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Application of Adaptive Neuro Fuzzy Inference System (ANFIS) in Predicting Thermal and Electrical Efficiency of a Photovoltaic Thermal (Pv/T) System

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ABSTRACT

The use of photovoltaic (PV/T) system that converts solar radiation to electricity and provide thermal needs concurrently stands as one of the most effective means of utilizing renewable energy. In recent times, machine-learning techniques have been extensively used in solar system applications due to their high accuracy in predicting the performances without necessarily going through physical modelling. The main objective of this study is to implement an intelligent algorithm adaptive neuro-fuzzy inference system (ANFIS) model to simulate and predict the thermal and electrical efficiencies of a water-based photovoltaic-thermal (PV/T) system. Thorough experimentation for the fabricated set-ups (conventional PV and a water-based PV/T system) was carried out. The real experimental results was validated using ANFIS model. Base on the results obtained it was confirmed that there was an excellent agreement between the predicted model outputs and the actual experimental data. However, the ANFIS model gave the highest prediction accuracy with the lowest error margin of 0.00021, 0.0089 and 0.0459 for MSE, RMSE and MAE with strong correlation (R^2) of 0.9998. Base on the results obtained it was concluded that this intelligent algorithm is a reliable tool in predicting the PV/T system performances.

Keywords: Photovoltaic thermal system: Adaptive neuro-fuzzy inference system: Solar radiation: Photovoltaic system and Data acquisition system

INTRODUCTION

Due to the accelerated rate of economic development during the past half-century, there has been a significant increase in the world's energy consumption, which is expected to continue over the next 50 years with some significant fluctuations. While the need for energy is increasing, its primary sources, namely fossil fuels, are starting to run out due to overuse, which

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has led to serious issues with global warming and climate change. (Al-Waeli et al., 2017; Lupu et al., 2018). Positively, the technologies for renewable energy (RE), including photovoltaics (PV), solar thermal, wind, and biofuels, are finally demonstrating maturity and the eventual promise of cost competitiveness.

Solar energy is the most plentiful, inexhaustible and pollutant free of all the renewable energy source on the earth (Parida et al., 2011). Photovoltaic (PV) systems convert photons emitted by the sun between 700 nm to 1100 nm into electricity (Hasan et al., 2017; Siecker et al., 2018). However, one of these systems' drawbacks is the PV module's reduced open circuit voltage brought on by the rise in cell temperature. But, by adding a cooling technique coupled to the PV module's back side, this drop could be avoided and reduced significantly. With a photovoltaic thermal (PV/T) system, solar energy is simultaneously converted to useful heat and electricity. In order to provide adequate regulation of the PV module temperature and to increase the efficiency of the PV through cooling techniques, the adoption of a co-generation component of a PV/T system can offer an efficient solution by effectively absorbing the heat produced in the PV cells. (Abdelrazik et al., 2018; Abdullah et al., 2020; Gaur et al., 2017; Siecker et al., 2017; Su et al., 2017). The productivity of PV/T systems mostly depends on collector design parameters, type of PV/T system unit and environmental conditions such as wind speed, humidity and solar irradiation (Al-Shamani et al., 2016; Khodadadi & Sheikholeslami, 2021). Furthermore, it is pertinent to develop models for estimating overall efficiency of these systems, even though data obtained are highly complex and nonlinear in nature, which makes it somewhat difficult to be constructed using physical models. In order to make reliable and accurate predictions, a significant number of experimental data, particularly for input and output variables, is necessary, which increases the numerical difficulty of the building. Also, a number of scholars and researchers have developed and put forth several approaches for assessing a photovoltaic system’s performance (Parida et al., 2011). Jaaz et al. (2018) numerically, studied the thermal and electrical performances for a compound parabolic PV/T system by using water jet impingement process to cool the rear side of the system. An improvement of 7% and 81% increment in the electrical efficiency and thermal efficiency were recorded. Nahar et al. (2017) examined the PV/T system's efficiency using both experimental and numerical methods. Based on their findings, at the peak of solar radiation, the system overall performance reached 84.4% and 80% for numerical and experimental test. The majority of current research projects have been centred on applying various artificial intelligence techniques to model and predict the behaviour of PV/T systems now. (Cao & Cao, 2006; Esfe

& Tilebon, 2020; Rodríguez et al., 2018; Sivaneasan et al., 2017). Ncane and Saha (2019) implemented ANN and fuzzy logic to predict the output of a solar photovoltaic power plant, a MATLAB Simulink was used to study to develop the models. Al-Waeli et al. (2018) performed a simulation for three different types PV/T systems: water based, PCM-based and Nanofluid-based systems using artificial neural network (ANN) models and the results of the simulation were found to agree with the experimental data. Azimi et al. (2022) used Response surface methodology to predict the electrical and thermal efficiencies of a Nano PCM based PV/T system. Najafi et al. (2018) developed three models: RBFANN, MLPANN and ANFIS, to predict the biodiesel production yields (BPY). Optimum value of BPY was obtained using RSM while the RBF model gave a better prediction accuracy. Afriyie Mensah et al. (2020) Used ANFIS to predict the heat release capacity (HRC) and total heat release (THR) for flammability prediction of extruded polystyrene material. Based on the outcome of their findings, ANFIS model presented an excellent prediction capability for prediction. Also Idris and Markom (2019) presented an overview on the application of hybrid predictive tool (ANFIS) for prediction of supercritical fluid technology (SFT) used in the extraction of organic residues. Similarly, Varol et al. (2010) Adopted ANN, ANFIS and support vector machine (SVM) to predict the thermal performances of a PCM-based PV/T system. Their findings showed that the SVM model performed better than the other models. As a result, it is obvious from the evaluation of earlier studies that relatively few works have been reported in the modelling of water-based PV/T systems. There are numerous anomalies in the modelling as a result of the fact that just a small number of experimental datasets were captured and utilized in the majority of their experiments during training and validation. To address this research gap, the main contribution of this present study is to develop an intelligent algorithm i.e. ANFIS model to simulate and predict the thermal and electrical efficiencies of a water-based PV/T system using over 360 data sets.

Therefore, the novelty of this work is justified by fabricating a water-based PV/T system integrated with a data acquisition system, and as well developing an intelligent algorithm to predict the output responses as a function of the input parameters for the PV/T systems in question.

MATERIALS AND METHODS

Methodology flow chart

The methodology flow chart presented in Fig.1 describes the procedure followed in order to achieve the objectives for this study.

