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RESEARCH ARTICLE

Optimizing Maximum Power Point Tracking Efficiency: Fuzzy Logic-Based Adaptive Step Size Control in the Perturb and Observe Algorithm

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ABSTRACT

This paper proposes an enhanced Maximum Power Point Tracking (MPPT) technique for photovoltaic (PV) systems by integrating a fuzzy logic controller (FLC) with a dynamically tuned step size. Unlike conventional methods, the developed approach utilizes the ratio of power and voltage variations ($\Delta P/\Delta V$) as the basis for adjusting the duty cycle through a customized fuzzy rule base. This design enables precise and stable tracking of the maximum power point (MPP) even under rapidly changing irradiance and temperature conditions. The algorithm was validated through MATLAB/Simulink simulations using a 100W PV module and a DC–DC boost converter. Two test scenarios were employed: one with stepwise irradiance variations between (0.2–1.0 kW/m²) and another with temperature shifts between (0–75°C). Results demonstrated that the proposed FL-based MPPT algorithm significantly outperforms the classical fixed-step P&O method. Notably, it achieved lower power ripple (0.05% vs. 0.4%), reduced overshoot (2.3% vs. 4.1%), and faster response time (0.1 s vs. 0.25 s). The findings confirm that the tailored FLC, governed by $\Delta P/\Delta V$-driven inference, offers a more robust and adaptive MPPT strategy suitable for real-world PV deployment.

Index Terms—DC–DC Boost Converter, Fuzzy Logic Controller (FLC), Maximum Power Point Tracking (MPPT), Perturb and Observe (P&O) Algorithm, Photovoltaic (PV) Systems, Renewable Energy

I. INTRODUCTION

The continual rise in global energy consumption necessitates a strategic pivot toward alternative energy resources. According to forecasts, global energy demand is anticipated to rise by approximately 56% by 2040 [1]. In light of this challenge, various countries have begun adopting renewable energy technologies as sustainable means to satisfy their growing energy needs. Nevertheless, despite the environmental benefits they offer, renewable options are still confronted with limitations, notably in terms of cost-effectiveness and efficiency [2]. A viable route to sustainability involves leveraging natural energy sources such as solar radiation, wind, hydropower, tidal movement, and geothermal activity [3]. These resources, being inherently renewable, offer the advantage of continual replenishment. Among them, solar photovoltaic (PV) energy has emerged as a compelling candidate for future energy systems due to its abundance, cleanliness, and broad deployment capabilities. Unlike other sources such as wind farms or biomass facilities, PV systems can be installed in a diverse range of environments, increasing their accessibility and potential impact [1, 4]. The rapid expansion of PV technologies is closely linked to their capacity to serve as both an environmentally friendly and economically viable solution. Photovoltaic systems generate power with minimal emissions, typically limited to the manufacturing phase of system components. Their performance, however, is highly sensitive to several operational factors, including incident solar irradiance, module temperature, weather conditions, material composition, and structural orientation [4-6]. Optimizing these parameters is essential to maximizing energy yield and ensuring consistent output. Photovoltaic modules are currently used in an extensive array of applications—from rural electrification and water pumping systems to lighting, remote sensing, and space satellite operations. Their silent operation, low maintenance requirements, and long lifespan contribute to their growing popularity. Still, significant challenges remain, particularly those related to high production costs, nonlinear current-voltage characteristics, and relatively low conversion efficiencies under dynamic atmospheric conditions [4, 5, 7].

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As such, ongoing research continues to focus on overcoming these obstacles to support broader PV system adoption and enhance system robustness. Three primary aspects determine the performance of a PV system: the intrinsic conversion efficiency of the solar cell, the functional efficiency of the power converter, and the effectiveness of the Maximum Power Point Tracking (MPPT) control algorithm [8, 9]. Enhancing the MPPT algorithm is considered one of the most cost-effective improvements, as it relies on software-level updates to optimize energy extraction without requiring hardware changes. Such enhancements are feasible in both newly installed and existing systems. Moreover, modern digital controllers and embedded systems have provided the technical foundation for more sophisticated and adaptive MPPT strategies [10, 11]. Recent decades have seen notable advancements in MPPT methodologies [12-15]. These algorithms are typically categorized into three classes: offline, online, and hybrid strategies [16-18]. Offline approaches rely on predefined models or environmental indicators like the short-circuit current (Isc) or open-circuit voltage (Voc) to predict the MPP, rather than measuring power directly [17-19]. Although easy to implement, their static nature often leads to suboptimal performance under rapidly shifting weather conditions. By contrast, online MPPT techniques dynamically respond to real-time environmental data to adjust the operating point for maximum output. Examples include Perturb and Observe (P&O) [13, 16, 20], Hill Climbing (HC) [13, 21], and Incremental Conductance (IC) [13, 22-25]. These methods rely on continuous voltage and current measurements to calculate power changes and guide system operation accordingly, offering superior tracking capability under fluctuating solar and temperature conditions. Hybrid MPPT approaches blend the advantages of both offline and online methods by incorporating intelligent control mechanisms. These typically involve a two-stage process: the first utilizes advanced controllers such as Proportional–Integral–Derivative (PID), Fuzzy Logic Controllers (FLCs), or Artificial Neural Networks (ANNs) to tune parameters and the second integrates these enhancements with traditional MPPT frameworks [26-28]. The outcome is often a more robust and adaptive tracking system, capable of adjusting to dynamic environmental factors and load variations. A growing body of research has explored hybrid solutions that substantially improve MPPT performance [29-32]. These systems outperform classical techniques by minimizing tracking errors, improving convergence speed, and ensuring higher power extraction. However, their complexity and computational demands may limit their adoption in cost-sensitive or embedded applications. Despite their effectiveness, classical MPPT algorithms like P&O, IC, and HC are not without limitations. Although they are widely used due to their simplicity and low hardware requirements, their effectiveness varies depending on sensor quality, system complexity, and environmental dynamics. A common drawback is their tendency to oscillate around the MPP, especially in the presence of high irradiance variation, resulting in energy losses. Additionally, trade-offs exist between convergence speed, stability, and implementation cost [33, 34]. The fixed step-size P&O algorithm, in particular, suffers from a fundamental constraint: large step sizes allow faster convergence but at the expense of overshoot and persistent oscillation, while smaller step sizes improve stability but slow down the system's responsiveness [35, 36]. This creates a dilemma in selecting an appropriate step size for real-world conditions. To address this limitation, researchers have proposed adaptive algorithms in which the step size dynamically adjusts based on the system's real-time electrical behavior. These improvements are commonly integrated into existing P&O or IC frameworks [24, 35, 37]. The adaptive adjustment is often governed by observed changes in power and voltage, allowing the algorithm to fine-tune its response, reduce oscillations, and improve tracking accuracy. This adaptability enhances the robustness of the system and leads to more consistent power extraction across varying environmental scenarios.

