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An IntelligentMPPT Method For PV Systems Operating Under Real Environmental Conditions

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ABSTRACT
The sun irradiance (G) and temperature (T) are the two main factors that affect the output power gained from the photovoltaic (PV) DC–DC converter. Therefore, to enhance the performance of the overall system; a mechanism to track the maximum power point (MPP) is required. Conventional maximum power point tracking approaches, such as observation and perturbation technique, experience difficulty in identifying the true MPP. Therefore, intelligent systems including fuzzy logic controllers (FLC) are introduced for the maximum power point tracking system (MPPT). The selection of the membership functions (MFs) and the fuzzy sets (FSs) numbers are crucial in the performance of the FLC based MPPT. Accordingly, this work presents numerous adaptive neuro-fuzzy systems to automatically adjustthe fuzzy logic controller membership functions as an alternative to the trial and error approach, which waste time and effort in MPPT design. For this purpose an adaptive neuro-fuzzy system is developed in MATLAB/Simulink to determine suitable MFs and the FSs for the fuzzy logic controller. The effects of different types of MFs and the FSs are deeply investigated using real data collected from the rooftop PV system. The investigations show that the fuzzy logic controller with a triangular membership function and seven fuzzy setsprovides the best results.

Keywords:*Adaptive neuro-fuzzy system;MPPT; Converter; Photovoltaic*

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I. INTRODUCTION

Solar energy is inexhaustible, free and clean and it is considered as the core of renewable energy (RE) in the recent times primarily because of running down of fossil fuels [1]. Among various RE resources, photovoltaic (PV) system plays a very important role either in grid-connected or islanding configurations [2,3]. However, the PV systems generate intermittent power under fluctuating weather which is the main issue that must be taken in consideration[4,5]. The power-voltage and current–voltage characteristics are responsible for the power generated from the PV cell [4]. Therefore, to work the PV generation at its peak; the MPPT mechanism is highly significant in PV system [6].

Numerous MPPT mechanisms have been introduced by many scholars since year 1960. Some well-known MMPT methods are incremental conductance (IC) method, perturb and observe (P&O) method and constant voltage (CV) method [4,7–9]. The method of P&O was extensively used due to its simple control method as well as the minimum number of its input parameters. However, the use of this algorithm leads to a loss in power due to an enormous oscillation in the area of maximum power point (MPP). Others, like IC methods has been proposed by some researchers [10,11], which somehow could eliminate the oscillations in the area of the MPP. However, this kind of methods need good and accuracte sensor to measure either voltage or current.

Recently, the MPPT-based Artificial intelligence (AI) is widely used in PV converter with great dynamics and high effectiveness. Various intelligent methods including fuzzy logic and artificial neural network (ANN) have been mentioned in the literature. In [12], The MPPT-based ANN in a PV inverter power conditioning unit has been suggested. In this study, the voltages and currents corresponding to a maximum power has been estimated by the ANN. However, large training data are required before it can be used in the controller.

The fuzzy logic controller (FLC) is adaptable to complex systems [13];therefore, it is employed for the MMPT [14]. The MFs and the rules are usually obtained in the conventional FLC using the trial and error process which does not often lead to a convincing performance. Therefore, the FLC have been incorporates with the neural network (NN) method to find the MFs together with its rules. The adaptive neuro fuzzy inference system (ANFIS) is one of the quite popular techniques that combine the FLC with NN.

The ANFIS controller has been used in many applications such as induction motor drive [15]. ANFIS based space vector modulation technique was used for a three-level inverter fed induction motor [16]. In [17], the authors have presented an approach to design and implement a decentralized power system stabilizer which is able to performing quite perfectly in a large range of variations of parameters of the system and conditions of loading by using ANFIS. Chang et al. in [18] has developed a weighted evolving fuzzy neural network to forecasting demand of electricity for each month inside country of Taiwan. In [19], the integrated diagnostic system is used for detecting islanding condition.In the diagnostic system, neuro fuzzy controller for grid-connected inverter-based distributed generation was investigated where the authors used the ANFIS for islanding detection. Shareef et al. in [20] have proposed an adaptive neuro fuzzy inference system approach to identify the real power transfer among generators where the 25-bus peninsula Malaysia equivalent system was exploited as a test system to demonstrate the usefulness of the ANFIS result output with contrast to the method of modified nodal equation. Thus from the literature, it is understood that the ANFIS has got excellent potential for the MPPT.

In this study, the MPPT is developed using four different ANFIS controllers to assess their performance.The rest of the work is organized as follows. The modeling of the PV system is mentioned in section 2. Adaptive neuro fuzzy inference system is described in section 3; meanwhile the ANFIS based MPPT is discussed in section 4. The results are discussed in section 5. Finally, the conclusion isrevealed in section 6.

II. MODELING OF THE PV SYSTEM

The G and T are in charge of the working point of PV system at the MPP [21,22]. Thecell current, *I*, which represent the mathematical model of the PV cell can be express as [23]:

$$I = I_{ph} - I_o\left(e^{\left(\frac{q(V+I.R_s)}{A.K_B.T_c}\right)} - 1\right) - \frac{V+I.R_s}{R_{sh}} \qquad (1)$$

whereI_{ph} is light-generated cell current (A), I_o is cell reverse saturation current (A), q is electronic charge, A is ideality factor, K_B is Boltzmann’s constant, and $T_c$is cell temperature (K).

