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Research Paper

AN ENHANCED HYBRID P&O–ANFIS-BASED MPPT CONTROL STRATEGY FOR PV SYSTEMS UNDER DYNAMIC AND PARTIAL SHADING CONDITIONS

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ABSTRACT:- Photovoltaic (PV) systems are widely used renewable energy sources; however, their efficiency is significantly affected by environmental factors such as temperature variations and partial shading conditions (PSC). Under PSC, conventional Maximum Power Point Tracking (MPPT) techniques such as Perturb and Observe (P&O) often fail to locate the global maximum power point (GMPP) and may get trapped at local maxima, resulting in reduced energy extraction. To overcome these challenges, this paper proposes a Hybrid P&O–Adaptive Neuro-Fuzzy Inference System (ANFIS)-based MPPT algorithm for PV systems operating under nonuniform irradiance conditions.

In the proposed approach, the P&O algorithm provides a fast initial search of the operating region, while the ANFIS controller refines and adapts the tracking process using intelligent learning capabilities to achieve high accuracy and robustness. The hybrid method effectively combines the simplicity of P&O with the adaptive intelligence of ANFIS to enhance tracking speed, minimize steady-state oscillations, and prevent convergence to local peaks. MATLAB/Simulink simulations are performed on a PV array under dynamic shading scenarios, and the results demonstrate that the proposed hybrid MPPT achieves faster convergence, higher tracking efficiency, and better dynamic response compared to conventional P&O and standalone ANFIS techniques.

The developed algorithm ensures optimal power extraction, improved system stability, and enhanced overall energy utilization, making it a suitable and efficient solution for real-time PV applications under partial shading conditions.

Index terms : Solar panels, Maximum power point tracking , P & O algorithm, ANFIS mppt.

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1. INTRODUCTION

The increasing demand for renewable energy sources has driven significant advancements in photovoltaic (PV) technology due to its clean, sustainable, and environmentally friendly characteristics. Despite these advantages, the performance of PV systems is heavily influenced by environmental factors such as solar irradiance, temperature, and shading conditions. Among these, partial shading conditions (PSC) pose a major challenge as they cause multiple peaks in the PV power–voltage (P–V) characteristics, leading to reduced power output and decreased overall efficiency of the system.

To extract the maximum available power from PV arrays, Maximum Power Point Tracking (MPPT) techniques are employed. Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), are simple and easy to implement but often fail to accurately track the Global Maximum Power Point (GMPP) under partial shading. These

methods tend to oscillate around the local maximum or converge slowly when irradiance changes rapidly, resulting in significant power losses and reduced system reliability.

In recent years, intelligent control techniques, such as Artificial Neural Networks (ANNs), Fuzzy Logic Controllers (FLCs), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have been introduced to enhance MPPT performance. Among them, ANFIS combines the learning capability of neural networks with the reasoning mechanism of fuzzy logic, allowing adaptive decision-making under nonlinear and uncertain conditions. However, standalone ANFIS models require extensive training data and computational effort, which may limit their real-time applicability in PV systems.

To address these limitations, this paper proposes a Hybrid P&O–ANFIS-based MPPT algorithm that integrates the fast convergence characteristics of the P&O method with the adaptive learning capability of ANFIS. In this hybrid framework, the P&O algorithm provides an initial tracking reference, while the ANFIS controller dynamically fine-tunes the operating point to achieve accurate tracking of the global maximum power point. The proposed hybrid approach not only enhances tracking speed but also minimizes steady-state oscillations and avoids local maxima under partial shading conditions.

Comprehensive simulations are performed in MATLAB/Simulink to evaluate the performance of the proposed algorithm. The results demonstrate that the hybrid P&O–ANFIS MPPT method outperforms conventional techniques in terms of tracking efficiency, dynamic response, and stability, making it a robust and efficient solution for modern PV systems operating under variable environmental conditions.

