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Prediction of Photovoltaic Power Output Based on Real Data Using Adaptive Neuro Fuzzy Inference System and Artificial Neural Network

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Abstract: This study discusses the performance of PV power output as it relates to different environmental factors such as solar irradiance and PV cells. An accurate forecast of solar power output is essential for effective energy management systems. A research study records data on parameters such as PV voltage output, PV current output, PV cell temperature, and solar irradiation. This information is then utilized to forecast PV power output. The prediction methods used include computational methods and AI techniques, particularly the Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN). The research finds significant differences in Mean Squared Error (MSE) values. The computational method produces the highest MSE value of 8.43×10^3, whereas ANFIS and ANN achieve significantly lower MSE values of 2.61×10^{-9} and 3.63×10^{-5}, respectively. Based on this analysis, it is concluded that the ANFIS configuration provides a more accurate forecast compared to the actual data.

Keywords: PV Power Output, ANFIS, ANN, MSE

1. Introduction

Many countries and regions are actively implementing measures to transform their energy systems due to the increasing severity of global environmental issues and the greenhouse effect. Energy plays a crucial role in meeting basic needs and driving the economic strength of each country and region. There is widespread backing for the advancement of renewable energy that is secure, dependable, and efficient. Solar energy has witnessed remarkable growth in recent years as the leading form of clean and renewable energy, utilizing photovoltaic (PV) technologies [1]. Through the utilization of the photovoltaic effect, photovoltaic power generation is a technology that directly transforms light energy into electricity. The fundamental element in this conversion process is the solar cell, which exists in various forms for power generation. Solar cells can be employed either independently to generate electricity or connected in series to form large-area solar cell modules [2].

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The performance of photovoltaic power generation is significantly influenced by the natural surroundings and environmental factors such as solar irradiance and PV cell temperature [3]. As a result, precise prediction of PV power plays a crucial role in energy management systems by enhancing reliability and ensuring the maintenance of required power parameters. The artificial intelligence (AI) is usually used for the PV output prediction [4]. Therefore, this study utilizes the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN), which are forms of artificial intelligence, to forecast the PV power output of an Off-Grid PV system. Other than using AI, this study also uses a computational approach to forecast the PV power output using the power output formula.

1.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS model is an artificial model that is based on the Takagi-Sugeno fuzzy inference system [5], [6]. The ANFIS model combines the advantages of neural networks and fuzzy logic. It can learn, adapt, recognize, and comprehend fuzzy information simultaneously. thus, ANFIS is well-suited to solving a wide range of complex control difficulties [7].

1.2 Artificial Neural Network (ANN)

The artificial neural network (ANN) is a method of artificial intelligence designed to imitate the operation of the human brain [8]. ANN excels in learning the mapping connection from training samples, making it useful for target prediction or classification problems. Backpropagation-based ANN is a common important method in neural network training. A neural network is generally trained in two steps: forward prediction and backward learning [9].

2. Materials and Methods

To develop a better understanding of this study, research on the working principles of the PV system, ANFIS, and ANN configuration was conducted. The computational method formulas to predict power output were also studied and applied in this study. Next, data collection parameters are the PV voltage output, PV current output, solar irradiance, and PV cell temperature. Prediction power output in the computational method was implemented by applying the solar irradiance and PV cell temperature parameters. ANFIS and ANN configuration were developed by MATLAB software using the parameters of PV voltage output, PV current output and PV power output. Results from the 3 methods will be compared and all results and findings will be discussed further.

2.1 Materials

(a) Data collection

The data was collected from a 405W PV panel that was manufactured by Hanwa QCells, while the inverter was sourced from Foshan Top One Power Technology [10]. The data is gathered through a global monitoring method, utilizing a Google form for recording and Microsoft Excel for data storage. The PV irradiance is measured using a solar power meter, while temperature readings are obtained using a thermometer. The PV voltage output and PV current output are collected directly from the PV inverter. The PV power output for real data is obtained by multiplying the PV voltage and PV current. Weather conditions are categorized into three options: sunny, cloudy, and rainy. Data is collected at certain times each day, particularly 9:00 a.m., 12:00 p.m., and 5:00 p.m.

