Comparison of MPP methods for photovoltaic system

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ABSTRACT

Solar electricity is usually a ubiquitous photovoltaic (PV) power source that converts sunlight into electricity. This makes solar energy a key factor in meeting the growing global demand. However, solar energy production from photovoltaic cells can be limited by many factors, so the power source needs to be optimized to reach the maximum level. One of the crucial technologies to enhance the power production of photovoltaic structures is maximum power point tracking (MPPT) measurement. This technology increases energy production by providing many advantages such as security, freedom, maximum energy efficiency, and environmental protection. MPPT continuously monitors the maximum power point of the photovoltaic structure to ensure the system operates at peak efficiency. This technology is indispensable in today's solar systems, enabling the use of solar energy and reducing dependence on fossil fuels. By optimizing solar energy production, MPPT technology plays a crucial role in supporting the future of energy. It helps reduce climate change and promotes environmentally friendly practices through the use of renewable energy. MPPT technology also increases solar reliability, reduces maintenance costs, and improves overall performance. This makes MPPT an essential part of the modern solar system, ensuring they are efficient and effective.

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1. INTRODUCTION

Green renewable energy is the best and growing business to generate electricity without harming the environment. Additionally, as the demand for strength increases, the solar electricity industry is also increasing. The biggest disadvantage is that solar panels are inefficient compared to other energy sources. Most studies show that solar panels are about 30% efficient in converting sunlight into energy. On the other hand, using controllers and additional equipment to make them efficient can be expensive, but maximum power point (MPP) technology is designed to utilize the full capacity of the solar panels. It is shown that in most cases, MPP can compensate for changes in solar panels and current characteristics. MPP lets the battery absorb extra energy in the form of voltage as well as current. The following text compares the performance of different MPP systems using the same circuit.

The photocurrent relies upon the nature of the sun's radiation and the temperature of the battery. Here, ISC refers to the short-circuited current of the cell at 25 °C, and 1 kW/m^2 is the short-circuit modern temperature coefficient of the cell [1]. A boost converter (DC-DC) is employed to manipulate the load and change the duty cycle to attain the maximum energy from the photovoltaic module [2]. MPP is essentially a real-time view of the operational content. The most common MPP system is the perturbation and observation (P&O) system. The main idea behind perturbation and observation (P&O) is to adjust the output current and voltage by decreasing or increasing the pulse width modulation (PWM) duty of the power converter and then controlling the direction of the photovoltaic output voltage converter [3]. Fuzzy logic is the second most popular MPP method and has three phases: logic library, fuzzing, and policy engine [4]. In neural networks, cumulative inputs and outputs (targets) are required for training. Depending on the output, each neuron estimates the activation degree of the signal linked to it using the activation function set by the layer. In each iteration, the error is calculated by analyzing the results of the target [5]. Gray wolf optimizer (GWO) is an algorithm inspired by the grey wolf. The MPP algorithm also follows three steps similar to the wolf: tracking, searching, circling, and attacking [6].

2. MODELLING OF SOLAR PANEL

The structure of the solar device can be classified as a PN semiconductor junction, which produces direct current when lit. The electrical components connected to the photovoltaic cell can be shown as a current resistor, a shunt resistor, a series resistor, and a diode, as shown in Figure 1. The parallel and series resistors constitute the leakage flowing inside the junction and the pressure drop at the peripheral contact point, respectively [7].

