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Design of an Efficient Maximum Power Point Tracker Based on ANFIS Using an Experimental Photovoltaic System Data

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Abstract: Maximum power point tracking (MPPT) techniques are a fundamental part in photovoltaic system design for increasing the generated output power of a photovoltaic array. Whilst varying techniques have been proposed, the adaptive neural-fuzzy inference system (ANFIS) is the most powerful method for an MPPT because of its fast response and less oscillation. However, accurate training data are a big challenge for designing an efficient ANFIS-MPPT. In this paper, an ANFIS-MPPT method based on a large experimental training data is designed to avoid the system from experiencing a high training error. Those data are collected throughout the whole of 2018 from experimental tests of a photovoltaic array installed at Brunel University, London, United Kingdom. Normally, data from experimental tests include errors and therefore are analyzed using a curve fitting technique to optimize the tuning of ANFIS model. To evaluate the performance, the proposed ANFIS-MPPT method is simulated using a MATLAB/Simulink model for a photovoltaic system. A real measurement test of a semi-cloudy day is used to calculate the average efficiency of the proposed method under varying climatic conditions. The results reveal that the proposed method accurately tracks the optimized maximum power point whilst achieving efficiencies of more than 99.3%.

Keywords: adaptive neural-fuzzy inference system; fuzzy logic control; maximum power point tracking; photovoltaic; perturb and observe; MPPT efficiency

1. Introduction

Today, the fossil fuel resource is used in generation of energy. This resource has caused global warming and air pollution due to the CO_2 emissions from this fuel. Moreover, the demand for energy is growing due to population growth. To address this complex issue, many researchers have turned to renewable energies in order to solve the shortage of energy in coming years and to reduce the side effects of the combustion of conventional fossil fuels. In general, renewable energies are those that come from natural resources, such as, wind, sunlight, tides and geothermal heat. The major renewable energy resources are wind turbines, photovoltaic (PV) systems, biomass, hydropower, and geothermal power. The PV system is one of the most attractive renewable energy resources because of its provision of sustainable, safe, and clean energy [1]. According to the International Energy Agency (IEA), global energy production from PV resources will reach 16% of global electricity by the 2050s [2]. However, low efficiency is a major challenge when installing this resource, because the generated power from a PV array depends upon the solar irradiations (G) and operating temperatures (T) of climatic conditions, which can result in losses of energy of up to 25% [3]. To enhance the efficiency of a

PV array, a maximum power point tracking (MPPT) controller is employed with a PV system, thus achieving maximum electrical generation under different climatic conditions. The principle work of this controller is that it generates a suitable duty cycle (D) to a power conversion system, such as a DC–DC converter, allowing the PV array to achieve continuous available maximum power generation. In general, efficiency, cost, and type of application are the key issues when aiming to propose the MPPT controller for a PV system [4]. Taking these into account, several types of MPPT techniques have been proposed for PV systems, and these can be classified into two types: Conventional techniques, such as perturb and observe (P&O) [5], incremental conductance (IC) [6], and artificial intelligence techniques (AI) like the fuzzy logic controller (FLC) [7], the artificial neural network (ANN) [8], and the adaptive neuro-fuzzy inference system (ANFIS) [9].

The P&O algorithm is a widely used technique used for PV-MPPT due to its simple implementation and low cost—however, it does face various issues, such as a slow tracking speed, high fluctuation and drift issues associated with fast changing irradiation [10,11]. Consequently, the IC-MPPT is designed to overcome the limitations of the P&O algorithm. The major advantage of this algorithm is that it has a high ability to reach to the Maximum Power Point (MPP) under a rapid change of environmental conditions [12]. However, instability and measurement noise are big problems facing the operating work of a PV system due to the use of a derivative operation in this algorithm [6]. Hence, several modulations based on the power–voltage curve of PV systems have been presented to address the issues of P&O and IC-MPPTs, such as in [12–14], but they are considered as being insufficient solutions [15]. Consequently, AI methods based on MPPT have been introduced to address these problems. Moreover, these methods do not need complex mathematics and accurate parameters when designing systems. Specially, the FLC-MPPT is classified as a high powerful controller for a PV system due to its faster tracking speed and lesser oscillation when compared with classical MPPT controllers [16]. Furthermore, it does not require training data, unlike the ANFIS and ANN methods, thus resulting in its operating for different types of PV arrays with the same MPPT proposal. However, the major disadvantage is the drift issue associated with a change in the solar irradiation and operating temperature [17]. This is because it heavily depends on the good knowledge of a PV system, resulting in incorrect fuzzy rules and inaccurate membership functions. To address this issue, many modulations have been presented, e.g., an adaptive and optimized defined membership function of the traditional FLC-MPPT, as evidenced in [18–20]. The ANN is considered another powerful technique for a nonlinear system such as a PV array. Its major advantage is that it provides heuristic output using a quantification of the real numerical data. Hence, an ANN based on MPPT has less oscillation around the MPP when compared with the FLC-MPPT. However, slow training and black box work are the main weaknesses of the ANN system [21]. To solve these limitations, the ANFIS is integrated with an ANN and an FLC, which offer the most powerful intelligence techniques. The MPPT technique based on ANFIS has a fast response and small amounts of oscillation under different weather conditions due to its smaller consumption time. However, getting accurate training data and tuning the ANFIS model are big challenges to design an efficient ANFIS-MPPT controller [9].

In this paper, ANFIS was used to determine the MPP of a PV array based on a large amount of real training data. Those for this model were collected from the experimental test of a PV array installed at Brunel University, London, UK, and then they were analyzed and optimized using a curve fitting technique to get an accurate design. The G and T of weather conditions were selected as the input, and the reference power (Pref.) of the PV array at the MPP as the output. In the same weather conditions, the actual PV power (Pact.) was measured using a sensed voltage and the current of a PV Simulink operation. These two power sources were compared, and the error (e) was given to a proportional-integral (PI) controller to generate the D of a DC–DC converter, and this D was converted to the signal (S) by a pulse width modulation (PWM) to adjust the operating MPP of the PV array, as shown in Figure 1. The results prove that the proposed method has the fastest tracking speed, least fluctuation around the MPP and highest power. Moreover, it is the most accurate for tracking the MPP and avoiding the drift phenomenon. Furthermore, it achieved the highest efficiency compared with the

FLC- and P&O-MPPTs. The rest of this paper is organized as follows. Section 2 introduces literature reviews based on the use of ANFIS with the PV-MPPT, while Section 3 covers the PV system. Section 4 discusses the MPPT using the ANFIS algorithms. The methodologies of collected and optimized data, as well as the training of the proposed ANFIS model are explained in Sections 5–7, respectively, whereas the results and discussion are presented in Section 8. The real measurement test results of one day are provided in Section 9, with Section 10 containing the conclusion.

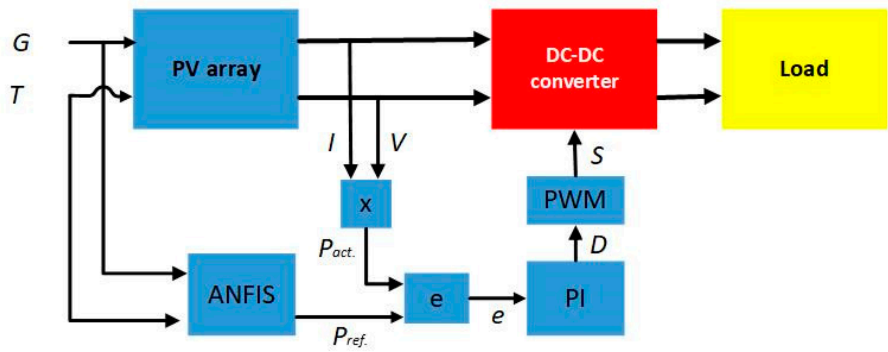


Figure 1. The diagram of photovoltaic (PV) system using an adaptive neuro-fuzzy inference system-maximum power point tracker (ANFIS-MPPT).

2. Related Works

The MPPT controller, based on artificial intelligent techniques, for a PV system has been widely used in recent years. As mentioned earlier, this is because it can solve the significant issues associated with the classical MPPT methods. Moreover, these methods do not need complex mathematics or accurate elements when proposing the system. Specifically, the ANFIS technique based on the MPPT controller is considered one of the most powerful methods for a PV system because it experiences less fluctuation around the optimized MPP, has a fast tracking speed, and has a low computation time. However, the main disadvantages are the lack of accurate training data and tuning of the ANFIS model. Hence, several types of ANFIS-MPPTs have been designed using different types of training data. Among them, in [22], the authors developed an MPPT technique based on adaptive ANFIS and hill climbing (HC) techniques to increase the generated energy from a PV system. This proposed technique is a combination of two stages to adjust the property duty cycle of a boost converter for MPP tracking. In the first stage, the duty cycle is estimated, whilst in the second, an exact duty cycle corresponding to the optimized MPP is determined. In order to construct the training of the ANFIS system, the ranges of the T and the G are determined according to the latitude and longitude of the site of the PV system. With same ideal, the authors in [23] presented an intelligent MPPT for a PV system using a hybrid ANFIS and particle swarm optimization (PSO) technique to reduce the converging time of the MPPT algorithm under partially shaded conditions. The G and T were selected as the input, whilst the optimal duty cycle was the output, which was optimized using the PSO algorithm. The data of the ANFIS system were collected from different scenarios of the PV operating system under varying partial shadings. Whereas these proposals increased the efficiency of the PV system, their implementations became overly complex due to an additional step unit.