(b) MATLAB

The parameters of ANFIS and ANN are the PV voltage output, PV current output and PV power output from the real data collected where the total of data is 87 data for 29 days. The data is stored in the MATLAB workshop and then imported into the configuration's apps. The data is classified into 4 classifications for ANFIS and 5 classifications for ANN. The classification is in Table 1.

Table 1: Data classification for ANFIS and ANN

Classification	ANFIS	ANN
Input	PV voltage output & PV current output	
Target	-	PV power output
Train	70% of the parameters collected	70% of the total data
Test & Valid	15% of the parameters collected	15% of the total data

2.2 Methods

Figure 1 shows the flowchart for this study.

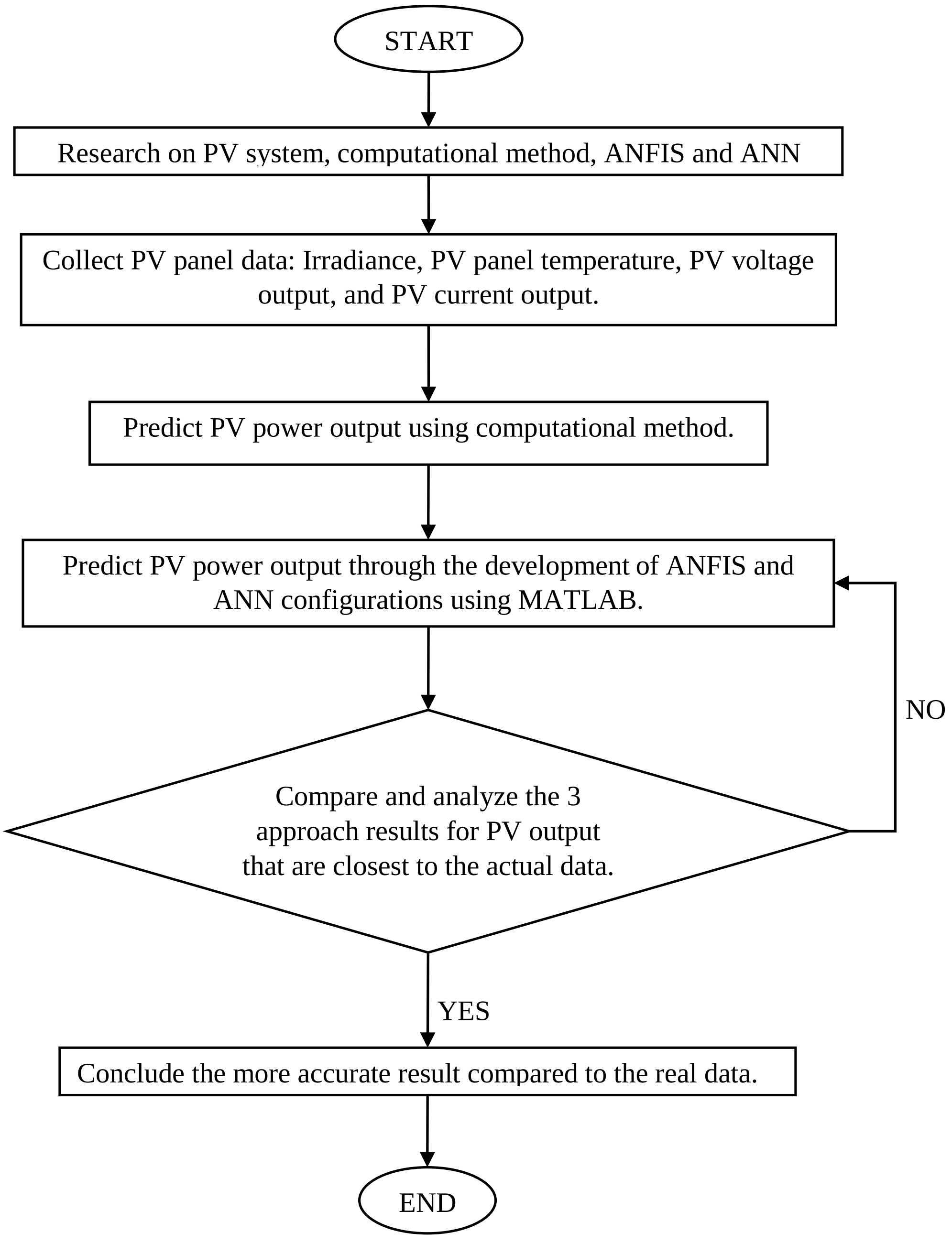

Figure 1: Project flowchart

2.3 Computational method

The computational method is constructed using the power output formula as in Eq. 1, Eq. 2, Eq. 3, and Eq. 4 [11].

$$P_{max} = P_{\max STC} \times f_{mm} \times f_{degrad} \times f_{temp\_p} \times f_g \times f_{clean} \times f_{unshade} \quad \text{Eq. 1}$$

$$f_{degrad} = f_{LID} \times f_{age} \quad \text{Eq. 2}$$

$$f_g = \frac{G_i}{1000} \quad \text{Eq. 3}$$

$$f_{temp\_p} = 1 + \left[\left(\frac{\gamma_{Pmax}}{100\%}\right) \times (T_{mod} - T_{STC})\right] \quad \text{Eq. 4}$$

Where:

P_{max}	=	maximum PV module power at ROC (W)
P_{maxSTC}	=	maximum power of PV module at STC (W)
f_{mm}	=	factor due to mismatch (dimensionless)
f_{degrad}	=	factor due to LID and aging (decimal)
$f_{(temp\_p)}$	=	factor due to temperature for power (dimensionless)
f_g	=	factor due to irradiance (dimensionless)
f_{clean}	=	factor due to dirt (dimensionless)
$f_{unshade}$	=	factor due to shading (dimensionless)
f_{LID}	=	factor due to light induced degradation (dimensionless)
f_{age}	=	factor due to aging (dimensionless)
G_i	=	in-plane solar irradiance (Wm^{-2})
γ_{Pmax}	=	temperature coefficient for maximum power
T_{mod}	=	module temperature
T_{STC}	=	temperature at STC (25°C)

