The Analysis of Dual Axis Solar Tracking System Controllers Based on Adaptive Neural Fuzzy Inference System (ANFIS)

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ABSTRACT

Artificial intelligence is commonly used in Photovoltaic (PV) control systems. Adaptive Neural Fuzzy Inference System (ANFIS) is one of the intelligent strategies that can be employed in the system controller. ANFIS technique shows high accuracy as it involved several processes which are the Fuzzy layer, Fuzzy Rule layer, Normalization layer, and Output Membership layer. The main objective of the proposed work is to model the dual-axis solar tracker using MATLAB software by utilizing the ANFIS technique, hence improving the performance of the solar system. The data used for training and testing are elevation angle and azimuth angle. 80% of the data is used for training and another 20% for testing in order to predict the solar radiation toward PV panels. A different set of input membership functions (MFs) is used in the system, which are Five MFs, Ten MFs, and Fifteen MFs. These MF are simulated to produce the best prediction of solar radiation. The results show

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average error gained for both training and testing data and minimum error indicates the accuracy of the predicted angle of dual axis solar tracker. In the finding, overall results show a good correlation between the actual and prediction value with 15 input MFs as it produced the lowest error value.

Keywords: *Dual Axis Solar Tracker; Adaptive Neural Fuzzy Inference System (ANFIS); Artificial Neural Networks (ANN); Membership Function (MF); Photovoltaic (PV); Artificial Intelligence (AI)*

Introduction

In recent years, global economic expansion and population growth have necessitated more energy, which is critical for both developing and developed countries' socioeconomic development [1]. Therefore, energy usage is extremely important. Renewable energy is obtained from natural resources where these resources, including sunshine, wind, biomass, thermal energy and others are stored in the earth's crust and have the benefit of being present in almost every part of the world in some form. They are almost infinite, and they have no effect on the climate or the environment. Fossil fuels, on the other hand, such as oil, coal, and natural gas, are limited in supply. Based on [2], the depletion of fossil fuels and their negative environmental effects, increase the use of clean and renewable energy sources. Therefore, generating electricity from renewables, and improving energy efficiency are becoming more important. Other than that, if we keep extracting them, they will ultimately run out. They do not refill as quickly as we humans consume them, despite the fact that they are formed naturally.

The rate of solar energy consumption is increasing in this new era today. Solar energy has been considered as a potential alternative energy source in recent years due to its unique traits of being free, eco-friendly, and widely available in most parts of the world [3]. Solar cells composed of silicon or other materials that convert sunlight directly into electricity are known as Photovoltaic (PV) cells [4]. Solar energy provides a clean alternative to fossil-fuel-generated electricity, with no pollution of the air or water, no global warming pollution, no risk of electricity price spikes, and no health risks. This is particularly relevant due to the growing concern about climate change [5]. The tiny PV solar cells can directly convert sunlight into solar energy, giving solar energy a significant advantage over other traditional power sources [6].

The solar panels can be mounted as a fixed type or tracker type. The power created from a PV system with tracker type (Dual Axis Solar Tracker) was compared by [7]. The system generated an average output power of 9838.35 W, whereas the fixed-type PV system only provided 8326.18 W of electricity. In addition, the earth constantly rotates around the sun, meaning that the sun’s position will always move every minute along with the earth’s rotation [8], and this required the implementation of solar tracker. The energy generated by utilizing a solar tracking system is larger compared to fixed type system as investigated by [9].

Solar tracking systems are separated into two categories based on the number of axes include in following the sun's trajectory, which are single and dual axis solar tracker. A single axis tracker can only rotate either vertically or horizontally at single time [10], however, a dual axis tracker can rotate vertically and horizontally at each time. As compared to this two-axis type, studies have been conducted to identify the rate of sun tracking between these two types of axes, and the results revealed that dual axis solar trackers have the maximum power efficiency than single axis solar trackers [10]. In [11], two degrees of freedom serve as rotation axes in dual axis trackers. With a dual axis solar tracker, panels will always be positioned at the best angle for maximum efficiency [12]. Other than that, to optimize the functionality of the panels, the selection of control methods is very important. The algorithm, microprocessor, motor, electronic circuits, artificial intelligence (AI), and technical approaches are some of the strategies that may be used as a controller to regulate the PV panel [13]. AI techniques are one of the recent and popular methods in control systems, based on their adaptability in doing predictions.