Main Points

- An adaptive fuzzy logic MPPT algorithm is proposed, using the ΔP/ΔV ratio to dynamically adjust the duty cycle, enabling fast and accurate MPPT under rapidly changing irradiance and temperature.
- The algorithm employs a customized fuzzy rule base with only 9 rules and hybrid membership functions, ensuring both simplicity and effective step size control (ΔD) with low computational cost.
- Simulation results confirm the method's superiority over classical P&O, achieving significant reductions in ripple, overshoot, and response time while maintaining robust performance under dynamic conditions.

While several previous studies have investigated the integration of fuzzy logic (FL) into P&O algorithms to enhance MPPT performance [38-40], most of these efforts rely on conventional fuzzy rule bases and generic step size tuning mechanisms. These approaches often lack responsiveness to complex real-time operating scenarios, particularly when irradiance and temperature vary rapidly and simultaneously. In contrast, the proposed method introduces a customized fuzzy rule base that was empirically optimized for high-frequency environmental disturbances. Moreover, the algorithm adapts the duty cycle based on a real-time evaluation of the ΔP/ΔV ratio, enabling a more granular and stable adjustment of step size (ΔD). This results in significant reductions in both overshoot and ripple, as confirmed in comparative simulations.

The novelty of this work also lies in its use of dynamically profiled temperature and irradiance test cases, which more accurately reflect real-world operating conditions than the fixed or slowly varying patterns employed in most prior studies. Thus, the developed method contributes a new layer of adaptability and robustness to fuzzy-based MPPT control.

This research proposes an adaptive MPPT enhancement for the conventional P&O algorithm by integrating a fuzzy logic (FL)-based variable step size controller. Using a boost converter and a 100W Ensko Solar-poly panel, the developed strategy is simulated and benchmarked against the standard fixed-step P&O method. The results demonstrate the superiority of the proposed FL-based system in minimizing ripple, limiting overshoot, and achieving faster convergence. Moreover, performance evaluation under dynamically changing irradiance and temperature conditions confirms the algorithm's robustness and its potential for real-world PV applications.

II. PHOTOVOLTAIC SYSTEM MODELING

To implement the proposed enhancement, a FLC was designed using a tailored rule base. Unlike traditional fuzzy MPPT schemes that rely on generic rule sets, this study developed a custom-designed set of fuzzy rules based on extensive simulation feedback under fast-changing irradiance and temperature conditions. The inputs to the fuzzy system are the changes in output voltage (ΔV) and power (ΔP), while the output (ΔD) represents a dynamically tuned step size used to adjust the Pulse Width Modulation (PWM) duty cycle. This ΔD is not computed using fixed thresholds or lookup tables but is inferred through real-time evaluation of the ratio ΔP/ΔV, enabling finer adaptation to nonlinear power variations. The fuzzy rule base was constructed with a mix of triangular and trapezoidal membership functions, specifically structured to ensure smooth duty cycle transitions under rapid perturbations. Moreover, the methodology incorporates dynamic test profiles that simulate realistic environmental transitions. This includes abrupt irradiance changes between (0.2–1 kW/m²) and sharp temperature variations between (0–75°C), providing a more robust basis for evaluating the proposed algorithm's effectiveness compared to fixed-step scenarios used in prior literature.

A PV cell is the fundamental building block in solar energy generation, serving as a semiconductor device that directly converts solar radiation into electrical energy through the PV effect. Typically, these cells are organized into modules where individual PV units are connected in series and/or parallel configurations to produce the desired output in terms of voltage, current, and power. Such arrangements enable the system to meet the electrical requirements of various loads across diverse applications. The efficiency and performance of PV systems are influenced by several factors. Solar irradiation, the amount of sunlight hitting the PV cells, plays a significant role in determining energy output. Additionally, temperature variations, spectral characteristics of sunlight, and shading conditions can impact the performance of PV modules. Furthermore, the accumulation of dirt or debris on the surface of the PV modules can also reduce their efficiency. The Ensko Solar-Poly 100W panel was modeled in MATLAB/Simulink based on the principles of the single-diode PV cell model shown in Fig. 1 and its corresponding output current equation (1). Under standard test conditions (25°C, 1000 W/m²), the polycrystalline module evaluated in this study exhibits a rated output of 100 W. At its MPP, the module operates at 18 V and 5.56 A. The Voc reaches 21.8 V, while the Isc is measured at 6.05 A. Furthermore, the panel includes a positive power tolerance of up to +5%.

$$I_{PV} = n_p I_{ph} - n_p I_{rs}\left[e^{\left(\frac{q(V_{PV}+R_S I_{PV})}{A.k.T.n_s}\right)} - 1\right] - n_p\left(\frac{q(V_{PV}+R_S I_{PV})}{n_S R_{Sh}}\right) \tag{1}$$

