ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) METHOD BASED OPTIMAL POWER POINT OF PV MODULES

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ABSTRACT. *The paper investigates the application of adaptive neuro-fuzzy inference system (ANFIS) method to determine the optimal output power of crystalline Silicon photovoltaic (PV) modules technology. It is well-known that crystalline Silicon of PV modules dominates the current PV market characterized with relatively high efficiency and cheaper investment costs compared to other PV modules technology. Because the electrical characteristics of crystalline Silicon-based module technology are almost the same, it is important to investigate the proposed algorithm regarding the training process, level of accuracy of training and validation including the network structure. The training process of proposed network is conducted based on electrical characteristics data of Sandia National Laboratory model under clear and cloudy skies weather conditions. Different types of PV modules based on Silicon technology are investigated to confirm the performance of method in determining the optimal power point.*
Keywords: ANFIS network, Multi-crystalline Silicon, Single-crystalline Silicon, Thin-film Silicon solar cells

1. **Introduction.** Although PV systems attract more attention than other types of electricity generation based on renewable energy, there are still a number of major challenges to maximize the system capacity. The optimal output power always varies depending on environmental conditions, module material costs and encapsulation. The high module cost is caused by complex metallurgical processes during separation, cutting and regulation of Silicon elements in solar cell manufacturing. This problem can be overcome by the development of new types of solar cell technology such as thin-film and tandem-junction solar cells, but these technologies are again still immature. Another problem is the need of power regulator unit such as an inverter and battery to adjust the solar cell output power according to the needs of the electricity demand. This problem was then overcome by the development of power electronics technology with high efficiency targets and the stability of inverter designs.

The most significant challenge in PV utilization is the characteristics of solar cells that are non-linear with random and dynamic output, making the maximum power point tracking gets very difficult. This problem is more complex with the diversification of crystalline and non-crystalline Silicon technologies. All the challenges raised here lead to low system efficiency. For Silicon-based technology, efficiency ranges from 10-15%, while non-crystalline technologies have even lower efficiency. It has relatively higher operational costs compared to other types of power plants. Therefore, the operation at the optimal

power point in PV system is very important. In this study, the prediction and estimation of the maximum output power were carried out utilizing the ANFIS method.

The artificial neural network method has been intensively utilized to determine the maximum point of a PV system. A very simple type of three layered feed-forward neural network (TFFN) is applied for the optimal duty ratio of buck-boost DC-DC converters based on input signals related to environmental conditions [1, 2]. However, this type of multi-layer perceptron (MLP) structure is constrained by slow computational training process. In fact, the network structure of TFFN is the most common structure among all artificial neural network used for the optimization process of PV systems. To maximize the performance of the TFFN structure with regard to achieving convergence levels during the training process, the selection of data for the training process is important. While the radial base function (RBF) method is used for reference controllers in maximum point tracking applications [3]. Combined with a neuro-fuzzy regulator, the RBF structure is able to improve the efficiency of the output of a PV system [4]. In terms of the adaptive neuro-fuzzy inference system structure, it seems very rarely used for the optimization process in the application of PV systems, except for one study that seeks to carry out a training process for all components of a PV system in conditions of climate variations [5]. In terms of modeling and simulation for Silicon technology, artificial neural networks have been considered established technologies [6]. All the facts above show that the artificial neural network method is still quite interesting to be developed for the process of optimizing PV systems, especially in terms of investigations regarding the training process, network structure and level of accuracy during the training and validation process.