Regarding to Eq. (1), the MPPT can be determine utilizing Iwhich varieswith G and T. The same relationship can be utilized to determine the MMPT in a PV module if the number of PV cells is known. The mathematical model can be used to determine the cell output current. However, this time consuming procedure and it is the main obstacle of the mathematical model. The 25 PV modules types SolarTIFSTF are used in this work to generate peak of 3 kW which are arrange in series-connected configuration. Table 1 shows the PV module characteristics.

Table 1: PV module characteristics

PV module	SolarTIFSTF
Maximum Power (P_{MPP})	120W
Open circuit voltage (V_{oc})	21.5 V
Short circuit current (I_{sc})	7.63 A
Voltage at maximum power (V_{MPP})	17.4 V
Current at maximum power (I_{MPP})	6.89 A
Nominal temperature	43.6º C
Nominal irradiance	1000 W/m^2

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Neural network (NN) with fuzzy logic (FL) makes an intelligent controller and it has been used in power electronic converters to solve many problems of nonlinearity [24]. Foremost advantage of the FL is its capability to represent the nonlinear input-output relationships by a place (if-then) rule to play that part. On the other hand, the key advantage of the NN is its excellent learning capability.

The robustness of the FLC depends on the shape of the membership functions and the rules. These parameters are usually obtained based on the trial and error process which is very difficult and time-consumption. Therefore, the MFs are sometimes obtained by incorporating the FLC with NN. This popular hybridization is known as adaptive neuro fuzzy inference system (ANFIS). ANFIS can effectively model the nonlinear systems with fast learning and high accuracy.

3.1 Anfis Architecture

The ANFIS play the main part to arrange a best membership function [25,26]. Based on input and output data set, ANFIS creates the fuzzy inference system (FIS).The membership function parameters can be attunedwith either a back-propagation algorithm only or by a least square estimation (LSE) algorithm. In FL perspective, only zero or first order Sugeno inference system proposed by Takagi-Sugeno can be used to systematically generate fuzzy rules from an input and output data. Fig. 1 shows the ANFIS structure for two inputs, one output with two rules.

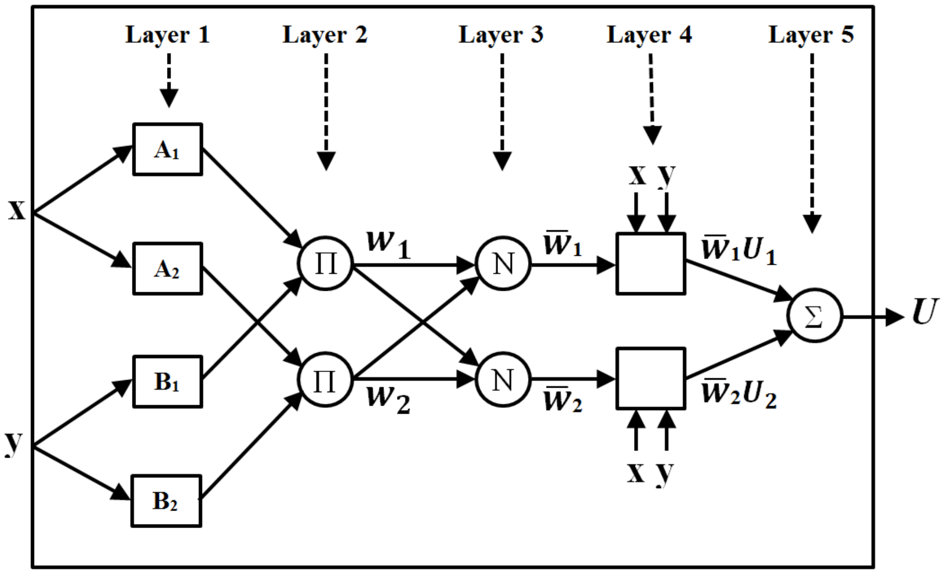


Fig. 1. ANFIS structure for two inputs (x) and (y) and one output U.

In this structure, the input nodes represent training data while output node represents forecasted data. The inputs for the ANFIS are (x,y), the output is (U), the circles symbolize fixed node and the squares symbolize adaptive node. ANFIS exhibit in Fig. 1 contains two rules:

Rule 1: IF x is A_1 and y is B_1, then $u_1 = p_1 x + q_1 y + r_1$ (2)

Rule 2: IF x is A_2 and y is B_2, then $u_2 = p_2 x + q_2 y + r_2$ (3)

where A_1, A_2, B_1 and B_2 are the nonlinear parameters and p_1, q_1, r_1, p_2, q_2 and r_2 are the linear parameters. ANFIS shown in Fig. 1 consists of five layers with different functions [26]. The first layer is the fuzzification layer. Every node in this layer is an adaptive node:

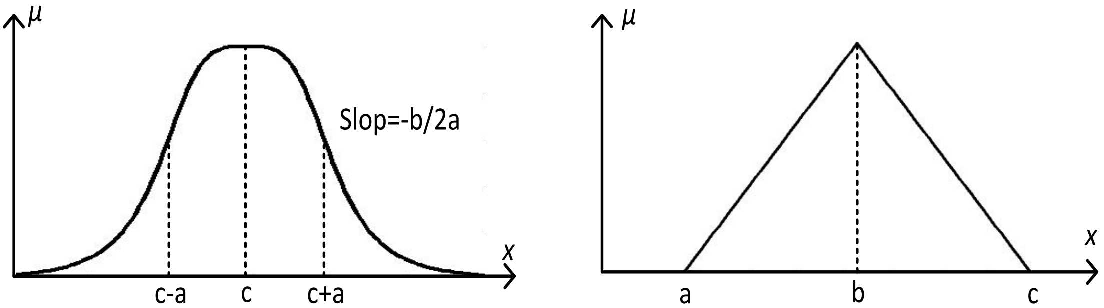
$$O_i^1 = \mu_{Ai}(x) \ , \ O_i^1 = \mu_{Bi}(y) \qquad \text{for } i=1,2 \quad (4)$$

where x, y are the input signals to this node, $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are membership functions to the linguistic variables A_i and B_i (positive big, positive medium, positive small.). The types of the membership functions used in this study are gbell and triangular membership function as exhibited in Fig. 2. In the fuzzification process, Eq. (5) is used for gbell membership function and Eq. (6) is used for triangular membership function.

