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## **A Review and Comparative Analysis of Maximum Power Point Tracking Techniques in Solar Photovoltaic Systems**

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### **ABSTRACT**

Solar photovoltaic (PV) systems have become one of the fastest-growing sources of electricity worldwide, yet a recurring challenge in their operation is ensuring that the module always works at its peak output. This peak shifts continuously with sunlight intensity and temperature, which is why Maximum Power Point Tracking (MPPT) controllers are built into virtually every grid-tied and off-grid inverter today. The choice of MPPT algorithm, however, is not trivial it affects efficiency, hardware cost, and how well the system handles sudden changes in weather. This paper examines four techniques that appear most frequently in both academic literature and commercial hardware: Perturb and Observe (P&O), Incremental Conductance (INC), Fuzzy Logic Control (FLC), and Artificial Neural Network (ANN)-based MPPT. Each method is reviewed in terms of its operating principle, tracking accuracy, speed of convergence, implementation cost, and response under partial shading. Structured comparison tables are included to make the differences concrete. The findings indicate that while P&O and INC cover the needs of most low-cost applications adequately, the intelligent methods FLC and ANN offer clear advantages in plants where variable weather and partial shading are regular occurrences.

**Keywords:-** MPPT, Solar Photovoltaic, Perturb and Observe, Incremental Conductance, Fuzzy Logic Control, Artificial Neural Network, Renewable Energy

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## INTRODUCTION

Global electricity demand keeps rising, and fossil fuel-based generation is under growing pressure to shrink its share. Solar PV has stepped into this gap faster than most analysts predicted a decade ago installed capacity worldwide crossed 1 TW in 2022, and India alone added roughly 15 GW in that same year [1]. Falling module prices have made rooftop and utility-scale solar economically attractive without subsidy in many regions, which means the engineering community now faces the practical challenge of squeezing maximum output from every panel installed.

The difficulty is that a PV module does not deliver a fixed voltage or current. Its power-voltage characteristic has a single peak called the maximum power point (MPP) that shifts whenever irradiance or cell temperature changes. A converter connected directly to the module will settle at whatever operating point the load dictates, and this is rarely the MPP. MPPT algorithms solve this by continuously adjusting the converter's duty cycle to keep the operating point at or near the peak. Even a modest improvement in tracking performance translates to real energy gains over the lifetime of an installation [2].

A wide range of MPPT methods exists in the literature, from straightforward hill-climbing routines to nature-inspired global optimisers. In practice, however, four techniques dominate actual deployments: Perturb and Observe (P&O), Incremental Conductance (INC), Fuzzy Logic Control (FLC), and Artificial Neural Network (ANN)-based MPPT. They represent a clear progression from simple and cheap to sophisticated and accurate, and comparing them systematically is useful for anyone specifying a solar system [3], [15].

This paper is structured as follows. Section 2 reviews related published work. Section 3 describes how each of the four

techniques works. Section 4 provides a comparative analysis supported by tables. Section 5 discusses practical guidance for algorithm selection. Section 6 states the conclusions.

## LITERATURE REVIEW

The foundational survey by Esham and Chapman [4] remains the most comprehensive early comparison of MPPT techniques, covering nineteen algorithms and evaluating them across hardware requirements, tracking speed, and complexity. One of their clearest conclusions was that no single method outperforms all others on every metric a finding that continues to hold and that motivates the kind of structured comparison presented here.

Hussein et al. [5] introduced the Incremental Conductance algorithm and validated it under rapidly varying irradiance profiles meant to simulate partly cloudy skies. Their experimental results showed consistently lower steady-state error compared to P&O under these dynamic conditions, though under slowly varying irradiance the two methods behaved similarly.

Femia et al. [9] took a closer look specifically at P&O and identified the relationship between perturbation step size and tracking performance. Steps set too large prevent convergence; steps set too small produce sluggish tracking. They proposed a calibration approach tied to the actual P-V curve of the module in use, which measurably reduced oscillation losses in hardware tests. Abdelsalam et al. [13] extended this work to microgrid-connected PV systems and developed an adaptive version of P&O that adjusts the step size dynamically based on measured irradiance slope.

Koutroulis et al. [6] investigated fuzzy logic-based MPPT on a microcontroller

platform and showed that a well-designed rule base produces faster settling and smaller steady-state oscillation than a fixed-step P&O controller, without requiring any model of the PV module. Separate hardware studies confirmed these findings across different module types and climatic conditions.

On the INC side, Safari and Mekhilef [10] demonstrated a direct-control INC implementation using a Cuk converter and reported tracking efficiencies above 98% over a wide irradiance range. Elgendy et al. [11] subsequently carried out a careful experimental assessment of INC under field conditions and noted that while INC's theoretical advantage over P&O is real, the margin narrows significantly when ADC resolution is limited. Liu et al. [14] proposed a variable step-size variant of INC that maintains good tracking speed while reducing oscillation at the MPP.