Next, the authors in [24] presented a comparative study among P&O-ANFIS, PSO-ANFIS and ANN-MPPTs for a stand-alone PV system under partial shade conditions. The training data of the ANN method were collected from a single operating test of the PV array, while the P&O-ANFIS and PSO-ANFIS were derived from the operational PV system, with P&O and PSO, respectively. In [25], the researchers designed an efficient ANFIS-MPPT method based on a large training dataset for PV systems. The inputs of the proposed ANFIS technique consisted of the G and T of climatic conditions, whilst the output was the optimized PV voltage at the MPP. The large training dataset was collected from Simulink operation tests of a PV module under a varying range of weather conditions to avoid the system having a high training error. In [26], the researchers modelled an intelligent MPPT controller based on ANFIS to solve the complexity of the tracking mechanism of a PV system. The T and G of the weather conditions were used as inputs of the training data of the proposed method, while the output was the value of maximum power from the PV array at a specific temperature operation and irradiance level.

In [27], the authors designed an intelligent MPPT technique based ANFIS for a solar PV system to reduce converge tracking time under a fast change in weather conditions. The key point of this proposal is that the maximum power of the PV module was adjusted under specific conditions. The proposed ANFIS-MPPT was trained by the G and T of the Simulink operation of a PV module under varying weather conditions, and the output was the maximum power. In [28], the scholars designed an intelligent MPPT controller based on ANFIS to generate the maximum power of a PV system in the standalone operation. The maximum power generation of the load was ensured by an adaptive ANFIS-MPPT with a quasi-Z-source inverter. The inputs of the proposed ANFIS method consisted of the G and T, whereas the output gave the optimism voltage at the MPP of each of the weather conditions. The training data were collected based on a simulation test of a single PV module under various environmental conditions. In [29], the authors proposed and implemented an intelligent MPPT method using an ANFIS model to enhance the performance of a PV system. The main contribution of this work was eliminating the need for inputting irradiance sensor. The PV voltage, PV current, and temperature operation were selected as the input, whilst the optimal PV voltage at the MPP was the output of the ANFIS model. The data of the ANFIS system were collected from Simulink operation tests of a PV system under varying climate conditions.

In [30], the authors designed an intelligent MPPT based on ANFIS for a PV system to generate maximum output power. This work involved utilizing the maximum power for energy storage using a single ended primary inductor converter (SEPIC). The G and T were selected as the input, with the optimal PV current at the MPP being the output of the ANFIS model. The data of ANFIS system were collected from characteristics of the PV array under varying weather conditions. In [31], the scholars designed and implemented an ANFIS-MPPT technique using an Field Programmable Gate Array (FPGA) board for standalone photovoltaic systems to demonstrate the usefulness of ANFIS. The solar irradiance and temperature operation were selected as the inputs of the ANFIS model, whilst the optimal current was the output. The training data were used to define the input membership function of the proposed method by assuming that the PV array was located in the south of Iraq. In [32], an intelligent approach to optimizing the efficiency of a PV system by the ANFIS-MPPT technique was presented. The system consisted of a PV array, an MPPT controller, a DC/DC converter and a DC motor pump. The PV current and PV power were selected as the input, with the duty cycle being the output of the proposed MPPT method. The data of ANFIS system were collected from several experiments performed on a PV array under varying values of the G and a constant T at 25 °C. In [33], an intelligent MPPT controller was proposed for a PV system using an ANFIS model to track the MPP under varying climatic conditions. The inputs of the proposed ANFIS technique consisted of the current and voltage of a PV module, whilst the output gave the propertied duty cycle for a power conversion system. The proposed ANFIS method generated change in the duty cycle based on a historical change of PV power and derivate in this value. In [34], authors designed an efficient MPPT technique based ANFIS for PV systems to determine the MPP under different weather conditions. The G and T were selected as the inputs of the ANFIS model, whereas the optimal voltage at the MPP was the output. The data of ANFIS model were collected from the power–voltage curve of a PV array under different weather conditions.

The results in [24–34] reported that the conventional ANFIS-MPPT based on theatrical data increased tracking speed and reduced oscillations. However, they were not achieving a higher efficiency when compared with hybrid methods because of a shortage of accurate training data. Consequently, the author in [35] proposed an intelligent MPPT technique based on ANFIS for standalone PV systems using a large amount of real data. The G and T were selected as the input of the

ANFIS model, whereas the optimal voltages at the MPP and duty cycle were the outputs. The training data of the proposed ANFIS system were collected from experimental testing of a PV array installed in Ottawa, Canada. With the same idea, scholars in [36] presented a novel methodology for maximum power point tracking of a grid-connected photovoltaic system using the experimental data of a PV system installed in Tokyo, Japan. The G and T were used as input training data of the proposed ANFIS method, and the output was the reference voltage. Though those proposed methods in [35,36] trained using the real data, they were not optimized. Hence, the MPPT tacker achieved a lower efficiency compared with a hybrid algorithm under different weather conditions. In this work, experimental training data were collected during one year from the experimental tests of a PV array installed at Brunel University London, London, United Kingdom, and then they were analyzed and optimized using the curve fitting technique to design an efficient MPPT controller for PV systems.

3. Photovoltaic System

The fundamental element of photovoltaic system is a solar cell. It converts the lighting into electrical energy. In typical solar cell, the resistances are not included, but in workable case, they are implanted and connected with PV diode, as shown in Figure 2.

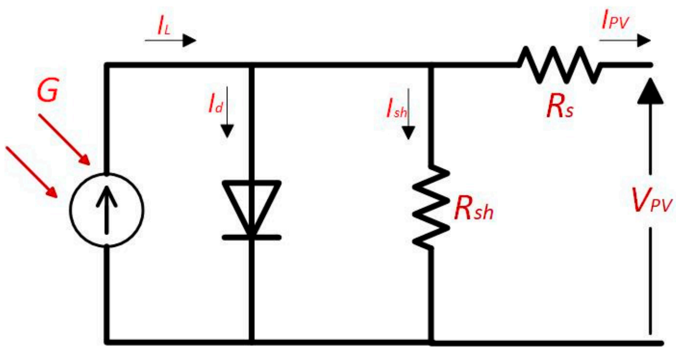


Figure 2. Equivalent circuit of PV cell [7].

This is because the p–n junction and semiconductor of the PV diode are non-ideal and resistant, respectively, resulting in the implantation of a shunt and series resistances. Kirchhoff's law, as given in Equation (1) [2], can find the current generator from the solar cell:

$$I_{PV} = I_L - I_d - I_{sh} \tag{1}$$

where I_L is the current generator, which is given in Equation (2):

$$I_L = G\{I_{SC}[1 + ka(T - T_{STC})]\} \tag{2}$$

where G is the solar irradiation, T is the ambiance temperature of climate conditions, I_{SC} is the short circuit current of PV cell, ka is the temperature coefficient, T_{STC} is the T of PV cell under a standard test conditions (STC), and I_d is the current of PV diode which given by Shockley's Equation (3):

$$I_d = I_0\left\{\exp\left(\frac{qV_d}{nkT}\right) - 1\right\} \tag{3}$$

where I_o is the current of PV diode at saturation conditions; V_d is the terminal voltage on PV diode; q and k are an electrical charge (1.69×10^{-19} C) and Boltzmann's fixed (1.38×10^{-23} J/K), respectively; and n is the PV diode factor. Now, the universal equation that describes the I–V characteristic chart of the PV cell is given by Equation (4):

$$I_{PV} = I_L - I_0\left[\exp\left(\frac{q(V_{PV} + I\,R_S)}{nkT}\right) - 1\right] - \left[\frac{V_{PV} + I\,R_S}{R_{sh}}\right] \quad (4)$$

where I_{PV} is the PV current and V_{PV} is the PV voltage. To obtain wanted voltage and current, The PV cells are connected in series and parallel in various topologies to get an optimized PV module, and then they are connected in varying configurations to get a desired PV array. In current work, the PV array consisted of a 925 W, five-module (Sharp NU-S5E3E 185) PV generator installed at Brunel University London, UK, as shown in Figure 3. The main parameters of the PV model are given in Table 1. To simulate the current–voltage characteristics, Equations (1)–(4) are used. As presented in Figure 4, there are individual points on the I–V characteristics of the PV array, which are recognized as the maximum power point (MPP) and the location of those points shifts regarding to the G and T of climatic conditions: The maximum available power of the PV array increases as the G increases; conversely, a PV generator is more efficient at low operation temperature [37]. To solve those problems, a power conversion system, such as a DC–DC converter and an MPPT controller are employed in PV systems, resulting in maximum power generation under various environmental conditions. In addition, this system improves the reliability and stability of the PV generation. A DC–DC boost converter has been widely used for photovoltaic conversion systems because of its easily adaptive MPPT controller. The DC–DC boost converter is usually used to regulate and provide a voltage on output side more than the input side. The voltage gain of a DC–DC boost converter is shown as in Equation (5):

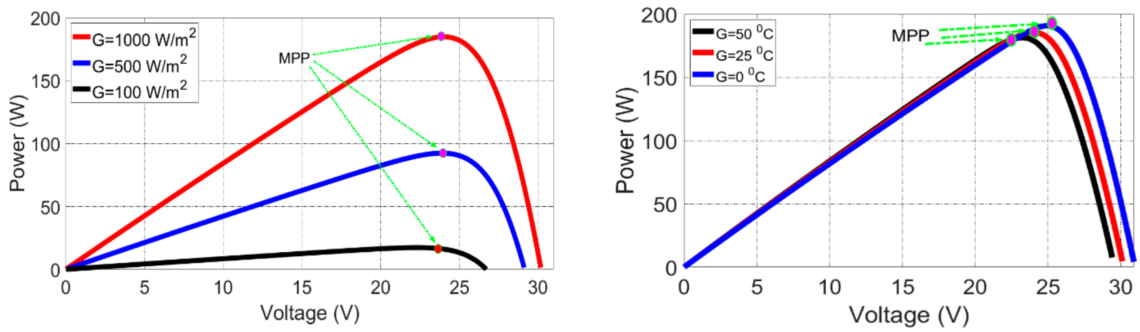
$$G_n = \frac{V_o}{V_i} = \frac{1}{(1 - D)} \quad (5)$$

where V_o is the output voltage, V_i is the input voltage, and D is the duty cycle of the MPPT controller, which is converted to a signal by the PWM. To generate this D, several proposals have been designed in recent years, such as the P&O, IC, FLC and ANN-MPPT methods.