The T_{mod} and $G_i$is from the data collection where the values are varied by time and day. There are a few parameters that need to be assumed and the value assumption is based on [11]. The value of f_{mm} and is assumed as 1 where the mismatch losses are assumed to take the worst-case scenario that might happen to the PV system even though the system might not always have a high value of mismatch losses. The value of $f_{unshade}$ is also set to 1 as the site of the PV panel is assumed to have no shading and there are no accurate tools to measure the shading effects on the PV panel. As for the value of f_{clean}, the value set is around 80% to 90%. Although efforts were made to clean the panel with a mop before data collection, the cleaning process was not always thorough as the mop was not washed regularly. As a result, the assumption regarding cleanliness was not taken as 100% clean and was not always accurate as there was no further calculation or tools considered for dirt losses. The value for f_{degrad} is assumed as 98% and γ_{Pmax} value is assumed as -0.34. The value for f_{degrad} and γ_{Pmax} is obtained from the PV data sheet [10].

2.4 Mean Square Error (MSE)

The MSE value is a metric used to assess the performance of a regression model or estimator by quantifying the average magnitude of errors between predicted and actual values. A lower MSE that is closer to 0 indicates superior model performance, as it signifies a smaller average squared difference between predictions and actual values. By using this calculation, it can show which method is more accurate in predicting the PV power output. The MSE formula is as shown in Eq. 5 [12].

$$MSE = \frac{\sum |X-Y|^2}{n} \qquad \text{Eq. 5}$$

Where the:

X = actual data

Y = predicted data

n = number of observations

The actual data is the total of actual PV power output collected every day from the PV inverter. The predicted data is the result of total PV power output using the computational method, ANFIS configuration, and ANN configuration. The number of observations is the total number of data collected which is 87 data collected for 29 days. The MSE has 3 different results which are for computational method, ANFIS and ANN configuration. The results are further discussed in the discussion section.