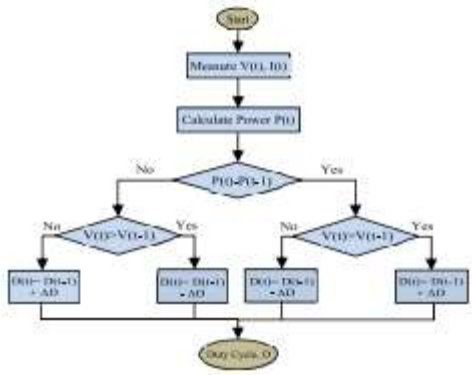


FIGURE 1. Flow chart of P&O algorithm

2. LITERATURE SURVEY

The performance of photovoltaic (PV) systems largely depends on the efficiency of their Maximum Power Point Tracking (MPPT) algorithms. Over the years, various MPPT methods have been developed to enhance power extraction from PV arrays under varying environmental conditions.

Conventional techniques, such as Perturb and Observe (P&O) and Incremental Conductance (INC), are widely used due to their simplicity and ease of implementation. The P&O method perturbs the operating voltage and observes the resulting change in power to locate the maximum power point (MPP). However, it suffers from steady-state oscillations and fails to track the Global Maximum Power Point (GMPP) under Partial Shading Conditions (PSC). Similarly, the INC algorithm provides better dynamic response but requires complex computations and may exhibit slow convergence during rapidly changing irradiance.

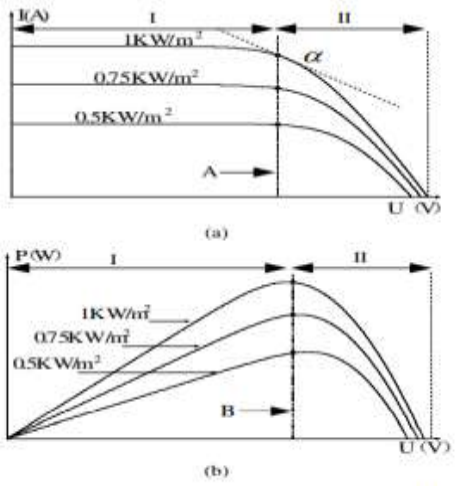


Fig. 1. Characteristic of ideal photovoltaic module

To overcome these drawbacks, soft computing-based MPPT methods have been introduced. Fuzzy Logic Controllers (FLCs) handle nonlinearity effectively and improve tracking accuracy but rely heavily on expert knowledge to define membership functions and rule bases. Artificial Neural Networks (ANNs) offer self-learning capabilities and faster response but demand extensive training data and can overfit to specific patterns. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine the learning capabilities of neural networks with the reasoning strength of fuzzy logic, resulting in adaptive and intelligent control performance. However, the computational complexity and training time limit their stand-alone use in real-time PV systems.

Recent studies have explored hybrid MPPT approaches, integrating classical and intelligent algorithms to combine their respective strengths. For example, hybrid P&O-Fuzzy and INC-ANN methods have demonstrated improved accuracy and reduced oscillations compared to standalone algorithms. Building on this, researchers have begun investigating hybrid P&O–ANFIS frameworks to achieve faster convergence, robust adaptation, and effective tracking of the global MPP under dynamic and partial shading scenarios.

The literature indicates a clear research gap in achieving fast, accurate, and stable MPPT operation under complex shading patterns while maintaining computational efficiency and real-time applicability—motivating the development of the proposed hybrid approach.

3. PROBLEM STATEMENT

Conventional MPPT techniques struggle to accurately track the global maximum power point when PV arrays experience partial shading, leading to significant power loss and reduced system performance. Although intelligent algorithms such as ANFIS offer adaptability and precision, they are computationally demanding and slow when implemented independently. Therefore, there is a need for a hybrid MPPT method that merges the simplicity and speed of traditional algorithms with the learning and adaptive capabilities of intelligent systems to achieve optimal tracking performance under partial shading conditions.

4. OBJECTIVES

The main objectives of this research are:

1. To design and develop a hybrid P&O–ANFIS-based MPPT algorithm capable of accurately locating the global maximum power point under partial shading and variable irradiance conditions.
2. To enhance the dynamic performance of PV systems by minimizing steady-state oscillations and improving convergence speed.
3. To compare the performance of the proposed hybrid method with conventional P&O and standalone ANFIS algorithms in terms of tracking efficiency, response time, and stability.
4. To implement and validate the proposed MPPT algorithm in a MATLAB/Simulink environment for realistic shading patterns and environmental variations.