Figure 3. The studied PV array installed at Brunel University London, UK.

Table 1. PV module characteristics.

Parameters	Value
Cell number	48
Dimensions	1.318 × 994 × 46 mm
Nominal power	185 W
Open circuit voltage	30.2 V
Maximum power voltage	24 V
short circuit current	8.54 A
Maximum power current	7.71 A
Temperature Coefficient (*Pmax*)	−0.485%/°C
Temperature Coefficient (*Isc*)	+0.053%/°C
Temperature Coefficient (*Voc*)	−104 mV/°C



(**a**) (**b**)

Figure 4. Power–voltage (P–V) characteristic of a PV array under: (**a**) Different values of *G* at a constant T of 25 °C; (**b**) different values of *T* at a constant *G* of 1000 W/m^2.

4. ANFIS Technique

The adaptive neural-fuzzy interference system (ANFIS) technique is considered a hybrid method based on the architecture of a neural network and fuzzy logic inference. The ANFIS technique has a number of nonlinear applications in many sectors, such as engineering, chemistry, manufacturing, and physics. Particularly, in the areas of electrical engineering, there are a PV array and a wind turbine. The ANFIS structure consists of five layers: Fuzzification, rules, normalization, consequent, and addition, as shown in Figure 5. In the first layer, every node of the training data is an adaptive node, with the node function using Equations (6) and (7):

$$A_{1,i} = \mu x_i(x) \quad for \;\; i = 1,2 \tag{6}$$

$$A_{1,i} = \mu y_{i-2}(y) \quad for \;\; i = \; 3,4 \tag{7}$$

where μ is the defined membership function and $A_{1,i}$ is the defined membership value for the inputs x and y. The subscripted 1 and i is the layer number and node number of the training data, respectively. The defined membership functions can be any shaped function, such as triangular, trapezoidal or Gaussian. The best membership functions achieve less training error. In Layer 2, every node is a fixed node based on one fuzzy rule. The output value is given by Equation (8):

$$A_{2,i} = \omega_i = \mu X_i\,(x)\mu Y_i\,(y) \quad i = 1,2 \tag{8}$$

In Layer 3, every node is fixed based on the normalization of the firing strength, using Equation (9):

$$A_{3,1} = \omega_i = \frac{\omega_i}{\omega_1 + w_2} \tag{9}$$

In Layer 4, every node is adapted and calculated based on the rule consequent, as given in Equation (10):

$$A_{4,1} = \omega_i f_i = \omega_i (p_i\, x + q_i\, y + r_i) \tag{10}$$

where p_i, q_i and r_i are consequent parameters which require being optimized in the training operation. In Layer 5, all input nodes are summed together to get the final output signal, as given in Equation (11):

$$A_{5,1} = \sum_i \omega_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{11}$$

The traditional ANFIS-MPPT method usually has two inputs and one output, such as in [9]. The operating temperature and irradiance level are usually used as inputs to the training data of the ANFIS method, and the output is the reference power. Under the same weather conditions, the actual PV power is calculated using the sensed voltage and current of the PV operation. These two power readings are compared, and the error is given to a PI controller to generate the signal of a DC–DC convertor by a PWM generator to adjust the operating MPP of the PV module. In general, the MPPT technique based on ANFIS has been designed to solve the limitations of an intelligent system. In addition, it can adjust its elements to give a faster response and less fluctuation under different weather conditions due to less time being consumed in the defuzzification stage. However, accurate training data and tuning ANFIS model are big challenges when designing an efficient ANFIS-MPPT.

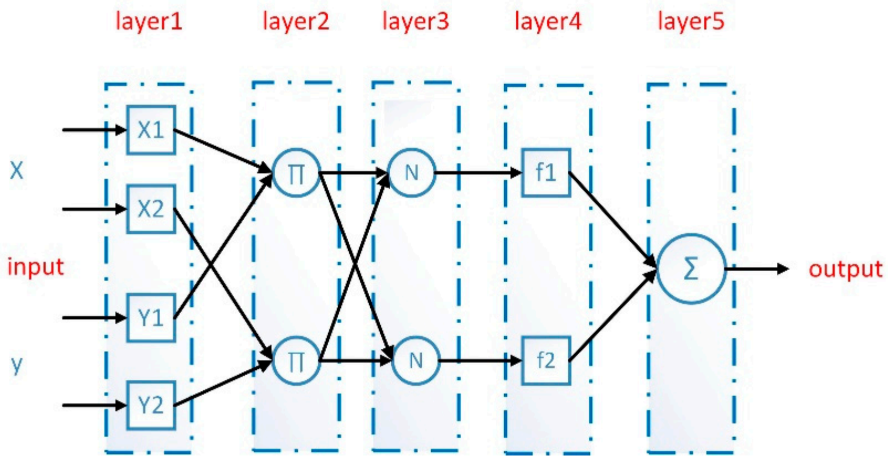


Figure 5. A block diagram of the ANFIS model [25].

5. Methodology of Collected Data

A micro-grid PV system was installed at Brunel University London, London, UK, to collect real training data, as shown in Figure 6. The PV array consisted of five PV modules connected in series. This PV array was connected to the micro-grid through a dedicated Sunny Boy inverter. The main reason for using this inverter is that it conformed to the regulations concerning small-scale PV generation. In addition, it has an inbuilt communication system, an anti-islanding unit and voltage protection. To measure and collect the electrical parameters of the PV system, the Sunny Boy controller pulse was connected to the inverter by RS485 transmission protocols. In addition, a weather station comprising of a pyrometer, hydrometer, anemometer and wind vane was installed and connected to the PV system for studying and analyzing the dependence of weather parameters. Though four parameters of weather conditions (irradiation, temperature, wind speed and humidity) were measured, the solar irradiation and ambiance temperature were selected to design the PV-MPPT systems because they are the most effective on PV systems than other parameters according to the general equation of a PV cell. The ranges of the ambient temperature and solar irradiance were determined according to the latitude and longitude of Uxbridge, London, UK. They were 51.531 and −0.474, respectively. Both the weather station and PV system were monitored and controlled through supervisory control and data acquisition (SCADA), and then the data were recorded by a data logger connected to a PC computer terminal and linked to the internet though Brunel university's local area network (LAN) using TCP/IP and SBC net port system commination. The collected data log daily at 5-minute intervals throughout the whole of 2018 and record by the Microsoft Excel software of a PC. In the night, the collected system switched off then woke up every 15 minutes to check whether it could reach the PV system, otherwise it returned to power-save mode. To avoid failure identification, the data were sent daily/hourly via external modem. About 48,500 data sets were collected for one year.

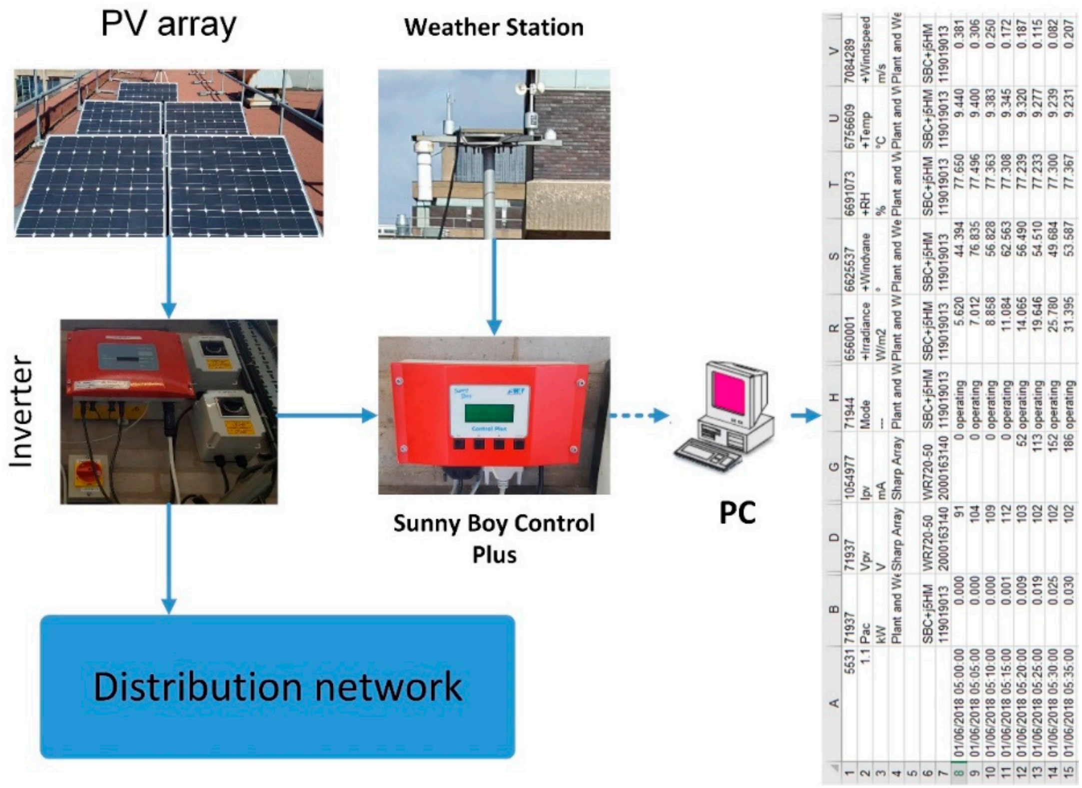


Figure 6. A general diagram of data collection system.