Furthermore, installing solar panels in the optimal position will extract the maximum amount of solar radiation. Various studies on this subject have been published due to the importance of tracking the sun's rays for effective performance. Several solar tracking strategies to optimise sun radiation toward PV panels, including fuzzy logic [14], ANFIS [13], [15], LDR sensor [10], [12], and algorithm techniques [16]. Regarding the investigation of the rate of absorption of sunlight against solar panels by using all these various methods, there are some conclusions that have been identified. ANFIS, for example, is an intelligent principle that combines layers of neural networks and fuzzy logic. This technique has the capability to track the sunray precisely because it has adaptation capability and rapid learning capacity.

On the other hand, fuzzy logic is one of the intelligent techniques which on its basis allows the translation from logic statement to nonlinear mapping. However, the construction of its model is much more complicated, and it also needs rules to conduct a process because it cannot recognize machine learning or neural networks. Furthermore, the algorithm technique is complex because each angle must be analysed individually in order to determine the proper position of the solar panel. Finally, the LDR method has a low response speed and is greatly affected by temperature, despite its building technique being simpler than other techniques. Overall, in terms of solar tracking system performance, the ANFIS method can be categorised as the best technique to be implemented in the system because of high prediction accuracy with minimum error.

This proposed research focuses on the Adaptive Neural Fuzzy Inference System (ANFIS) technique by integrating fuzzy logic and neural network layers in designing and controlling solar tracking system [17]. The goal of the ANFIS system is to represent a fuzzy system as a network structure by fuzzifying a neural network using a learning mechanism derived from artificial neural networks (ANN). The proposed system analyse and predicted the best angles that followed the sun's position throughout the sky. Furthermore, it also improves the accuracy of determining the sun's best position. Therefore, it lowers the error (MSE) and improves the prediction rate of output solar radiation.

Methodology

This section explained the ANFIS implementation in the solar system. ANFIS adjusts the membership function and related parameters to approach the required data sets using the neural network training process [18]. The adaptive neural fuzzy inference system is a useful neural network method for solving problems with function approximation. A mapping relationship between the input and output data is provided by an ANFIS, where the optimal distribution of membership functions is determined using a hybrid learning method [19]. The learning methods used in the ANFIS are a backpropagation algorithm and a hybrid algorithm [20]. This inference system is generally built using five layers in total as shown in Figure 1. The node function describes each ANFIS layer, which is made up of many nodes. The nodes in the previous layer provide the inputs for the current layers [21].

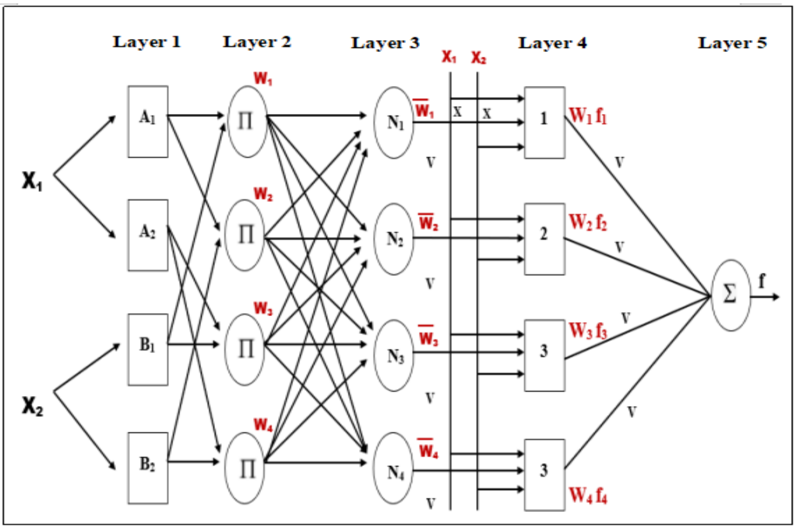

Figure 1: Block diagram of ANFIS modeling

Layer 1 is the fuzzy layer, where the main operation in the fuzzy logic principle is the fuzzification process. Each node in the fuzzy layer represents the degree of membership function from the input. The fuzzification method scales and fuzzy values become input variables by converting crisps input to linguistics variables using membership functions [22]. In other words, this layer will take the input value and determine the membership function. The adaptive node i of this layer has the following node function, which refers to the Grade of Membership on fuzzy set formula by Equations 1 and 2.