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad (5)$$

$$\mu_{Ai}(x) = \begin{cases} \frac{x-a_i}{b_i-a_i} a < x < b \\ 1 + \frac{b_i - x}{c_i - b_i} b < x < c \end{cases} \qquad (6)$$

where a_i, b_i and c_i are parameter sets from the input membership function.



(a) (b)

Fig. 2. Membership functions types used in this study (a) gbell MF (b) triangular MF

The product of all input signals is the output of second layer (rules layer) which performs the inference process as can be specific in Eq. (7):

$$O_i^2 = w_i = \mu_{Ai}(x) \cap \mu_{Bi}(y) \qquad (7)$$

The normalization layer is the third layer in the ANFIS system. Every node provides the ratio of the i^{th} rule's firing strength to the total firing level as shown in Eq. (8):

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \qquad (8)$$

Each node of the layers computes the activation level of every rule, the fuzzy rules number are equivalent to the number of layers. They calculate the weights (w) which are normalized. The forth layer is theconsequent layer where the output of this layer can be expressed as in Eq. (9):

$$O_i^4 = \bar{w}_i u_i = \bar{w}_i (p_i x + q_i y + r_i) \qquad (9)$$

This layer output is generated from the inference of the rules. It establishes an adaptive correlation between normalized firing value and result function.The final layer is the defuzzification layer where the output is obtained by summing all incoming signals and transforming the fuzzy classification results into a crisp value, as shown in the Eq. (10):

$$O_i^5 = \sum_i \bar{w}_i u_i = \frac{\sum_i w_i u_i}{\sum_i w_i} \qquad (10)$$

As exhibited in Fig. 1, there are two adaptive nodes which arethe first node and the fourth node. However, the first node (fuzzification layer) there are three premise parameters named (a_i, b_i, c_i), and three consequent parameters named (p_i, q_i, r_i) in the fourth node (consequent layer) [26].

3.2 ANFIS learning algorithm

The goal of the learning algorithm is to adjust the premise parameter (a_i, b_i, c_i) and the consequent parameters (p_i, q_i, r_i) so that the output of ANFIS is compatible with the data that has been trained. When the premise parameters are settled to fix values the output can be represent in Eq. (11):

$$U = \frac{w_1}{w_1 + w_2} u_1 + \frac{w_2}{w_1 + w_2} u_2 \qquad (11)$$

Next substituting Eq. (9) into Eq. (12):

$$U = \bar{w}_1 u_1 + \bar{w}_2 u_2 \qquad (12)$$

Knowing $u_i = p_i x + q_i y + r_i$ and substituting it into Eq. (12) yields:

$$U = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \qquad (13)$$

Finally, rearrange the Eq. (13), the output can be written as the Eq. (14):

$$U = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1 r_1) + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2 r_2) \qquad (14)$$

Eq. (14) is a linear synthesis of consequent parameters (p_1, q_1, r_1, p_2, q_2, r_2). Least square estimation (LSE) algorithm can be adopted to determine the optimal consequent parameter's value. Oncethe premise parameters are not fixed, a hybrid algorithm which it combined gradient descent back-propagation and LSE algorithms is used to solve the problem. The hybrid algorithm includes two passes which are least square estimation (LSE) and backward pass (gradient descent). The forward pass is mainly implemented to make consequent parameters optimized when the premise parameters are fixed while the function of the backward pass is to optimize the premise parameters. Therefore, it has been verified that the hybrid algorithm is extremely efficient to train the ANFIS [27].

IV. ANFIS BASED MPPT

Two types of MFs have been considered in this work which are triangular and gbell membership functions. In each type, five and seven FS have been used. Therefore, four ANFIS can be employed for MPPT which are:

- Triangular MF-five FS (5-tri) based MPPT
- Triangular MF-seven FS (7-tri) based MPPT
- gbell MF-five FS (5-gbell) based MPPT
- gbell MF-seven FS (7-gbell) based MPPT

The most important issue regarding the ANFIS is the training data to identify the MFs and the FSs. In this work, the input training data are the G and T; meanwhile the output training data is cell output current, I. The inputtraining data (G and T) are generated using (15) and (16). These data are used to determine the output training data (I) through Table 1 and Eq. (1).

$$G_i = rand * (G_{max} - G_{min}) + G_{min} \quad (15)$$

$$T_i = rand * (T_{max} - T_{min}) + T_{min} \quad (16)$$

Regarding to (15) and (16), the limitation for the G and T should be define. Fig. 3 shows the historical data fluctuation regarding G and T;hence, the following values have been adopted in this work:

- G_{max} has been define as 1500 W/m^2
- G_{min} has been define as 0
- T_{max} has been define as 45ºC
- T_{min} has been define as 0

These maximum values have been chosen more than the historical data fluctuation and the minimum values have been chosen less than historical data fluctuation to ensure that all the generated data using (15) and (16) are covered the required data fluctuation.