6. Curve Fitting Technique

It is very common in engineering practice to obtain and record real data from device systems. Engineers use these data to understand underlying properties and solve issues of the system. However, it is not easy or even possible to determine the relationship that describes the behavior of the system using the real data. The regression analysis of data is a statistical procedure and can be used to identify the relationships among different points. Whilst there are varying methods of the regression, curve fitting technique is considered as one of the best methods which is utilized in this work. This technique is attempted to find a mathematical function that can describe the measurements of real data as accurately as possible. It is not necessary that the obtained function pass through all the real data points. However, the smallest possible error of a fitting curve should be received, and defined as in Equation (12):

$$p = \sum_{i=1}^{n} r_i^2 = \sum_{i=1}^{n} [y_i - (a_1 x_i + a_0)]^2 \tag{12}$$

where r_i is the residual vector of each data point, y_i the value of the straight line evaluated at x_i, a_i and a_0 are the coefficients of curve fitting, and n is the number of data. For example, the equations of the curve fitting coefficients for five points are written as Equations (13)–(17):

$$a_1 x_1 + a_0 = y_1 \tag{13}$$

$$a_1 x_2 + a_0 = y_2 \tag{14}$$

$$a_1 x_3 + a_0 = y_3 \tag{15}$$

$$a_1 x_4 + a_0 = y_4 \tag{16}$$

$$a_1 x_5 + a_0 = y_5 \tag{17}$$

Now, those above five equations are written in a more compact method using a matrix notation, as defined in Equation (18):

$$Ab = y \tag{18}$$

where

$$A = \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ x_3 & 1 \\ x_4 & 1 \\ x_5 & 1 \end{bmatrix}, \; b = \begin{bmatrix} a_1 \\ a_0 \end{bmatrix}, \; y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix}$$

Now, the residual matrix notation is written as Equation (19):

$$r = y - Ab \tag{19}$$

Substituting Equation (19) into Equation (12), the following is obtained:

$$p = \sum_{i=1}^{n} r_i^2 = r^T r = y^T y - 2y^T Ab + b^T A^T Ab \tag{20}$$

where r^T is the transposed residual matrix notation. To minimize the value of p, the derivation process is used. This gives us Equation (21):

$$\frac{\partial p}{\partial b} = 0 = -2y^T A + 2A^T Ab \tag{21}$$

Now, the coefficients of fitting curve (b) are defined in Equation (22):

$$b = \left(A^T A\right)^{-1} y^T A \tag{22}$$

In this application, the y-axis is the PV power and the x-axis is the irradiance and temperature of weather conditions. In addition, the second order polynomial of last squares is used to get a best fit. To draw those fitting curves, MATLAB code is generated based on Equations (22) and (12). As seen in Figure 7, the power generation of a PV array increases as solar irradiance increases; conversely, it is better for a low temperature operation than a raised one. In addition, the PV-generated power almost depends on the irradiance as linearity. In contrast, the operating temperature is less effective on PV power generation as well as non-optimized linearity. Those conceptions will be used in Section 7 to adjust the defined membership function of the proposed ANFIS model.

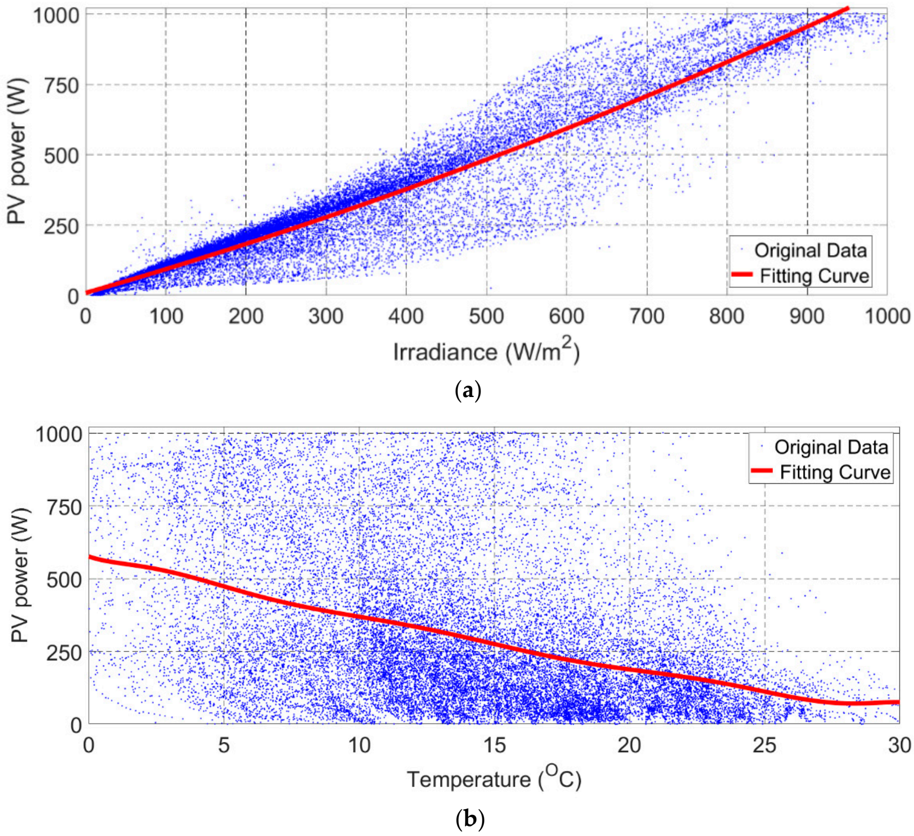


Figure 7. Fitting curve of (**a**) PV power versus irradiance; (**b**) PV power versus temperature.

7. Training of Proposed ANFIS Network

Using a MATLAB/Simulink model, an efficient ANFIS-MPPT method based on large PV system data set was designed to stop the system from having a high training error. The inputs of the proposed ANFIS technique consisted of the irradiance and temperature, which were collected by a weather station, and the reference power was measured from the PV installed array as the output of the ANFIS system. The estimation accurate PV power depends on the training dataset; therefore, it was very important to select training data with wide variations of the solar irradiance and operating temperature [38]. Hence, Hence, 40 days data were used, which consists of 10 days per season, such that different weather conditions are included . About 6200 data sets were used to train the proposed ANFIS model. The selected data were used to train ANFIS as it generates more accurate model in comparison to using the whole data set, as shown in Table 2. To select the best membership function for the ANFIS model, different types of membership functions were tested. The linear type for the output membership functions and the triangular type for the input membership functions (trimf) achieved less tolerance of the mean square error (MSE) about 0.0708, as shown in Table 3. In addition, triangular membership functions have a simple formula and high computational efficiency [31]. As mentioned in Section 6, the PV generated power depends proportionally on the irradiance. In contrast, the operating temperature has less effect on the PV power generation on non-optimized linearity . According to those conceptions, the numbers of input membership functions (mf) of solar irradiance were selected more than the numbers of input membership functions of operating temperature to predict accurate power generations under varying conditions. In addition, the variable second input was adjusted according to the fitting curve of the operating temperature. Hence, the state of non-optimized linearity was avoided in the second input. Those membership functions for each input were learned by the ANFIS model based on 15 fuzzy rules derived from eight input-defined membership functions, as shown in Figure 8. The fuzzy inference system was trained based on the hybrid optimization method by combining the back propagation gradient techniques and the least squares. The surface training data indicates that the reference power increased smoothly, with an increase in the radiation level and a decrease in the temperature, as shown in Figure 9.

Table 2. Simulation ANFIS model based on optimized data vs. total data.

Model	Training Time	Number of Epochs	Error (%)
Optimized data	Very short	50	8
Total data	Too long	980	14

Table 3. Mean square error (MSE) for different input membership functions.

