

# AI-Enhanced Maximum Power Point Tracking for PV–Battery Systems: Modeling, Simulation, and Comparative Analysis

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**Abstract**—The integration of photovoltaic (PV) systems with energy storage is essential to ensure reliable power delivery under variable environmental conditions. A critical component in such systems is the maximum power point tracking (MPPT) controller, which directly influences overall efficiency. Conventional methods, such as Perturb and Observe (P&O), are widely used due to their simplicity but suffer from steady-state oscillations and slow response under rapidly changing irradiance. This paper presents a comparative study between a conventional P&O-based MPPT with multistage battery charging and an artificial intelligence (AI)-enhanced fuzzy logic MPPT integrated with the same charging strategy. System models of the PV array, DC-DC buck converter, and lithium-ion battery are developed to provide an accurate simulation framework. Results demonstrate that the fuzzy MPPT effectively mitigates oscillations, improves tracking efficiency, and ensures smoother battery charging profiles compared to the conventional approach, albeit with increased computational complexity and simulation time.

**Keywords**—Maximum Power Point Tracking (MPPT), Photovoltaic Systems, Fuzzy Logic Control, Multistage Battery Charging, Renewable Energy Storage

## I. INTRODUCTION

Solar photovoltaic (PV) technology has become increasingly central to renewable energy systems thanks to its scalability, decreasing costs, and suitability for both grid-connected and off-grid applications. The power output of PV panels, however, is inherently variable, depending sensitively on irradiance, temperature, and shading; such non-idealities complicate efforts to maintain efficient energy harvesting and stable system performance [1]. Maximum Power Point Tracking (MPPT) algorithms aim to ensure PV arrays operate at or near their maximum power point despite environmental fluctuations. [2] Among the simplest and most common are Perturb and Observe (P&O) and Incremental Conductance (INC), which require low computational effort and are straightforward to implement in hardware and simulation. However, P&O is especially known to create steady-state oscillations around the maximum power point and to respond slowly when irradiance changes rapidly, reducing harvested energy and sometimes mis-tracking the actual peak under non-uniform or changing conditions. [3]

Lithium-ion battery storage is often used in stand-alone or off-grid PV systems. Proper charging strategy is critical, not only for extracting usable energy efficiently but also for minimizing battery stress and aging. Multistage charging protocols such as constant current (CC), followed by constant voltage (CV), and ending with float or tapering phases are standard because they balance fast charging speed with battery safety and voltage constraints. [4] All of these strategies rely on accurate battery models that represent open-circuit voltage (OCV), internal resistance, and transient dynamics (e.g., via equivalent circuit / Thevenin / RC dual-polarization models). Crucially, the inherent power oscillations generated by conventional MPPT algorithms like P&O translate directly into current and voltage ripples at the battery terminals. Recent studies have quantified that these high-frequency micro-cycles significantly accelerate solid electrolyte interphase (SEI) layer degradation and reduce the overall efficiency of multistage charging protocols [5], [6].

To improve upon the limitations of conventional MPPT under dynamic conditions and mitigate the resulting electrical stress on battery storage, several artificial intelligence and

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heuristic methods have been explored. State-of-the-art reviews emphasize that Fuzzy Logic Controllers (FLCs) remain highly favorable for PV integration because they provide robust, model-free optimization without the massive training datasets required by deep learning approaches [7]. FLCs have been applied to adapt MPPT perturbation steps or make duty-cycle decisions in response to PV power or derivative signals; such controllers often reduce oscillations and improve tracking accuracy, particularly under variable irradiance or temperature transitions [8], [9]. The primary motivation for employing Fuzzy Logic in this study lies in its ability to translate the heuristic, rule-based logic of the P&O algorithm into smooth, continuous control actions without requiring an exact mathematical model of the highly non-linear PV system. Hybrid fuzzy-P&O or optimized fuzzy MPPTs have also been studied, and in many cases deliver better performance (lower oscillation, faster settling) but at a cost of additional implementation complexity or longer simulation/computation time [10]. By comparing a baseline conventional P&O + multistage charging strategy against an AI-enhanced fuzzy MPPT + multistage charger within an identical simulation model, this work examines trade-offs in charging time, energy harvesting, oscillation magnitude, and battery stress proxies. To address the gaps in existing comparative studies, the explicit scientific contributions of this paper are formulated as follows:

- Design and implementation of a targeted Fuzzy MPPT controller that utilizes the change in PV power ( $\dot{P}$ ) and voltage ( $\dot{V}$ ) to smoothly optimize duty cycle adjustments, effectively eliminating the steady-state oscillations inherent to conventional methods.
- A rigorous comparative simulation protocol that evaluates both controllers under extended dynamic conditions, moving beyond standard step-responses to quantify the actual State of Charge (SOC) progression and total accumulated energy transfer.
- An integrated analysis of MPPT performance on battery health, demonstrating qualitatively and quantitatively how the mitigation of MPPT-induced current ripples by the Fuzzy controller reduces electrical stress during multistage charging, thereby promoting long-term battery reliability.

The remainder of this paper is organized as follows. Section II presents related work on conventional and AI-based

MPPT strategies. Section III introduces the system modeling, including the PV module, DC-DC buck converter, and lithium-ion battery. Section IV details the control strategies, covering the perturb and observe algorithm, multistage charging, and fuzzy logic-based MPPT. Section V discusses the simulation results, comparing the performance of the conventional and AI-enhanced controllers. Finally, Section VI concludes the paper and highlights potential future directions toward hybrid intelligent optimization methods.