$$O_1,\ i=\mu Ai(x)\ for\ i=1,2,3\ or \tag{1}$$

$$O_1,\ i=\mu Bi\text{-}3(y)\ for\ i=4,5,6 \tag{2}$$

where either ‘x’ or ‘y’ is the node I input, and ‘Ai’ or ‘Bi’ can be a possible linguistic name for this node. In other words, the membership grade of a fuzzy set ‘A1’, ‘A2’, and ‘A3’ or (B1, B2, and B3) is output O_1 from this layer, and it describes the degree to which the provided input ‘x’ or ‘y’ meets the quantifier ‘A’ (or B).

Next is Layer 2, known as the Fuzzy Rule Layer. The fuzzy logic operators are used at this layer. Each node output in this layer represents the rule process's firing strength. The AND operator is used to multiply the incoming signals from layer 1 to obtain the output of firing strengths in this layer. Each node is a fixed node where the output from this layer is equal to the product of all incoming signals, as indicated in Equation 3.

$$O_2,\ i=w\ i=\mu Ai\ (x)\ \mu Bi\ (y)\ i=1,2,3 \tag{3}$$

For the normalising layer, which is Layer 3, every node in this tier is a fixed node with the label "N." The node determines the ratio of the firing strength of the rule to the sum of the firing strengths of all rules. Every node i in this layer has an adaptive node, and the node functions according to Equation 4.

$$O_3,\ i=wi\ fi=wi\ ri\ i=1,2,3 \tag{4}$$

This node's parameter set is represented by ri, and the following parameters are the parameters in this section.

Every node has a node function and is adaptable in Layer 4, which is known as the Output Membership Layer. The output membership layer can be defined using Equation 5.

$$O_4,\ i=wi\ fi=wi\ (pix+qiy+ri) \tag{5}$$

where wi is the normalised firing strength from layer 3 (pi,qi,ri) and the parameter set of subsequent parameters. In other words, each node layer gets its output based on the previous layer. The defuzzification values are returned by this layer, which computes a parameter function from layer 3 and its parameter known as the consequent parameter. The last Layer 5 is the Defuzzification Layer, where it is generally a single node that aggregates the entire output as the sum of all incoming signals and is used to provide a single output for the ANFIS model.

This study technique using ANFIS simulation for a dual axis solar tracker is based on the flowchart illustrated in Figure 2. The process for the prediction of ANFIS starts with defining input and output data where input data were elevation and azimuth angle while output data is solar radiation. In this process, all the data will be categorized into Training and Testing and it's stored in a separate folder on MATLAB workspace, and this process is conducted before the simulation of ANFIS.

Next is to load Training and Testing data into Neuro-Fuzzy Designer in the MATLAB simulation model. Then, the process continued with generating FIS where in this section, several options and parameters need to be selected such as Options for FIS generation, number of Input MFs, and types for membership function use. There are four selection options available in this ANFIS simulation, and the Grid Partition system has been chosen for this study with the integration of fuzzy logic controller on its system.

Next, for the input MF, three sets of input are used which are Five, Ten and Fifteen MF while for the MF's type, the Gaussian membership function is selected. The various number of inputs MFs selected is to identify the effect of this parameter on prediction's accuracy. Other than that, process flow continued with setting up the value of error tolerance and epoch (iteration) before train (prediction) is simulated. Error tolerance refers to the rate of error need to achieve by ANFIS when the simulation for data prediction is conducted. From this research, error tolerance is set to zero while epoch or iteration is hundred. The precision achieves when the error value gained from the simulation is near or the same as the error tolerance set up. If the predicted value does not match the actual output, a new set of input MFs will be created, and the process will be repeated until the value of output data before and after ANFIS implementation is almost the same. When the prediction is exact, the final step is to record the ANFIS simulation's output performance.