5. METHODOLOGY

A PV module consists of a number of interconnected solar cells encapsulated into a

single unit. In order to predict the power extracted from the solar modules and the module current-voltage (I-V) characteristics, it is important to model the solar cell. Once the I-V characteristics of a single solar cell are determined using the model, one must then expand that model to determine the behavior of a PV array or module.

A. PVARRAY :

Model A PV array comprises many solar cells wired in series and in parallel. A solar cell model is shown in Fig. 1.

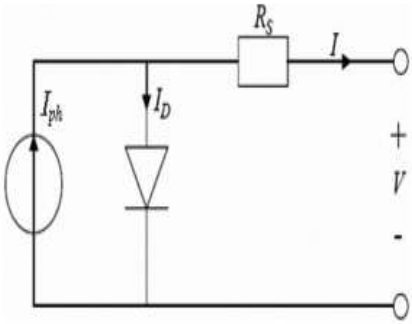


Figure 1: Simplified equivalent circuit of solar cell

In this study adaptive neural fuzzy inference system (ANFIS) was used to formulate the MPPT algorithm. ANFIS combines the learning abilities of ANN and the ability of fuzzy logic to handle imprecise and ambiguous data in non linear and time varying problems. Fuzzy Logic and control Fuzzy systems are knowledge-based or rule-based systems. The main part of the Fuzzy systems is the IF-THEN rules in the sense that all the other three components (fuzzy inference engine, fuzzifier, and defuzzifiers) are used to interpret these rules and make them usable for specific problems [12]. The first step involves formulation of the rules from human experts or domain knowledge. The next step is to combine these rules into a single system. Fuzzy logic can be applied to systems that are nonlinear and difficult to model using mathematical tools, especially those that are too vague or too complicated to be described by simple mathematical equations. A fuzzy inference system (FIS) essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The fuzzifier maps input numbers into corresponding fuzzy membership functions. This is required in order to activate rules written using linguistic variables. The defuzzifier then maps output fuzzy sets into a crisp number. Given a fuzzy set that encompasses a range of output values, the defuzzifier returns one number, thereby moving from a fuzzy set to a crisp number.

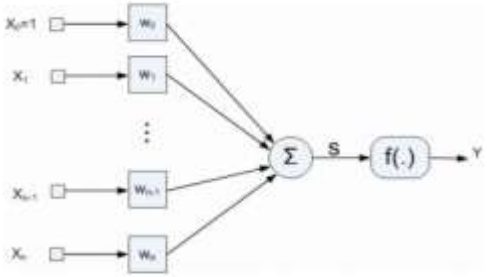


Figure 5: Structure of an Artificial Neuron

A. Artificial Neural Networks

Artificial Neural networks are based on the way neurons in a human brain operate in order to solve problems. A neuron is the information processing unit indispensable for the operation of the neural network. It accepts n number of inputs and delivers one output. Each input (Xl to xn) has a weight (WI to wn) associated with it. The net weight (uJ of each neuron is the dot product of all the inputs and their corresponding weights. The net value is then applied to an activation function (f(uJ). If output of the function (yJ exceeds the threshold value of the neuron then the neuron is turned on or 'fired'. The signal is then passed on in the direction of propagation. The structure of the neuron is illustrated by Fig. 5. Most neural networks consist of one or more layers of neurons. The input layer distributes the network inputs to the subsequent layers. It is followed by one or more hidden layers. The computation is usually done by the hidden layers and the output is passed on to the output layer.

B. ANFIS

based MPPT Controller Structure In the proposed MPPT, ANFIS was used to formulate a control algorithm for optimizing the power that can be delivered to a load in a PV system. Modeling of the ANFIS based MPPT system involved data modeling, building the ANFIS structure, training and testing of the proposed model. The proposed MPPT scheme is shown in Fig. 6. It consists of an ANFIS system controller, a PWM block and a de-de converter. The ANFIS controller integrates a fuzzy logic controller (FLC) for tuning the converter duty cycle. The controller operation is divided into two stages. The first stage involves prediction of the module's maximum voltage (Vmax) under varying weather conditions by the ANFIS system. The maximum power point voltage predicted from ANFIS is used to calculate one of the two inputs to the FLC as follows:

$$\Delta V = V_{in} - V_{\max} \qquad (12)$$

The other input to the FLC is the irradiance value. In the second stage the FLC uses these two inputs to compute the desired duty cycle D. The duty cycle is then taken through the PWM block which generates the control signals for switching of the converter.