Within this modeling framework, R_S and R_{sh} correspond to the internal series and shunt resistances of the PV cell. The output current is denoted as I_{PV}, while V_{PV} signifies the terminal voltage of the cell. The photocurrent I_{ph}, which arises due to incident solar irradiance, plays a major role in determining performance. Meanwhile, I_{rs} represents the reverse saturation current under dark conditions. The absolute temperature is denoted by T in Kelvin. The total number of parallel-connected cell strings is represented by n_p, whereas n_s indicates the number of cells connected in series. Constants k and q stand for Boltzmann's constant and elementary charge, respectively. Finally, the junction quality factor is given by A, capturing the influence of the semiconductor material on the diode behavior. To validate the developed MPPT approach during rapid atmospheric changes and compare it with the conventional fixed step size P&O method, the characteristics of the PV panel are analyzed in two cases. The first case examines the panel's performance under variable irradiance levels (0.2 kW/m², 0.4 kW/m², 0.6 kW/m², 0.8 kW/m², and 1 kW/m²) with constant temperature (25°C), while the second case evaluates the effects of variable temperature levels (0°C, 25°C, 50°C, and 75°C) with constant irradiance (0.95 kW/m²). The results are presented in Figs. 2 and 3, respectively. The different levels of solar irradiance and temperature were applied for 10 seconds, as shown in Figs. 4 and 5, respectively.

III. DEVELOPED FUZZY LOGIC-BASED VARIABLE STEP PERTURB AND OBSERVE ALGORITHM

The conventional P&O method for MPPT uses a fixed step size to optimize the operating point of a PV panel. However, this approach inherently involves a trade-off between two critical performance factors:

- Stability: Minimizing oscillations near the MPP.
- Convergence Speed: Accelerating the system's ability to reach the MPP after environmental changes.

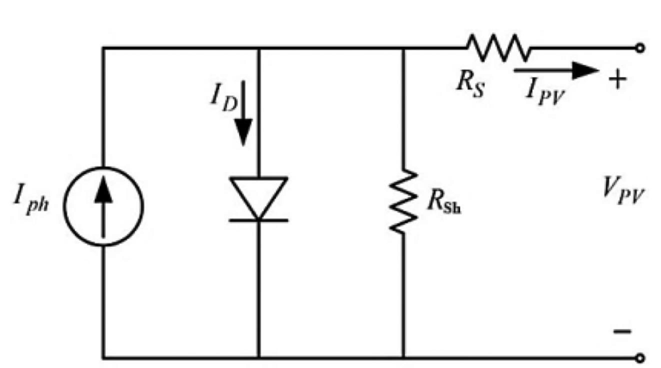

Fig. 1. Single-diode equivalent model of a solar cell.

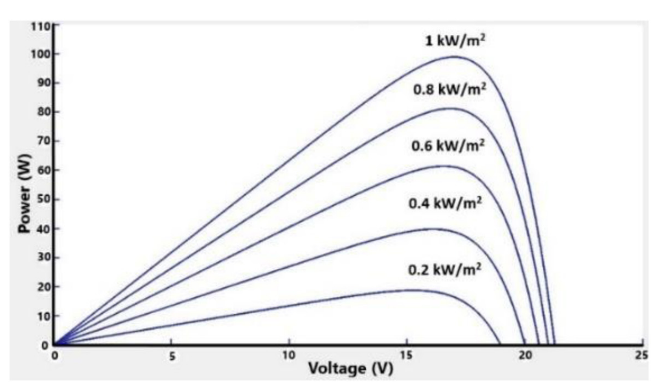

Fig. 2. P–V curves for different irradiance levels (T = 25°C).

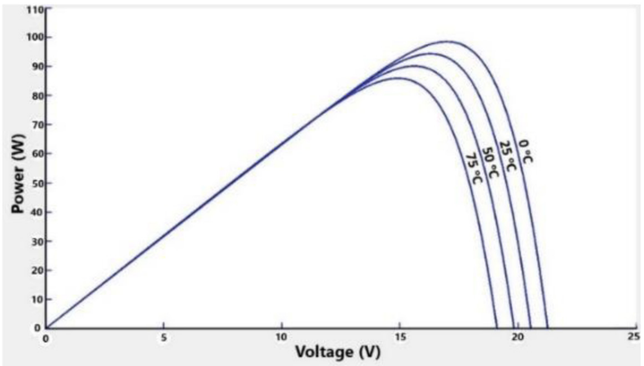

Fig. 3. P–V curves for different temperature levels (irradiance = 0.95 kW/m²).

To address these challenges, a variable step size method is proposed in this study. The new algorithm adjusts the step size (ΔD) dynamically using the ratio of change in power (ΔP) to change in voltage (ΔV), allowing faster convergence when far from the MPP and more stability when near it. The flowchart of this fuzzy-based control strategy is illustrated in Fig. 6, which outlines the signal processing flow from input sampling to control action. The heart of this approach is a FLC, which takes ΔP and ΔV as inputs. During the fuzzification stage, these values are converted into fuzzy variables using trapezoidal membership functions for the extremes (NL, PL) and triangular functions for intermediate values (NS, Z, PS), as shown in Figs. 7 and 8. The output ΔD is fuzzified similarly using a hybrid of these functions (Fig. 9). The fuzzy rule base, provided in Table I, defines a matrix of IF–THEN conditions based on linguistic variables. Suppose that the change in power ΔP is categorized as Positive Medium (PM) and the change in voltage ΔV is categorized as Negative Small (NS). Referring to the customized fuzzy rule table (Table I), the intersection of row PM and column NS yields an output of Zero. This indicates that no change in the duty cycle (ΔD) is required, as the system is likely near the MPP and any aggressive adjustment may result in overshoot or oscillation. The rule is interpreted as: If ΔP is PM and ΔV is NS → Then ΔD is Zero.