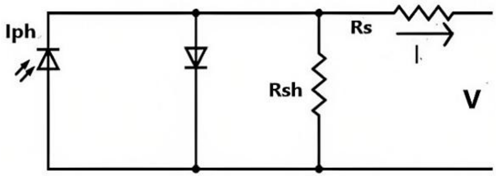

Figure 1. PV modelling

The numerical model correlating the output current to the output voltage is represented by (1) [8].

$$I = I_{ph} - I_o\left(e^{\frac{q(V+IR_S)}{mNskT}} - 1\right) - \frac{V+IR_S}{R_{sh}} \quad (1)$$

Here I_{ph} indicates the current generated by the incident light (∝ solar irradiance), V and I represent the output voltage and current of the array, q implies the charge of the electron $(1.602e^{-19}C)$, I_o expresses the diode's reverse saturation current, k refers to the Boltzmann constant $(1.381e^{-23}J/K)$, R_{sh} and R_s are the PV shunt and series resistances, and T (Kelvin) is the operating temperature of the cell [8]. The photocurrent (Iph) largely depends on the incoming solar radiation level and working temperature of the cell, which can be demonstrated as (2).

$$Iph = [Isc + K_1(Tc - Tref)]\lambda \quad (2)$$

Here Isc indicates the short-circuit current generated by the photovoltaic cell at 25 °C and 1 kW/m^2, K_1 represents the temperature coefficient for the short-circuit current of the cell, $Tref$ refers to the temperature of the photovoltaic cell (25 °C), and λ represents the solar insolation level in kW/m^2.

2.1. MPP model

The overall performance of a photovoltaic (PV) array depends on the load characteristics to which it is related. Whilst directly linked to a load, the PV array rarely operates at its MPP [9]. To optimize the load and extract maximum energy from the PV module, a DC-DC boost converter is employed to regulate the voltage cycle. This converter, in combination with an MPP controller, guarantees maximum power output from the sun panel beneath various operating conditions [10].

2.2. DC-DC converter

A boost converter is a type of DC-DC power converter that steps up the input voltage, generating a higher output voltage to meet specific power requirements. Figure 2 illustrates a boost converter circuit utilizing MOSFET switches. The boost converter operates in two distinct modes:

- Mode 1: When the MOSFET is switched on, the inductor stores energy, causing its current to increase while the diode remains off.
- Mode 2: When the MOSFET is turned off, the inductor discharges its stored energy through the diode, delivering the necessary output voltage to the load.

The power flow is regulated by controlling the MOSFET's on/off switching time [11]. The relation between input voltage and output voltage is given by (3).

$$\frac{V_o}{V_i} = \frac{1}{1-D} \tag{3}$$

Here V_i implies PV input voltage, V_o represents the voltage of the boost converter, and D indicates the duty cycle.

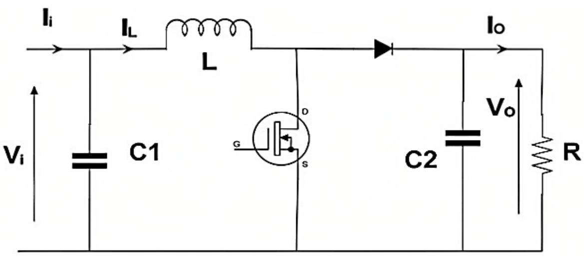

Figure 2. Boost converter circuit diagram

3. MPP CONTROLLER

MPP is essentially a flight technique used to find the operating point where the solar panel obtains the maximum power from the photovoltaic array. Five MPP concepts are discussed and simulated. There are many technologies to monitor the maximum power of photovoltaic systems, but this paper focuses on five MPP technologies: perturb and observe (P&O), fuzzy logic controller (FLC), artificial neural network (ANN), autonomy based adaptive network fuzzy inference system (ANFIS), and gray wolf optimization (GWO).

3.1. Perturb and observe (P&O)

The main premise of perturbation and observation (P&O) is to calibrate the output voltage and wattage by decreasing or increasing the PWM duty cycle of the power converter and then controlling the changes in the PV output voltage [12], [13]. At any time j, if the output power P(j) of the photovoltaic array and the output voltage V(j) of the photovoltaic array is higher than the previously calculated power P(j-1), then the direction of the effect remains the same and V(j-1) does not change, otherwise, the result is the opposite [14]. The flowchart of this algorithm includes four scenarios, which are described as follows:

- With $\Delta P < 0$ & $V(j) > V(j-1)$, results in $D(j+1) = D(j) - \Delta D$
- With $\Delta P < 0$ & $V(j) > V(j-1)$, results in $D(j+1) = D(j) + \Delta D$
- With $\Delta P > 0$ & $V(j) < V(j-1)$, results in $D(j+1) = D(j) - \Delta D$
- With $\Delta P > 0$ & $V(j) < V(j-1)$, results in $D(j+1) = D(j) + \Delta D$

Here, D is the simulated and selected value from the error [15]. Use MATLAB to simulate and implement the P&O algorithm. Depending on the sign of the slope, the duty cycle needs to be perturbed to track the pressure. The flowchart of a typical P&O MPP algorithm illustrates this process in Figure 3.

3.2. Fuzzy logic controller (FLC)

FLCs can be chosen to avoid inconsistencies, control material errors, and do not require accurate mathematical models [16]. The fuzzy controller design consists of the following three stages:

- Fuzzification: Using fuzzy membership functions, the system's real input parameters E and CE are transformed into fuzzy linguistic variables [17].
- Rule engine and inference base: All parameter instructions are stored in a fuzzy rule base, which is a set of if-then logic rules. It is based on professional decision-making and management activities. The operating technology, called the fuzzy inference engine, converts the basic fuzzy rules into fuzzy expressions and infers conclusions based on fuzzy configuration rules [18].
- De-fuzzification: The inference engine evaluates the rules according to the control step level for a given set of fuzzy inputs that are being defuzzified. By combining the outputs produced by each rule, this method converts the basic fuzzy control process into real numbers for the outputs. The center of area (COA) method is used to defuzzify the output loop control parameters [19].

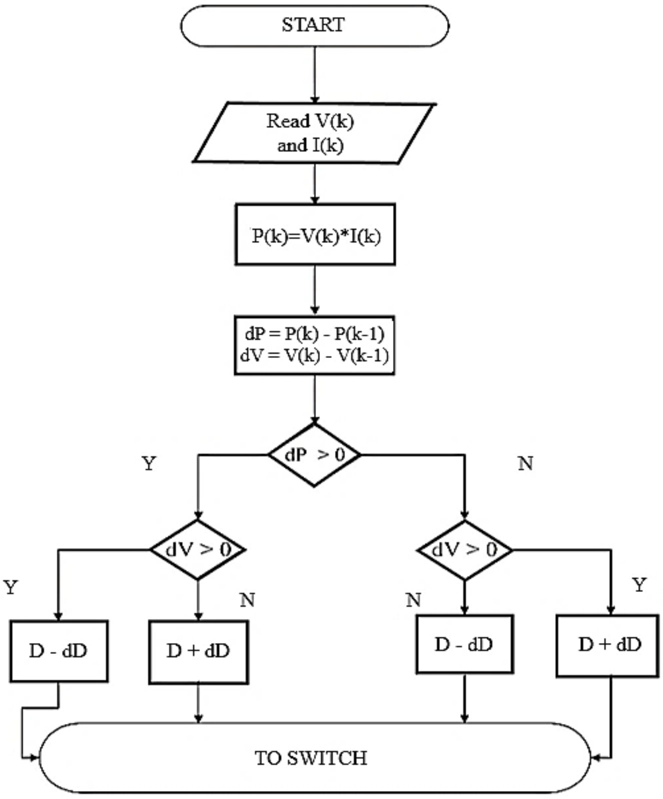

Figure 3. Flowchart of P&O algorithm

3.3. Artificial neural network (ANN)

Artificial neural networks replicate the brain's neural architecture, consisting of interconnected neurons that process complex information. These neurons communicate through weighted connections, transmitting signals to adjacent neurons [20], [21]. Training should have strategies and results (targets). Depending on the output, each neuron estimates the activation level of the signal connected to it using the activation function specified for that layer. The error of each iteration is calculated by analyzing the results of the target [22]. By repeating this process, the difference will be reduced until the desired level is reached [23]. In this study, a multilayer perceptron (MLP) neural network is used. In this study, there are three layers: input layer, output layer, and hidden layer. The neural network is trained using a squared error criterion, with the hidden layer utilizing a tangent sigmoid transfer function and the output layer using a linear transfer function [24]. This study's MPP controller comprises two stages: first, training an artificial neural network (ANN) in MATLAB to determine optimal voltage and current parameters, and second, utilizing a variable controller to refine the MPP through iterative loop corrections [25].