## II. RELATED WORK

Several studies have investigated improvements to photovoltaic power conversion through more efficient MPPT strategies. Conventional approaches such as Perturb and Observe (P&O) remain widely used but often suffer from oscillations and slower dynamic response under varying irradiance conditions [11]. To address these issues, fuzzy logic controllers have been widely applied, demonstrating faster convergence and improved stability compared with conventional methods [2], [9]. Hybrid approaches that combine fuzzy logic with traditional techniques have also been reported, achieving better adaptability under partial shading [12]. On the storage side, accurate battery modelling and charging strategies have been shown to directly influence system reliability. Advanced equivalent circuit models of lithium-ion batteries have been developed to improve estimation of state of charge and extend battery lifetime under multi-stage charging profiles [4], [13]. Within this context, our study builds upon these contributions by comparing a conventional P&O MPPT combined with a multi-stage charging strategy against an AI-enhanced fuzzy logic MPPT under realistic operating conditions. This comparison aims to highlight the practical trade-offs between simplicity and enhanced performance in PV–battery systems.

## III. SYSTEM MODELLING AND CHARACTERISTICS

The proposed system as in Figure (1) consists of a PV panel connected through a protection diode and a smoothing capacitor to a DC-DC buck converter. The converter is controlled by a maximum power point tracking (MPPT) algorithm; either Perturb and Observe (P&O) or Fuzzy Logic Control (FLC) to regulate the duty cycle of the IGBT switch. The regulated output charges a lithium-ion battery, which serves as the storage element. The overall configuration ensures maximum power extraction from the PV source while maintaining efficient and stable battery charging.

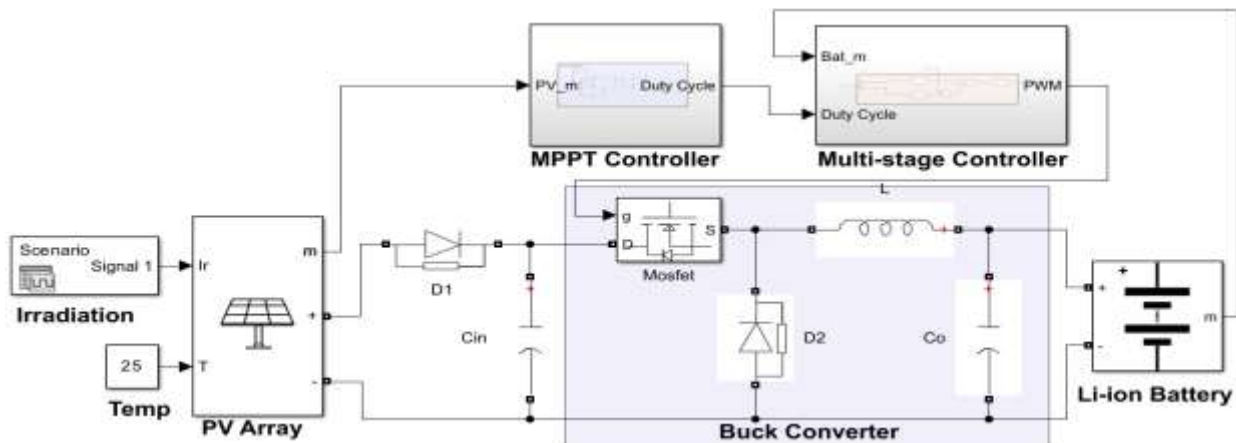


Fig. 1. Block diagram of the simulated standalone PV–battery system

### A. Photovoltaic Panel

The operation of solar cells is based on the photovoltaic effect, a phenomenon first observed by Edmond Becquerel in 1839, in which photons incident on a semiconductor material excite electrons from the valence band to the conduction band, generating electron-hole pairs [14]. When these charge carriers are separated by the internal electric field of the p-n junction, a photocurrent is produced. This fundamental process underlies all modern photovoltaic (PV) technologies.

A basic PV cell can be represented by an equivalent circuit consisting of a current source in parallel with a diode, along with a series resistance  $R_s$  (representing ohmic losses in the contacts and semiconductor) and a shunt resistance  $R_{sh}$  (accounting for leakage currents) [15]. The simplified equivalent circuit model is shown in Figure (2).

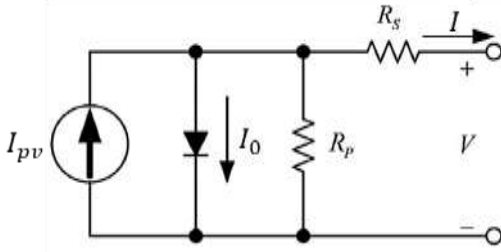


Fig. 2. PV cell equivalent circuit diagram

The output current-voltage (I) relationship of a PV cell is generally expressed by the single-diode equation:

$$I = I_{pv} - I_0 \left( e^{\frac{q(V+IR_s)}{NkT}} - 1 \right) - \frac{V+IR_s}{R_p} \quad (1)$$

where  $I_{pv}$  is the photo-generated current (proportional to irradiance),  $I_0$  is the diode saturation current,  $q$  is the electron charge,  $N$  is the diode ideality factor,  $k$  is Boltzmann's constant, and  $T$  is the cell temperature in Kelvin [16].

For a PV module composed of  $N_s$  series-connected cells and  $N_p$  parallel strings, the model can be generalized as:

$$I = N_p I_{ph} - N_p I_0 \left[ \exp \left( \frac{q \left( V + I \frac{N_s}{N_p} R_s \right)}{N_s k T} \right) - 1 \right] - \frac{V + I \frac{N_s}{N_p} R_s}{\frac{N_s}{N_p} R_p} \quad (2)$$

This model captures the nonlinear behavior of PV arrays, enabling accurate simulation of power output under varying irradiance and temperature [17].