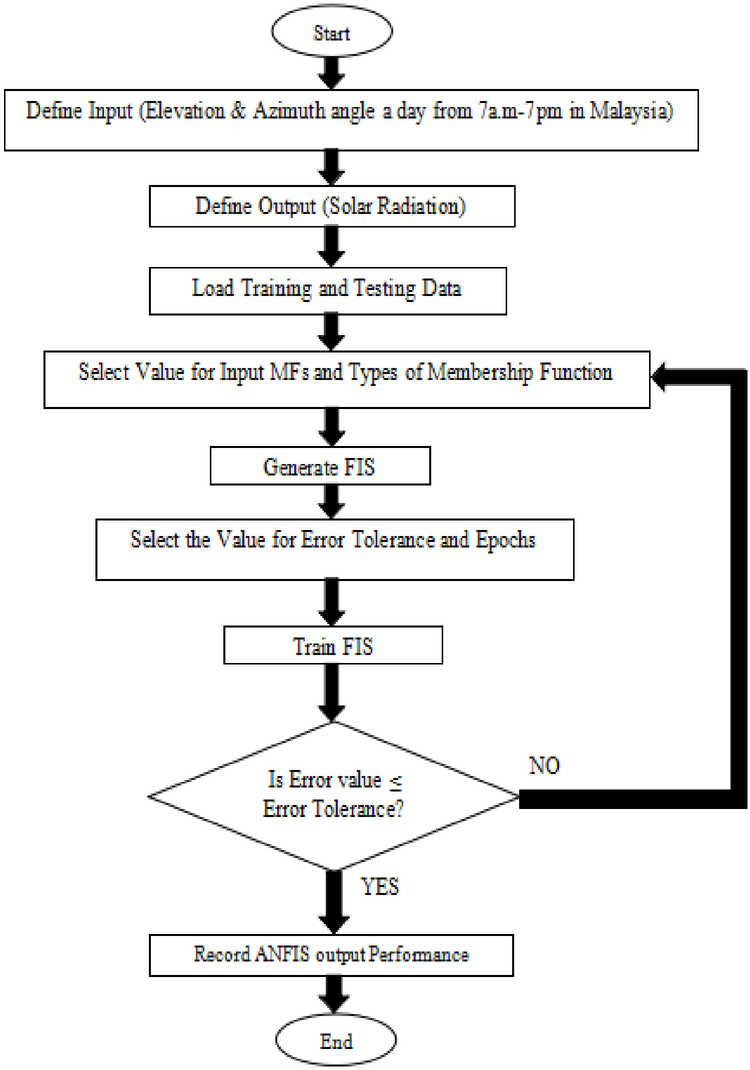

Figure 2: Flowchart for ANFIS dual axis solar tracker

Result and Discussion

The results and discussion for the proposed Dual Axis Solar Tracking System with ANFIS controller are presented in this part. The data for ANFIS is applied using MATLAB to assess the output value of solar radiation on solar panels.

This simulation is based on two types of input value, elevation and azimuth angle in the targeted area which is Shah Alam, Selangor, Malaysia. The prediction conducted which are training and testing data are used to investigate the effect of the ANFIS technique on the solar tracking system. The training and testing procedures are repeated using three different sets of input membership functions: 5MFs, 10MFs, and 15MFs. The MFs are chosen to quantify the impact on the low, medium and large value of MFs. Next, the total data used is 49 data, where 80% (39 data) was used for training and another 20% (10 data) was used for testing.

ANFIS training process

The result shown in Figures 3, 4 and 5 is the training data for 5MF, 10MF and 15MF, respectively. Based on the obtained graph, the 'blue circle' represent the actual data while the 'Red Dot' are the prediction data for the training process after the ANFIS method is applied. The graphs show that the different numbers of MF affected the accuracy of prediction data. The 15MFs show a good result compared to the lowest value of MF which is 5MFs. It can be observed that the large number of MFs able to rise the ANFIS intelligence level, hence increasing the prediction for the output data.