3.4. Adaptive neuro-fuzzy inference system (ANFIS)

The combination of FLC and ANN enables the development of a method called an adaptive neuro-fuzzy inference system (ANFIS). The proposed AFIS-based MPP controller consists of the AFIS reference model, the FL power controller, and the DC-DC boost converter. The MPP controller works by determining the maximum capacity of the PV installation in terms of temperature and solar irradiance and converting it into the correct solar module maximum power (MPP) period [26], [27]. This model uses ANFIS to estimate the maximum power of optoelectronic devices at specific application temperatures and irradiance conditions. Measure the actual photovoltaic module's power output under identical irradiance and temperature conditions and compare it to the value utilized in the ANFIS model. The discrepancy between the two power values is computed, yielding an error signal that is then input into the FL power controller to produce a control signal. This control signal is subsequently transmitted to the PWM generator during pulse width modulation [28]. The PWM generator produces a frequency signal that adjusts the duty cycle of the DC-DC power converter, enabling the photovoltaic module to operate at its maximum power point (MPP).

3.5. Gray wolf optimizer (GWO)

The GWO algorithm draws inspiration from the collective behavior of grey wolves, providing a novel approach to optimize functions that are challenging to express or solve analytically [29]. Throughout the optimization process, the wolf's position in the search space is iteratively updated, along with the global best solutions, to converge towards the optimal result [30], [31]. The attacking behavior can be exhibited by (5) and (6).

$$\vec{e} = |\vec{c} \cdot \vec{x}p(t) - \vec{x}p(t)| \tag{5}$$

$$\vec{x}(t+1) = \vec{x}p(t) - \vec{a} \cdot \vec{e} \tag{6}$$

Where t stands as the present iterator, meanwhile $\vec{a}$, $\vec{c}$, and $\vec{e}$ are representing coefficient vectors. The $\vec{x}p(t)$ is the position vector of the prey, while $\vec{x}$ specifying the position vector of the wolf [32]. Estimated values of vectors $\vec{a}$ and $\vec{c}$ are as (7) and (8).

$$\vec{a} = 2\vec{b} \cdot \vec{r_1} - \vec{b} \tag{7}$$

$$\vec{c} = 2\vec{r_2} \tag{8}$$

Where the component of $\vec{b}$ decreases linearly from 2 to 0. The random vectors $\vec{r_1}$, $\vec{r_2}$ are in the range of [0, 1].

4. SIMULATION AND RESULTS

The simulations were performed using five MPP techniques: perturbation and observation (P&O), fuzzy logic controller (FLC), artificial neural network (ANN), adaptive network-based fuzzy inference system (ANFIS), and gray wolf optimizer (GWO) [33]. Figure 4 shows the power output curve using perturb and observe technique. In Figure 4, X-axis measures time and Y-axis measures power. At x_1 = 0.25 cm and x_2 = 0.75 cm power obtained is y_1 = 610.7 W and y_1 = 609.3 W with slope 2.973. This figure is periodic in nature and has non-symmetric oscillation as output.

Figure 5 shows the power output curve using the fuzzy logic controller (FLC). In Figure 5, the X-axis measures time, while the Y-axis measures power. At x_1 = 0.25 cm and x_2 = 0.75 cm power obtained is y_1 = 347.0 W and y_2 = 330.3 W respectively with slope 27.948. Here, pulsating DC is seen after 0.1 sec. Figure 6 shows the power output curve using an artificial neural network (ANN). In Figure 6, the X-axis measures time, while the Y-axis measures power. At x_1 = 0.25 cm and x_2 = 0.75 cm power obtained is y_1 = 318.8 W and y_2 = 313.6 W respectively with slope 0.9275. This curve remains transient till 0.05 sec and then becomes stable.