3. Results and Discussion

This part represents the result and analysis of this study. The analysis includes the data collection analysis, PV power output comparison between the computational method, ANFIS and ANN configuration to the real data, the percentage error for each method applied and the MSE for each method.

3.1 Results of data collection

Figure 2 provided shows the data collection of PV power output from the PV inverter over a span of 29 days. Each day consists of three data collection points: 9.00 am, 12.00 pm, and 5.00 pm. The 9.00 am data point marks the beginning of a new day for data collection.

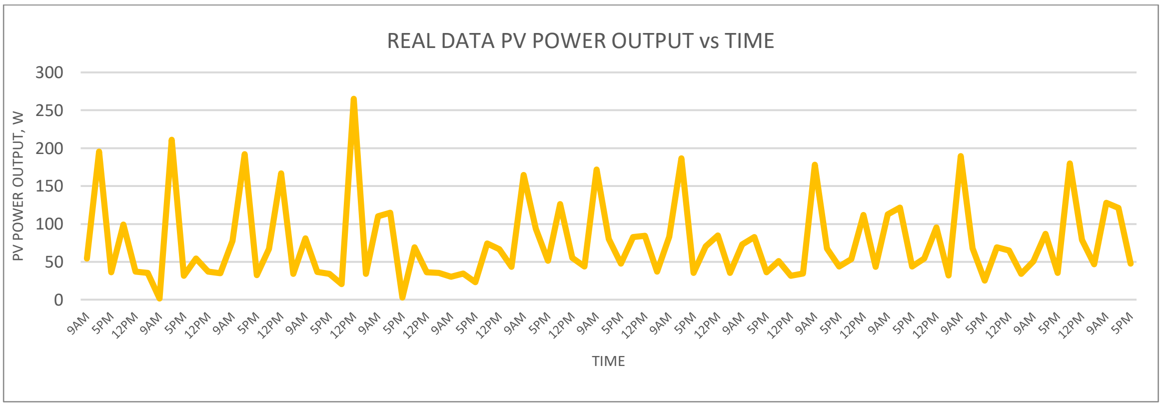

Figure 2: PV power output vs time graph

The graph is analyzed, and Table 2 shows the highest and lowest value of PV power output.

Table 2: Highest and lowest value of PV power output

Time	Date	PV power output, W	PV voltage output, V	PV current output, A	Irradiance, Wm-2	PV cell temperature, °C
Highest PV power output						
9.00 am	8/6/2023	189.72	37.2	5.1	509.2	42.6
12.00 pm	9/1/2023	265.24	34.9	7.6	742.1	43
5.00 pm	22/5/2023	51.48	39.6	1.3	580.6	47.8
Lowest PV power output						

9.00 am	3/1/2023	1.6	1	1.6	405.4	32.3
12.00 pm	31/5/2023	31.68	39.6	0.8	412.9	41.1
5.00 pm	10/1/2023	2.8	28	0.1	16	26.4

From the data analysis, the PV voltage output and PV current output are influenced by the irradiance and temperature of the PV cells. Higher solar irradiance leads to increased current and voltage outputs as the system requires more power to convert solar energy into electricity. In the case of the low power output, there are several factors that can affect the value of power output despite having high irradiance and PV cell temperature. The factors include system efficiency, inverter issues, mismatch losses, and electrical losses. At 5:00 pm on 10/1/2023, the power output was observed to be low because of unfavorable weather conditions. The weather conditions recorded at that time were cloudy, with a high possibility of rain.