There were several previous researches with more focused on the application of AN-FIS network in PV system application. Photovoltaic modules have non-linearity nature characteristics output where they are highly dependent on the geographical location and weather conditions by means of sunlight intensity, ambient temperature and shading problems. The modeling and simulation of PV generation system is presented with ANFIS network in order to overcome the variation of input parameters and to find the best PV modeling and configuration [7]. Due to the unpredictable input parameters, the complexity in tracking mechanism is unavoidable to extract the maximum available power and energy of PV panels. In this case, it is important to have the control mechanism which is accurate and fast response to the variation of input parameters and the ANFIS network has been successfully utilized to model the PV panel and to determine the maximum power point by the optimal tuning of DC-DC converter duty ratio [8]. The ANFIS control network has been also used to solve the problems of partial shading where the multiple peaks occur that makes the conventional control unable to distinguish between the global and local maximum points [10]. Another research attempts to improve performance of ANFIS control network in determining the optimal duty of DC-DC converter with the hybrid combination of conventional hill-climbing control method for the purpose of enhancing the tracking speed, tracking accuracy and energy gain factor [10]. In addition, the ANFIS-reference model controller combined with other conventional controllers has more efficient and better dynamic response using field programmable gate array (FPGA) board design [11]. From these previous researches, the ANFIS performance is identified with excellent reliability and good prediction accuracy compared to other types of artificial neural network under dynamic and non-linear input parameters.

The research method carried out follows the principle of artificial neural network design, namely training data collection, training process and validation process. Training data collection is done by implementing a mathematical model recommended by Sandia National Laboratory. In this model, the data combination of maximum power as a function of the intensity of sunlight and cell temperature is constructed. This maximum power will later be targeted in the training process. Next, the training process is conducted with the combination of existing data. The purpose of this training process is to determine

the network structure that is marked by the number of hidden nodes. The small number of hidden nodes shows the simplicity of the network. After that, the validation process is performed to confirm the network with the lowest training error. Of course, the data used for training process is different from the data used for validation process. For this purpose, data for validation is taken from two different weather conditions, namely sunny and cloudy weather conditions. The level of accuracy during the validation process is done by using the sum of square error (SSE) indicator. The lower SSE value means that network performance has been designed very accurately and is ready to test with any weather input conditions. The stages described here apply to the development of artificial neural networks based on ANFIS method as the target of research.

2. **Adaptive Neuro-Fuzzy Inference System (ANFIS) Method.** The ANFIS neural network is usually designed for single output. This method is often called Sugeno type fuzzy inference systems (FIS). This method is a hybrid combination of learning algorithms between least-square method and back propagation method with gradient descent for training process FIS membership functions parameters. The consequence of this approach is that the training process can be very fast with the configuration of network structures that can be obtained immediately. During the training process, once the number of epochs is achieved, the training process is stopped.
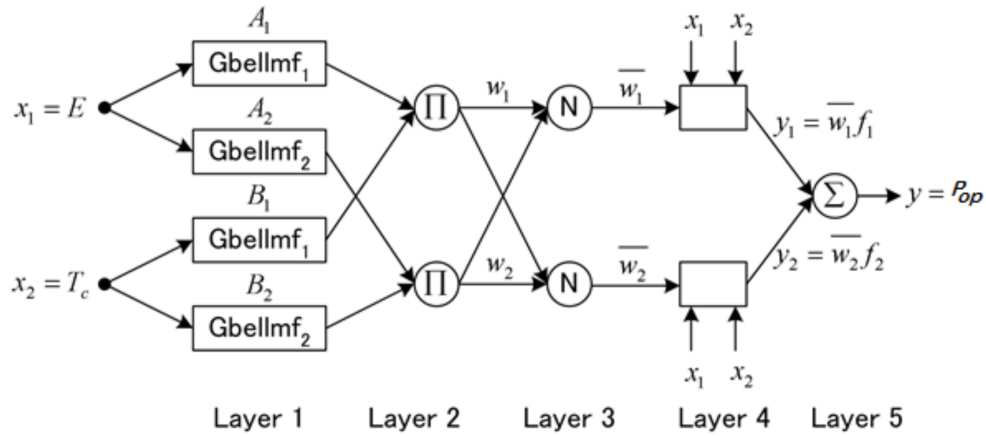

FIGURE 1. Basic structure of ANFIS network

The basic configuration of ANFIS network is shown in Figure 1. The *if-then rules* based on the first order Sugeno fuzzy model can be expressed as follows [12].