Purpose	Function	Error
Triangular mf.	trimf	0.0708
Trapezoidal mf.	trapmf	0.1085
Generalized bell curve mf.	gbellmf	0.0787
Gaussian curve mf.	gaussmf	0.0766
Two-sided Gaussian curve mf.	gauss2mf	0.0894
PI-shaped curve mf.	pimf	0.1215
Difference of two sigmoid mf.	dsigmf	0.0808
Product of two sigmoid mf.	psigmf	0.0819

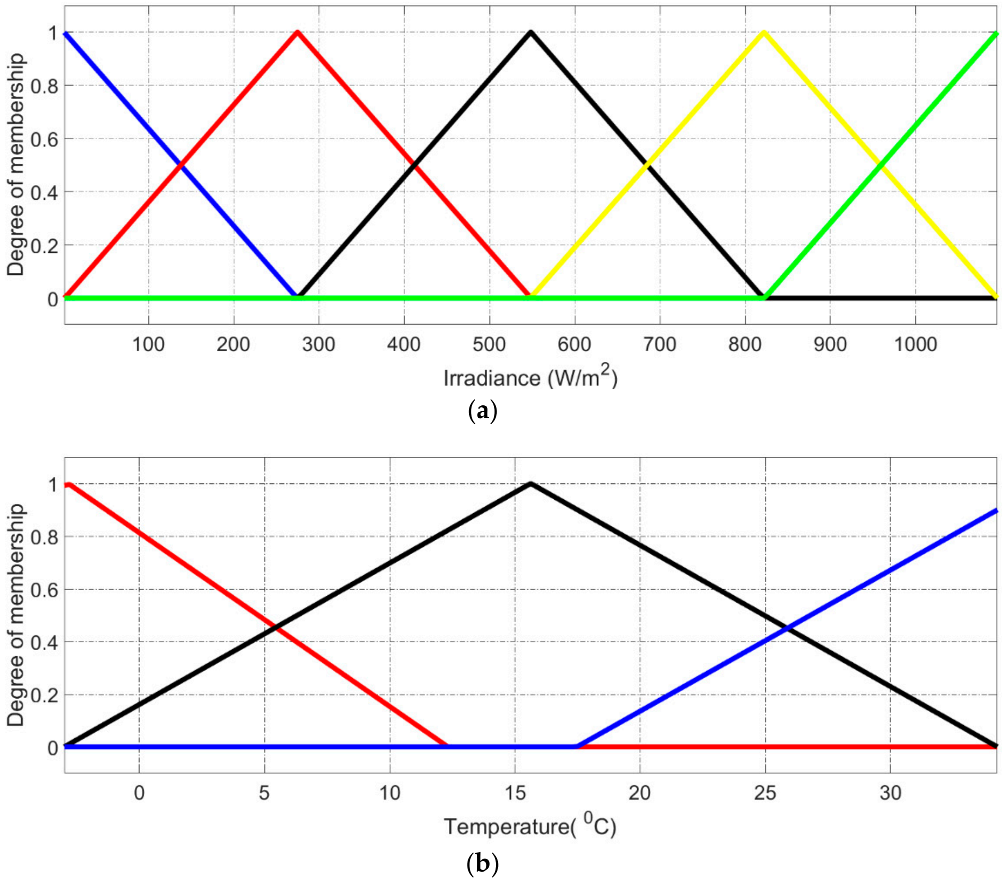


Figure 8. The defined membership function for (**a**) irradiance and (**b**) temperature.

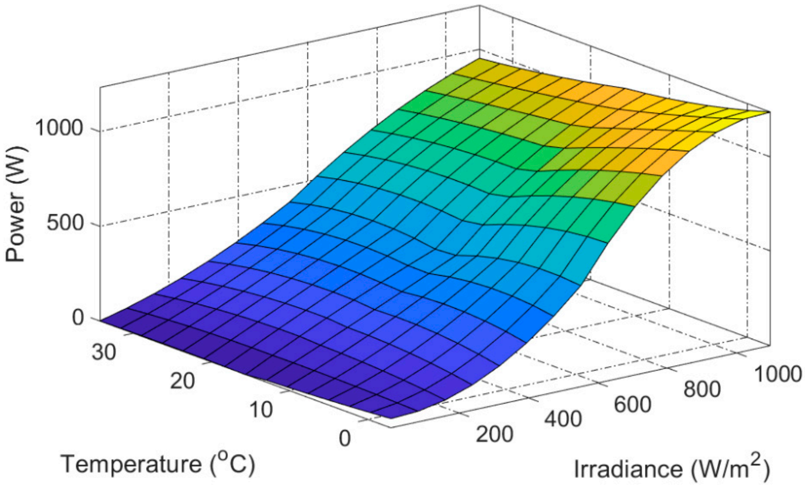
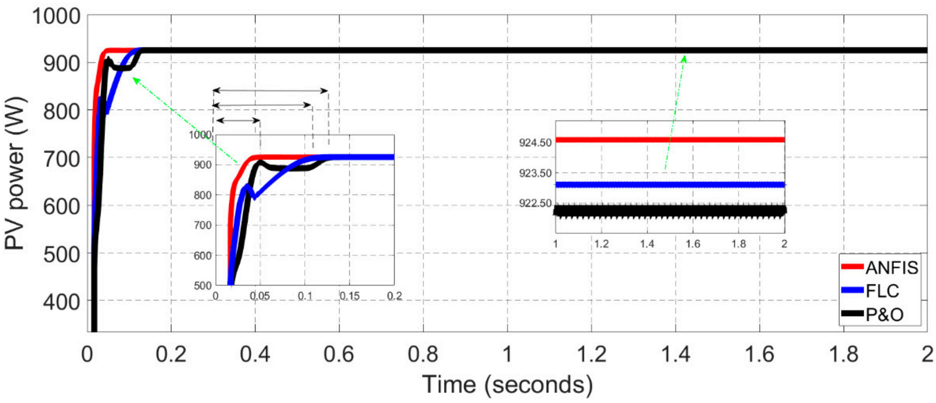


Figure 9. A surface between inputs irradiance and temperature vs PV power.

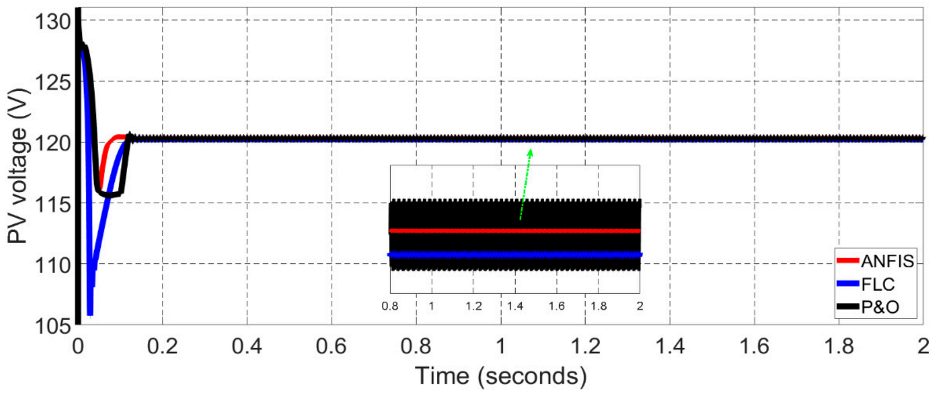
8. Results and Discussion

To assess the performance, a MATLAB/Simulink model for a stand-alone PV system simulated the P&O-MPPT, FLC-MPPT and ANFIS-MPPT systems. This PV system consisted of a PV array, a DC–DC boost converter, and an MPPT controller and load. The main parameters of the PV model are given in Table 1. The PV array consisted of five PV modules connected in series. The simulation was separated into two parts: Fixed and variation regarding an input G. The input G and T of the first part were fixed at 1000 W/m^2 and 25 °C, respectively. As presented in the zoomed part of Figure 10a, the converging time of the power tracker for the ANFIS-MPPT method was the highest when compared to the FLC-MPPT and the P&O-MPPT, being about 0.07, 0.11 and 0.13 s, respectively. Moreover, it had the least smooth fluctuation around the MPP for the steady-state, thus resulting in less computation time, as shown in the zoom-in of Figure 10b,c. Furthermore, it is more accurate for addressing the optimized MPP when compared with the FLC-MPPT, as presented in the zoomed part of Figure 10b, due to the large and accurate training dataset. As a result, the PV voltage at the MPP for the ANFIS-MPPT was in the middle of the optimized voltage of the P&O-MPPT, while the PV voltage at the MPP for the FLC-MPPT was to the right of the optimized voltage of the P&O-MPPT with medium oscillation. However, the fluctuation problem was the highest in the P&O-MPPT, owing to the continuous perturbation of the P&O tracker for reaching the optimized MPP. Therefore, the lost power in the ANFIS-MPPT was less than for the FLC-MPPT and the P&O-MPPT. As a result, the output power of the ANFIS-MPPT, the FLC-MPPT and the P&O-MPPT, after they reached the optimized MPP, were about 924.50, 923.25 and 922.50 W, respectively, as presented in the zoomed part of Figure 10a.