3.2 PV power output comparison between computational method, ANFIS and ANN

Based on Figure 3, more than half of the computational method result diverges from the real data compared to ANFIS and ANN. There are 45 results that are too high from the real data and 17 results that are too low compared to the real data. There are several reasons as to why this can happen. One of the reasons is the computational method cannot adapt to the PV changing conditions on the PV environment and the PV system because the PV system has complex and nonlinear characteristics. In the power output formula, the losses of mismatch, dirt and shading are fixed and didn't vary over time.

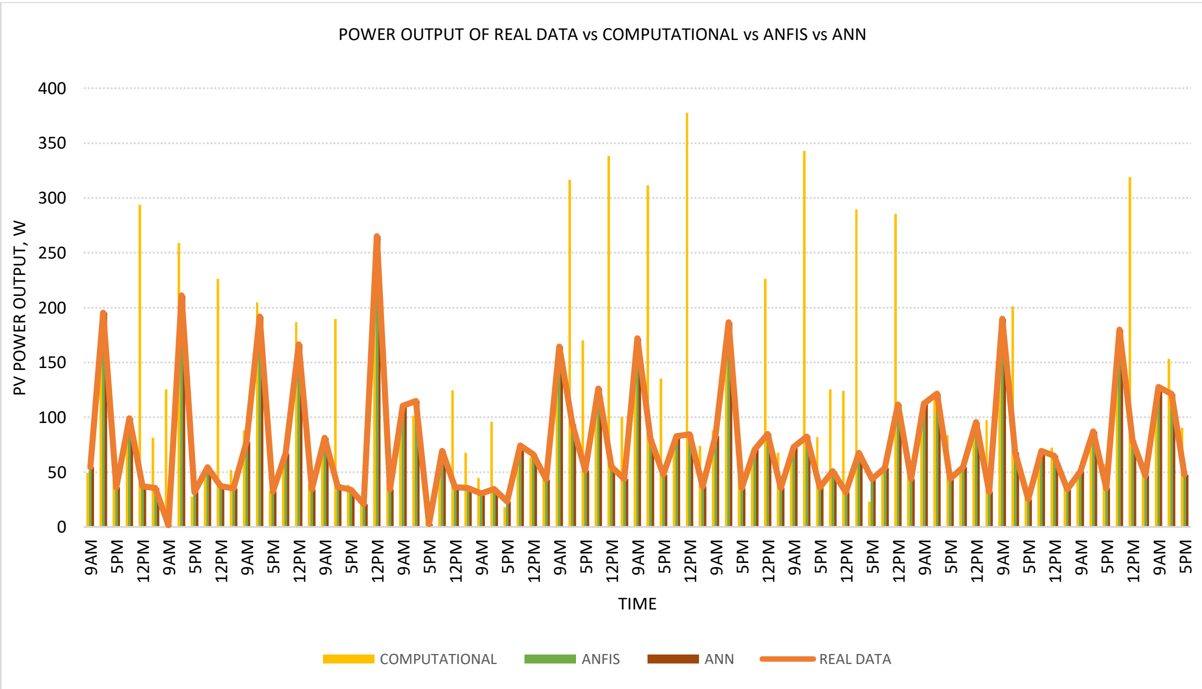

Figure 3: Power Output of real data vs. computational method vs. ANFIS vs. ANN graph

Figure 3 also illustrates that both ANFIS and ANN produce results that closely match the actual data. This can be attributed to their ability to identify intricate relationships between input variables and power output, accommodate nonlinear interactions, and consistently improve the accuracy of their predictions. These models utilize historical data to learn, adjust internal parameters, and handle uncertainties and missing data. Advanced techniques like backpropagation and neural networks can be employed to optimize these models and minimize prediction errors.