The corresponding power is simply given by:

$$P_{pv} = V \times I \quad (3)$$

Yielding the well-known P-V characteristic curve, which exhibits a single maximum power point (MPP) under uniform conditions. Variations in irradiance shift the curve vertically (scaling  $I_{ph}$ ), while temperature mainly influences the open-circuit voltage ( $V_{oc}$ ), reducing the MPP voltage as temperature increases [18].

Such modelling is essential for designing control strategies like MPPT, which must continuously adapt to track the dynamic maximum power point as environmental conditions change.

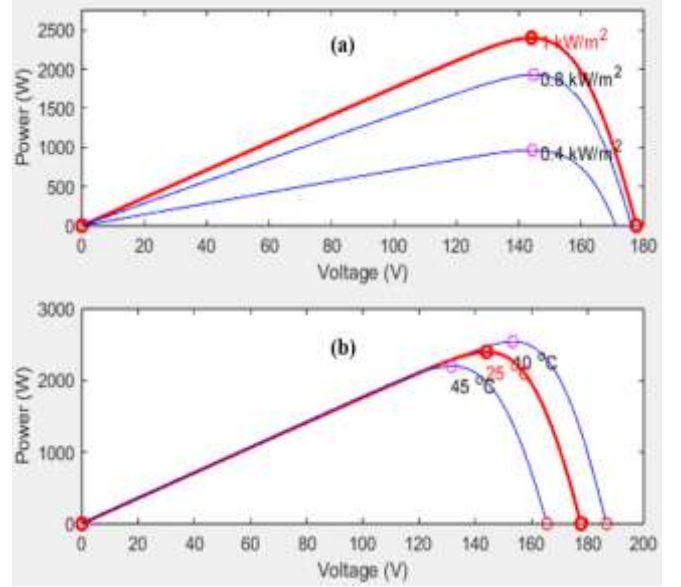


Fig. 3. characteristic curves of the PV array used with 2 parallel strings and 4 series-connected modules per string (a) mpp at different irradiance levels, (b) mpp at different temperatures

### B. DC-DC Converter

In PV-battery systems, a DC-DC converter is typically used to regulate the voltage and current delivered from the PV array to the storage element. [19] Among the available topologies, the buck converter is widely adopted due to its simplicity, efficiency, and suitability for charging batteries where the PV voltage is often higher than the battery voltage. A buck converter consists of a controlled switch (MOSFET or IGBT), a diode, an inductor, and an output capacitor. By adjusting the duty cycle of the switch, the converter steps down the input voltage to a desired lower output voltage. The ideal voltage conversion ratio is given by:

$$V_0 = D \cdot V_s \quad (4)$$

Where  $V_0$  is the output voltage,  $V_s$  is the input (PV) voltage, and  $D$  is the duty cycle of the switching signal, with  $0 \leq D \leq 1$  [20]

The average output current can similarly be expressed as:

$$I_0 = \frac{I_s}{D} \quad (5)$$

With  $I_s$  representing the input current. In continuous conduction mode (CCM), the inductor current never falls to zero, and the converter dynamics are described by:

$$L \frac{di_L}{dt} = V_s D - V_0 \quad (6)$$

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$$C \frac{dV_0}{dt} = i_L - \frac{V_0}{R_{load}} \quad (7)$$

Where  $L$  is the inductor value,  $C$  is the output capacitor, and  $R_{load}$  is the equivalent resistance of the load (or battery input)

When connected to a PV system, the buck converter also acts as the interface for MPPT algorithms. The duty cycle  $D$  is continuously adjusted by the MPPT controller (e.g., P&O, fuzzy logic) to ensure that the PV operates at its maximum power point. Thus, the converter's switching function directly governs both power transfer efficiency and dynamic response. Modern implementations also consider non-idealities such as switch voltage drops, diode reverse recovery, and parasitic resistances, which slightly modify the ideal transfer function. However, under most MPPT control simulations, the ideal buck model provides sufficient accuracy.

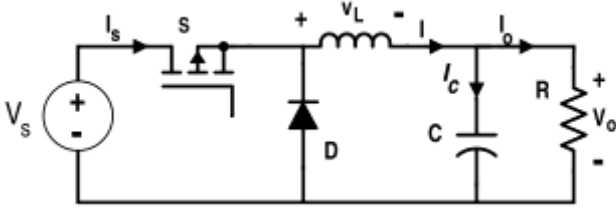


Fig. 4. DC-DC Buck Converter circuit diagram with load

### C. Lithium-Ion Battery

Lithium-ion batteries (LIBs) are the preferred choice for photovoltaic (PV) energy storage systems due to their high energy density, low self-discharge rate, and long cycle life compared to lead-acid and nickel-based chemistries [21]. In PV applications, the battery not only stores excess energy but also stabilizes system operation during irradiance fluctuations and load variations. The most widely used mathematical representation of a lithium-ion cell is the Thevenin-based equivalent circuit model (Figure 5). It typically consists of an open-circuit voltage (OCV) source, an internal resistance  $R_0$ , and one or more RC networks to capture transient dynamics [4].

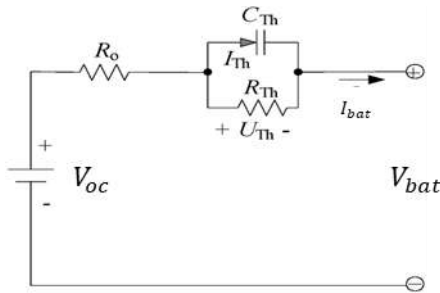


Fig. 5. Thevenin circuit diagram of lithium-ion battery cell

$$V_{bat} = V_{OC}(SOC) - I_{bat}R_0 - \sum_{i=1}^n V_{RC,i} \quad (8)$$

Where:

- $V_{bat}$  is the terminal voltage,
- $V_{OC}(SOC)$  is the open-circuit voltage as a function of the state of charge (SOC),
- $I_{bat}$  is the battery current (positive during discharge, negative during charge),

- $R_0$  is the ohmic resistance,
- $V_{RC,i}$  represents the voltage drop across each RC pair.