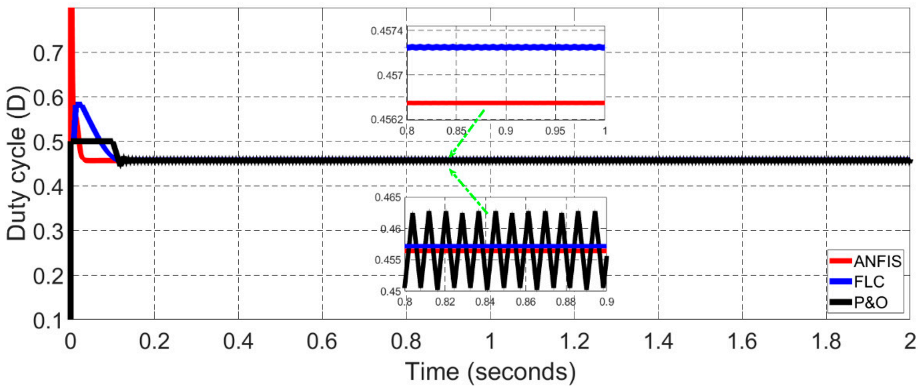
In the second part, the input G level was rapidly increased from 200 to 1000 W/m^2 at 1 to 2 s, whereas the T operation was kept at 25 °C. As presented in Figure 11a, the power tracker of the ANFIS-MPPT turned out to be accurate in addressing the valid direction due to its large training and optimized tuning of the proposed model, whereas that of the FLC-MPPT and the P&O-MPPT was lost it when the input irradiation changed suddenly. As a result, they took a longer time than the MPPT based on the ANFIS to address the drift issue phenomenon, as shown in Figure 11. In addition, it was more robust in addressing the right direction during a rapid change in solar irradiance. In another words, this issue was more effective on the P&O-MPPT then the FLC-MPPT. To assess the ANFIS-MPPT further, Table 4 compares its properties with the FLC-MPPT and the P&O-MPPT. As can be seen, the ANFIS-MPPT had the highest converging time to reach the tricking power into a steady state conditions, the least fluctuation, and the highest output power. Moreover, it was the most accurate in tracking the MPP and avoiding the drift phenomenon.



(**a**)



(**b**)



(**c**)

Figure 10. PV array system for the ANFIS method versus the P&O and FLC methods under a fixed irradiation condition: (**a**) Power, (**b**) voltage, and (**c**) duty cycle.

Table 4. A comparison of the properties of the ANFIC, perturb and observe (P&O) and fuzzy logic controller (FLC)-MPPT.

MPPT	Converging Time (s)	Oscillation	Drift Problem	Output Power (W)
ANFIS-MPPT	0.07	low	avoidance	924.50
FLC-MPPT	0.11	medium	suffering	923.25
P&O-MPPT	0.13	High	suffering	922.50

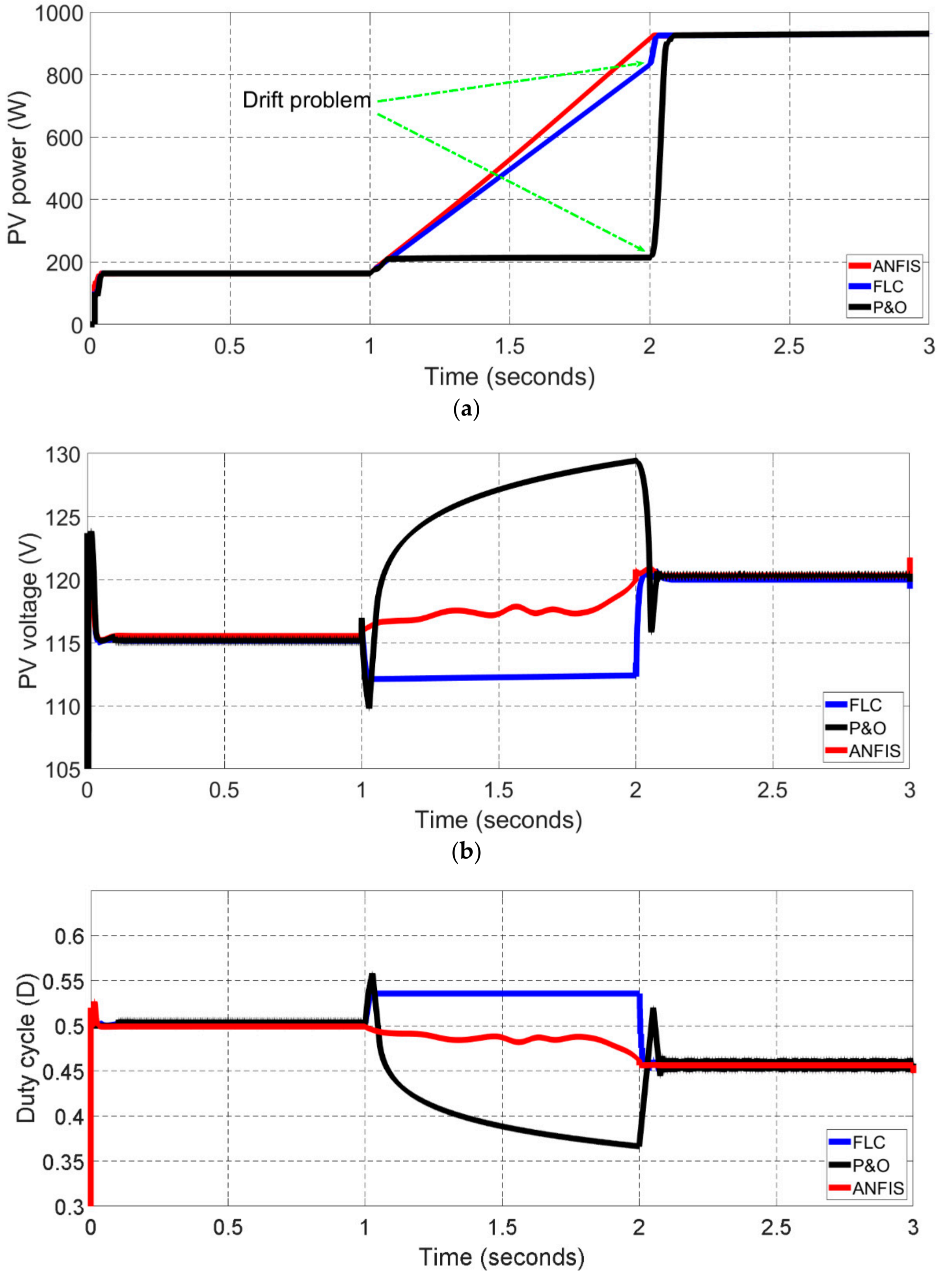


Figure 11. (**a**) PV array system for ANFIS versus the P&O and FLC methods under a rapid change in climatic conditions: (**a**) Power, (**b**) voltage, and (**c**) duty cycle.

9. Real Measurement Test

To evaluate this proposal, the three previous techniques were compared based on real measurements of the input solar irradiance and temperature for one day on 10 June 2018 (05.00 am–20.00 pm), as shown in Figure 12a,b. Those data were collected as mentioned in Section 5. The comparison between the ANFIS-MPPT and the P&O-MPPT is shown in Figure 13a. Obviously, the power tracker of the latter method was almost as perfect as the former during a slow moving in the weather conditions due to the large and constant step size of the incremental duty cycle. However, it drifted away from the correct direction when the G and T rapidly increased, because it was not able to cope with the rapid change in the input G. That is, the issue became much more spectacular when the input G suddenly changed. However, the tracking power of the P&O-MPPT addressed the appropriate direction under the different cases of decreasing irradiation, as shown in the zoomed part of Figure 13a.

The comparison between the ANFIS-MPPT and the FLC-MPPT is presented in Figure 13b. While the latter method suffers from the drift problem under rapid changes in atmospheric conditions (increasing and decreasing the climatic conditions), as shown in the zoomed part of Figure 13b, the problem can be seen as being minimal when compared to the P&O-MPPT. This is because the MPPT tracking of FLC enabled it to address the problem early. In contrast, the tracking power of the ANFIS-MPPT was based on large training data, and, as such, it avoided the problem under different weather conditions. To determine the efficiency of the MPPT controller, the average MPPT efficiency formula was utilized, as presented in Equation (23) [39]:

$$\eta \cdot MPPT(avarge) = \frac{\int P_{out}(t)dt}{\int P_{\max}(t)dt} \tag{23}$$

where P_{out} and P_{max} are the actual and theoretical power of the PV array, respectively. The actual PV power was determined using the simulated voltage and current of the PV array and then multiplied. The theoretical power was calculated based on Equations (1)–(4). The tracking time (t) was determined regarding the ability of the MPPT power tracker to reach the optimized MPP under different climatic conditions. Whereas the efficiency of the ANFIS-MPPT for a beginning day appeared to be the lowest, it achieved an average efficiency of 99.3% under all the different climatic conditions, while those for the FLC and the P&O-MPPT were 96.8% and 92.6%, respectively, as presented in Figure 14a,b.