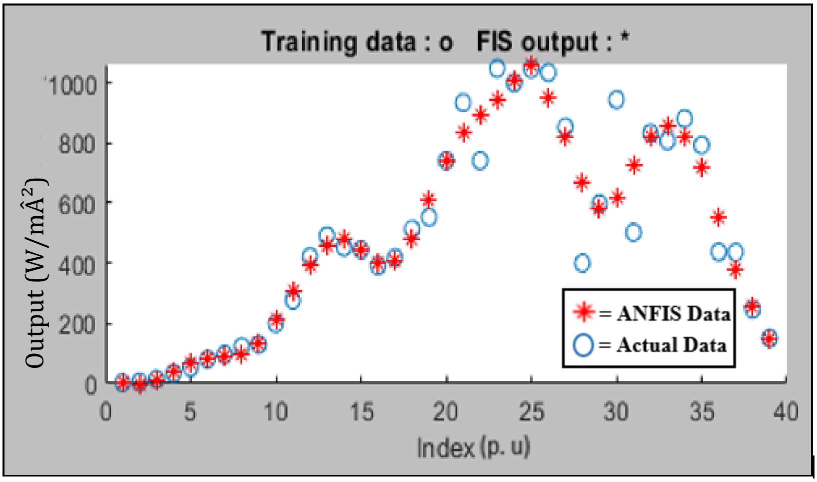

Figure 3: 5MFs

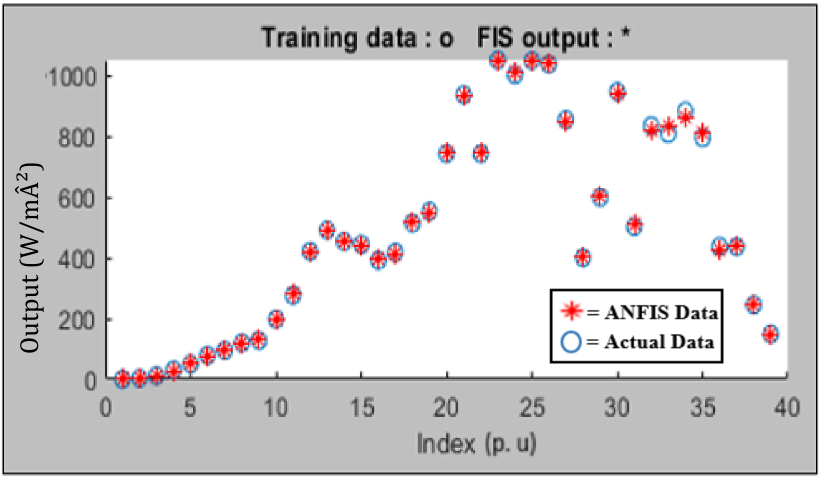

Figure 4: 10MFs

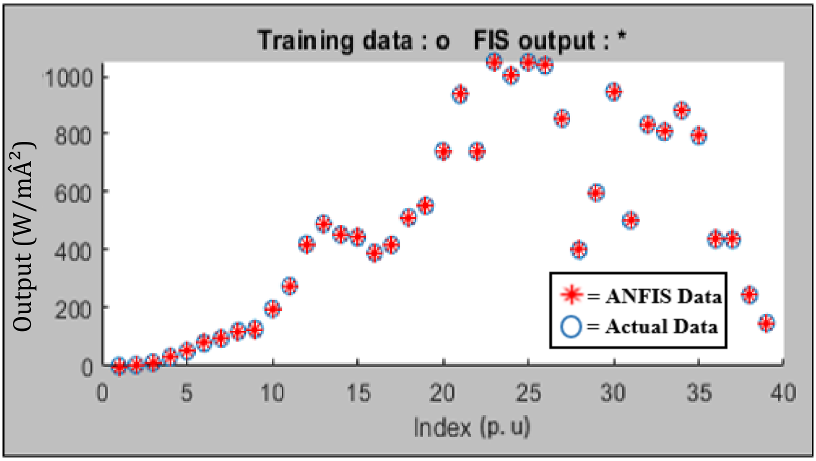

Figure 5: 15MFs

ANFIS testing process

The graph illustrated in Figures 6, 7, and 8 indicate the simulation results of testing data for 5MF, 10MF and 15MF, respectively.