This model balances accuracy and simplicity, making it suitable for real-time simulation and control applications [22].

SOC is a key indicator of battery health and available capacity, typically defined as:

$$SOC(t) = SOC(0) - \frac{1}{C_{nom}} \int_0^t I_{bat}(\tau) d\tau \quad (9)$$

Where  $C_{nom}$  is the nominal battery capacity (Ah). SOC estimation is essential for energy management, since overcharging ( $>100\%$  SOC) or deep discharging ( $<20\%$  SOC) can significantly reduce the lifespan of lithium-ion batteries [23]. The OCV is a nonlinear function of SOC, often obtained experimentally through charge–discharge tests. For lithium-ion batteries, the OCV curve is relatively flat in the mid-SOC range (30–80%) but becomes steep at low and high SOC levels, which complicates accurate SOC estimation [24].

An empirical relationship can be expressed as:

$$V_{OC}(SOC) = a_0 + a_1 SOC + a_2 SOC^2 + a_3 SOC^3 \quad (10)$$

Where coefficients  $a_i$  are determined through curve fitting [25].

Lithium-ion batteries experience capacity fade and internal resistance growth over repeated cycles, influenced by temperature, relative charge/discharge currents (C-rate), and depth of discharge. Round-trip efficiency typically ranges between 90–95%, depending on operating conditions. While aging models can be integrated for long-term studies, in most MPPT and charging simulations a first-order ECM with SOC dynamics is sufficient.

## IV. CONTROL STRATEGIES

### A. Perturb and Observe (P&O) MPPT

The Perturb and Observe (P&O) algorithm is one of the most widely used maximum power point tracking (MPPT) techniques due to its simplicity and low computational requirements. The principle is based on perturbing the operating voltage (or duty cycle of the DC-DC converter) and observing the corresponding change in output power of the PV module. If the power increases after perturbation, the operating point is moved further in the same direction; otherwise, it is reversed [26]. The change in PV power can be expressed as:

$$\Delta P = P(k) - P(k-1) \quad (11)$$

With  $k$  being the iteration index. The decision logic is summarized as follows [27]

- If  $\Delta P > 0$  and  $\Delta V > 0 \rightarrow$  increase duty cycle.
- If  $\Delta P > 0$  and  $\Delta V < 0 \rightarrow$  decrease duty cycle.
- If  $\Delta P < 0$  and  $\Delta V > 0 \rightarrow$  decrease duty cycle.
- If  $\Delta P < 0$  and  $\Delta V < 0 \rightarrow$  increase duty cycle.

This iterative process pushes the PV system toward the maximum power point (MPP). A typical block diagram of the P&O algorithm is shown in Figure 6.

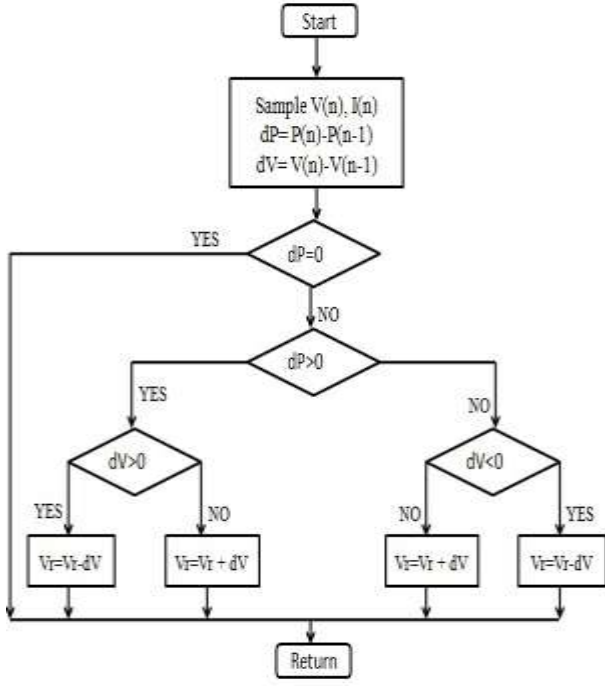


Fig. 6. MPPT Perturb and Observe block diagram

Despite its simplicity, the main drawback of P&O is the oscillation around the MPP under steady-state conditions and its relatively slow dynamic response under rapidly changing irradiance. These limitations motivate the use of enhanced strategies such as multi-stage charging and artificial intelligence-based controllers, which are discussed in the following sections.

### B. Multi-Stage Charging

Lithium-ion batteries require carefully managed charging strategies to ensure safety, extend cycle life, and optimize performance [23]. A multi-stage charging profile is typically adopted, consisting of constant current (CC), constant voltage (CV), and trickle/discharge balancing stages.

1) *Constant Current (CC) Stage*: In the first stage, the battery is charged with a fixed current  $I_{ch}$ , while the voltage gradually increases until it reaches the predefined cut-off voltage  $V_{CV}$ . The governing equation is:

$$V_b(t) = V_{oc}(SOC) + R_{int} \cdot I_{ch} \quad (12)$$

Where  $V_{oc}(SOC)$  is the open-circuit voltage as a function of state of charge (SOC), and  $R_{int}$  is the internal resistance of the cell [28]

2) *Constant Voltage (CV) Stage*: Once the terminal voltage reaches  $V_{CV}$ , the charging mode switches to constant voltage. The current then decreases exponentially as the battery approaches full charge:

$$I_b(t) = I_0 \cdot e^{-t/\tau} \quad (13)$$

Where  $I_0$  is the initial current at the beginning of CV stage, and  $\tau$  is the time constant determined by cell chemistry [29].