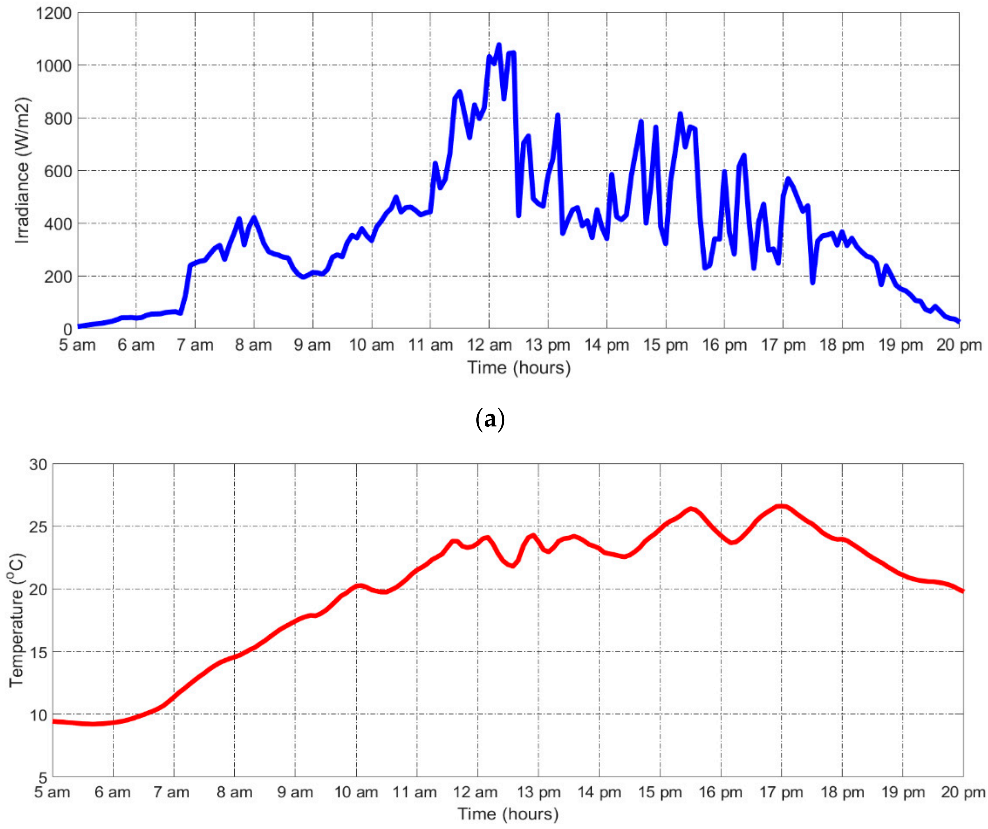


Figure 12. (**a**) Real measurement test of one day of: (**a**) Solar irradiance and (**b**) operating temperature.

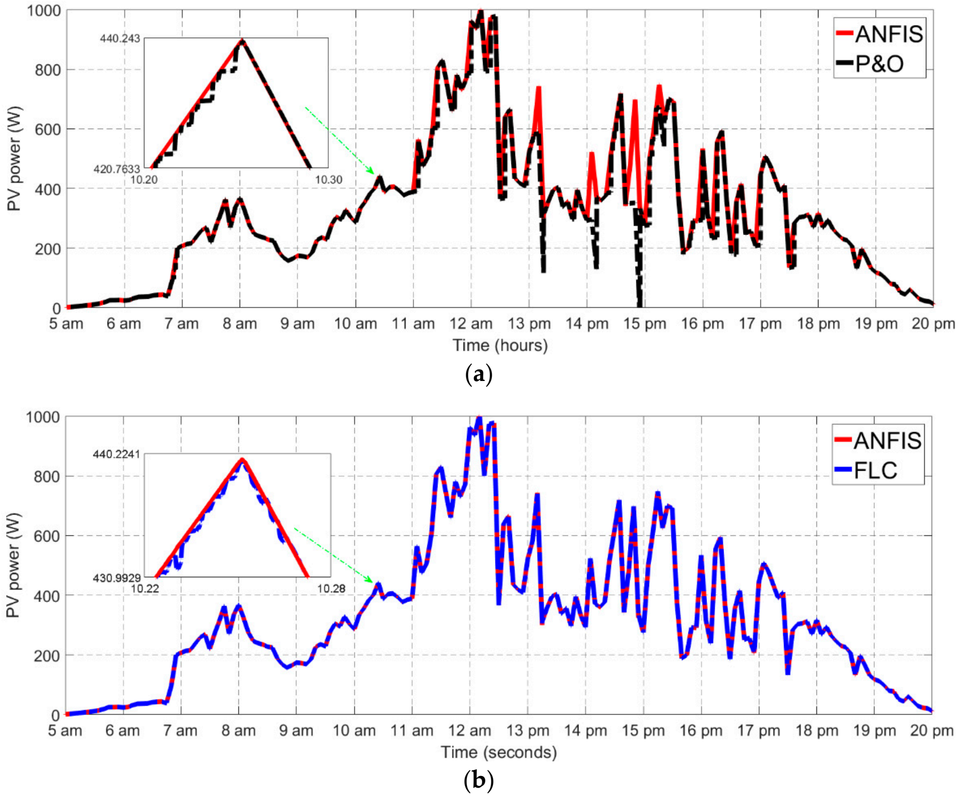


Figure 13. (**a**) Tracking power for P&O versus the ANFIS method and (**b**) tracking power for the FLC versus the ANFIS technique.

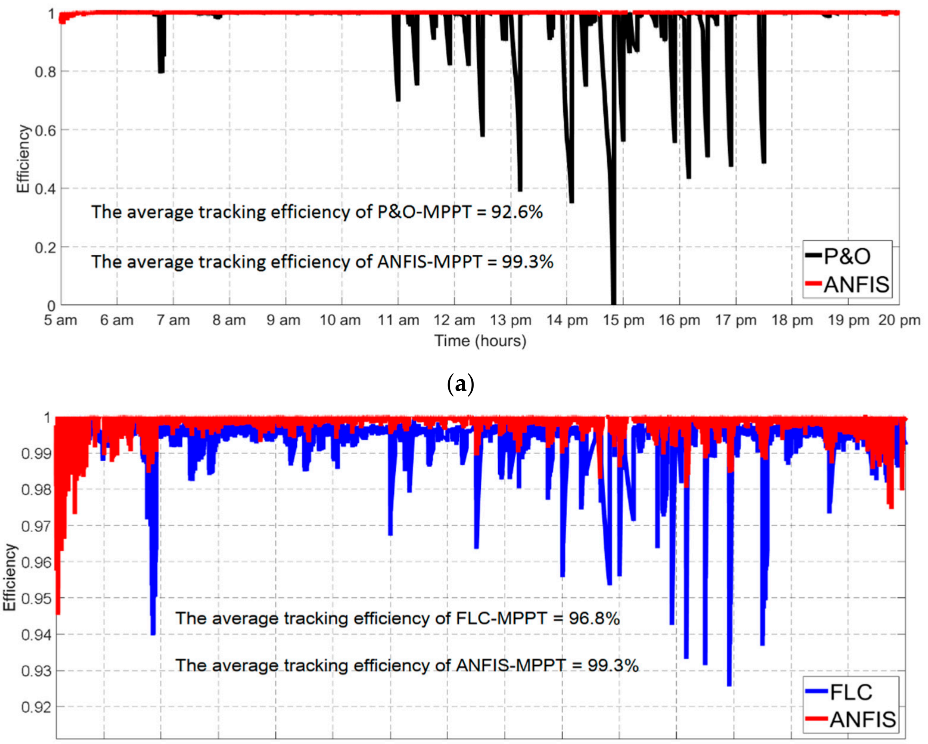


Figure 14. The efficiency of the generated power of the PV array under the real measurement test for: (**a**) the P&O-MPPT versus the ANFIS-MPPT; and (**b**) the FL-MPPT versus the ANFIS-MPPT.

10. Conclusion

An efficient MPPT technique based on ANFIS using a real photovoltaic system data has been designed. The large training dataset was collected during one year from the experimental testing of a PV array installed at Brunel University London, Uxbridge, UK, and then they were analyzed and optimized using a fitting curve technique to avoid the system from having a high training error. The solar irradiation and ambiance temperature were selected as the inputs, whilst the maximum available power from the PV array was the output of what is termed the ANFIS model. Under the same weather conditions, actual PV power was measured using a sensed voltage and the current of a PV Simulink operation. These two power outputs were compared, and the error was given to a PI controller to generate the signal of a DC–DC converter by the PWM generator to adjust the operating MPP of the PV array. To sum up, a literature review on the ANFIS-MPPT for a PV system has been presented. The methodologies of the collected and optimized data as well as the tuning of proposed ANFIS model have been explained. The P&O-MPPT, the FLC-MPPT and the proposed ANFIS method were simulated and then compared regarding their popular features. The real test outcomes for a semi-cloudy day were used to determine the efficiency of the proposed technique under varying climatic conditions. The results have demonstrated that the proposed method exhibits higher generated power and no deviation from the optimized MPP during different climate conditions than the alternative ones proposed, achieving efficiencies of greater than 99.3%. Finally, the implementation of this proposal can considered simpler than hybrid methods.