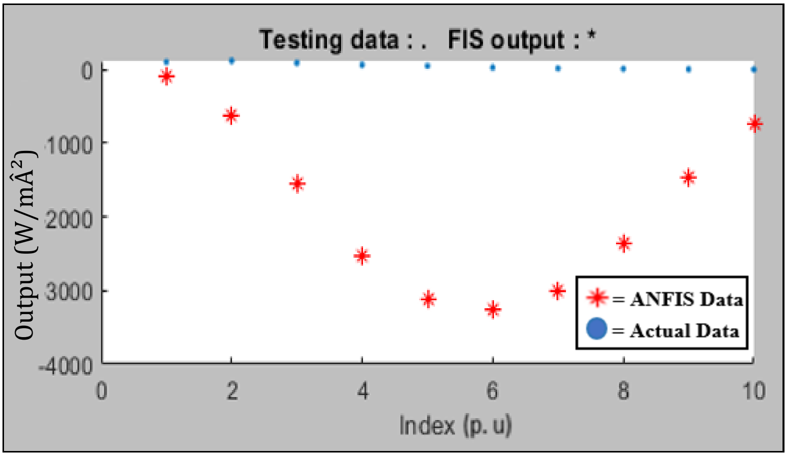

Figure 6: 5MFs

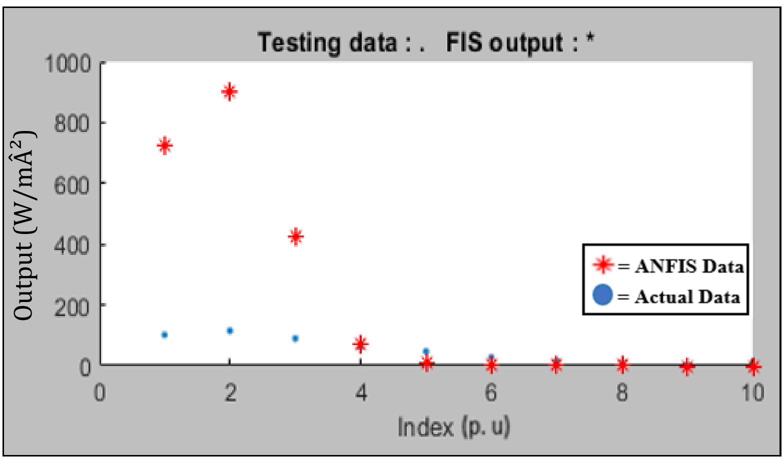

Figure 7: 10MFs

Figures 6, 7 and 8 show generated output for ANFIS testing process in MATLAB. ‘blue dot’ represents the actual data while ‘red dot’ are the testing data after ANFIS is implemented into the system. Compared to the training phase, the results reveal that when a different set of membership functions is utilised, the accuracy of prediction for data before and after ANFIS varies. From the results, 15MFs show the most accurate data while 5 MFs generate the lowest accuracy of prediction. The same goes to training process, by increasing the number of inputs, the model's accuracy and capability improved, and it was able to anticipate the process in membrane technology. Next, the comparison between actual and ANFIS (prediction) will be discussed.

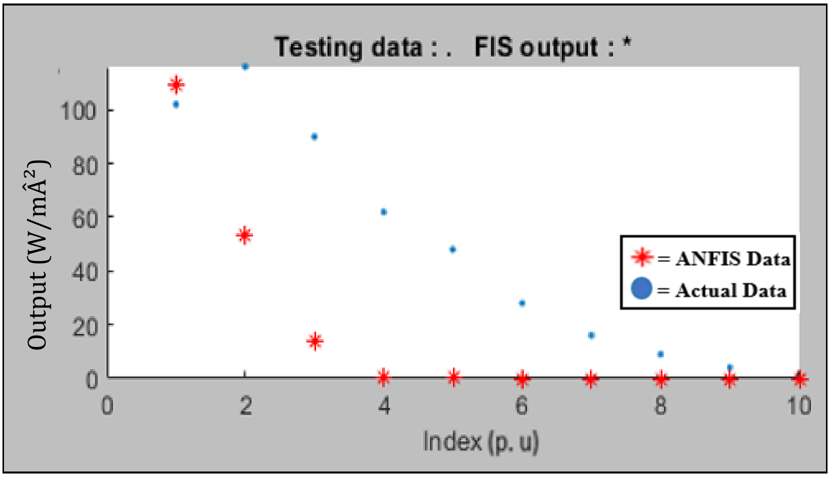

Figure 8: 15MFs

Comparison graph between actual and ANFIS output

The plotted graph for the solar radiation based on actual and ANFIS output is shown in Figures 9, 10 and 11. Based on the graphs, the 'X-Axis' is the number of samples used in the system and 'Y-Axis' represent the value of solar radiation. The 'blue line' shows the actual data while the 'orange line' represents ANFIS data. The curve generated from both outputs is in the form of bell-shaped because the membership function selected for this system is Gaussian type.