3) *Trickle/Equalization Stage*: In some applications, a final balancing or trickle charge stage is applied to ensure all cells in the pack reach uniform SOC. This is particularly important in series-connected packs to prevent capacity mismatch [30].

### C. Fuzzy Logic-Based MPPT

Fuzzy logic control (FLC) has been widely adopted in renewable energy systems due to its ability to handle nonlinearities, parameter uncertainties, and noisy measurements without requiring an exact mathematical model [31].

Unlike conventional P&O, which follows a fixed step-size perturbation, fuzzy logic can adapt its control actions dynamically, reducing oscillations around the maximum power point (MPP) and improving transient response. A fuzzy logic MPPT system typically consists of three stages: fuzzification, inference engine, and defuzzification [32].

In Fuzzification, Input variables, usually change in PV power ( $\Delta P$ ) and change in PV voltage ( $\Delta V$ ), are mapped into linguistic variables such as Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Big (PB) using membership functions. For example:

$$\Delta P = P(k) - P(k-1), \Delta V = V(k) - V(k-1) \quad (14)$$

Inference Engine is A set of IF-THEN rules govern the control action. An example rule is:

IF ( $\Delta P$  is PB) AND ( $\Delta V$  is NS) THEN (Duty cycle is ZE).

While in defuzzification, the fuzzy output (change in duty cycle,  $\Delta D$ ) is converted into a crisp value using methods like the centroid method:

$$\Delta D = \frac{\sum_i \mu_i \cdot d_i}{\sum_i \mu_i} \quad (15)$$

Where  $\mu_i$  is the membership degree and  $d_i$  is the corresponding output value.

Several studies have shown that fuzzy logic-based MPPT improves both tracking efficiency and system stability compared to conventional methods.

## V. RESULTS AND DISCUSSION

### A. Simulation Setup

The proposed PV system with battery storage was simulated in MATLAB/Simulink to evaluate the performance of the conventional perturb-and-observe (P&O) and the proposed fuzzy logic-based MPPT controllers. The PV array consists of 300 W modules arranged in a 4-series by 2-parallel configuration, interfaced with a DC-DC buck converter operating at a 1000 Hz switching frequency.

The complete PV panel, battery, and buck converter parameters are listed in Tables I–III.

TABLE I. PV MODULE SPECIFICATIONS

Parameter	Value
Cells per module	72
Maximum Power ( $P_{max}$ )	300 W
Open Circuit Voltage ( $V_{oc}$ )	44.4 V
Short Circuit Current ( $I_{sc}$ )	8.9 A
Nominal Voltage ( $V_{mpp}$ )	36 V
Nominal Current ( $I_{mpp}$ )	8.33 A

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TABLE II. LITHIUM-ION BATTERY SPECIFICATIONS

Parameter	Value
Nominal Voltage	48 V
Capacity	100 Ah
Initial SOC	50 %
Maximum Voltage	55.87 V
Minimum Voltage	36 V

TABLE III. BUCK CONVERTER PARAMETERS

Parameter	Value
Inductor (L)	8.04 mH
Capacitor (C)	330 $\mu$ F
Switching Frequency	1000 Hz
Duty Cycle Range	0.4 - 0.6

To ensure a rigorous comparative evaluation, a continuous simulation horizon of 50 seconds was considered. Due to the heavy computational load of the high-frequency switching model, this duration effectively corresponds to several minutes of real system operation. Crucially, rather than relying solely on steady-state conditions, the system was subjected to dynamic step-changes and ramp-variations in solar irradiance. Both controllers were evaluated under these identical dynamic profiles to allow for an accurate, fair comparison of transient tracking speeds, steady-state ripples, and overall battery State of Charge (SOC) progression.

Regarding the fuzzy approach, a Mamdani-type Fuzzy Inference System (FIS) was designed to evaluate the change in PV power ( $dP_{pv}$ ) and voltage ( $dV_{pv}$ ) to output the required duty cycle adjustment ( $\Delta D$ ). To ensure reproducibility, the FLC parameters are explicitly defined: the input ranges are set to  $[-30, 30]$  for ( $dP_{pv}$ ) and  $[-16.1, 16.1]$  for ( $dV_{pv}$ ), with the output symmetrically bounded at  $[-16.1, 16.1]$ . Five linguistic variables (NB, NS, ZE, PS, PB) utilizing standard triangular membership functions (trimf) map the inputs to a 25-rule control base shown in figures (7-8) and Table IV. Finally, the Center of Gravity (Centroid) method is used to defuzzify the output into a continuous control signal.

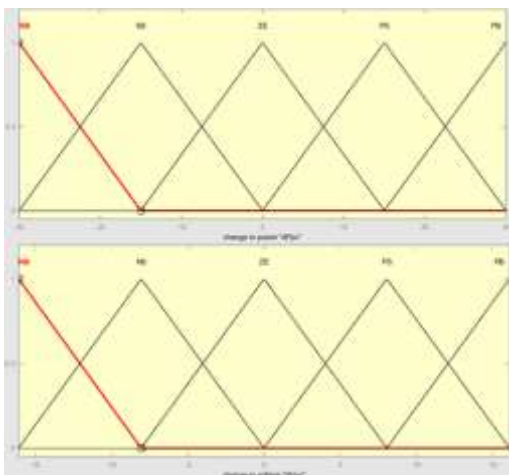


Fig. 7. Membership functions of input variables

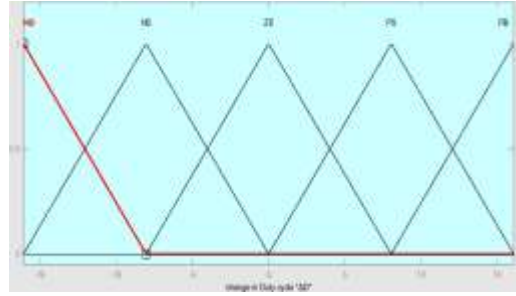


Fig. 8. Membership functions of output variable

TABLE IV. PROPOSED FUZZY CONTROL RULES

$dP_{pv} \setminus dV_{pv}$	NB	NS	ZE	PS	PB
NB	PS	PB	NB	NB	NS
NS	PS	PS	NS	NS	NS
ZE	ZE	ZE	ZE	ZE	ZE
PS	NS	NS	PS	PS	PS
PB	NS	NB	PB	PB	PS