Rule 1: If x_1 is A_1 and x_2 is B_1, then $y_1 = p_1x_1 + q_1x_2 + r_1$
Rule 2: If x_1 is A_2 and x_2 is B_2, then $y_2 = p_2x_1 + q_2x_2 + r_2$

where A_1, A_2, B_1 and B_2 are the premise parameters, while the p, q and r represent the coefficient parameters of the nth rules through the first order polynomial Equation (1) as follows.

$$y_n = p_nx_1 + q_nx_2 + r_n \tag{1}$$

where x_1, x_2 are the input signals and y_n are the output signal according to the fuzzy rules that have been previously set up. The basic structure of ANFIS network consists of 5 layers, where each layer yields specified outputs, denoted with O_l.

Layer 1: The layer is utilized to produce the *grade of membership function* from the input signal. Each node in this layer is an adaptive node where the output of this layer is denoted in (2) as follows.

$$O_1 = \mu_{A_i}(x) \tag{2}$$

where $\mu_{A_i}(x)$ is the membership function of linguistic variable A from each node. This is the most important process in ANFIS network by selection of type and number of membership function of each input signal. In this research, the generalized bell membership function *gbellmf* is chosen and set up two-times for each the input signal of sunlight intensity or irradiance (E) and cell temperature (T_c). Although the default setting is selected in training process of ANFIS network, such approach is quite accurate to do mapping between the input signals and the optimal output power (P_{op}) of PV modules. The number of membership function of each input signal can be simultaneously added to increase the accuracy level, but the progress of simulation might be slower.

Layer 2: The layer is used to produce the firing strength. It demonstrates with π that implies a basic multiplier. Each node produces the firing strength by duplicating rules created in the previous layer. The result of this layer is denoted in (3) as follows.

$$O_2 = w_i = \prod_{j=1}^{m} \mu_{A_i}(x) \tag{3}$$

Layer 3: The layer is for the firing strength normalization obtained in layer 2, denoted by N. The ith node of layer 3 ascertains the proportion of the ith rule's firing strength to the total rule's firing strength. The formula is simply expressed in (4) as follows.

$$O_3 = N = \frac{w_i}{w_1 + w_2} \tag{4}$$

Layer 4: The layer is to ascertain the rule yields which are dependent on the subsequent coefficient parameters of p, q and r. The equivalent with Layer 1, this layer contains adaptive node and alters the yield parameters. The yield of this layer is basically the augmentation between the normalized firing strength and the first order polynomial which is expressed in (5) as follows.

$$O_4 = y_i = \overline{w_l}(p_i x_1 + q_i x_2 + r_i) \tag{5}$$

for $i = 1, 2, 3, \ldots.$.

Layer 5: The layer is to give a single fixed node, signified by sigma. The yield of this node is the total submission of all input signals from the past layers. The mathematical expression of this layer is represented in (6) as follows.

$$O_5 = \Sigma_i y_i = \overline{w_1}(p_1 x_1 + q_1 x_2 + r_1) + \overline{w_2}(p_2 x_1 + q_2 x_2 + r_2) \tag{6}$$

In this layer, the subsequent coefficient parameters of p, q and r are obtained by the least square error method.

3. **Matlab Code of ANFIS Network.** This research is expected to take the benefits of ANFIS method that are suitable for maximum power optimization of various types of PV modules technology. The optimal recommendation are the simplicity of network structure and training processes and the level of accuracy which is important in the application of the maximum point tracking control of PV modules. The training and validation process using artificial neural networks based ANFIS network is based on the matlab program in the listing code and explained in Table 1 as follows.

The m-code is available for training and validation of each PV modules. For instance, the PV module type of ASE-50-ATF/17 is marked by naming files such as ase_input, and ase_target. This program is quite effective because the input variables are just changed for other types of PV module for the same training and validation process.