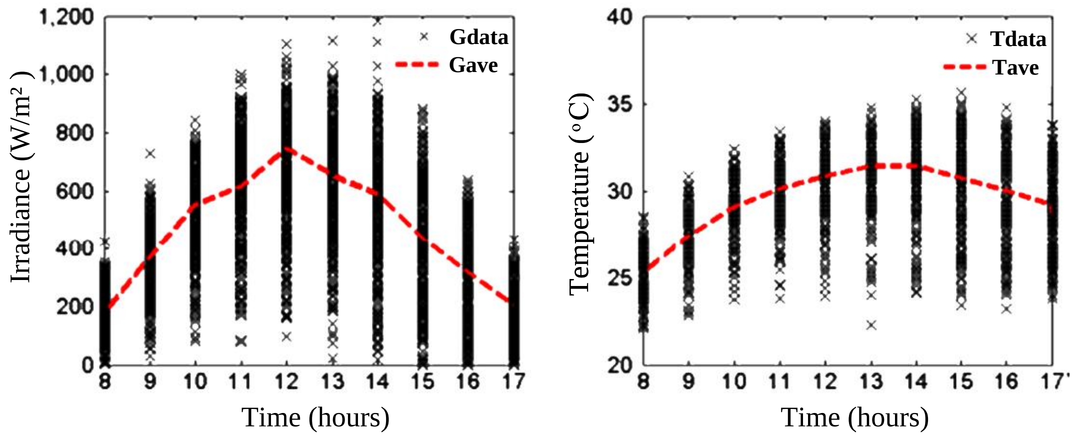


Fig. 3. Measured hourly irradiation and temperature data for one year [28]

V. RESULTS AND DISCUSSION

The trained four ANFIS based MPPT have been evaluated using the input data (G and T) for five days which are 22th of March 2016, 6th of April 2016, 21th of April2016, 13th of May 2016, and 28th of May 2016 which are collectedfrom the rooftop PV system. In this work, the aim is to investigate the effectiveness of four ANFIS under real data condition using same meteorological data which are collected through the HOBOwarePro software.

The ANFISeffectiveness-based MPPT has been evaluated using statistical analysis. For this analysis, three types of indices have been used which are standard deviation (SDEV), mean square error (MSE), and extracted energies. The SDEV evaluates the rate of variation in compare to the average value. High SDEVgive indication that the data points are misled out over the values targeted meanwhile a minimum SDEVindicates that the data points are near to the target value. Table 2 shows the effectiveness comparison of the ANFIS technique. The ANFIS with 7-tri has achieved the better performance than the other ANFIS controllers.

Table 2: Standard deviation

Date	5-gbell	5-tri	7-gbell	7-tri
22th of March	42.53635921	2.365545196	11.05373443	**1.420979117**
6th of April	47.8999527	2.336575017	10.63208146	**1.789202154**
21th of April	50.35506522	2.931421759	13.18874316	**1.759782241**
13th of May	37.86859254	2.931387998	11.26272372	**1.930723743**
28th of May	22.59633954	1.651998636	8.950492785	**1.134269898**

The second index is the mean square error (MSE). The quality of the signal is inversely proportional to the MSE where the ANFIS output is move away from the accurate maximum powerwhen the MSE is increased; meanwhile the decreasing in the MSE rate indicates that the output power is near to the accurate maximum power. Table 3 shows the performance comparison using the MSE rates. Since the ANFIS with 7-tri achieved the lower MSE; therefore, it achieved the robust performance compare with the other ANFIS controllers.

Table 3: Mean square error

Date	5-gbell	5-tri	7-gbell	7-tri
22th of March	2940.994578	6.667560774	227.9960801	**2.377348134**
6th of April	3995.880805	6.910230339	246.436941	**3.817990887**
21th ofApril	4679.006908	11.15435667	360.5945928	**3.881629246**
13th of May	2173.950798	10.50674669	239.835553	**4.268295513**
28th of May	778.2052292	2.954146174	139.5908919	**1.346164582**

Table 4 shows the extract energies based on four types of ANFIS. The extracted energies show that some controllers produce power larger than others. However, the maximum of energy is extracted by (7-tri), as boldfaced, and the minimum energy is extract by (5-gbell). The relative errors between (7-tri), and (5-gbell) vary from 0.9% (on 28th of May) to 6.01% (on 21th ofApril). Getting 6% more energy is not ignorable in measurement of performance of the energy. It is important to note that for very sunny days, as 22th of March, 13th of May, and 28th of May, which correspond to the maximum extracted energy, the errors are significantly small.

Table 4: Extracted energies (Wh)

Date	5-gbell	5-tri	7-gbell	7-tri
22th of March	1077.169328	1109.794271	1100.54038	**1110.231903**
6th of April	791.6295322	831.69533	821.3478589	**832.1146168**
21th of April	709.7169443	754.4337633	742.3689948	**755.1490077**
13th of May	1071.569131	1097.406613	1088.158081	**1098.055203**
28th of May	1668.904962	1684.79999	1677.560145	**1685.030462**

To further evaluate the performance of various ANFIS models, statistics analysis is conducted using Q-Q plots for five days as shown in Figs. 4-8. Ordinarily, the essential idea is to calculate the theoretically predicted value for every point of the data. In case of the data which go behind the assumed distribution, the points on the Q-Q plot will fall around on a straight line. As can be seen from Figs. 4-8, the ANFIS based triangular MFs with five and seven FS achieve better perform than the ANFIS based gbell MFs with five and seven FS.