This logic demonstrates how the controller scales its response based on system behavior. For instance, had ΔP been PL and ΔV alsoPM, the output ΔD would have been NM—indicating the need for a substantial correction to return to the MPP. In the inference process, the rules are evaluated using the fuzzy inputs. Each rule's degree of activation (firing strength) is calculated through fuzzy AND operations. The controller aggregates the consequences of the fired rules and converts them into a crisp ΔD value via defuzzification, which is then applied to adjust the PWM duty cycle of the DC–DC converter. This structure differs from traditional implementations by using ΔP/ΔV as the sensitivity driver and by employing a non-standard fuzzy rule matrix. As a result, the controller can quickly enlarge the step size when large mismatches occur and shrink it when convergence is needed, achieving adaptive control in real time. Fig. 6 summarizes the entire logic: from sensing ΔP and ΔV, passing through fuzzification, firing rules from Table I, generating fuzzy outputs, and finally adjusting the duty cycle.

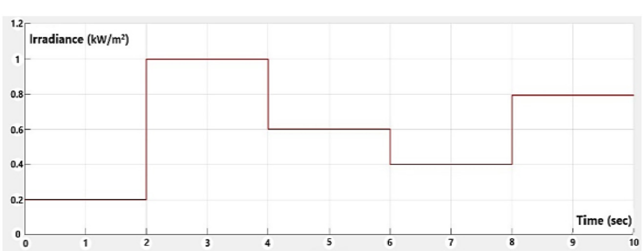

Fig. 4. Various levels of solar irradiance were applied for a duration of 10 seconds.

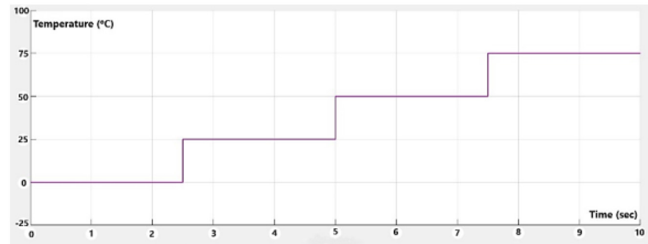

Fig. 5. Various levels of temperature were applied for a duration of 10 seconds.

IV. MODEL OF THE SYSTEM

To assess the effectiveness of the proposed FL-based variable step size MPPT method, a complete system model was developed in MATLAB/Simulink. The structural layout is presented in the updated schematic diagram shown in Fig. 10. The system continuously monitors the PV module's output current (*IPV*) and voltage (*VPV*), which are used to calculate real-time changes in power (ΔP) and voltage (ΔV). These two dynamic values are then utilized to compute the ΔP/ΔV ratio, which serves as the primary decision-making input for the fuzzy controller. A FLC forms the core of the MPPT system. It receives the ΔP/ΔV ratio and maps it into fuzzy linguistic variables through a fuzzification process. The system applies a set of customized fuzzy rules, developed specifically for this study, to infer the optimal

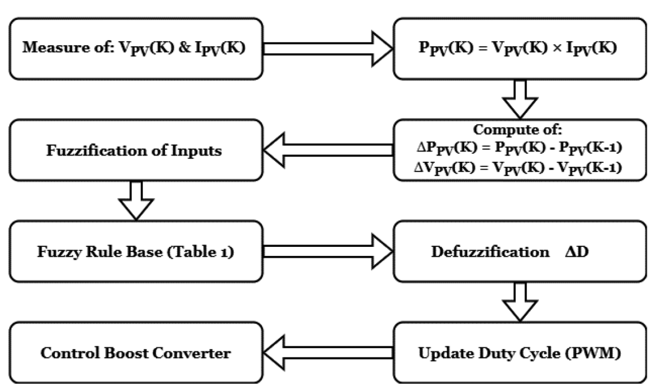

Fig. 6. Various levels of temperature were applied for a duration of 10 seconds.

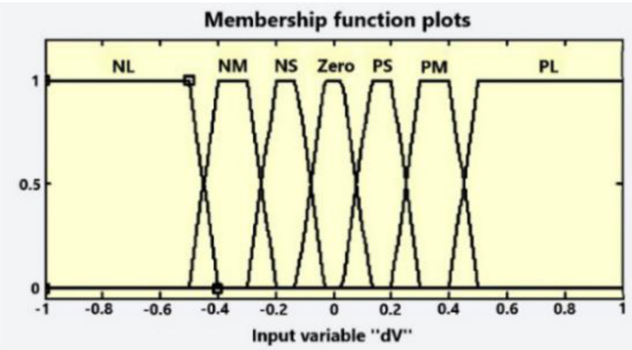

Fig. 7. Membership function for voltage changes.

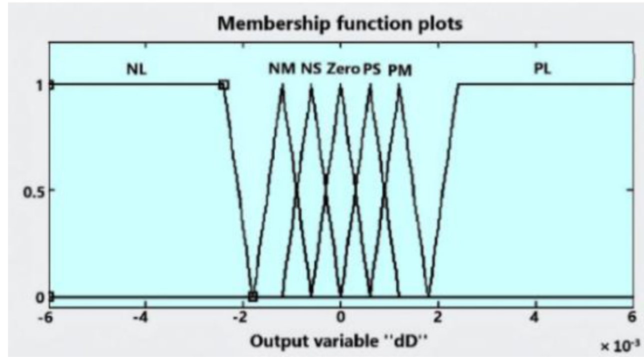

Fig. 9. Membership function for duty cycle steps.

adjustment in duty cycle step size (ΔD). The inference engine uses hybrid membership functions—trapezoidal shapes for large variations and triangular shapes for fine-tuned corrections—to provide smooth yet responsive control over the operating point. The crisp output ΔD obtained after defuzzification is applied to the PWM generator, which modifies the duty cycle of the DC–DC boost converter. This dynamic modulation ensures that the operating point remains closely aligned with the MPP, even under rapidly fluctuating environmental conditions such as changes in irradiance and temperature.

This adaptive structure, based on FL and slope-driven step tuning, not only enhances convergence speed but also minimizes output ripple and overshoot, making it well-suited for real-world PV systems with variable input profiles.