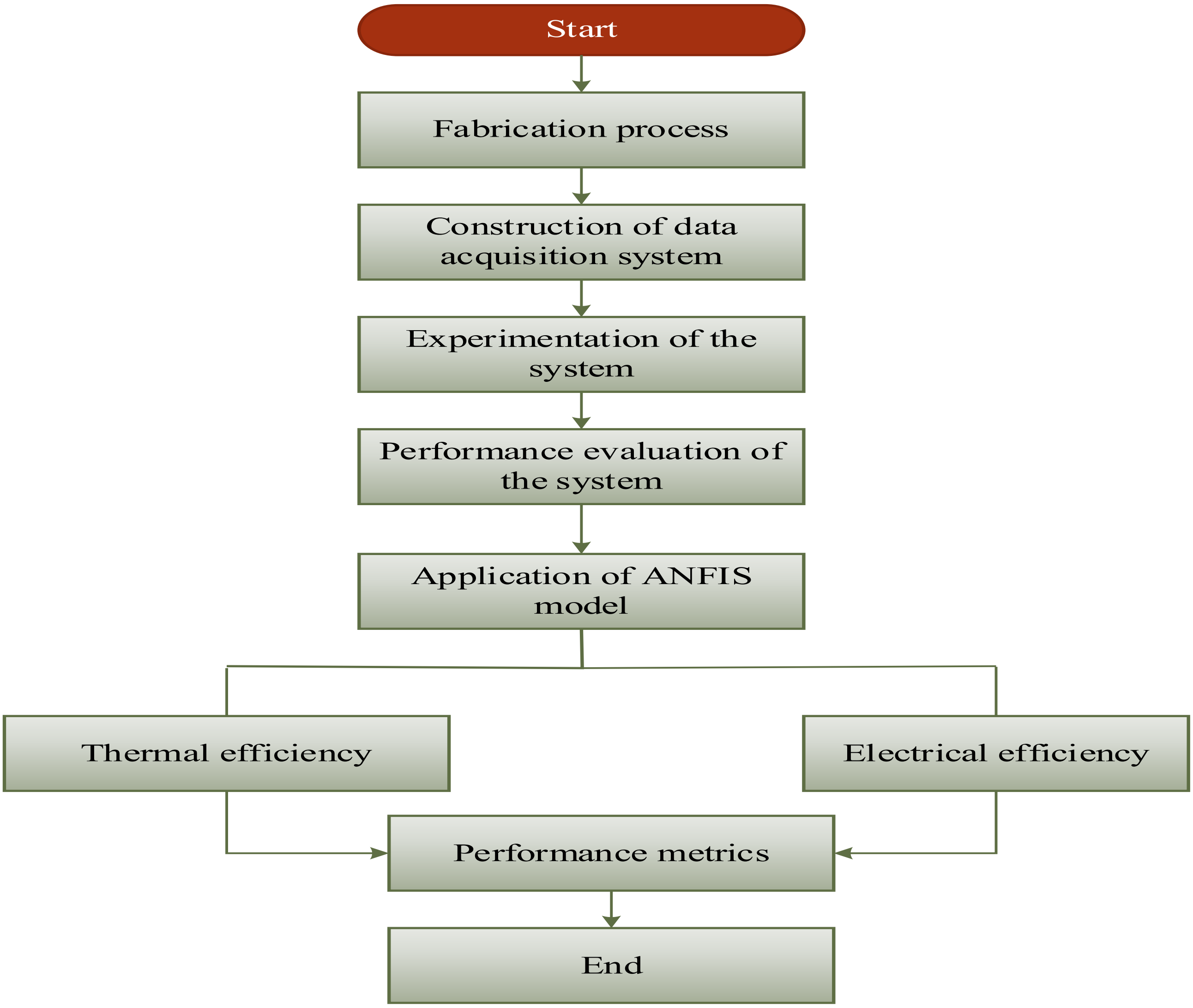


Fig.1. Methodology flow chart

Description of the (PV/T) system

The schematic diagrams for the hybrid photovoltaic thermal (PV/T) are presented in Fig. 2- 3 comprising the PV/T collector, supporting frame, DC pump respectively. The conventional photovoltaic (PV) modules used for this experiment comprises of two identical units with specifications outlined in Table 2. A thermal collector comprising of copper tubes as shown in Fig.3 was attached to the rear side of one the PV modules while the other unit of PV was left without a collector. Fiberglass material was used to insulate the modified PV module from all the sides and edges before it was covered to avoid thermal losses. The hybrid water-based PV/T system and the conventional PV were both mounted sided by side and was set at angle of 9^0 southwards based on the findings of (Khatib et al., 2015) in the energy research centre of Federal Polytechnic Bida, Niger State Nigeria as shown in Fig.4. The experimental data for both systems were collected and tested under same climatic condition to enable proper evaluation of the experimental results.

Experimentation of the system

In order to have closed flow circuit for the working fluid contained in the storage tank, a spiral-type heat exchanger with a cyclic flow was used for cooling the system with the aid of a brushless D.C water pump, as depicted in Fig. 4. This heat exchanger enables heat from the copper manifold outlet to travel through the water in the storage tank without making direct contact between the two fluids. In order to ensure that the fluid temperature in the tank rises noticeably for household and other uses, forced circulation is therefore continued. Interestingly, a data acquisition system was used to capture all data generated by the Photovoltaic thermal (PV/T) system. This the data acquisition system was constructed by interconnecting temperature, voltage, current, flow rate, and solar radiation sensors altogether into a single device which maps all the readings simultaneously. Four temperature sensors were attached to the inlets and outlets of the thermal collector alongside PV surfaces to measure system temperatures respectively. In addition, voltage and current sensors were used to measure the load voltage and current while a radiation sensor was used to measure solar intensity levels. The electrical structure of the experimental set-up comprises the following: battery, DC loads, charge controller, and data acquisition system.