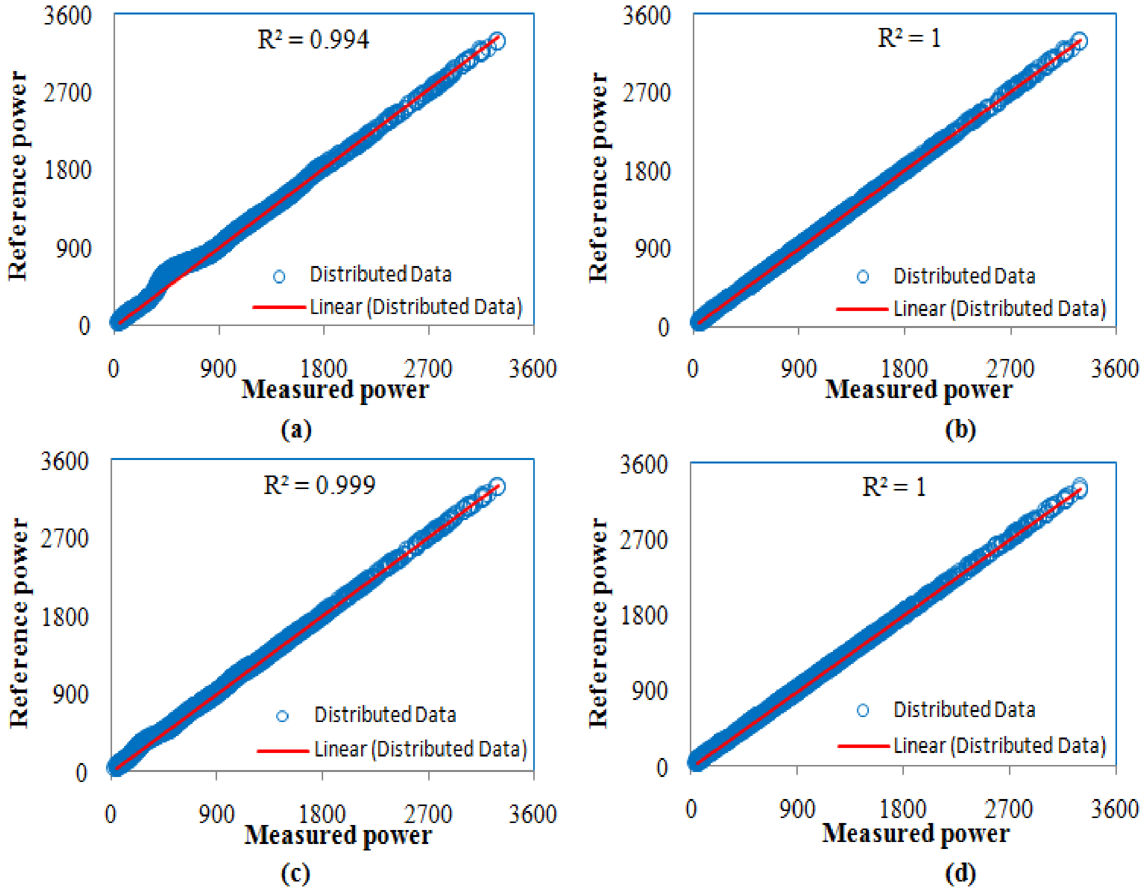


Fig. 4.Q-Q plot for the 22th of Marchusing (a) 5-gbell, (b) 5-tri, (c) 7-gbell, and (d) 7-tri