Matlab code:

```
1 clc
2 clear
3 fid = fopen('ase_input.txt','r');
4 datac = fscanf(fid,'%f',[2,inf]);
```

```
5 x1 = datac(1,:)/1000;
6 x2 = datac(2,:)/100;
7 inputc = [x1;x2];
8 fid2 = fopen('ase_target.txt','r');
9 datacout = fscanf(fid2,'%f',[1,inf]);
10 Pmp = datacout(1,:);
11 An = Pmp/100;
12 %training
13 epoch_n = 50;
14 in_fis = genfis1([inputc' An'],2,'gbellmf');
15 out_fis = anfis([inputc' An'],in_fis,epoch_n);
16 X = evalfis(inputc',out_fis);
17 A1 = X';
18 A = [An;A1];
19 j = 150; %number of data for training
20 subplot(2,1,1),plot((1:j),x1,'b-',(1:j),x2,'r-');
21 set(gca,'xlim',[0 j]);
22 legend('E(x1000 W/m2)','Tc(x100 C)');
23 ylabel('data input')
24 xlabel('hours')
25 subplot(2,1,2),plot((1:j),A(1,:)*100,'b-',(1:j),A(2,:)*100,'r-');
26 set(gca,'xlim',[0 j]);
27 legend('target','optimum');
28 ylabel('P(W)')
29 xlabel('hours')
30 %testing clear sky
31 fid3 = fopen('ase_clear.txt','r');
32 datac = fscanf(fid3,'%f',[2,inf]);
33 y1 = datac(1,:)/1000;
34 y2 = datac(2,:)/100;
35 input_test1 = [y1;y2];
36 fid4 = fopen('ase_clearid.txt','r');
37 datacout = fscanf(fid4,'%f',[1,inf]);
38 P_ideal = datacout(1,:);
39 Ay = P_ideal/100;
40 Y = evalfis(input_test1',out_fis);
41 A2 = Y';
42 B = [Ay;A2];
43 SSE1 = sum((Ay-A2).^2)
44 figure(2);
45 q = 139; %number of data for testing clear sky
46 subplot(2,1,1),plot((1:q),y1,'b-',(1:q),y2,'r-');
47 set(gca,'xlim',[0 q]);
48 legend('E(x1000 W/m2)','Tc(x100 C)');
49 ylabel('clear sky')
50 xlabel('hours')
51 subplot(2,1,2),plot((1:q),B(1,:)*100,'b-',(1:q),B(2,:)*100,'r-');
52 set(gca,'xlim',[0 q]);
53 legend('target','optimum');
54 ylabel('P(W)')
55 xlabel('hours')
56 %testing cloud sky
```

```
57 fid3 = fopen('ase_cloud.txt','r');
58 datac = fscanf(fid3,'%f',[2,inf]);
59 z1 = datac(1,:)/1000;
60 z2 = datac(2,:)/100;
61 input_test2 = [z1;z2];
62 fid4 = fopen('ase_cloudid.txt','r');
63 datacout = fscanf(fid4,'%f',[1,inf]);
64 P_ideal1 = datacout(1,:);
65 Az = P_ideal1/100;
66 Z = evalfis(input_test2',out_fis);
67 A3 = Z';
68 B = [Az;A3];
69 SSE2 = sum((Az-A3).^2)
70 figure(3);
71 k = 289; %number of data for testing cloud sky
72 subplot(2,1,1),plot((1:k),z1,'b-',(1:k),z2,'r-');
73 set(gca,'xlim',[0 k]);
74 legend('E(x1000 W/m2)','Tc(x100 C)');
75 ylabel('cloud sky')
76 xlabel('hours')
77 subplot(2,1,2),plot((1:k),B(1,:)*100,'b-',(1:k),B(2,:)*100,'r-');
78 set(gca,'xlim',[0 k]);
79 legend('target','optimum');
80 ylabel('P(W)')
81 xlabel('hours')
```

TABLE 1. Description of matlab code

Lines	Description
1-11	The input-output data of PV modules loading from text files including the normalization process for neural network training data preparation.
12-29	The ANFIS network training process, taking the number of simulation time of 50, number of training data of 150, utilizing the *gbellmf* as an activation function and plotting the training results by the input-output data combination.
30-55	The ANFIS network testing process under clear sky condition with the number of testing data of 139 (the remained data number that is not used for training process), the normalization of input-output data testing and plotting the testing results by the input-output data combination.
56-81	The ANFIS network testing process under cloudy sky condition with the number of testing data of 289, the normalization of input-output data testing and plotting the testing results by the input-output data combination.