Figure 7 shows the power output curve using adaptive network-based fuzzy interference system (ANFIS). In Figure 7, the X-axis measures time, while the Y-axis measures power. At x_1 = 0.25 cm and x_2 = 0.75 cm power obtained is y_1 = 190.7 W and y_2 = 185.9 W respectively with slope 9.677. The graph remains transient till 0.1 sec and then becomes stable in nature. Figure 8 shows the power output curve using gray wolf optimizer (GWO). In Figure 8, the X-axis measures time, while the Y-axis measures power. At x_1 = 0.25 cm and x_2 = 0.75 cm power obtained is y_1 = 105.2 W and y_2 = 109.2 W respectively with slope 7.985. Pulsating DC after 0.1 sec following a drop at 0.05 sec is observed.

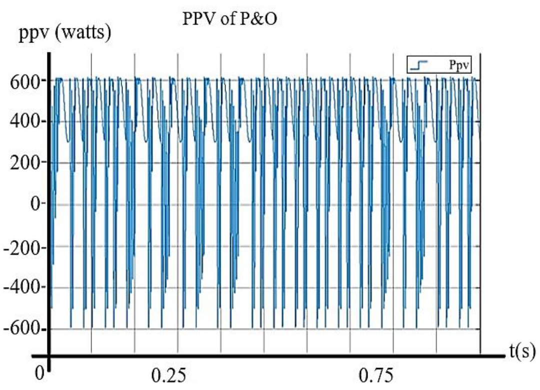

Figure 4. Output power curve of P&O

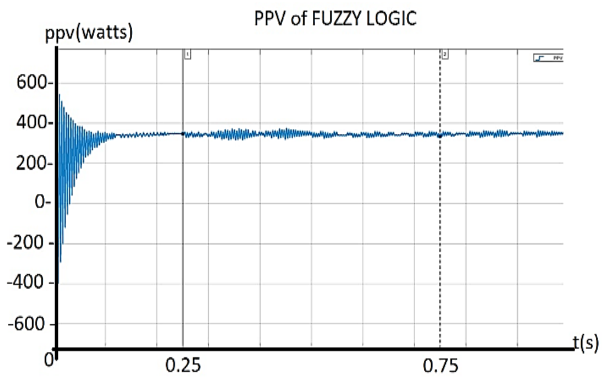

Figure 5. Output power curve of fuzzy logic

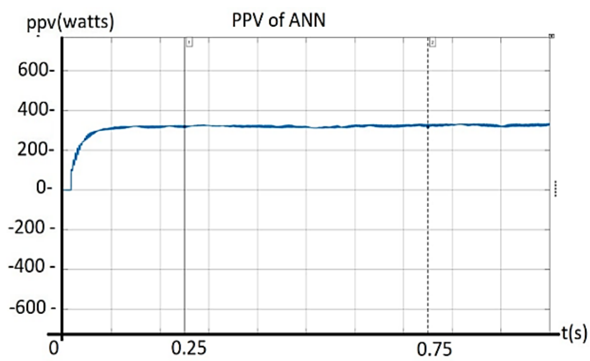

Figure 6. Output power curve of ANN

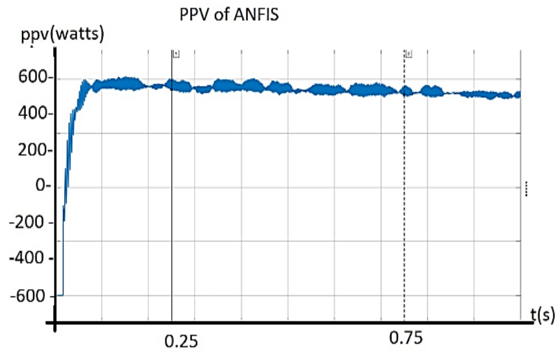

Figure 7. Output power curve of ANFIS

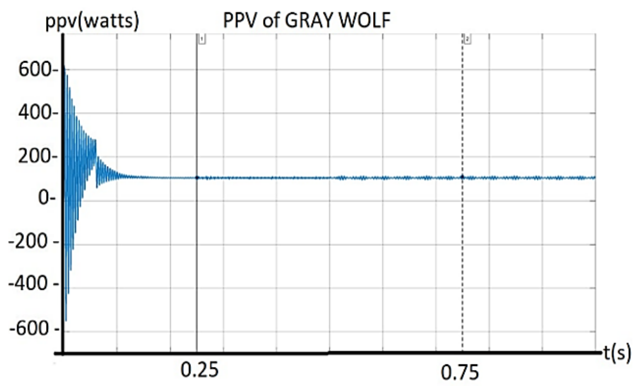

Figure 8. Output power curve of GWO

Table 1 shows the efficiency and slope of the five MPP methods presented in this paper. The highest efficiency is achieved in the case of the P&O method, wherein efficiency is calculated by (9).

$$Efficiency = \frac{Output\ Power}{Input\ Power} \times 100 \quad (9)$$

Efficiency comparison of different MPP techniques is depicted in Figure 9. This figure is simulated at a fixed temperature of 25 °C and irradiance of 1000 kW/m^2. The simple circuit and small load at the output terminal of the MPP model result in exceptional performance of the P&O algorithm, considering an input power of 610.425 W, making it more efficient than the rest four techniques.