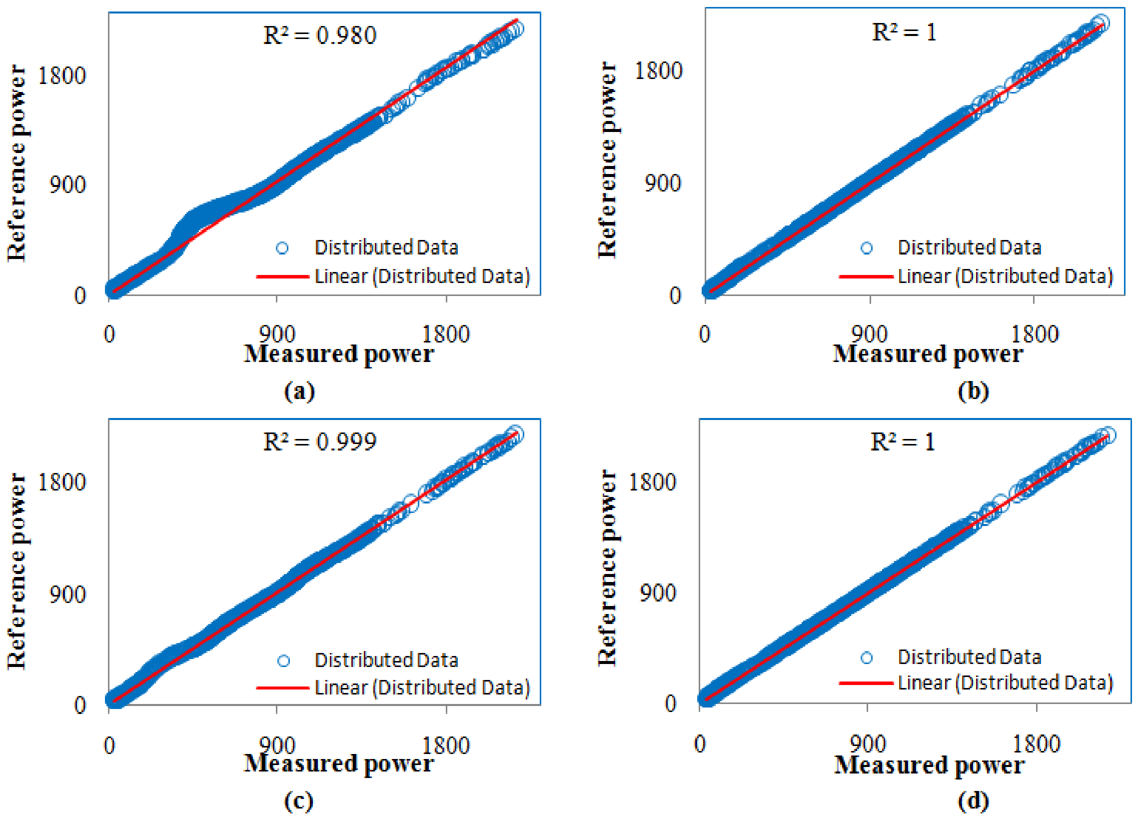


Fig. 5.Q-Q plot for the 6th of Aprilusing (a) 5-gbell, (b) 5-tri, (c) 7-gbell, and (d) 7-tri

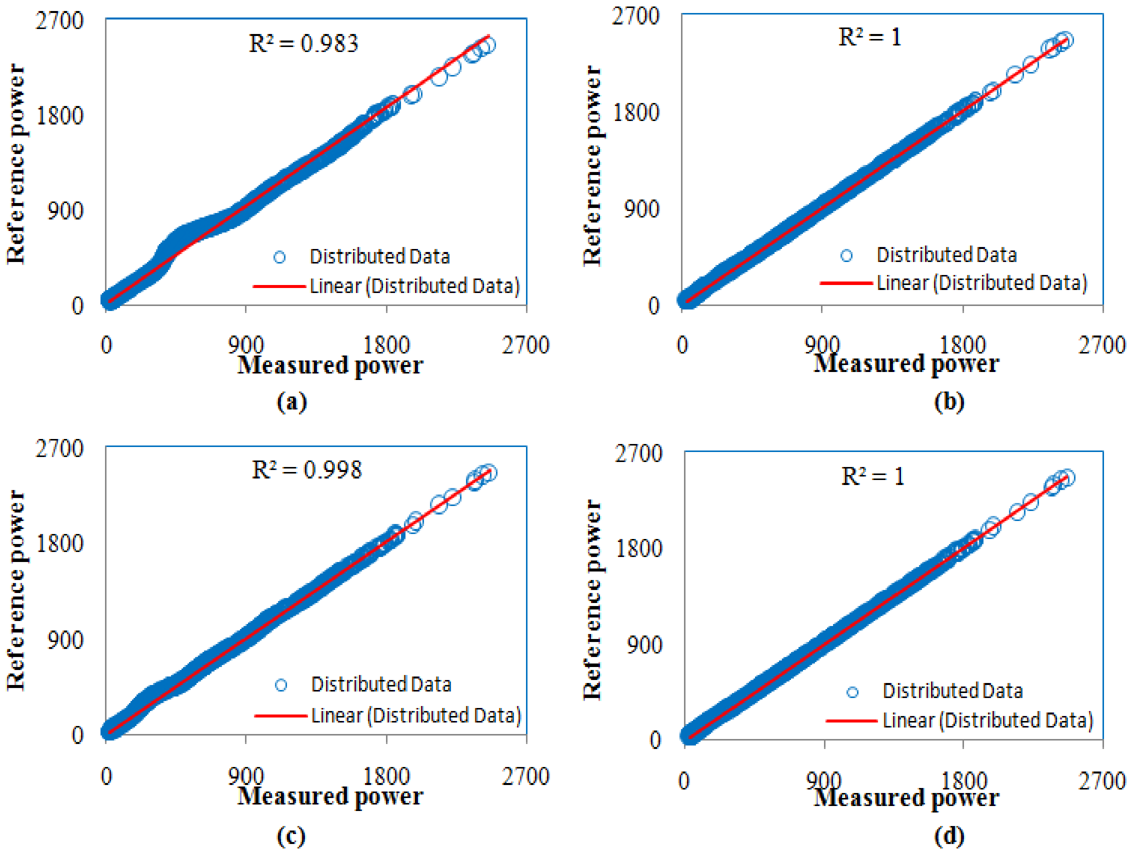


Fig. 6.Q-Q plot for the 21th of Aprilusing (a) 5-gbell, (b) 5-tri, (c) 7-gbell, and (d) 7-tri