C. Neural Fuzzy Systems

A neural fuzzy system combines fuzzy logic and neural network systems. For a given input/output data set, the membership functions (MFs) of the constructed fuzzy inference system (FIS) are tuned using either a back propagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. Rule] : IF V is NB and RAD is B THEN D is NB Rule2: IF V is NM and RAD is S THEN Dis NM Rule3:IF ~V is PB and RAD is MTHEND is PM

D . PERTURB AND OBSERVE (P&O) This algorithm creates a slight disturbance in the system, which causes the module's power to change. At this stage, if the module's power increases due to the disturbance, it will continue in the same direction [12]. And when it reaches the stable state, the algorithm oscillates at the closest point of maximum received power. However, the perturbation is done with very few changes, resulting in finding the optimal point as much as possible. Fig. 1, shows the P&O algorithm diagram. When the electrical parameters of PV power and voltage increase, the disturbance will increase the value of 1D to add with cycle D. This function will form a cycle, and the search point will move towards MPP. In this algorithm, if the PV power decreases and its voltage increases [13], its working cycle will change, and it will do the opposite because the input parameters of this algorithm are current and voltage. Equation (1) is the duty cycle where PV is the voltage, and VL is the load voltage in the PV system [14]. Also, in Equation (2), Ton and Toff are the amount and time of conduction.

$$D = 1 - \frac{V_{PV}}{V_L}$$

$$D = \frac{T_{on}}{T_{on} + T_{off}}$$

E. FUZZY LOGIC CONTROL (FLC) The structure of fuzzy logic systems is simple and understandable [15]. It can also be used confidently, especially when faced with imprecise inputs. The advantage of this controller is that it works with imprecise inputs. Also, not needing a precise mathematical model and being non-linear are other features of this algorithm. FLC for MPPT uses two input parameters, E error and CE error change at time k, which are defined by (3) and (4), while the system output cycle of this algorithm is task D

$$E(k) = \frac{P(k)-P(k-1)}{V(k)-V(k-1)}$$

$$CE(k) = E(k)-E(k-1)$$

PV MODEL UNDER SHADING CONDITIONS

To study the partial shading conditions, the PV system should be modelled from the cell level up to modules. Fig. 8, depicts a single-diode model, which is the most common representation of a PV cell [26]. The PV model based on two diodes [27], is close to reality and more accurate in expressing the solar cell. However, it requires more computation time [28], and on the other hand, it does not affect our study results. Thus, the single diode model of Fig. 8 is used in this study.

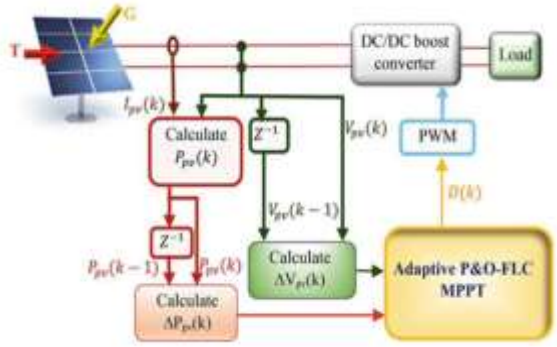


Fig 5. Schematic of the combined algorithm.

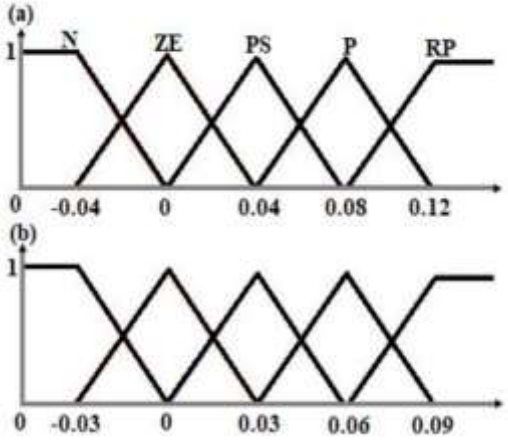


Fig 6. Membership functions, an Input of 1P-V, and b output 1D

TABLE 3. Variables of the rules P&O–FLC of the proposed algorithm.