4. **Simulation Results and Discussion.** In the training and validation process, the input and actual output files are separated which are denoted as the input signal and output signal, respectively. For the training process, the conditions of irradiance and cell temperature of half-day from 6:00 a.m. to 12:00 noon under clear sky condition are taken as the training data. Meanwhile, the target data is the actual measurement results taken from the mathematical model of PV modules designed by Sandia National Laboratory [13, 14]. With this approach, the input-target data combination yields 150 number of
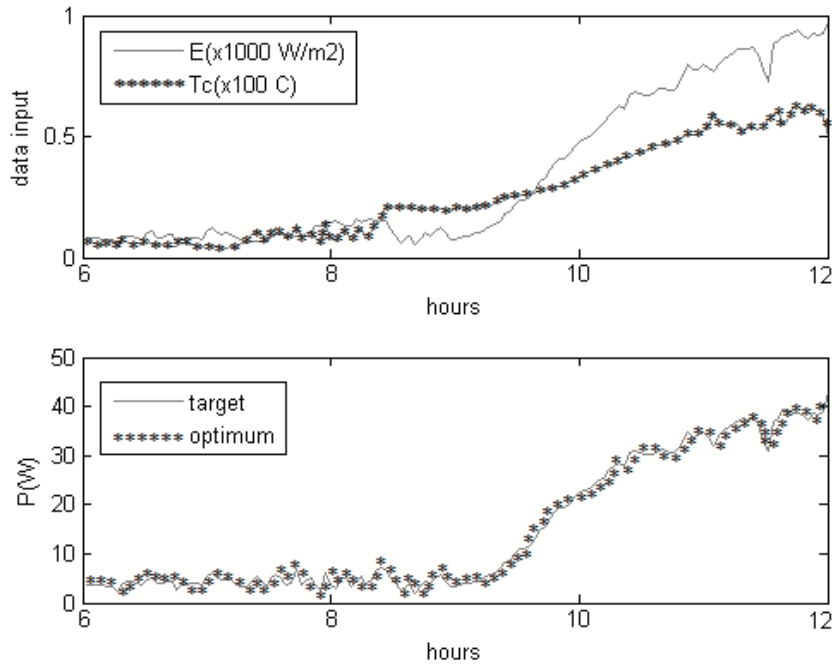
FIGURE 2. Training results

training data patterns. The typical input signal of training data with the ANFIS method is shown in Figure 2.

It is important to measure the performance of ANFIS network in different technologies of PV modules. For this reason, there are four typical solar modules technologies that have been tested in this study, i.e., ASE-50-ATF/17, Kyocera KC-80, BP Solar BP585 and AstroPower AP-8225. The first two PV modules are the multi-crystalline Silicon solar cell technologies. The ASE-50-ATF/17 implements the octagon technology based edge defined film-fed growth (EFG) to enable the number of material and consumed energy during manufacture can be reduced. Meanwhile, the Kyocera KC-80 is the Silicon wafer solar cell technology as a part of innovation and development of solar cell to increase the efficiency energy conversion. In comparison, the BP Solar BP585 is the single-crystalline Silicon technology that is potentially suitable for application for limited space with expecting maximum output energy. The last type of PV modules is AstroPower AP-8225 with thin-film Silicon solar cell technology with the target to obtain the trade-off performance of multi- and single crystalline modules utilizing the process of subtraction of serial multi crystal Silicon with low cost.

The algorithm of ANFIS method is highly determined by the choice of the type of membership function and the number of membership functions set for each input. In this study, the generalized Bell membership function *gbellmf* with 2 membership functions for each input is selected. To limit the number of repetition process of calculation, the value 'epoch' is set for 50 times. For the validation process, two different weather conditions are tested, which are clear and cloudy weather conditions. For clear sky condition, the data combination $P_{mp} = [E, T_c]$ from 12:00 noon to 6:00 p.m. is taken which produces a total validation data of 139. Meanwhile, the cloudy sky condition, there are 289 data patterns for validation by assuming the measurements taken from 6:00 a.m. to 6:00 p.m. The typical data validation for cloudy sky conditions is presented in Figure 3.