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References

1. Singh, G. Solar power generation by PV (photovoltaic) technology: A review. *Energy* **2013**, *53*, 1–13. [CrossRef]
2. Al-Majidi, S.D.; Abbod, M.F.; Al-Raweshidy, H.S. A Modified P&O-MPPT based on Pythagorean Theorem and CV-MPPT for PV Systems. In Proceedings of the 2018 53rd International Universities Power Engineering Conference (UPEC), Glasgow, UK, 4–7 September 2018; pp. 1–6.
3. Roman, E.; Alonso, R.; Ibañez, P.; Elorduizapatarietxe, S.; Goitia, D. Intelligent PV Module for Grid-Connected PV Systems. *IEEE Trans. Ind. Electron.* **2006**, *53*, 1066–1073. [CrossRef]
4. Salam, Z.; Ahmed, J.; Merugu, B.S. The application of soft computing methods for MPPT of PV system: A technological and status review. *Appl. Energy* **2013**, *107*, 135–148. [CrossRef]
5. Mohammed, S.S.; Devaraj, D.; Ahamed, T.I. A novel hybrid Maximum Power Point Tracking Technique using Perturb & Observe algorithm and Learning Automata for solar PV system. *Energy* **2016**, *112*, 1096–1106.
6. Atkinson, D.J.; Elgendy, M.A.; Zahawi, B. Assessment of the Incremental Conductance Maximum Power Point Tracking Algorithm. *IEEE Trans. Sustain. Energy* **2013**, *4*, 108–117.
7. Al-Majidi, S.D.; Abbod, M.F.; Al-Raweshidy, H.S. A novel maximum power point tracking technique based on fuzzy logic for photovoltaic systems. *Int. J. Hydrogen Energy* **2018**, *43*, 14158–14171. [CrossRef]
8. Algarín, C.R.; Hernández, D.S.; Leal, D.R. A Low-Cost Maximum Power Point Tracking System Based on Neural Network Inverse Model Controller. *Electronics* **2018**, *7*, 4. [CrossRef]
9. Enany, M.A.; Farahat, M.A.; Nasr, A. Modeling and evaluation of main maximum power point tracking algorithms for photovoltaics systems. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1578–1586. [CrossRef]
10. Ali, A.I.M.; Sayed, M.A.; Mohamed, E.E.M. Modified efficient perturb and observe maximum power point tracking technique for grid-tied PV system. *Int. J. Electr. Power Energy Syst.* **2018**, *99*, 192–202. [CrossRef]

11. Wan, Y.; Mao, M.; Zhou, L.; Zhang, Q.; Xi, X.; Zheng, C. A Novel Nature-Inspired Maximum Power Point Tracking (MPPT) Controller Based on SSA-GWO Algorithm for Partially Shaded Photovoltaic Systems. *Electronics* **2019**, *8*, 680. [CrossRef]
12. Ramos-Hernanz, J.; Lopez-Guede, J.M.; Barambones, O.; Zulueta, E.; Fernandez-Gamiz, U. Novel control algorithm for MPPT with Boost converters in photovoltaic systems. *Int. J. Hydrogen Energy* **2017**, *42*, 17831–17855. [CrossRef]
13. Xiao, W.; Dunford, W.G. A modified adaptive hill climbing MPPT method for photovoltaic power systems. In Proceedings of the 2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551), Aachen, Germany, 20–25 June 2004; pp. 1957–1963.
14. Loukriz, A.; Haddadi, M.; Messalti, S. Simulation and experimental design of a new advanced variable step size Incremental Conductance MPPT algorithm for PV systems. *ISA Trans.* **2016**, *62*, 30–38. [CrossRef] [PubMed]
15. Sivakumar, P.; Kader, A.A.; Kaliavaradhan, Y.; Arutchelvi, M. Analysis and enhancement of PV efficiency with incremental conductance MPPT technique under non-linear loading conditions. *Renew. Energy* **2015**, *81*, 543–550. [CrossRef]
16. Ben Salah, C.; Ouali, M. Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems. *Electr. Power Syst. Res.* **2011**, *81*, 43–50. [CrossRef]
17. Wang, Y.; Yang, Y.; Fang, G.; Zhang, B.; Wen, H.; Tang, H.; Fu, L.; Chen, X. An Advanced Maximum Power Point Tracking Method for Photovoltaic Systems by Using Variable. *Electronics* **2018**, *7*, 355. [CrossRef]
18. Soufi, Y.; Bechouat, M.; Kahla, S. Fuzzy-PSO controller design for maximum power point tracking in photovoltaic system. *Int. J. Hydrogen Energy* **2016**, *42*, 8680–8688. [CrossRef]
19. Guenounou, O.; Dahhou, B.; Chabour, F. Adaptive fuzzy controller based MPPT for photovoltaic systems. *Energy Convers. Manag.* **2014**, *78*, 843–850. [CrossRef]
20. Li, X.; Wen, H.; Hu, Y.; Jiang, L. A novel beta parameter based fuzzy-logic controller for photovoltaic MPPT application. *Renew. Energy* **2019**, *130*, 416–427. [CrossRef]
21. Jiang, L.L.; Nayanasiri, D.; Maskell, D.L.; Vilathgamuwa, D.M. A hybrid maximum power point tracking for partially shaded photovoltaic systems in the tropics. *Renew. Energy* **2015**, *76*, 53–65. [CrossRef]
22. Lasheen, M.; Abdel-salam, M. A novel hybrid Maximum Power Point Tracking Technique using Hill Climbing and ANFIS Techniques for PV Applications. *Energy Convers. Manag.* **2017**, *171*, 1–31.
23. Farzaneh, J.; Keypour, R.; Karsaz, A. A novel fast maximum power point tracking for a PV system using hybrid PSO-ANFIS algorithm under partial shading conditions. *Int. J. Ind. Electron. Control Optim.* **2019**, *2*, 47–58.
24. Muthuramalingam, M.; Manoharan, P. Comparative analysis of distributed MPPT controllers for partially shaded stand alone photovoltaic systems. *Energy Convers. Manag.* **2014**, *86*, 286–299. [CrossRef]
25. Abido, M.A.; Khalid, M.S.; Worku, M.Y. An Efficient ANFIS-Based PI Controller for Maximum Power Point Tracking of PV Systems. *Arab. J. Sci. Eng.* **2015**, *40*, 2641–2651. [CrossRef]
26. Kharb, R.K.; Shimi, S.; Chatterji, S.; Ansari, M.F. Modeling of solar PV module and maximum power point tracking using ANFIS. *Renew. Sustain. Energy Rev.* **2014**, *33*, 602–612. [CrossRef]
27. Abu-Rub, H.; Iqbal, A.; Ahmed, S.M. Adaptive neuro-fuzzy inference system-based maximum power point tracking of solar PV modules for fast varying solar radiations. *Int. J. Sustain. Energy* **2012**, *31*, 383–398. [CrossRef]
28. Abu-Rub, H.; Iqbal, A.; Ahmed, S.M.; Peng, F.Z.; Li, Y.; Baoming, G. Quasi-Z-Source Inverter-Based Photovoltaic Generation System with Maximum Power Tracking Control Using ANFIS. *IEEE Trans. Sustain. Energy* **2013**, *4*, 11–20. [CrossRef]
29. Bin-halabi, A.; Abdennour, A.; Mashaly, H. An Accurate ANFIS-based MPPT for Solar PV System. *Int. J. Adv. Comput. Res.* **2014**, *4*, 588–595.
30. Murdianto, F.D.; Penangsang, O.; Priyadi, A.; Dwi, M.F. Modeling and simulation of MPPT-bidirectional using adaptive neuro fuzzy inference system (ANFIS) in distributed energy generation system. In Proceedings of the 2015 International Seminar on Intelligent Technology and Its Applications (ISITIA), Surabaya, Indonesia, 20–21 May 2015; pp. 207–212.
31. Aldair, A.A.; Obed, A.A.; Halihal, A.F. Design and implementation of ANFIS-reference model controller based MPPT using FPGA for photovoltaic system. *Renew. Sustain. Energy Rev.* **2017**, *82*, 2202–2217. [CrossRef]

32. Mayssa, F.; Sbita, L. Advanced ANFIS-MPPT control algorithm for sunshine photovoltaic pumping systems. In Proceedings of the 2012 First International Conference on Renewable Energies and Vehicular Technology, Hammamet, Tunisia, 26–28 March 2012; pp. 167–172.
33. Tarek, B.; Said, D.; Benbouzid, M. Maximum Power Point Tracking Control for Photovoltaic System Using Adaptive Neuro-Fuzzy "ANFIS". In Proceedings of the 2013 Eighth International Conference and Exhibition on Ecological Vehicles and Renewable Energies (EVER), Monte Carlo, Monaco, 27–30 March 2013; pp. 1–7.
34. Ounnas, D.; Ramdani, M.; Chenikher, S.; Bouktir, T. An Efficient Maximum Power Point Tracking Controller for Photovoltaic Systems Using Takagi–Sugeno Fuzzy Models. *Arab. J. Sci. Eng.* **2017**, *62*, 4971–4982. [CrossRef]
35. Khosrojerdi, F.; Taheri, S.; Crétu, A.-M. An adaptive neuro-fuzzy inference system-based MPPT controller for photovoltaic arrays. In Proceedings of the 2016 IEEE Electrical Power and Energy Conference (EPEC), Ottawa, ON, Canada, 12–14 October 2016.
36. Chaouachi, A.; Kamel, R.M.; Nagasaka, K. A novel multi-model neuro-fuzzy-based MPPT for three-phase grid-connected photovoltaic system. *Sol. Energy* **2010**, *84*, 2219–2229. [CrossRef]
37. Kadri, R.; Andrei, H.; Gaubert, J.-P.; Ivanovici, T.; Champenois, G.; Andrei, P. Modeling of the photovoltaic cell circuit parameters for optimum connection model and real-time emulator with partial shadow conditions. *Energy* **2012**, *42*, 57–67. [CrossRef]
38. Hiyama, T.; Kitabayashi, K. Neural Network Based Estimation of Maximum Power Generation from PV Module Using Environmental Information Takashi Hiyama. *IEEE Trans. Energy Convers.* **1997**, *12*, 241–247. [CrossRef]
39. Ahmed, J.; Salam, Z. A Modified P&O Maximum Power Point Tracking Method with Reduced Steady State Oscillation and Improved Tracking Efficiency. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1.