ΔPpv / ΔVpv	N	ZE	PS	P	PB
PB	N	N	N	ZE	ZE
ZE	ZE	ZE	PS	P	PB
P	N	N	ZE	ZE	PS
ZE	ZE	ZE	PS	P	PB
N	ZE	PS	P	PB	PB
PS	N	ZE	ZE	PS	P

The cell output current is expressed as

$$I_{pv} = I_L - I_D - \frac{V + R_S I}{R_P}$$
$$= I_L - I_L\left[\exp\left(\frac{V + R_S I}{V_t a}\right) - 1\right] - \frac{V + R_S I}{R_P}$$

where Vt = kT/q, also the generated current of the PV cell has a direct relationship with the amount of radiation received from sunlight, so the surface temperature of its pigments is

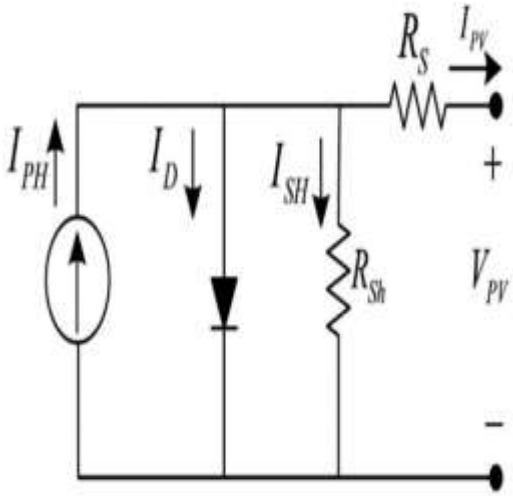


FIGURE 8. PV Cell model.

calculated based on the following relationship [29]:

$$I_L = I_{Ln} + K_i \Delta T \frac{G}{G_n}$$

Also, the amount of saturated current can be expressed from the following equation.

$$I_s = I_{sn}\left(\frac{T_n}{T}\right)^3 \exp\left[\frac{qE_g}{ak}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right]$$

$$I_{sn} = \frac{I_{scn}}{\exp\left(\frac{V_{ocn}}{aV_m}\right) - 1}$$

Also, Rs and Rp and Equation (7) can be obtained by matching the maximum power measured by the solar photovoltaic cells with the power value of the MPP data sheet [30]. By changing V from 0 to Vocn / Ns, the corresponding values of I are obtained by solving Equation (7) with the help of numerical methods. Therefore, the P-V curve of the photovoltaic system is obtained by directly multiplying the Ns of the series cell by the voltage and the Np of the parallel cell by the current.

TABLE 4. PV parameters.

Model Type	ODA20-18-M
(Pmax)	25W
(Isc)	1.14 A
(Imp)	1.07 A
(Voc)	22.50 V
(Vmp)	18.75 V
Efficiency Cells (%)	18.69 %

Generally, Photovoltaic systems for generating energy from sunlight include a large number of modules that will be connected in different ways [31], [32]. Consider a PV system including two chains with parallel connections, as shown in Fig. 9. Chain 1 includes m2, m1 and m3 series modules, and chain 2 includes m5, m4 and m6 modules. Here, m4, m1, and m5 PV modules receive 1 kW per square meter (kW/m2) and m3, m2, and m6 modules receive 0.6 KW per square meter [33]. The series connection of the modules is to achieve higher voltage for the higher power output to be controlled by the MPPT algorithm. In the case of partial shading due to trees, clouds, dust, etc. Each module can receive a reduced amount of sunlight [34]. When some cells are in the shade, the current