3.3 MSE value comparison between computational method, ANFIS and ANN

Referring to Figure 4, the computational method exhibits a significantly higher MSE value, whereas ANFIS and ANN demonstrate a low MSE value. Both ANFIS and ANN have their own strengths and applications. ANFIS's incorporation of fuzzy logic, rule-based inference, and hybrid learning algorithms. ANN is made up of related layers of artificial neurons that receive data, analyze it, and develop predictions. ANN is excellent in learning detailed relationships and patterns in training data and can successfully capture data nonlinearities. ANN may improve its performance through iterative training by adjusting its internal parameters using optimization methods such as backpropagation. In comparison, ANFIS typically yields more accurate predictions of PV power output compared to both the computational method and ANN, as indicated by its lower MSE value.

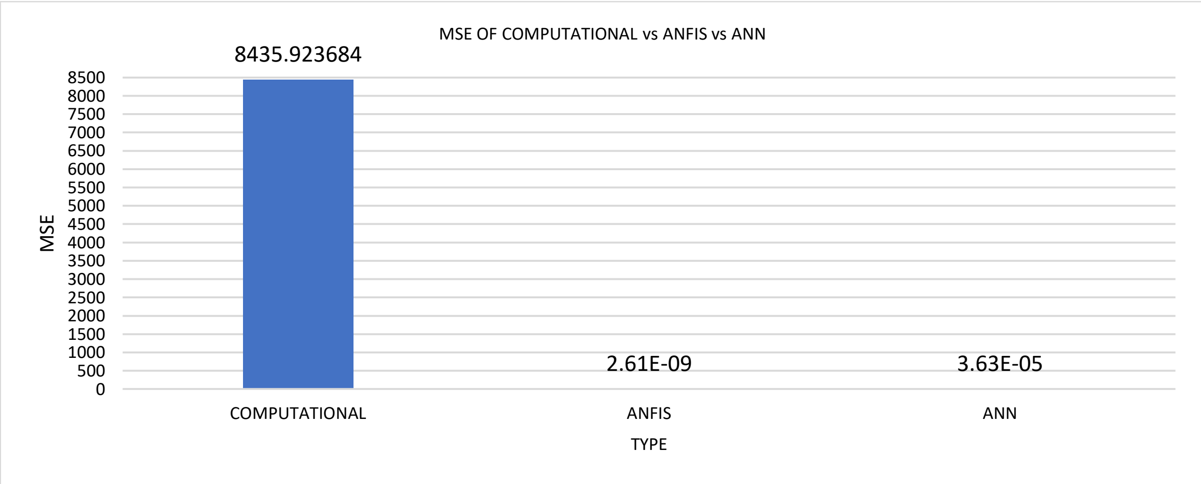

Figure 4: MSE of Computational method vs ANFIS vs ANN graph

4. Conclusion

In conclusion, the objectives of this study were to collect real power output data from an Off-Grid PV system at UTHM, predict the PV system power output using a computational method, develop ANFIS and ANN configurations for forecasting the PV power output, and analyze the performance of PV power output between ANFIS, ANN, and the computational method. Through the data collection process, real power output data from the Off-Grid PV system was obtained, providing a basis for further analysis. The computational method was utilized to predict the PV power output, while ANFIS and ANN configurations were developed to enhance the forecasting accuracy.

The performance analysis revealed that ANFIS demonstrated superior predictive capabilities compared to ANN and the computational method. The integration of fuzzy logic, rule-based inference, and hybrid learning algorithms in ANFIS contributed to its ability to capture complex relationships and nonlinearities within the PV system, resulting in more accurate predictions. Overall, this study highlights the effectiveness of ANFIS in forecasting PV power output, surpassing the computational method and ANN. These findings emphasize the importance of considering advanced modelling techniques when aiming for accurate power output predictions in PV systems.

In future research, it is recommended to enhance the data collection method to ensure ease of data collection and the ability to collect data at any given time. Further research can focus on refining the ANFIS and ANN configurations, exploring additional input variables, and investigating methods to optimize the computational method. Additionally, including more diversified data and analyzing model performance under various environment conditions will further improve overall understanding of PV output forecasts.

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