \times 2$  membership functions acquire a high precision with minimum number of rules especially when open circuit changes in wide range. A high precision ANFIS estimated output is used on MPPT with FLC tracking model. The MPPT

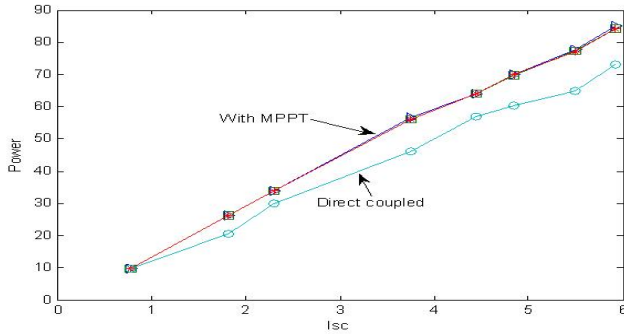


Figure 15: Differences in generated power of 85W PV with and without MPPT at low Temp

with FLC is designed to accept a percentage deflection in MPP to avoid a system fluctuation due to a bit deviation on  $V_{max}$ . The MPPT system tracking  $V_{max}$  with approximate 99% compared with experiment reading with high saving in output power compared with direct coupled PV panels.

The MPPT with ANFIS model can predict  $V_{max}$  using Genfis2 in Matlab Toolbox function to find out directly a minimum number of input data clusters with minimum number of rules. Also, ANFIS Model can estimate a per unit data of both panels to generalize the predict output for PV panels and systems with alterable number of cells.

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