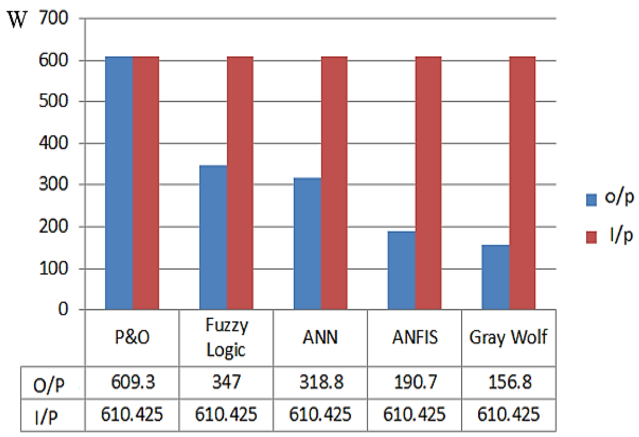

Figure 9. Efficiency comparison of different MPP techniques

Table 1. Efficiency and slope of different MPP methods

S. No	MPP methods	Input power (W)	Output power (W)	Efficiency (%)	Slope
1	P&O	610.452	609.3	99.8	2.973
2	Fuzzy logic	610.452	347	56.8	27.948
3	ANN	610.452	318.8	52.2	0.9725
4	ANFIS	610.452	190.7	31.2	9.677
5	GWO	610.452	156.8	25.6	7.985

5. CONCLUSION

This paper utilizes maximum power point tracking (MPPT) technology to enhance power generation efficiency. The main advantage of these technologies is that they work in any climate. It gets maximum power from available PV units and is independent of environmental conditions. This paper explains the various features and how to use different techniques to achieve maximum power point and integration while maintaining performance. It can be deduced from the results of the simulation that the P&O method has better performance than FLC, ANN, ANFIS, and GWO in decreasing order of efficiency respectively, and it has more accuracy for functioning at maximum power point. Amongst the five algorithms for piloting the maximum power point of a PV generator, the least slope was observed in the case of the ANN method which indicates that the ANN method has the highest stability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Surender Reddy Salkuti	✓			✓	✓	✓	✓			✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author, [SRS], on reasonable requests.

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