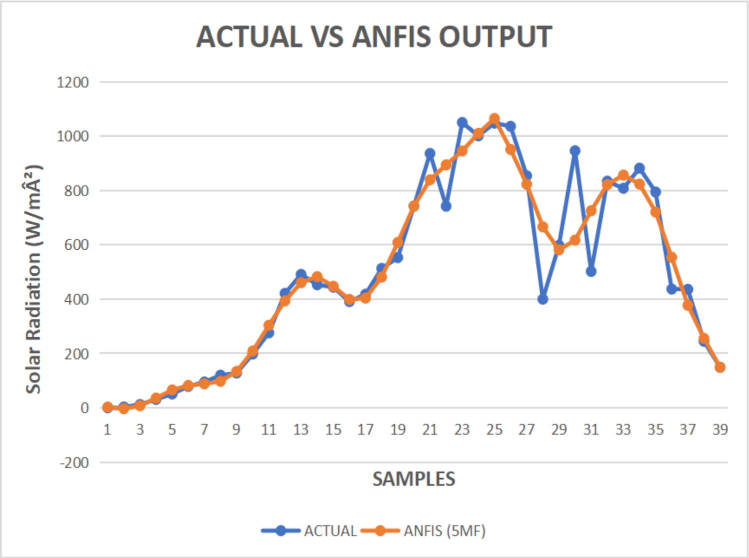

Figure 9: Comparison between actual vs ANFIS output for 5 membership function

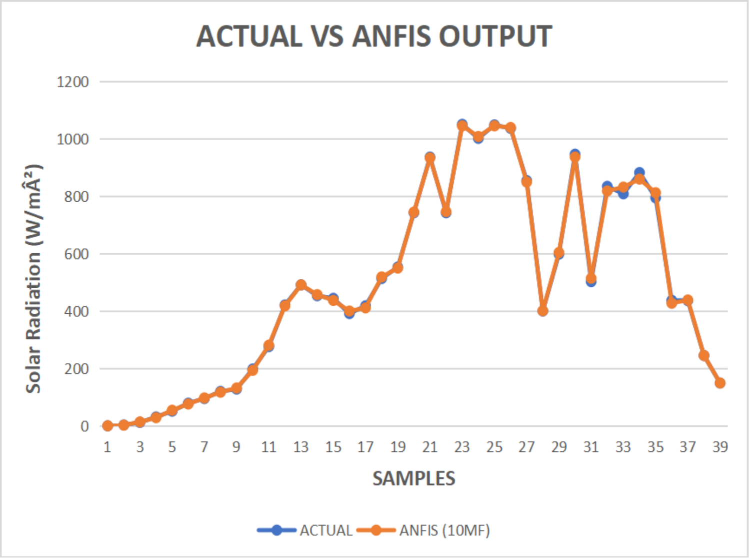

Figure 10: Comparison between actual vs ANFIS output for 10 membership function

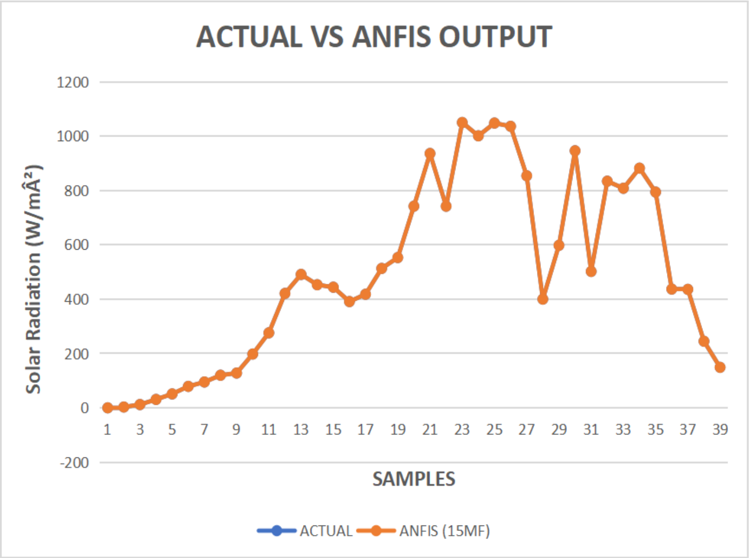

Figure 11: Comparison between actual vs ANFIS output for 15 membership function

Average data obtain for different input MFs

The data in Table 1 summarized the different MF used for 100 iterations on Gaussian MF's type using 49 data.