V. SIMULATION RESULTS AND DISCUSSION

Considering that irradiance and temperature can rapidly change due to atmospheric conditions, and to assess the developed FL–P&O algorithm in comparison to the classical P&O algorithm, five irradiance step signals and four temperature step signals were modeled in the MATLAB/Simulink environment, as illustrated in Figs. 4 and 5. To reflect realistic operating scenarios, the irradiance profile was designed with abrupt transitions (e.g., from 0.6 to 1.0 kW/m² within seconds), while the temperature steps span a wide range from 0°C to 75°C. This testing framework was deliberately chosen to validate the responsiveness and adaptability of the proposed fuzzy-based controller under rapid environmental shifts. Fig. 11 illustrates how the FL–P&O algorithm performs in maintaining alignment with the MPP, with the resulting power output corresponding to the irradiance variation profile outlined in Fig. 4. The results indicate that both the conventional P&O and the proposed FL-enhanced version are capable of effectively tracking the MPP, even amid abrupt shifts in irradiance levels. However, the FL–P&O method exhibits significantly smoother transitions and reduced ripple. This improvement can be attributed to the dynamic adaptation of the step size (ΔD) using the ΔP/ΔV ratio, which allows the controller to modulate the duty cycle more gradually and responsively in real time.

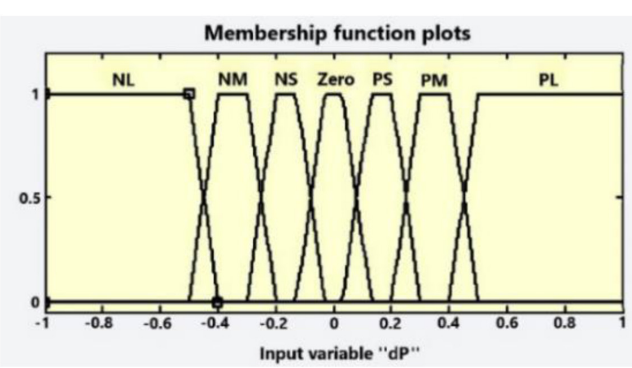

Fig. 8. Membership function for power changes.

Similarly, under scenarios involving changes in module temperature, as defined in the conditions of Fig. 5, both algorithms continue to demonstrate reliable dynamic tracking behavior, as reflected in the outcomes shown in Fig. 12. In this context, the proposed FL–P&O algorithm maintains higher output power stability, which demonstrates its ability to decouple thermal effects and power perturbations more effectively. This is a direct consequence of the tailored fuzzy rule base and its sensitivity to input variations, enabling precise control even when thermal inertia might delay system response.

TABLE I.
CUSTOMIZED FUZZY RULE BASE

	ΔV						
ΔP	**NL**	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NM	NS	Z	PS	PM
NM	NL	NM	NS	Z	PS	PM	PL
NS	NM	NS	Z	PS	PM	PL	PL
Z	NS	Z	PS	PS	PM	PM	PM
PS	Z	PS	PM	PM	PM	PL	PL
PM	PS	PM	PL	PL	PL	PL	PL
PL	PM	PL	PL	PL	PL	PL	PL

NL, negative large; NM, negative medium; NS, negative small; PL, postive large; PM, positive medium; PS, postive small.

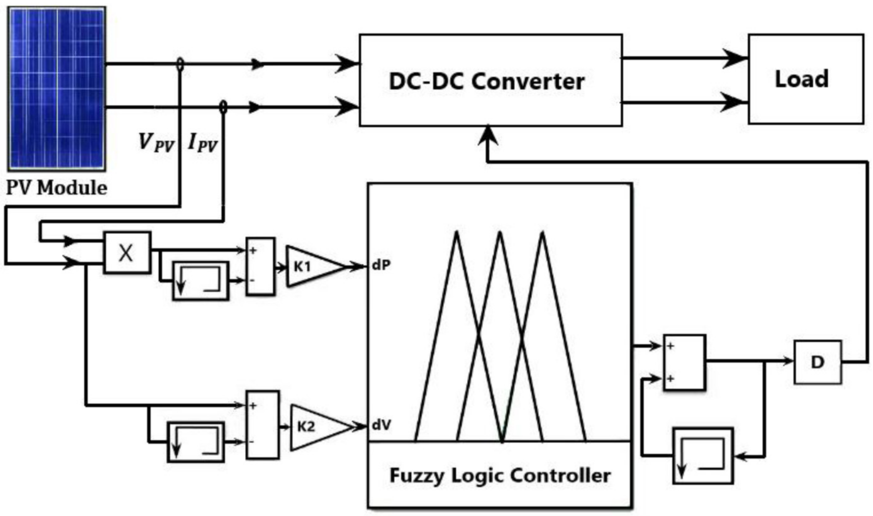

Fig. 10. Block diagram of the proposed Fuzzy Logic—Perturb and Observe Maximum Power Point Tracking system.

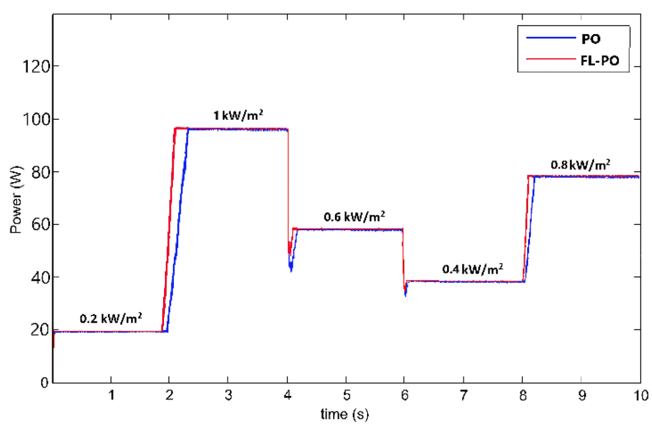

Fig. 11. Output power under variable irradiance: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