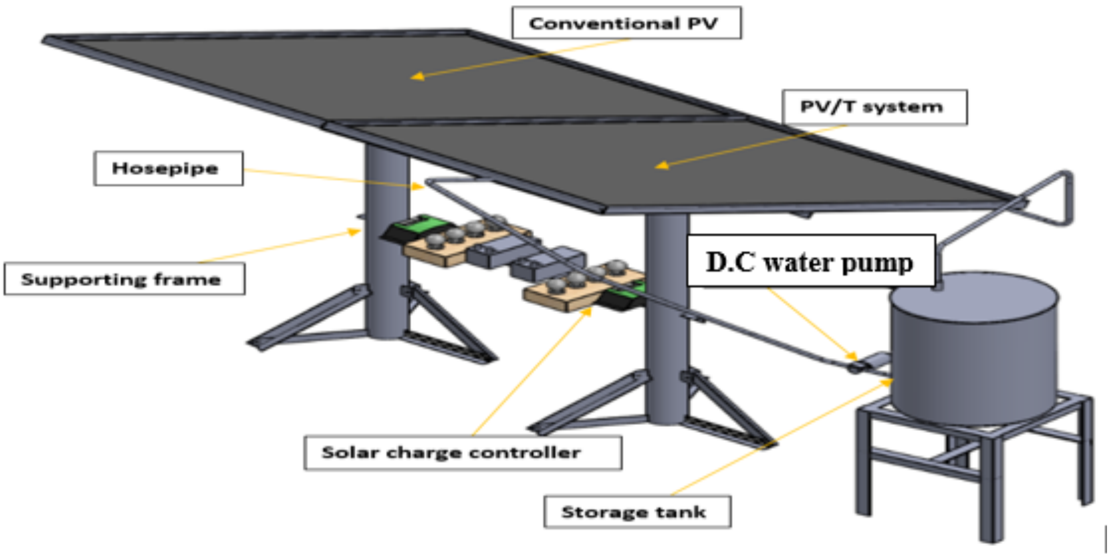


Fig. 2: Schematic view of PV/T set-up

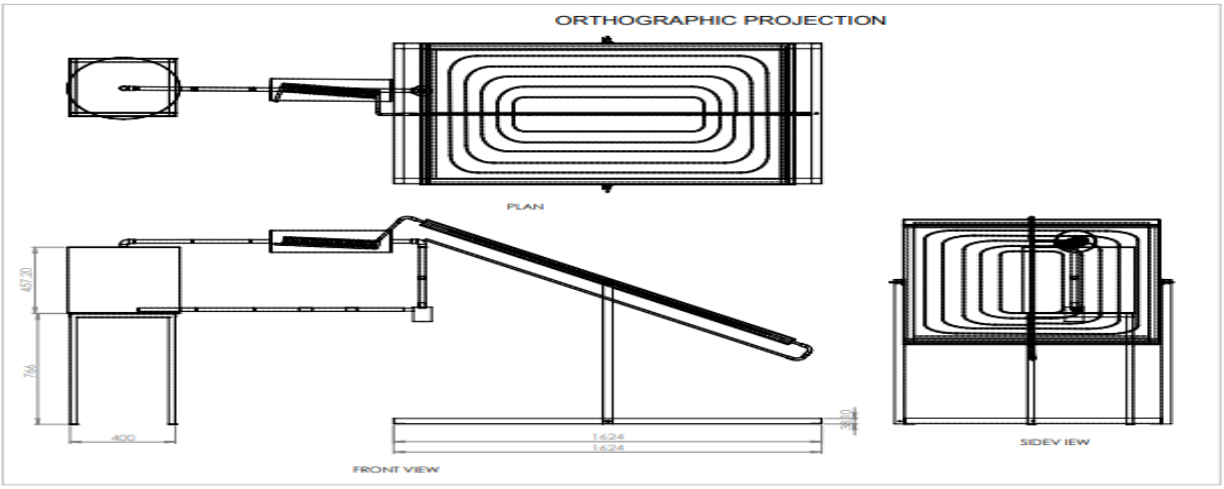


Fig. 3: Orthographic view

Table 2: Specification of the Photovoltaic module

Electrical Properties	Specifications
maximum power (Pmax) (W)	250 W
voltage at Pmax (V)	30.4 V
current at Pmax (A)	8.22 A
open-circuit voltage (Voc) (V)	37.5 V
short-circuit current (Isc) (A)	8.74 A
cell type	Monocrystalline
module Efficiency (%)	15.54
dimensions (mm)	1638 (h) × 982 (w) × 40 (d)

weight (kg)	20

Performance evaluation of Photovoltaic thermal (PV/T) system efficiency

The maximum useful energy gain (heat transfer) in a solar collector occurs when the whole collector temperature becomes the same with that of the fluid inlet temperature. The expression for this maximum useful energy gain of the collector (Q_u) was obtained by multiplying the heat removal factor times the maximum energy gain. Thus, the performance of the PV/T system was calculated using Eq. (1) – Eq. (5) as illustrated below:

$$Q_u = A_c F_R \left[S - U_L \left(T_i - T_a \right) \right] \tag{1}$$

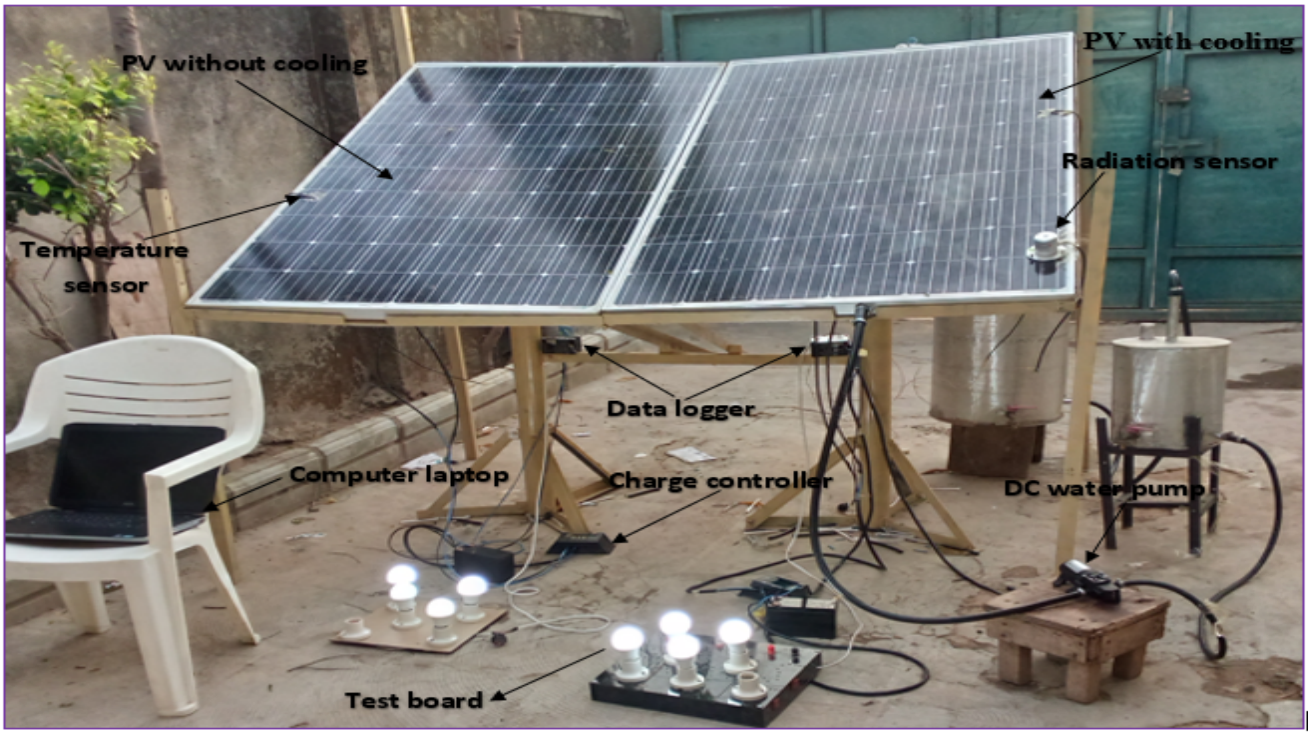


Fig. 4: Experimental setup

For the sake of simplicity, equation (7) was modified as the new Whillier Bliss equation (Hottel & Whillier, 1955; Tiwari et al., 2018) given as:

$$Q_u = \dot{m} c_p (T_o - T_i) \tag{2}$$

Where $\dot{m}$ is given as the mass flow rate, C_p is specific heat capacity of water while $T_o - T_i$ denote the difference between inlet and outlet temperatures of the collector respectively.

The thermal efficiency ($\eta_{thermal}$) signifies the performance of the PV/T system to generate heat and is given as the ratio of useful heat gain Q_u to the overall incident irradiance on the PV/T system (Aberoumand et al., 2018; Al-Waeli et al., 2018) is obtained using the relation:

$$\eta_{thermal} = \frac{Q_u}{I_s \times A_c} \tag{3}$$

Where I_s is denotes solar intensity and A_c is the collector area.

Also, the electrical efficiency (η_e) of a PV module is given as the ratio of measured output power (P_m) to the overall incident solar radiation (Namjoo et al., 2011):

$$\eta_{elect} = \frac{P_m}{I_s \times A_{pv}} = \frac{I_m \times V_m}{I_s \times A_{pv}} \tag{4}$$

Where A_{pv} is PV panel area with I_m and V_m being the maximum current and voltage of the panel respectively.

Application of Adaptive Neuro-Fuzzy Inference System (ANFIS) Modelling

The modelling process was performed for communication between the input and output variables as shown in Fig. 5. ANFIS is considered a hybrid model since it combines artificial neural network (ANN) topology and fuzzy inference system (FIS) to give a combined effect of the two components (Idris & Markom, 2019; Najafi et al., 2018). One of the most crucial characteristics of ANFIS models that makes it more attractive compared to other stochastic models is its ability of defining complicated and multivariable nonlinear problems.

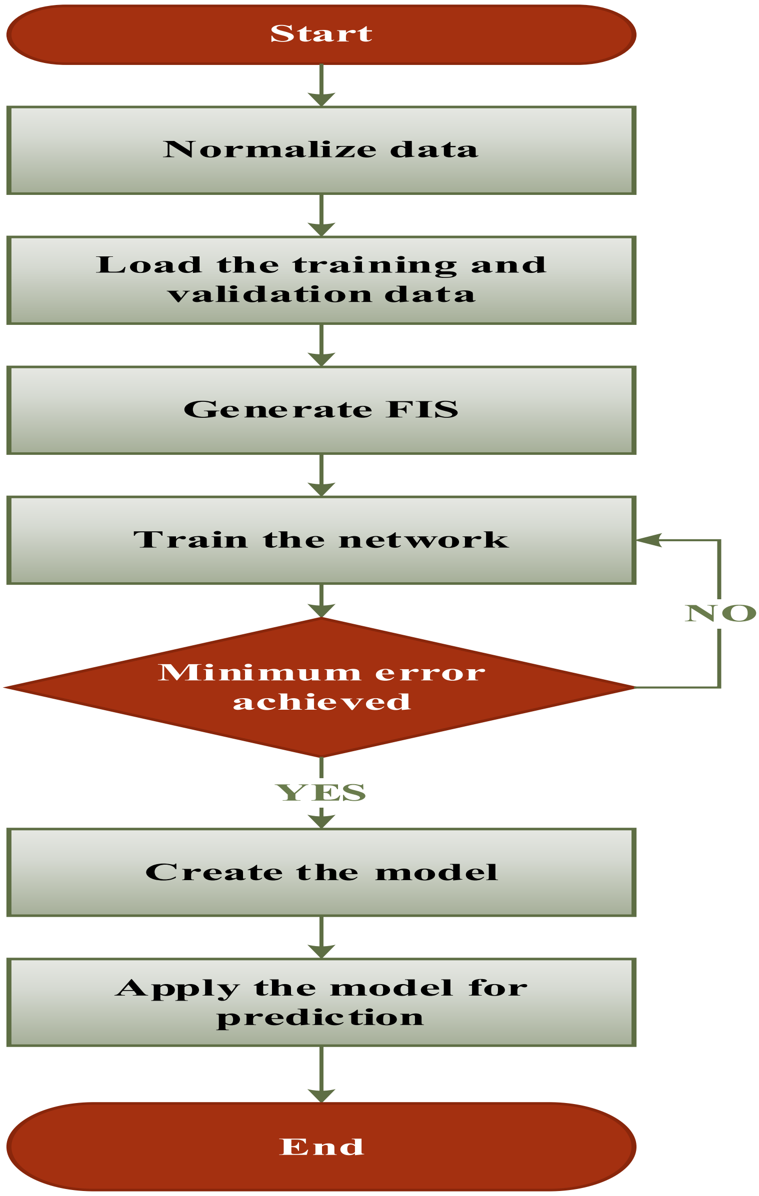


Fig. 5: Flow chart for ANFIS modelling

The PV/T systems used in this study was modelled and simulated using neuro-fuzzy designer application embedded inside MATLAB R2022B. This neuro-fuzzy designer provides a very simple platform for enabling ANFIS predictions. The computer used for the training of the model has the following specifications: 64-bit operating system and 8 GB installed RAM with an i5-2450M CPU @ 2.50GHz processor speed. The input parameters used in simulating the ANFIS model comprises solar radiation, current, and voltage while the output parameters were electrical, thermal and total efficiencies of the PV/T system respectively. The data-sets used in the experiment comprises three hundred and sixty (360) data-sets, and were separated into two categories viz. 70% training and 30% validation of the model respectively. In the scope of this study, three input variables and one out variable were used for all the models. Thus, to enhance the capacity of generalization for the model prediction, input and output variables were transformed into exponential in order to ease prediction using the formula in Eq. 5.

$$Y_2 = \log(1 + Y) \tag{5}$$

Where Y_2 represents the exponential transformed data and Y is the transformed data for any given input and output variables.