6. SIMULINK RESULTS & OUTPUTS

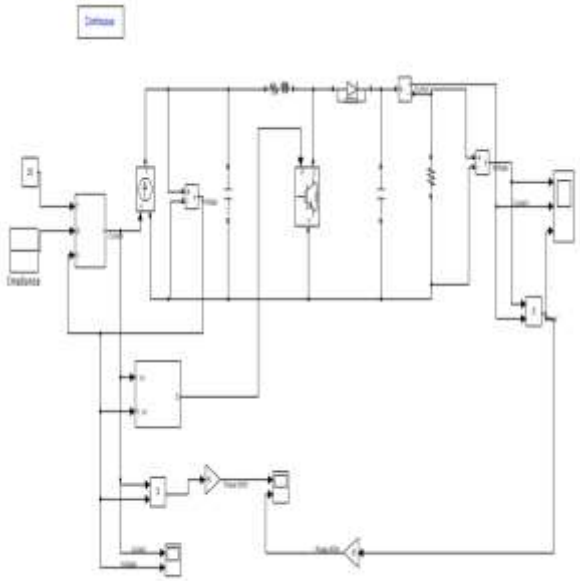


Fig 7. Simulink circuit diagram

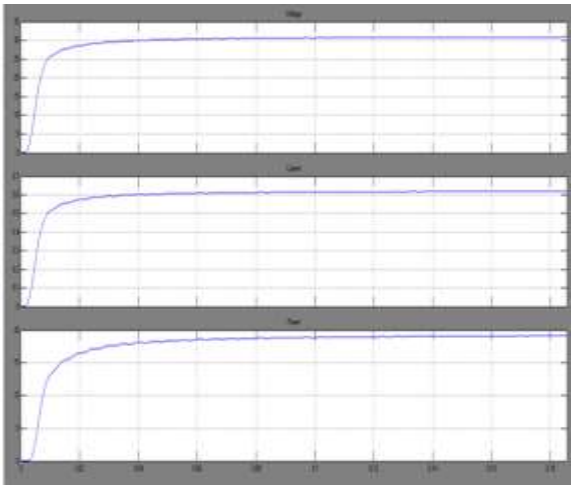


Fig 8. Voltage Current And Power Of Pv Panels Using proposed ANFIS P & O Based Mppt

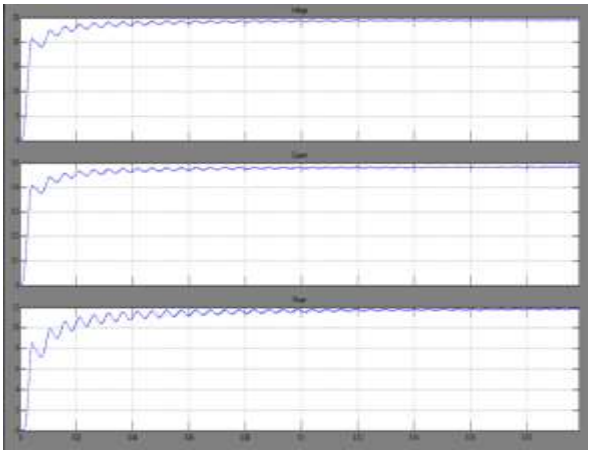


Fig 9. Voltage Current And Power Of Pv Panels Using P & O Based Mppt

7. CONCLUSION

This paper presented a hybrid P&O–ANFIS-based MPPT algorithm designed to improve the power extraction efficiency of photovoltaic (PV) systems operating under partial shading and rapidly changing environmental conditions. The proposed approach effectively combines the fast convergence and simplicity of the Perturb and Observe (P&O) method with the adaptive learning and intelligent decision-making capabilities of the Adaptive Neuro-Fuzzy Inference System (ANFIS).

Simulation results obtained using MATLAB/Simulink demonstrated that the hybrid algorithm successfully tracks the Global Maximum Power Point (GMPP) with higher accuracy and faster dynamic response compared to conventional P&O and standalone ANFIS methods. The hybrid MPPT exhibited reduced steady-state oscillations, improved stability, and enhanced overall tracking efficiency under both uniform and non-uniform irradiance conditions.