## B. Performance Metrics

To compare the controllers, the following indices were used:

- Tracking Efficiency ( $\eta_{MPPT}$ )

$$\eta_{MPPT} = \frac{P_{tracked}}{P_{mpp}} \times 100 \quad (16)$$

- SOC Progression: battery charging progress during the simulation window.
- Oscillation Behaviour: quantified by the ripple in charging current and voltage.
- Charging Time Reduction (hypothetical long-term projection):

$$\%Reduction = \frac{T_{P\&O} - T_{Fuzzy}}{T_{P\&O}} \times 100 \quad (17)$$

## C. Simulation Results

To evaluate the dynamic tracking capabilities of the proposed MPPT control strategies, a highly variable solar irradiance profile was applied to the PV array, as illustrated in Figure (9). The figure displays both the programmed reference sequence (a) and the actual measured irradiance at the PV array input (b), accounting for the physical dynamics of the simulation environment. This profile includes sudden step drops and gradual ramps to simulate fast-moving cloud cover and slow shading. This irradiance variation serves as the direct cause for the dynamic fluctuations observed in the system's subsequent power, voltage, and current responses.

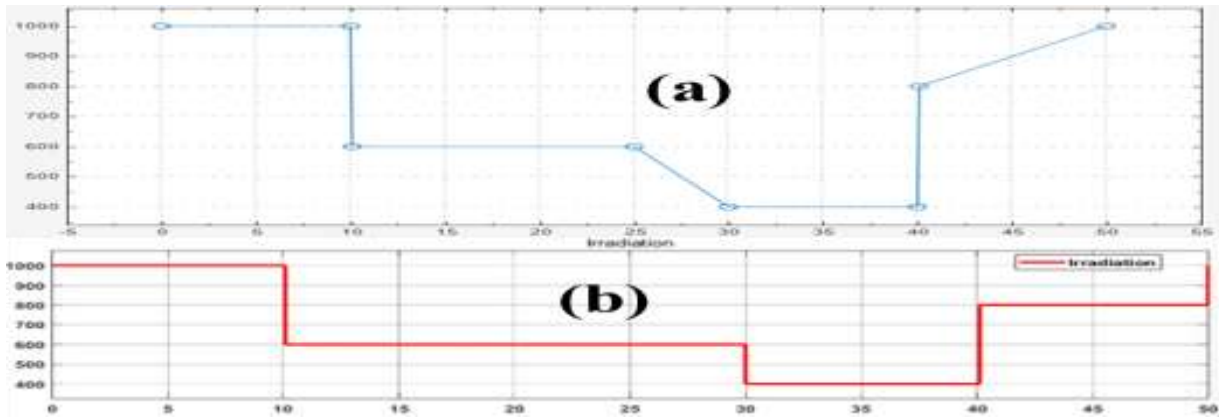


Fig. 9. Dynamic solar irradiation profile applied to the PV system

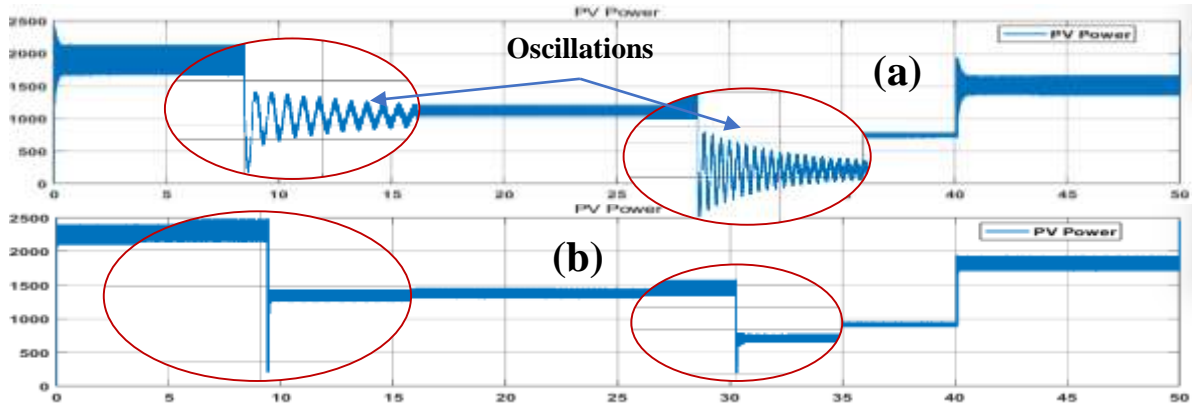


Fig. 10. PV power signal showing oscillations for (a) P&O controller, and less for (b) FLC controller

1) *PV Power Response:* Figure (10) illustrates the PV power tracking response under both the P&O and fuzzy logic MPPT control strategies. While the theoretical maximum power target remains similar for both methods, an analysis of the waveforms reveals stark differences in steady-state stability and transient tracking. The conventional P&O method exhibits continuous, pronounced power oscillations around the Maximum Power Point (MPP), a recognized drawback of its inherent fixed-step perturbation logic. In contrast, the proposed fuzzy logic MPPT dynamically adjusts the duty cycle based on the  $dP_{pv}$  and  $dV_{pv}$  inputs, resulting in a visible and significant dampening of these steady-state oscillations. Furthermore, during dynamic irradiance variations, the fuzzy controller achieves a markedly faster transient settling response without overshooting, compared to the delayed response of the P&O algorithm. This suppression of oscillatory behavior directly minimizes the dynamic power losses inherent to continuous P&O perturbations, ensuring a highly stable, efficient, and sustained power delivery to the battery system.