In addition, the transformed data sets were converted back into their original values after the prediction by the model. A default membership function for the model was selected and a hybrid learning algorithm was adopted in the training process. The model structure for the predicted responses of the PV/T system is illustrated in Fig. 6, which consist of two inputs, three membership functions of each input and one output.

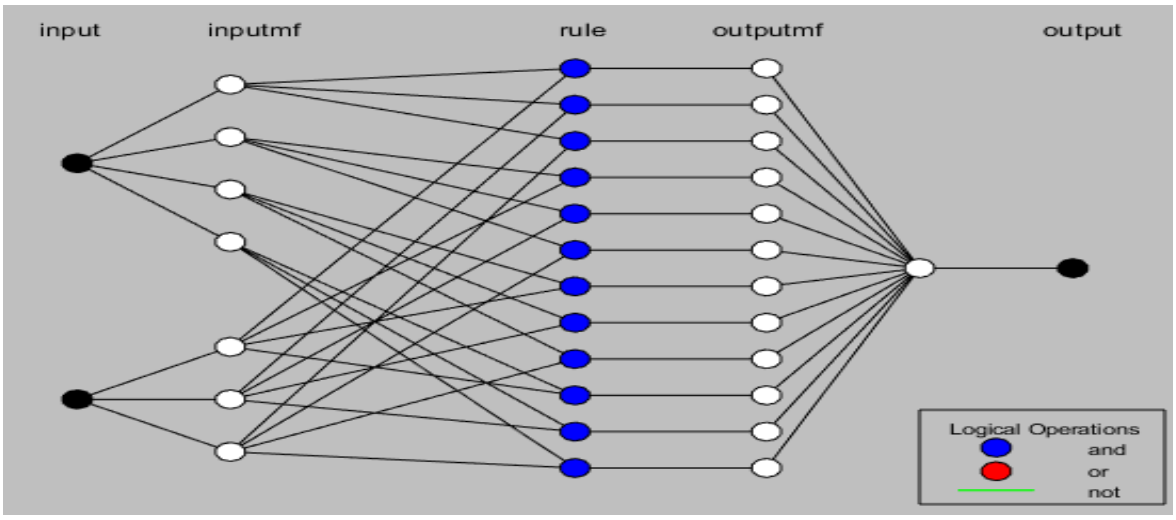


Fig. 6: Schematic representative structure of ANFIS model

Prediction Accuracy Assessment

A number of criteria's can be used to assess the performance of PV/T system power generation forecasting model. The capacities of ANFIS models for predicting electrical and thermal efficiencies of PV/T system was evaluated and compared using various performance metrics. The root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE) which measures the magnitude of the difference between the predicted and the target values, and determination correlation coefficient of scattering around the best fit line determined by least square method (R^2) were used to verify the accuracy of the model. The correlation coefficient describes the degree of collinearity between simulated and measured data was and ranges from -1 to 1. If R = 0, it implies no linear relationship exists. If R = 1 or -1, a perfect positive or negative linear relationship exists between these variables. The following formulas were used in computing the prediction accuracies of the models (Al-Waeli et al., 2019; Najafi et al., 2018):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - p_i\right)^2} \tag{6}$$

$$R = \sqrt{\left(1 - \left(\frac{\sum_{i=1}^{n} t_i - p_i}{\sum_{i=1}^{n} t_i{}^2}\right)\right)} \tag{7}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - p_i)^2 \tag{8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(t_i - p_i) \tag{9}$$

Where p is the predicted value, t is the target value and N is the number of data points.