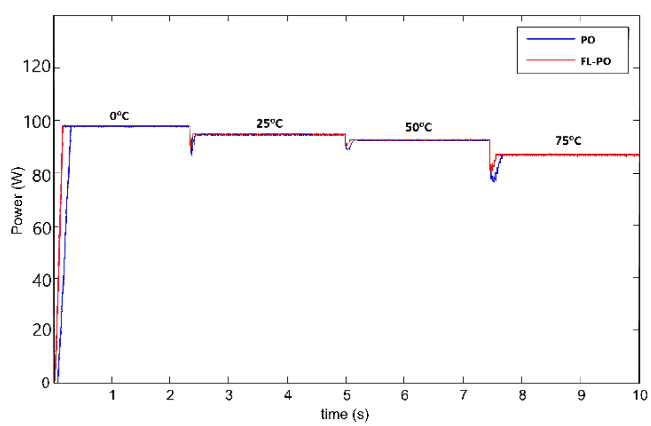

Fig. 12. Output power under variable temperature: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

Fig. 13 showcases the duty cycle responses generated by both the enhanced FL–P&O algorithm utilizing a variable step size and the traditional P&O approach employing a fixed step. These responses are illustrated for the time window spanning from 1 to 2 seconds, corresponding to the scenario previously outlined in Fig. 11. Notably, the FL–P&O algorithm exhibits a more refined duty cycle behavior, characterized by smaller oscillations and faster convergence toward stability. This directly supports the claim that the customized FL design with real-time ΔP/ΔV evaluation enhances both the system's dynamic performance and its tracking accuracy.

A. Maximum Power Point Tracking

Figure 14 compares the MPPT performance of the classical fixed-step P&O algorithm and the developed fuzzy-based variable-step method. While both algorithms are capable of following the MPP under dynamic irradiance, the proposed FL–P&O method shows significantly improved stability and reduced fluctuation near the MPP. This enhancement is directly attributed to the novel step size adjustment mechanism based on the ΔP/ΔV ratio. By continuously analyzing the slope of the power–voltage curve, the fuzzy controller dynamically modulates the step size (ΔD) to ensure smooth tracking without excessive oscillation. This contrasts with the fixed nature of the classical P&O, which tends to overreact near the MPP due to its inability to scale its response based on real-time system conditions.

Furthermore, the integration of a tailored fuzzy rule base, optimized for different operating zones, provides an additional layer of control precision, enabling the system to adapt quickly during irradiance transients while maintaining alignment with the optimal operating point.

B. Ripple

Ripple, defined as the variation in power once the system stabilizes near the MPP, is a critical performance metric in MPPT algorithms. Fig. 15 and the corresponding data in Table II clearly demonstrate the superiority of the FL–P&O method in minimizing ripple, achieving a reduction to 0.05% compared to 0.4% in the classical approach.

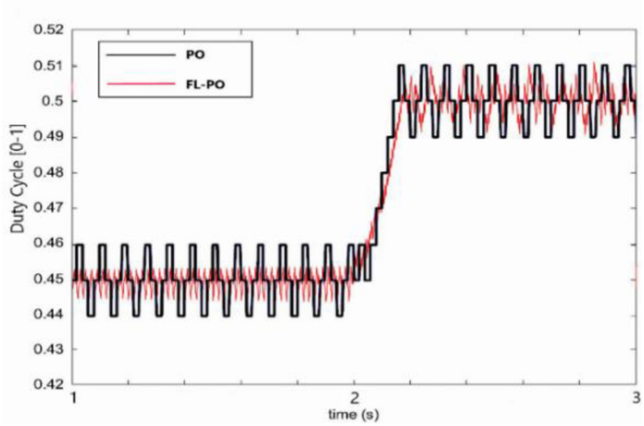

Fig. 13. DC–DC Pulse Width Modulation ratio: Traditional P&O algorithm (black curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

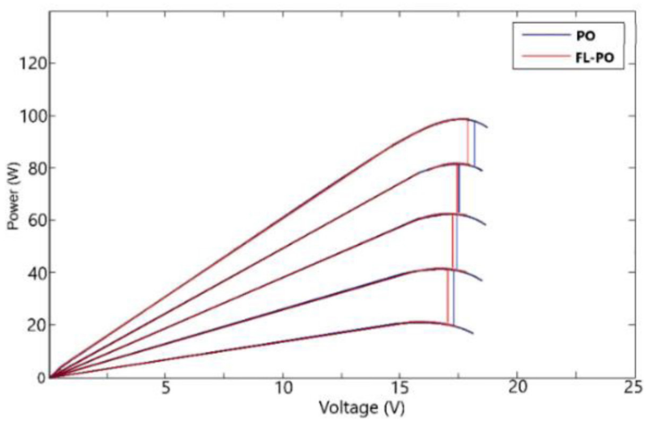

Fig. 14. Maximum Power Point Tracking: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

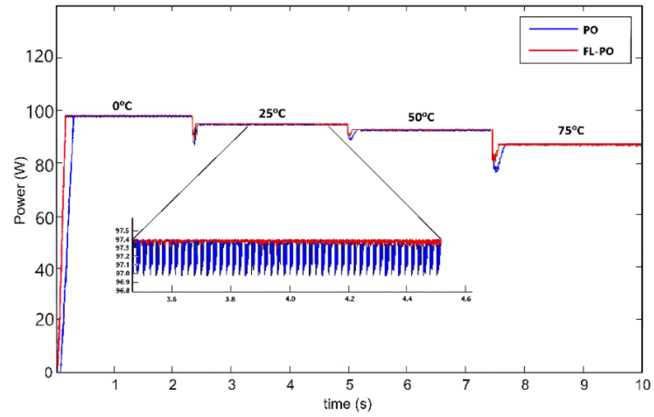

Fig. 15. Ripple improvement: traditional Perturb and Observe algorithm (blue curve), developed fuzzy logic–Perturb and Observe algorithm (red curve).

TABLE II.
IMPROVEMENTS ACHIEVED BY THE FUZZY LOGIC–PERTURB AND OBSERVE ALGORITHM

Parameter	Conventional P&O	Developed FL–P&O	Improvement (%)
Ripple (%)	0.4	0.05	87.5
Overshoot (%)	4.1	2.3	43.9
Response time (sec)	0.25	0.1	60

FL-P&O, fuzzy logic–Perturb and Observe; P&O, Perturb and Observe.