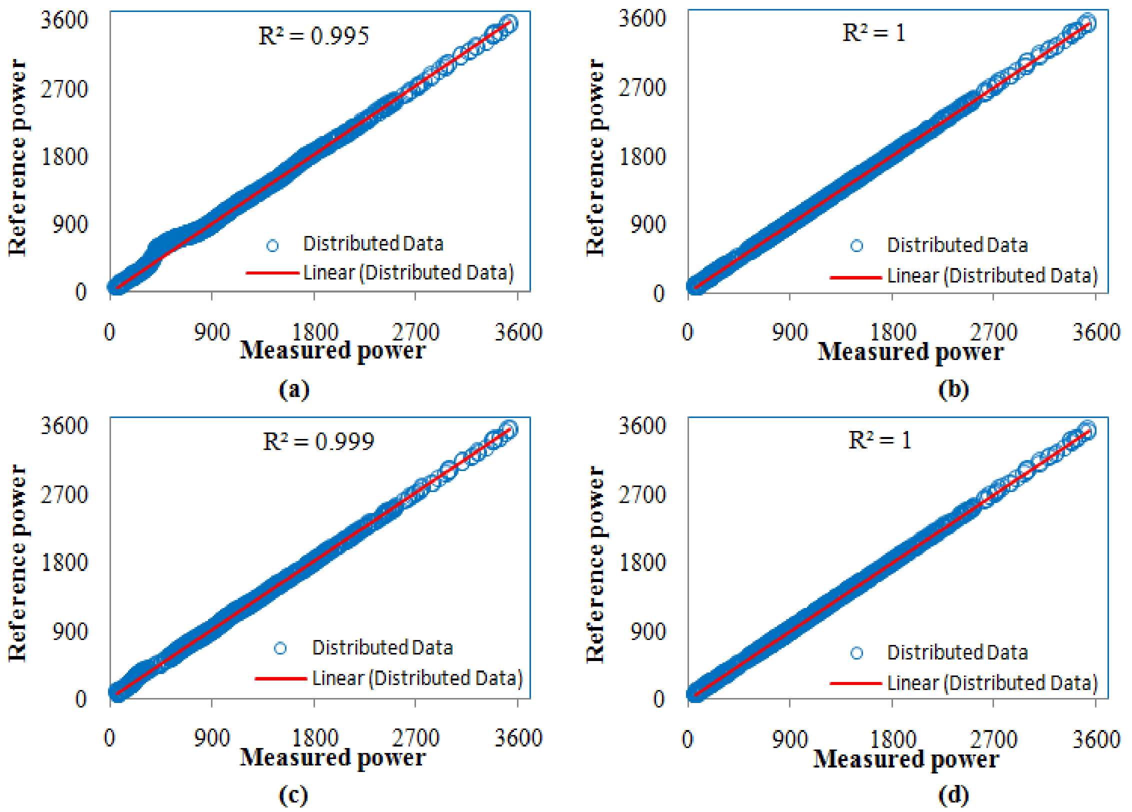


Fig. 7.Q-Q plot for the 13th of Mayusing (a) 5-gbell, (b) 5-tri, (c) 7-gbell, and (d) 7-tri

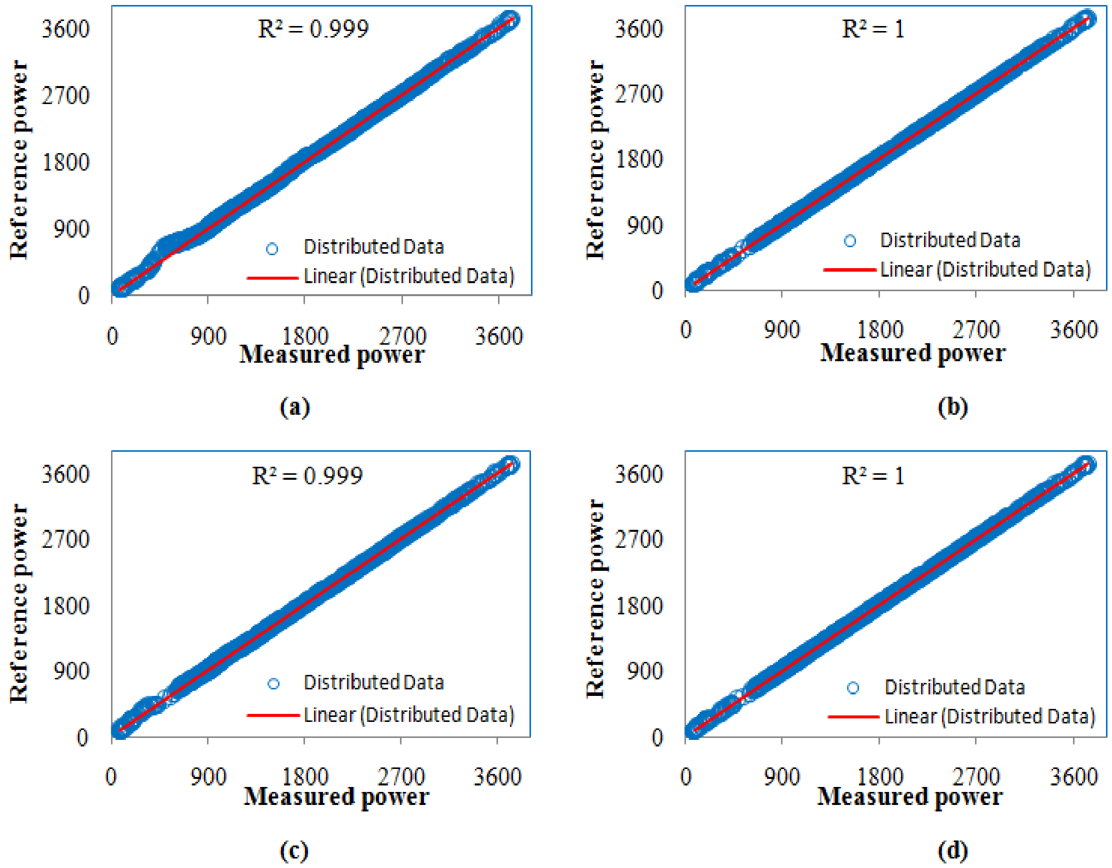


Fig. 8.Q-Q plot for the 28th of Mayusing (a) 5-gbell, (b) 5-tri, (c) 7-gbell, and (d) 7-tri

The Q-Q plots for five days are compared in Fig. 9. The figure indicates that the triangular membership function achieved better performance than the gbell membership function. However, the 7-tri show robust and superior performance compared with the 7-gbell.