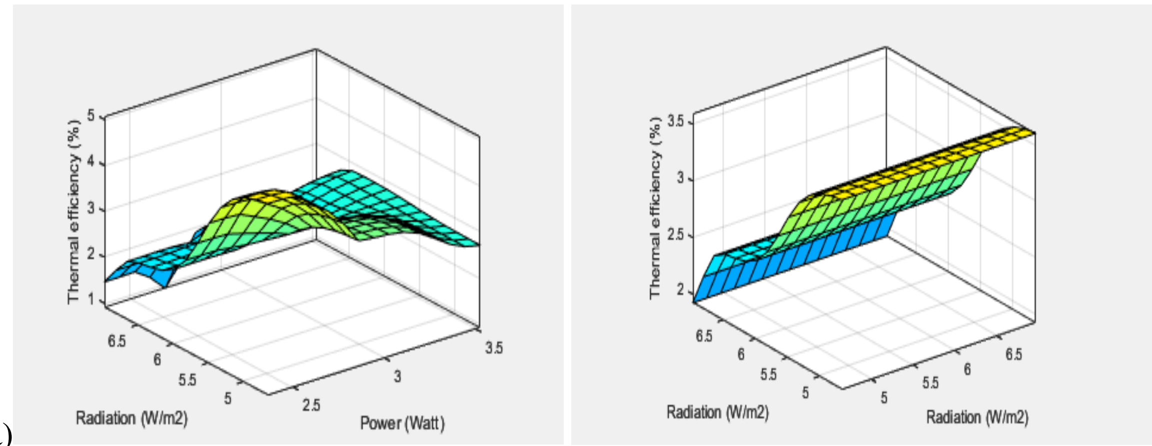
RESULTS AND DISCUSSION

ANFIS Results and Analysis

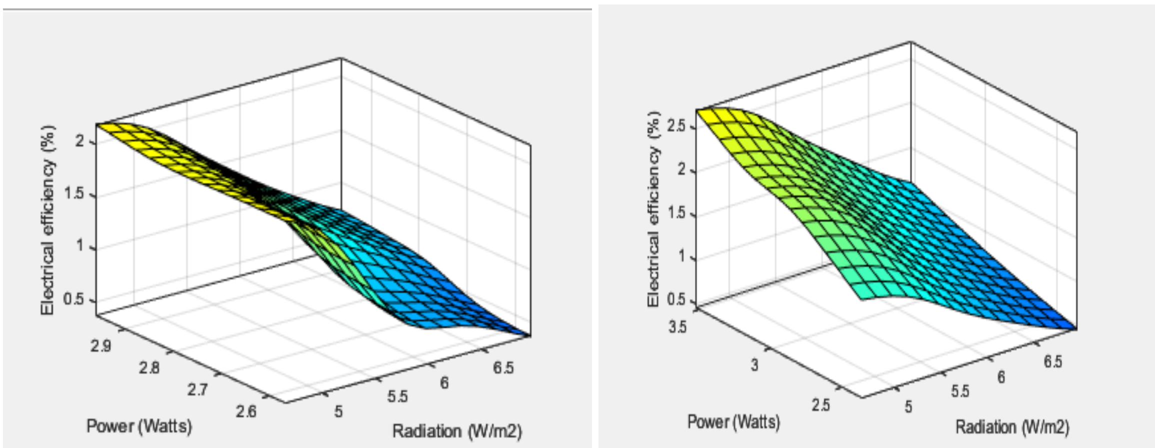
In this present work, three different ANFIS models have been developed which comprises the thermal and electrical efficiency models for the water-based PV/T system, and solely the electrical efficiency model for the conventional PV system respectively. In order to provide more elements of validation, the results obtained for each of the models were compared with one another as presented in Table 4. While the input parameters viz. power and solar radiation remained unchanged, the output parameters were varied based on the type of output needed to determine the target response for electrical, thermal and total efficiencies respectively. In essence, a comprehensive comparative study in the performance of the two systems has been investigated. The results for error performance metrics for the ANFIS model is presented in Table 4. These results depict the capacity of ANFIS models in predicting the efficiency of the PV/T system. While strong correlation values were recorded, a high error margin was observed in thermal efficiency model for RMSE and MSE respectively. Fig. 7 shows the variations in the electrical and thermal efficiency for the proposed systems. Based on the analysis carried out, the ANFIS models with the transformed exponential values gave a good prediction for the PV/T systems due to the recorded values of low RMSE compared to the model with real data.

Table 4: Performance parameter results for ANFIS model

Error performance Metrics	Thermal efficiency **(ANFIS Model 1)**	Electrical efficiency (PV/T) **(ANFIS Model 2)**	Electrical efficiency (PV) **(ANFIS Model 3)**
MSE	36.5176	0.0440	0.0021
RMSE	6.0430	0.2097	0.0089
MAE	0.2243	0.0197	0.0459
R^2	0.6876	0.9920	0.9994



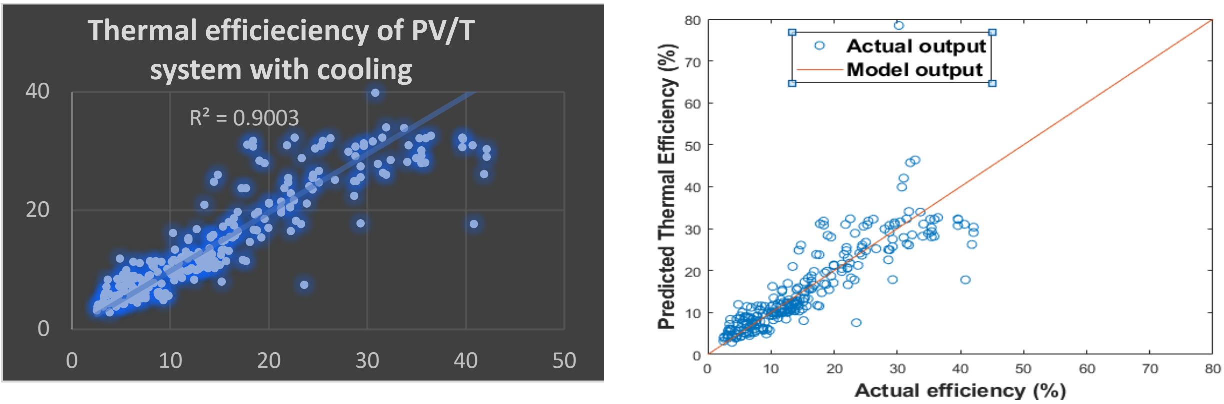
(a)



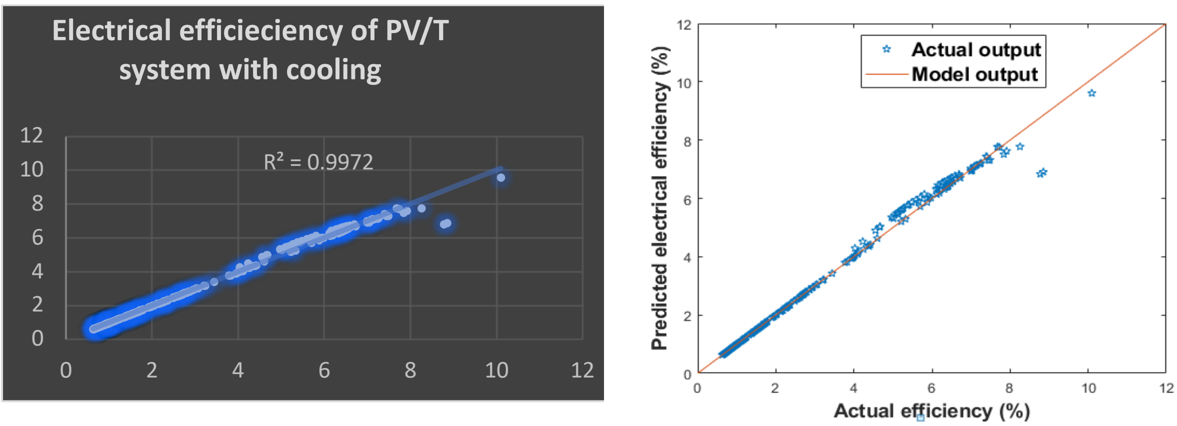
(b)

Fig. 7: 3D surface ANFIS output (a) thermal efficiency (%) as a function of radiation and power (b) electrical efficiency (%) as a function of power and radiation.