This significant improvement stems from the use of a FLC that adaptively fine tunes the step size (ΔD) based on the real-time ΔP/ΔV ratio. By doing so, the controller can attenuate its adjustments as the system approaches the MPP, preventing the overshooting and hunting behavior typically seen in fixed-step P&O implementations. Moreover, the customized fuzzy rule base plays a vital role in smoothing the control action. It was explicitly designed to provide smaller corrective steps in steady-state conditions, thanks to the employment of triangular membership functions for near-zero input changes, thereby ensuring minimal fluctuations in output power.

C. Overshoot

Overshoot represents the extent to which the system's output power temporarily exceeds the true MPP before settling. This phenomenon is especially pronounced in classical P&O algorithms, which apply the same step size regardless of proximity to the MPP. As shown in Fig. 16 and Table II, the proposed FL–P&O method significantly reduces overshoot to 2.3%, compared to 4.1% observed with the fixed-step approach. This reduction in overshoot is achieved through the intelligent adjustment of the duty cycle via the FLC. By interpreting the ΔP/ΔV ratio, the controller can detect when the system is nearing the MPP and decrease the aggressiveness of the control action accordingly. Additionally, the asymmetry introduced through the fuzzy membership functions—specifically the use of trapezoidal shapes for large deviations and triangular ones for minor variations—enables smoother convergence and avoids sharp overshoots that would otherwise destabilize the tracking process.

D. Response Time

Response time reflects the MPPT controller's ability to react promptly to sudden environmental changes—such as sharp variations in solar irradiance or temperature. A shorter response time ensures that the PV system can quickly realign its operating point to harvest the maximum available energy Fig. 17 and Table II show that the proposed FL–P&O algorithm achieves a substantially improved response time of 0.1 seconds, outperforming the 0.25 seconds of the fixed-step P&O. This enhancement results from the dynamic adjustment of the step size (ΔD) based on the real-time ΔP/ΔV gradient. When the system is far from the MPP, the fuzzy controller intelligently assigns larger step values to accelerate convergence. As the MPP is approached, the controller automatically reduces the step size to avoid overshooting or oscillation. Such adaptive responsiveness is not possible in conventional methods where the step size remains constant, leading either to delays or instability. The fuzzy rule base in this work was optimized to enable fast yet stable reactions to transient scenarios.

E. Reliability and Robustness Testing

To comprehensively evaluate the robustness and reliability of the developed FL–P&O algorithm, two dynamic test scenarios were designed in the MATLAB/Simulink environment. The first scenario involved a fluctuating irradiance profile while maintaining a constant temperature of 25°C. In the second, temperature was varied over time with a fixed irradiance of 1000 W/m².

Fig. 17 illustrates that, under rapidly changing irradiance conditions, the proposed method exhibits minimal tracking deviation and quick convergence to the MPP. The circled regions highlight the algorithm's superior tracking consistency compared to the classical P&O approach. Similarly, Fig. 18 demonstrates that the algorithm sustains high tracking accuracy during sudden temperature shifts, confirming its capability to operate reliably in thermally unstable environments. The enhanced robustness is primarily attributed to the adaptive nature of the FLC, which interprets both the direction and magnitude of ΔP/ΔV to make context-aware control decisions. The controller scales the step size (ΔD) according to environmental dynamics—reacting swiftly when large deviations are detected and stabilizing control near steady-state conditions. Moreover, the hybrid use of trapezoidal and triangular membership functions, combined with a tailored fuzzy rule base, ensures optimal responsiveness across a wide range of input conditions. These design choices allow the system to suppress overshoot and ripple while ensuring prompt adaptation, even under unpredictable atmospheric changes.

This robustness is quantitatively evident in Table II, where the developed FL–P&O algorithm shows significant improvements in ripple (–87.5%), overshoot (–43.9%), and response time (–60%) compared to the conventional method. Such performance ensures higher energy harvesting efficiency and operational stability in real-world PV deployments subject to weather volatility.

F. Comparative Evaluation with Recent Studies

To further highlight the numerical contribution of the proposed method, Table III presents a comparative evaluation with two widely cited MPPT strategies are presented. It can be observed that the FL-based variable step size method introduced in this work significantly reduces ripple, overshoot, and response time while requiring only voltage and current measurements and using a lightweight fuzzy rule base.

While numerous state-of-the-art MPPT techniques based on modified P&O algorithms, such as ANN, IC with adaptive step size, or heuristic-based fuzzy approaches, have demonstrated performance enhancements in various scenarios, the author's proposed method distinguishes itself through its minimal computational complexity, rule base simplification, and effective dynamic adaptation to rapid environmental changes.

Unlike many recent techniques that require extensive training data or complex multi-sensor inputs (e.g., [27], [32]), the author's approach

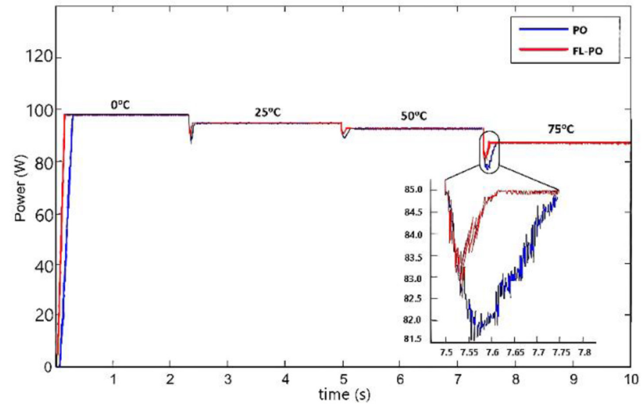

Fig. 16. Overshoot improvement and response time improvement: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