The results confirm that integrating intelligent control with traditional MPPT strategies provides a practical and effective solution for modern PV systems, ensuring maximum energy utilization and greater system reliability. Future work may focus on hardware implementation of the proposed algorithm and real-time validation using embedded controllers to further assess its performance and scalability for large-scale grid-connected PV applications

8. FUTURE SCOPE

The proposed Hybrid P&O–ANFIS-based MPPT algorithm has demonstrated significant improvements in tracking efficiency, dynamic response, and power stability for photovoltaic (PV) systems under partial shading conditions. However, further research and development can enhance its performance and practical applicability. The following directions are suggested for future work:

1. Hardware Implementation:
   The algorithm can be implemented on real-time embedded platforms such as DSPs, FPGAs, or microcontrollers to validate its performance under actual field conditions and to evaluate computational efficiency and response time.
2. Integration with Energy Storage Systems:
   Future studies may explore combining the hybrid MPPT with Battery Energy Storage Systems (BESS) or supercapacitors to improve overall system reliability, energy management, and grid support functions.
3. Extension to Grid-Connected and Hybrid Systems:
   The algorithm can be adapted for grid-tied PV systems, PV–wind hybrid setups, or microgrid applications, where dynamic load and grid variations demand advanced adaptive control.
4. Optimization Using Metaheuristic Algorithms:
   Techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or Grey Wolf Optimization (GWO) can be combined with ANFIS to further optimize controller parameters and enhance global tracking accuracy.

5. Experimental Validation Under Real Shading Patterns:
   Extensive experimental testing under different partial shading scenarios and environmental conditions can be conducted to compare the system's robustness and efficiency with other hybrid MPPT algorithms.
6. Machine Learning-Based Predictive MPPT:
   Incorporating machine learning or deep learning models can allow predictive control of MPPT by forecasting irradiance and temperature profiles, thereby further improving real-time performance and power stability.

This future scope ensures continuous advancement of the proposed hybrid MPPT system toward real-time, intelligent, and energy-optimized PV applications suitable for smart grid and distributed generation environments.

9. REFERENCES

[1] A. Salem, H. Van Khang, I. N. Jiya, and K. G. Robbersmyr, ''Hybrid three-phase transformer-based multilevel inverter with reduced component count,'' IEEE Access, vol. 10, pp. 47754–47763, 2022.

[2] A. Mukhatov, N. G. M. Thao, and T. D. Do, ''Linear quadratic regulator and fuzzy control for grid-connected photovoltaic systems,'' Energies, vol. 15, no. 4, p. 1286, Feb. 2022.

[3] N. Zanib, M. Batool, S. Riaz, and F. Nawaz, ''Performance analysis of renewable energy based distributed generation system using ANN tuned UPQC,'' IEEE Access, vol. 10, pp. 110034–110049, 2022.

[4] A. A. Khan, Y. W. Lu, W. Eberle, L. Wang, U. A. Khan, M. Agamy, and H. Cha, ''Single-stage bidirectional buck–boost inverters using a single inductor and eliminating the common-mode leakage current,'' IEEE Trans. Power Electron., vol. 35, no. 2, pp. 1269–1281, Feb. 2020.

[5] M. Aly, E. M. Ahmed, H. Rezk, and E. A. Mohamed, ''Marine predators algorithm optimized reduced sensor fuzzy-logic based maximum power point tracking of fuel cell-battery standalone applications,'' IEEE Access, vol. 9, pp. 27987–28000, 2021.

[6] P. Sahu and R. Dey, ''Maximum power point tracking using adjustable gain based model reference adaptive control,'' J. Power Electron., vol. 22, no. 1, pp. 138–150, Jan. 2022.

[7] V. F. Pires, A. Cordeiro, D. Foito, A. J. Pires, H. Chen, J. F. Martins, and R. Castro, ''A cascaded dual four-leg inverter for photovoltaic systems with capability to compensate unbalanced distribution networks,'' IEEE J. Emerg. Sel. Topics Ind. Electron., vol. 4, no. 3, pp. 960–968, Jul. 2023.

[8] J. Maeng, J. Jeong, I. Park, M. Shim, and C. Kim, ''A time-based direct MPPT technique for low-power photovoltaic energy harvesting,'' IEEE Trans. Ind. Electron., vol. 71, no. 5, pp. 5375–5380, May 2024.