As elucidated on Fig. 7, ANFIS model output reveal that electrical efficiency of PV systems decrease as a result of increase in the surface temperature of the PV panel. Conversely, the electrical efficiency suddenly began to increase when there was reduction in surface temperature of the PV module due to the effect of cooling at the rear side of the PV/T system. ANFIS models outputs reveal that there a linear relationship exists between power and thermal efficiency. As the output power increases, the thermal efficiency increases and vice versa as depicted in Fig. 7 (a). In addition, it could be observed that there was an inverse relationship between radiation and electrical efficiency in Fig. 7 (b), electrical efficiency is enhanced with a corresponding decrease in the amount of solar radiation. This implies that, high intensity of solar radiation during the day could eventually raise surface temperature of the PV module, which will in turn reduces the electrical output efficiency. Therefore, by introducing cooling fluid to the system via the rear side of the PV to absorb the excess heat generated by the system, the electrical efficiency will henceforth be enhance efficiently better compared to the system without the cooling fluid.



(a)



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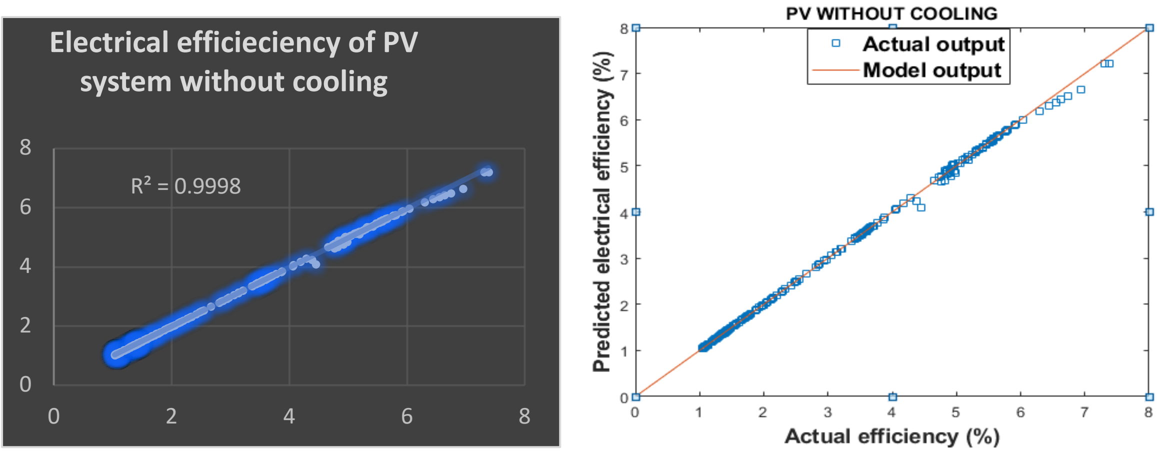

(c)

Fig. 8: Scatter charts for actual values against predicted values obtained by ANFIS model for: (a) PV/T thermal efficiency (b) PV/T electrical efficiency (c) conventional PV electrical efficiency

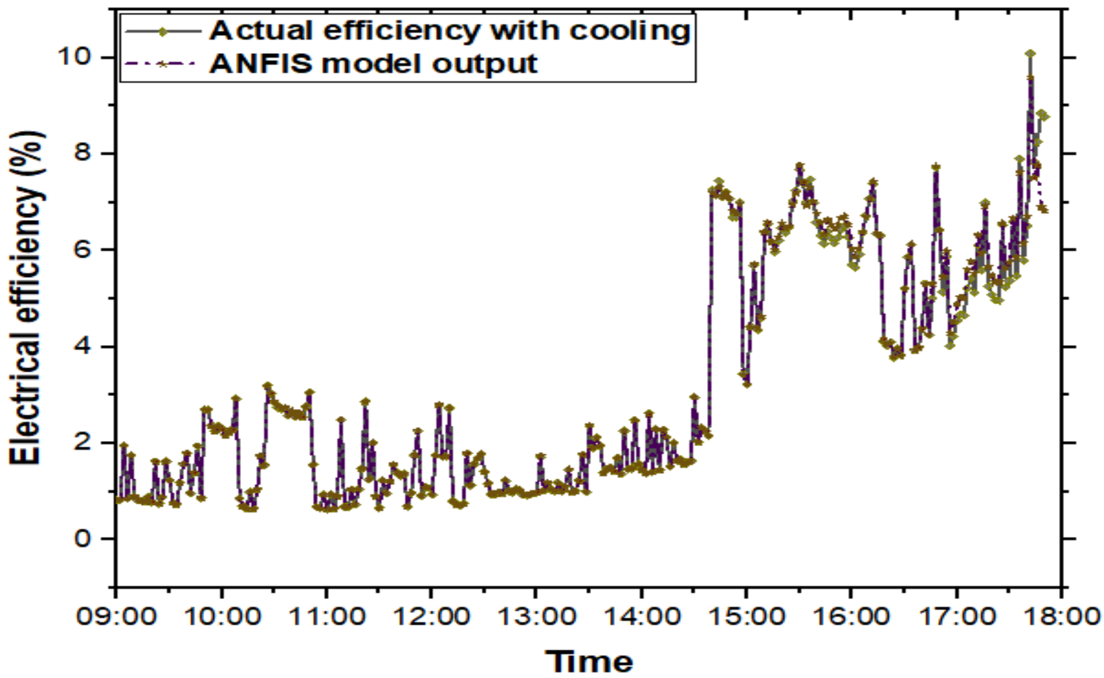

Fig. 9: Comparison of ANFIS model with Actual output (Electrical efficiency)

Additionally, Fig. 8 shows the scatter charts of output values against predicted values for the ANFIS model. Based on Fig. 8 (a) the actual and predicted values of thermal efficiency for the system with cooling have a linearity of 68.76% (0.6876), and based on Fig. 8 (b) and (c) the actual and predicted values of electrical efficiency for the systems with and without cooling, have a linearity of 99.2% (0.9920) and 99.94% (0.9994) respectively. As could be observed

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from the two plots, the actual and predicted values were fitted to the centre the line, which shows that the model was neither under fitted nor over fitted and was very good for prediction for electrical efficiency better than the latter.