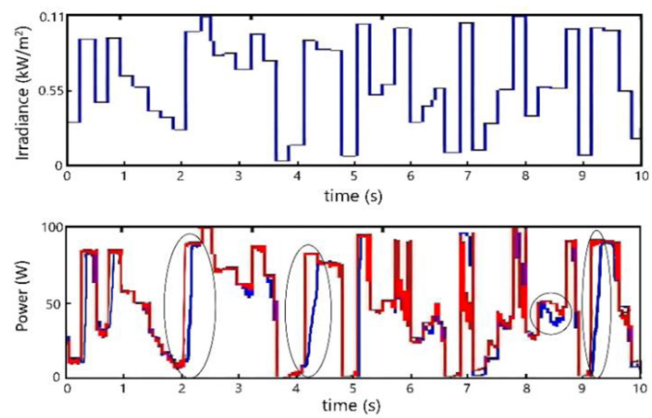

Fig. 17. Maximum Power Point Tracking under fixed temperature (25°C) and random irradiance input: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

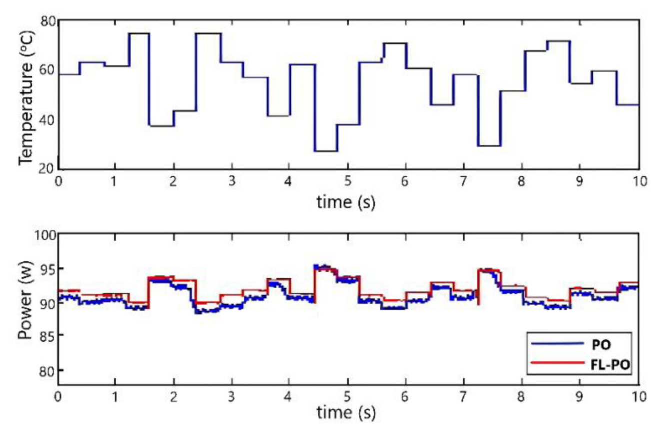

Fig. 18. Maximum Power Point Tracking under fixed irradiance (1000 W/m²) and random temperature input: traditional Perturb and Observe algorithm (blue curve), developed Fuzzy Logic–Perturb and Observe algorithm (red curve).

TABLE III.
COMPARATIVE MAXIMUM POWER POINT TRACKING PERFORMANCE METRICS ACROSS DIFFERENT TECHNIQUES

Study	MPPT Method	Ripple (%)	Overshoot (%)	Response Time (s)
Liu et al. [37]	IC	~0.3	~3.2	~0.25
Al-Diab et al. [35]	P&O	~0.4	~4.0	~0.30
This Study	FL–P&O	0.05	2.3	0.10

FL-P&O, fuzzy logic–Perturb and Observe; MPPT, Maximum Power Point Tracking; P&O, Perturb and Observe; INC, incremental conductance

- maintains low computational overhead, making it suitable for low-cost embedded systems;
- uses only voltage and current sensors, avoiding dependency on irradiance or temperature measurements; and
- exhibits superior ripple reduction (0.05% vs. 0.4% in fixed-step P&O) and faster settling times under irradiance/temperature fluctuations, as proven in Section E.

In terms of sensor requirements, the proposed FL-based adaptive P&O algorithm maintains simplicity by relying only on voltage (V) and current (I) sensors—similar to the conventional P&O method. Unlike other recent approaches that require additional irradiance (G) or temperature (T) sensors to improve accuracy, the author's method achieves high tracking performance without increasing system complexity or cost. This makes it attractive for practical deployment in low-cost PV systems.

However, the proposed algorithm, like most fuzzy-based approaches, may require tuning of membership functions and rule bases when adapted to different PV technologies or converter topologies. This customization process, though not computationally intensive, could be considered a limitation in terms of generalizability without prior calibration.

VI. CONCLUSION

This research presents a novel enhancement to the classical P&O algorithm by integrating a FL controller equipped with an adaptive step size mechanism based on the $\Delta P/\Delta V$ ratio. The proposed FL–P&O approach enables dynamic adjustment of the PWM duty cycle, allowing the DC–DC boost converter to maintain precise operation near the Maximum Power Point (MPP) across a wide range of environmental conditions. The controller's architecture incorporates a customized fuzzy rule base and hybrid membership functions (trapezoidal and triangular), specifically designed to balance rapid convergence with minimal output ripple. This formulation enables the system to apply aggressive adjustments under significant deviations and fine-tuned corrections near the MPP, resulting in enhanced tracking accuracy. Extensive simulations in MATLAB/Simulink validated the system's superiority over the fixed-step P&O algorithm. The tests included two dynamic profiles: varying irradiance at constant temperature and varying temperature under constant irradiance. Results consistently demonstrated superior behavior in the proposed method, with reductions in ripple by 87.5%, overshoot by 43.9%, and response time by 60%, as detailed in Table II. Beyond quantitative gains, the algorithm proved robust under sudden atmospheric changes, showing reliable MPP convergence and minimal oscillation. These attributes not only improve energy harvesting efficiency but also extend the lifespan of system components by avoiding stress from power instability. The key findings of this study are

- dynamic step size adjustment driven by $\Delta P/\Delta V$ enables faster and smoother MPPT convergence;
- tailored fuzzy rule base and hybrid membership functions contribute to high robustness and stability;
- significant reduction in energy losses compared to the classical P&O method under all test scenarios.

Moreover, although partial shading conditions (PSCs) were not explicitly simulated in this study, the structure of the proposed FL-based variable step size P&O algorithm suggests high potential for handling such conditions. By adaptively adjusting the duty cycle based on fuzzy rules, the method can better distinguish true global peaks from local maxima, enhancing MPPT reliability under non-uniform irradiance. Future work will include experimental validation under PSC to confirm this potential.

While the current validation was simulation-based, the author acknowledges that this may limit the generalizability of the findings. Therefore, future work will involve hardware implementation in a physical PV system using embedded controllers to verify the method's real-world applicability, especially under conditions, such as partial shading, sensor noise, and low-light scenarios. The proposed flexible architecture also enables potential hybridization with AI-based optimizers for further adaptability.

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Declaration of Interests: The author has no conflicts of interest to declare.

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