Table 1: Error value for a different set of membership functions (MF)

Number of input MF	Average training error	Average testing error
5MF	90.3618	2197.1362
10 MF	8.0445	334.5203
15MF	0.0637	41.3420

To achieve the prediction value in ANFIS simulation, there are several steps to be followed. First is to select the data for the training and testing process to be loaded into the system. In this study, the amount of data utilized for training purposes exceeds the number of data used for testing purposes. The objective for this selection is due to the size of the data, which is the larger the data used for training, the better the model learns. Next is to select the type of membership function, which has several models which are Triangle, Trapezoidal, Gaussian, and Sigmoid membership functions, where each type of model will generate a different curve. Then, the selection number for the input membership function, where this parameter will be affected by the output prediction by ANFIS, either the result is close to the actual value (minimum error) or vice versa. After the selection of input and types of membership functions were made up, next is to train the FIS. In this section, the value of error tolerance and the Epoch (iteration) need to be set up. The output data prediction can be assumed as accurate when it achieved the minimum value of error while for the epoch, the more the epoch value, the more precise prediction output will be generated. The last step are testing the FIS, which is the actual and ANFIS data will be automatically plotted to evaluate the result.

From the overall results shown in Figure 3 to Figure 11, the data represent that the ANFIS technique was able to make an accurate prediction output. All the parameters such as types and number of MF to be used, how much the iteration is to be repeated and the selection for train or test data is very important to optimize the effectiveness of ANFIS prediction toward the whole system. Regarding this analysis, different types of MF have a significant impact on the overall performance of fuzzy representation. The MF are the basic building blocks of fuzzy set theory, the fuzziness of a fuzzy set is dictated by its MF. As a result, the forms of MF are critical for a certain case since they affect a fuzzy inference system. The Gaussian membership function was chosen in this simulation because it is a popular technique for specifying fuzzy sets due to its smoothness and concise notation. As illustrated by [24], this function has the advantage of always being smooth and nonzero.

The objective of using various input numbers of MF is to identify which type will generate the precision of output data for both training and testing when the ANFIS simulate. In line with [13], the output value will be more accurate when the input membership function increase and produce a small error value at the end of the ANFIS process. By referring to the result generated in Figures 9, 10 and 11, the closeness of data between actual and ANFIS implementation is increased when the value of MF is added up which shows the accuracy of the system. Based on error data stated in Table 1, when the number of inputs MF is 5MF, the value of average training and testing error is high which are 90.3618 and 2197.1362, respectively. However, at 10MF, the error reduces to 8.0445 for training and 334.5203 for testing, showing the high accuracy of the model as well as its high capability in the prediction of the membrane process [25]. Furthermore, the input is increased to 15MF, and the error is 0.0637 in training, which shows that the data are almost identical to the actual value of solar radiation while for Testing the error reduces to 41.3420. Hence, this error shows that the number of MF has a bigger impact because it decides how long it takes to compute [26]. Thus, the best model for achieving the highest system performance can be found by adjusting the number/type of MFs.

Conclusion

ANFIS has been successfully utilised to operate solar tracking systems by accurately anticipating the optimum elevation and azimuth angles. The simulations revealed a high rate of prediction and a small Mean Square Error (MSE), where the prediction result by using ANFIS could achieve a similar value to actual data. Other than that, this study has proven that the prediction will be more accurate when the value of the input membership function is large. This can be found when by using 15MF, the optimum efficiency is obtained. In comparison to other concepts, the evaluation findings demonstrate that ANFIS could be more effective at driving solar tracking systems to follow the sun's path across the sky. In conclusion, the objective of the research is achieved, where the modelling of dual axis solar tracker by using MATLAB software was successfully implemented and the analysis shows the performance of the tracking system is improved by using the ANFIS method.

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Conflict of Interests

All Authors declare that they have no conflict of interest.

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