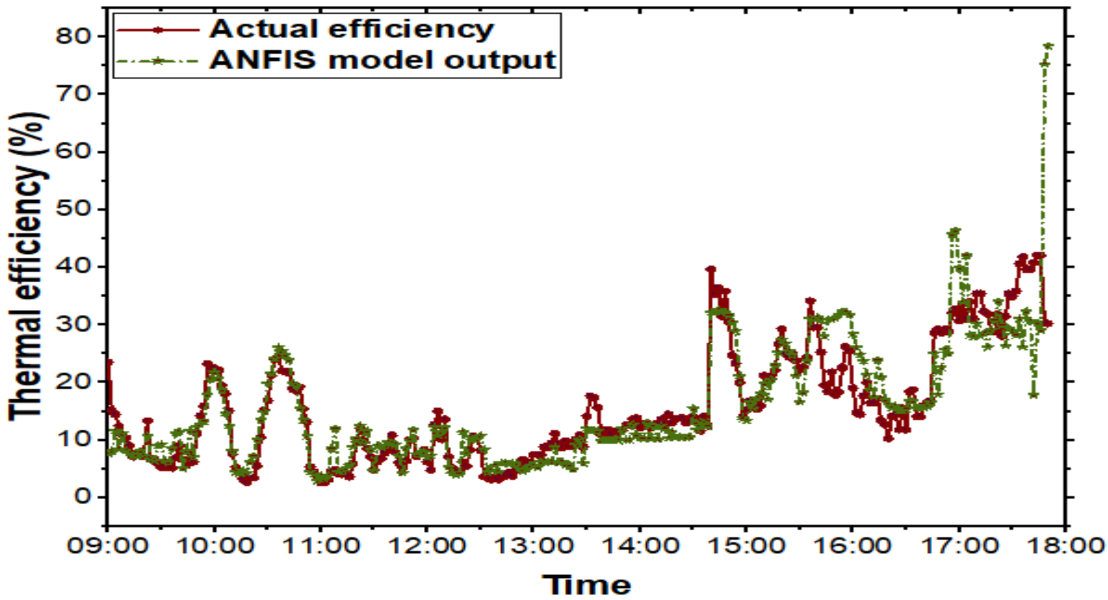

Fig. 10: Comparison of ANFIS model with Actual output (Thermal efficiency)

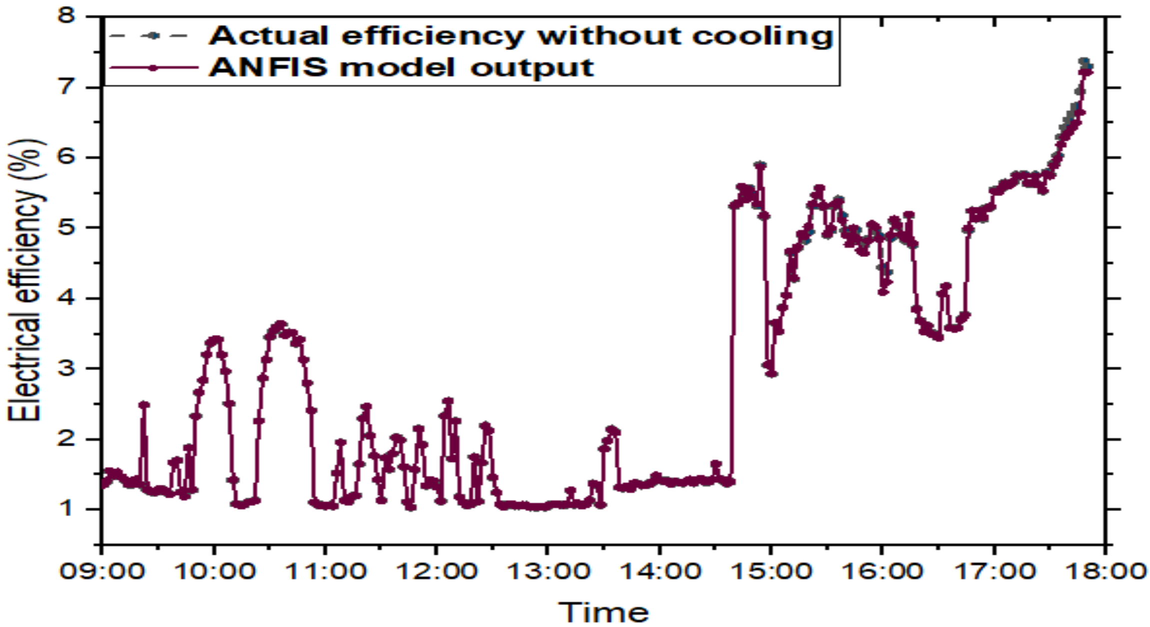

Fig. 11: Comparison of ANFIS model with Actual output (Electrical efficiency)

Considering Fig. 9, 10 and 11 as a single entity, it could be clearly observed from the curves presented, that the adopted modelling method exhibits high accuracy for difference variations of solar irradiance and the recorded amount of power input. The model outputs of ANFIS exhibited a similar behaviour with the simulated results in all the three models developed for the electrical and thermal efficiencies respectively.

CONCLUSION

The main objective of this study was to implement ANFIS models in assessing the manner prediction of electrical and thermal output of a water-based photovoltaic thermal (PV/T) system. To achieve the stated objectives, two different experimental set-ups for PV systems with and without cooling was fabricated and tested under the same working condition in order to investigate the effect of cooling on the surface of the PV module. The developed ANFIS model display a good correlation and validation of the experimental results. It was proven that the use of normalized data for training ANFIS model has excellently improved its accuracy of predicting output responses for the PV/T systems. Thus, statistical parameter comparison deduced that ANFIS model has high accuracy and reliability in terms of prediction, since it is able to capture the nonlinearities of experimental data with higher coefficient of determination (R^2) and lower RMSE. Hence, the results revealed that the developed intelligent algorithm for ANFIS model is reliable in the prediction of electrical and thermal output of a hybrid photovoltaic thermal (PV/T) system.

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CONFLICT OF INTEREST

The authors declare no conflict of interest

Authorship Contribution Statement

M.I. Ibrahim: Conceptualization, Software, Validation, Writing-original draft, Methodology, Results. **D.M. Kulla:** Conceptualization, Investigation, Supervision, Discussion, Final shaping & editing**. S. Umaru:** Conceptualization, Investigation, Validation, Supervision. **A. Dalhatu:** Conceptualization, Investigation, Review, Supervision: **M.Z. Abdullah** Conceptualization, Investigation, Supervision**. I.I. Enagi:** Conceptualization, Investigation, Software.

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