2) *Duty Cycle Dynamics:* Figure (11) compares the control effort specifically the duty cycle ( $\Delta D$ ) responses generated by both the P&O and fuzzy logic controllers. The conventional P&O algorithm produces a continuous, triangular tracking trajectory, which is a direct manifestation of its constant-step perturbation mechanism perpetually searching around the MPP. In contrast, the fuzzy logic controller generates a more discrete, step-like waveform characterized by sharper transient transitions. This behavior reflects the rapid, non-linear mapping of the fuzzy inference

system as it aggressively scales the duty cycle step size in response to the dynamic  $dP_{pv}$  and  $dV_{pv}$  inputs. While these instantaneous control transitions can introduce higher switching activity in the DC-DC buck converter potentially increasing localized electromagnetic interference (EMI) this represents a necessary control trade-off. The primary advantage of this aggressive, rule-based adjustment is that the fuzzy controller rapidly forces the system to the optimal operating point and immediately locks the duty cycle. This completely eliminates the perpetual steady-state hunting seen in the P&O method, yielding significantly improved steady-state accuracy.

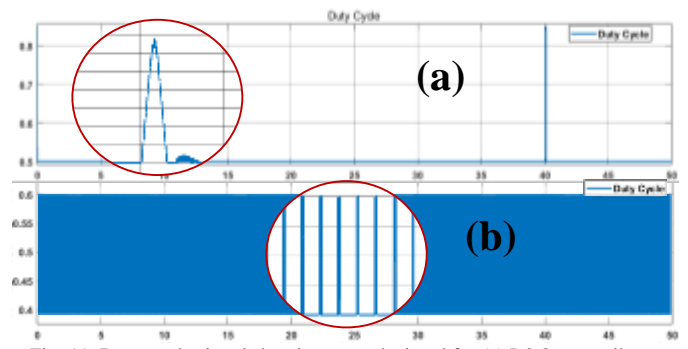


Fig. 11. Duty cycle signal showing smooth signal for (a) P&O controller, and step-like signal for (b) FLC controller

3) *Battery SOC, Current and Voltage:* Figures (12-13) present the charging behavior of the battery. Under P&O control, the battery current shows pronounced oscillations, with ripple reflected in the voltage profile as well. This oscillatory behavior not only reduces charging efficiency but

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also introduces additional electrical stress on the battery and converter components. In contrast, the fuzzy controller yielded a smoother charging process. Both current and voltage curves show significantly reduced ripple, indicating more stable charging conditions. This difference is a key advantage of fuzzy control, particularly for battery life extension and system reliability. Furthermore, by utilizing a 50s simulation horizon to capture the accumulated energy transfer, a distinct difference in the State of Charge (SOC) progression ( $\Delta$ SOC) was observed. Under P&O control, the

battery SOC increased from 50% to 50.33%. Conversely, the proposed fuzzy controller achieved a higher charging rate, increasing the SOC from 50% to 50.40%. This quantifiable increase in accumulated charge, combined with the smoother current and voltage delivery, confirms that the fuzzy controller provides superior charging quality, minimizes hardware wear, and maximizes overall long-term energy efficiency.

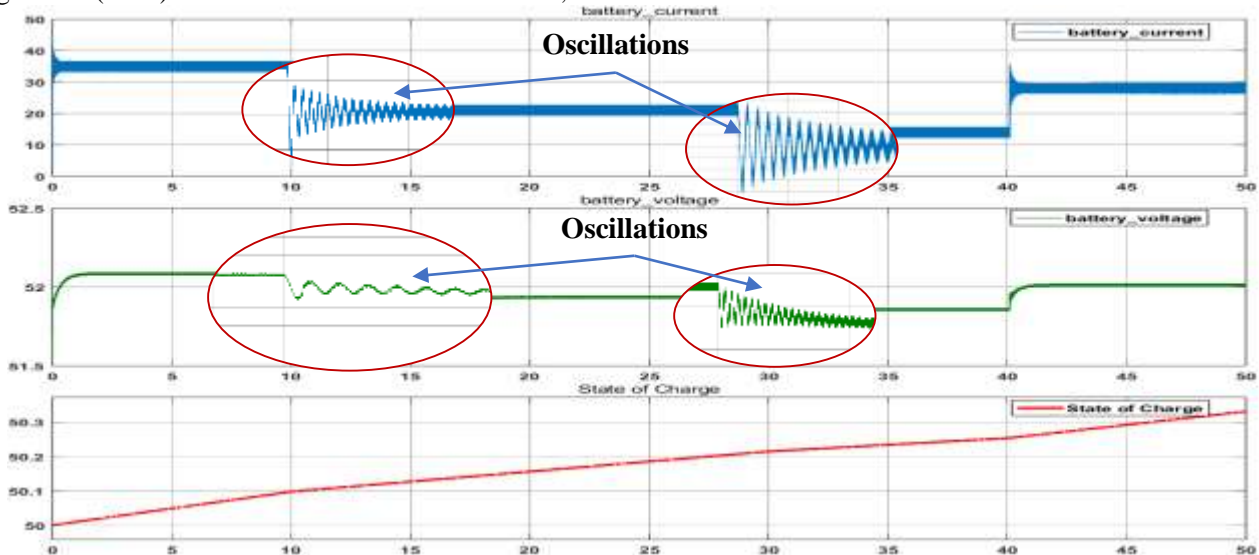


Fig. 12. Battery charging SOC, current and voltage under P&O MPPT showing significant oscillations.