The results of training process are marked with training errors and several other indicators as depicted in Table 2. It can be seen that the structure of ANFIS network can be confirmed similarly for each PV module during the training process. However, the accuracy performance is slightly different which is depending on the training data pattern. This
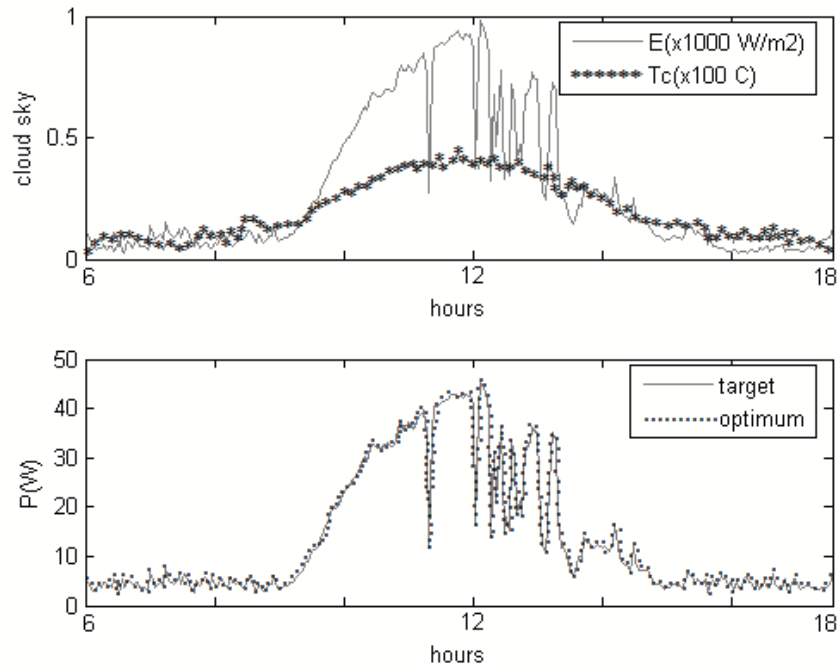
FIGURE 3. Validation results

TABLE 2. Results of training process

Indicators	ASE-50-ATF/17	Kyocera KC-80	BP Solar BP585	AstroPower AP-8225
Error training	4.39×10^{-5}	5.79×10^{-5}	7.13×10^{-5}	9.30×10^{-5}
No. of nodes	21	21	21	21
No. of linear parameters	12	12	12	12
No. of nonlinear parameters	12	12	12	12
Total number of parameters	24	24	24	24
Number of training data pairs	150	150	150	150
Number of checking data pairs	0	0	0	0
Number of fuzzy rules	4	4	4	4

TABLE 3. Sum of square error (SSE)

Irradiance conditions	ASE-50-ATF/17	Kyocera KC-80	BP Solar BP585	AstroPower AP-8225
Clear sky	9.29×10^{-6}	2.97×10^{-5}	6.26×10^{-5}	3.24×10^{-5}
Cloudy sky	5.02×10^{-5}	5.49×10^{-5}	1.38×10^{-4}	1.18×10^{-4}

is one of the advantages of ANFIS method compared to other artificial neural network methods, besides the proposed method has a high level of estimation accuracy in 10^{-5} for each type of PV modules. The validation results indicate the high accuracy performance as shown in Table 3 for clear and cloudy sky measurements. It can be seen that the validation results of ANFIS method for testing the multi-crystalline Silicon modules show the high accuracy estimation and relatively stable even though the type of input signal is changed. In addition, there is slight decrease in estimation performance indicated by slight increase in validation error for single-crystalline and thin-film PV Silicon modules.

5. **Conclusions.** The paper has presented the benefit of adaptive neuro-fuzzy inference system (ANFIS) method for the output power estimation of crystalline Silicon PV modules. The simulation results indicate that the proposed method basically has good performance during the training and validation process with the high level of accuracy or low error measurements. It implies that the method has better capability to map all types of PV modules with varying input-output signal criteria. Further study, it is important to generalize the performance ANFIS network for the maximum power estimation of the type of non-crystalline Silicon based PV modules technology utilizing similar network algorithm.

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