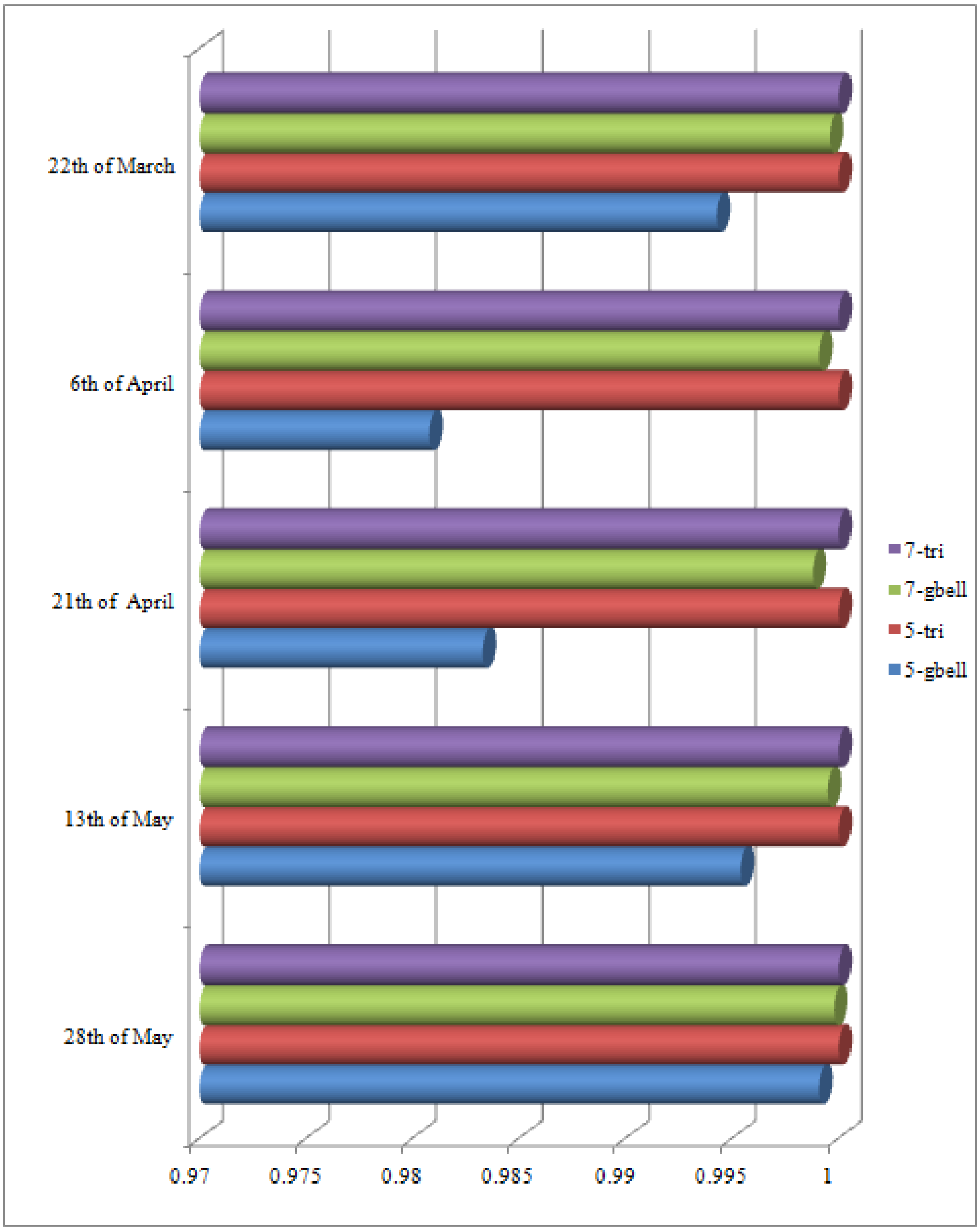


Fig. 9. The Q-Q comparison for five days

VI. CONCLUSION

This paper introduced a new and effective maximum power point tracking method based on adaptive neuro-fuzzy controller for 3 kW peak PV systems consisting of the 25 SolarTIFSTF PV modules. The proposed method is simple in tuning. To select the best FLC-based MPPT, four ANFIS controllers have been developed to track the MPP for PV system. Three types of indices have been used to evaluate the effectiveness of the system which are SDEV, MSE and extracted energy. To evaluate the reliability and efficiency of the proposed algorithm, the ANFIS model was tested using real data obtained from the rooftop PV system in 22th of March 2016, 6th of April 2016, 21th of April 2016, 13th of May 2016, and 28th of May 2016. ANFIS with 7 triangular MF has superior performance to track the MPP than the other ANFIS controllers where it achieved lowest SDEV, MSE and highest extracted energy. Furthermore, it can be concluded that the choice of the MF type is more important than the choice of the number of the FS in the design of the ANFIS controllers.

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