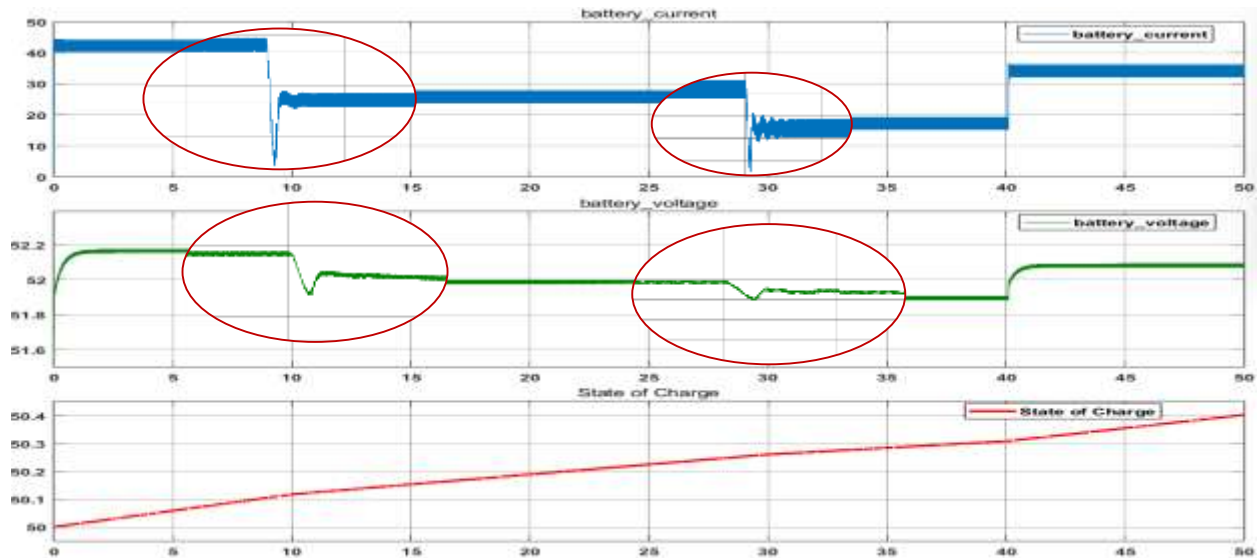


Fig. 13. Battery charging SOC, current and voltage under fuzzy MPPT with reduced ripple.

### D. Comparative Analysis

The results demonstrate that although both methods extract similar PV power, the fuzzy controller ensures higher charging quality by reducing oscillations in both current and voltage. This has two major implications:

- **Efficiency:** smoother duty cycle transitions minimize unnecessary switching losses.
- **Battery Health:** reduced current ripple decreases thermal and electrochemical stress on the cells, extending battery life.

Table V shows the battery charging behavior when using the MPPT P&O and fuzzy MPPT algorithms. Table VI compares the performance metrics obtained with these two algorithms.

TABLE V. BATTERY CHARGING BEHAVIOR

Controller	Initial SOC (%)	Final SOC (%)	$\Delta$ SOC (%)
P&O MPPT	50.00	50.33	+0.33
Fuzzy MPPT	50.00	50.40	+0.40

TABLE VI. COMPARATIVE PERFORMANCE METRICS

Metric	P&O MPPT	Fuzzy MPPT
Tracking Efficiency (%)	~96	~97.5
SOC Progression (%)	0.33	0.40
Battery Current Oscillation (App)	High (~1–2 A)	Low (~0.3–0.5 A)
Battery Voltage Oscillation (Vpp)	Noticeable (~1 V)	Minimal (~0.2 V)
PV Power Oscillation (Wpp)	Noticeable	Significantly lower
Duty Cycle Ripple (%)	Low (smooth)	High (step-like)

## VI. CONCLUSION

This work presented a comparative study between a conventional Perturb and Observe (P&O) maximum power point tracking (MPPT) algorithm combined with a multi-stage charging controller, and an artificial intelligence (AI) enhanced fuzzy logic MPPT integrated with the same charging strategy. The analysis focused on battery voltage, current, and state of charge (SOC) under identical operating conditions.

The results demonstrated clear quantitative and qualitative advantages of the proposed AI-enhanced approach. By extending the simulation horizon, significant differences in energy harvesting emerged; the fuzzy logic MPPT achieved a higher SOC progression ( $\Delta SOC = 0.40\%$ ) compared to the conventional P&O method ( $\Delta SOC = 0.33\%$ ). Furthermore, the fuzzy logic MPPT effectively eliminated the steady-state oscillations observed in the battery current and voltage under the P&O method. This stable, oscillation-free tracking translates directly to smoother charging behavior, reduced electrical and thermal stress on the battery cells, and consequently, an enhanced expected battery lifespan. However, this benefit comes at the cost of higher computational burden and control complexity, highlighting a critical trade-off for system designers.

While the scientific contributions of this study are currently established through a simulation framework, this methodology was essential to safely isolate and quantify the high-frequency electro-thermal stress proxies (voltage and current ripples) without risking irreversible degradation to physical lithium-ion cells. Overall, the study confirms that fuzzy logic-based MPPT provides superior control performance over the traditional P&O method, proving that AI-based control strategies hold strong potential for advancing renewable energy storage systems where long-term battery reliability is paramount. Future work will focus on bridging the gap between simulation and practical implementation through Hardware-in-the-Loop (HIL) testing [33] and physical experimental validation to confirm these advantages in real-world environments, alongside exploring hybrid optimization models such as Particle Swarm Optimization (PSO) or Artificial Neural Networks (ANN).

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