[9] L. Mamouri, T. Mesbahi, and V. Frick, ''MPPT technique with improved FOCV control applied to a full active rectifier for low-voltage piezoelectric energy harvesting,'' IEEE Trans. Circuits Syst. II, Exp. Briefs, vol. 71, no. 2, pp. 532–536, Feb. 2024.

[10] S. Jain, S. V. S. P. K. Ch, V. Sonti, A. Keskar, J. X. Johnson, S. Ghosh, and R. N. Patel, ''High-performance hybrid MPPT algorithm based singlestage solar PV fed induction motor drive for standalone pump application,'' IEEE Trans. Ind. Appl., vol. 59, no. 6, pp. 7103–7115, Nov. 2023.

[11] X. Yue, S. Javvaji, Z. Tang, K. A. A. Makinwa, and S. Du, ''A bias-flip rectifier with duty-cycle-based MPPT for piezoelectric energy harvesting,'' IEEE J. Solid-State Circuits, vol. 59, no. 6, pp. 1771–1781, Jun. 2024.

[12] S. E. Babaa, M. Armstrong, and V. Pickert, ''Overview of maximum power point tracking control methods for PV systems,'' J. Power Energy Eng., vol. 2, no. 8, pp. 59–72, 2014.

[13] D. Xu, H. Chen, X. Wang, V. Pires, J. Martins, A. Anuchin, X. Li, R. Palka, and J. Gu, ‘‘Coupling analysis of differential power processingbased PV system and its decoupling implementation of synchronous MPPT control,’’ IEEE Trans. Ind. Electron., vol. 70, no. 7, pp. 6973–6983, Jul. 2023.

[14] J. D. B. Rodriguez, E. Franco, G. Petrone, C. A. R. Paja, and G. Spagnuolo, ‘‘Maximum power point tracking architectures for photovoltaic systems in mismatching conditions: A review,’’ IET Power Electron., vol. 7, no. 6, pp. 1396–1413, Jan. 2014.

[15] X. Li, H. Wen, Y. Hu, L. Jiang, and W. Xiao, ‘‘Modified beta algorithm for GMPPT and partial shading detection in photovoltaic systems,’’ IEEE Trans. Power Electron., vol. 33, no. 3, pp. 2172–2186, Mar. 2018.

[16] L. Farah, A. Hussain, A. Kerrouche, C. Ieracitano, J. Ahmad, and M. Mahmud, ‘‘A highly-efficient fuzzy-based controller with high reduction inputs and membership functions for a grid-connected photovoltaic system,’’ IEEE Access, vol. 8, pp. 163225–163237, 2020.

[17] W. Jinpeng, Y. Qinxue, Z. Bo, Jeremy-Gillbanks, and Z. Xin, ‘‘Study on MPPT algorithm based on an efficient hybrid conjugate gradient method in a photovoltaic system,’’ IEEE Access, vol. 11, pp. 4219–4227, 2023.

[18] M. H. Ibrahim, S. P. Ang, M. N. Dani, M. I. Rahman, R. Petra, and S. M. Sulthan, ‘‘Optimizing step-size of perturb & observe and incremental conductance MPPT techniques using PSO for grid-tied PV system,’’ IEEE Access, vol. 11, pp. 13079–13090, 2023.

[19] H. Karimi, P. Tarassodi, A. Siadatan, and M. Sepehrinour, ‘‘Designing and manufacturing a solar tracking of photovoltaic (PV) panels for produce maximum power electrical,’’ in Proc. Int. Symp. Power Electron., Electr. Drives, Autom. Motion (SPEEDAM), Napoli, Italy, Jun. 2024, pp. 498–502.

[20] J. Linares-Flores, A. Hernández-Mendez, J. A. Juárez-Abad, M. A. Contreras-Ordaz, C. García-Rodriguez, and J. F. GuerreroCastellanos, ‘‘MPPT novel controller based on passivity for the PV solar panel-boost power converter combination,’’ IEEE Trans. Ind. Appl., vol. 59, no. 5, pp. 6436–6444, Sep. 2023.