Neural network approaches to MPPT were explored by Veerachary et al. [7], who demonstrated that a trained feed-forward ANN could locate the MPP with very high accuracy and respond within a fraction of the time needed by hill-climbing methods. The main practical constraint identified was the need for representative training data and periodic retraining.

Lian et al. [8] and Hadji et al. [12] explored hybrid approaches combining conventional local trackers with global search algorithms useful for partial shading but at the cost of greater computational overhead. Liu et al. [15] presented a broader algorithmic overview of advanced MPPT control strategies and identified ANN-based methods as the most promising direction for large-scale grid-connected plants.

The present paper draws on all of this prior work to build a structured side-by-side comparison that is practical rather than

exhaustive. The focus is on the four techniques most likely to be encountered in real hardware, evaluated against criteria that matter in engineering decisions.

## **OVERVIEW OF MPPT TECHNIQUES**

### **Perturb and Observe (P&O)**

P&O is built on a simple idea: nudge the operating voltage up or down by a small fixed amount, then check what happened to output power. If power went up, keep moving in the same direction. If power went down, reverse direction. Repeat this every sampling interval and the operating point will converge on the MPP [4].

The method requires only a voltage sensor and a current sensor, which makes it cheap and straightforward to implement on even an 8-bit microcontroller. It has been in production inverters for decades and its behaviour is well understood. The downside is that the operating point never truly stops oscillating it keeps nudging back and forth around the MPP even under stable sunshine, wasting a small fraction of potential output continuously.

A more serious issue arises during fast-moving clouds: as irradiance rises quickly, the algorithm can mistake the power increase from better sunlight for a confirmation that its last perturbation was correct, and briefly track in the wrong direction [9], [13]. Perturbation step size is also a design compromise large steps respond faster but oscillate more; small steps oscillate less but track sluggishly.

### **Incremental Conductance (INC)**

INC is grounded in calculus rather than trial-and-error. The power delivered by a PV module peaks where  $dP/dV = 0$ . Expanding this using the product rule gives the condition  $I + V(dI/dV) = 0$ , which can be rewritten as  $dI/dV = -I/V$ . The algorithm evaluates this condition at each sample: if instantaneous conductance

(I/V) equals incremental conductance ( $dI/dV$ ) in magnitude, the operating point is at the MPP and should stay put; otherwise, the sign of the difference indicates which direction to move [5].

Because INC stops perturbing once it finds the MPP, steady-state oscillation can theoretically reach zero a meaningful advantage over P&O. In practice, measurement noise means some residual oscillation remains, but it is considerably smaller.

The cost is a more demanding hardware implementation: reliable computation of  $dI/dV$  requires higher ADC resolution, particularly at low irradiance where the current signal is small and noise becomes proportionally significant [10], [11]. A variable step-size version can improve both speed and accuracy by adjusting the perturbation magnitude based on how far the operating point is from the MPP [14].

#### **Fuzzy Logic Control (FLC)-Based MPPT**

Fuzzy logic controllers handle the MPPT problem differently. Rather than computing a precise mathematical condition, they translate the current state of the system into linguistic terms and apply expert-defined rules to decide the next action. Two input variables are typically used: the error term  $E = \Delta P/\Delta V$  (the slope of the P-V curve at the current point) and its rate of change  $\Delta E$  from one sample to the next.

These are mapped to linguistic levels such as negative large, negative small, zero, positive small, and positive large. A rule base then maps each combination of input levels to an output duty cycle change for example, 'if E is positive-small and  $\Delta E$  is zero, then increase duty cycle by a small amount' [6]. Five to seven levels per variable are common, producing rule tables with 25 to 49 entries.

The main attraction of this design is robustness: because no analytical model of the PV module is involved, the controller handles parameter variations, module ageing, and manufacturing tolerances gracefully. Dynamic response is typically faster than P&O or INC, and oscillation at the MPP is much reduced.

The significant limitation is that the membership functions and rule base have to be tuned for a specific system configuration there is no standard procedure, and a poorly tuned FLC performs worse than a well-set P&O. Getting the design right takes engineering effort and, ideally, hardware testing [3].

#### **Artificial Neural Network (ANN)-Based MPPT**

ANN-based MPPT takes a data-driven approach. A feed-forward neural network typically with one or two hidden layers is trained offline on a dataset that maps measured conditions (usually irradiance G and cell temperature T) to the corresponding MPP voltage  $V_{mpp}$  or optimal duty cycle. Once trained, the network can predict the MPP location directly from sensor readings without any iterative search [7].

This gives ANN-based MPPT its main advantage: tracking speed is bounded only by the sensor and computation loop, not by the convergence dynamics of a hill-climbing algorithm. Under rapidly changing irradiance, a well-trained ANN can follow the MPP with negligible lag. Accuracy depends heavily on the diversity and coverage of the training dataset a network trained on a narrow range of conditions will extrapolate poorly outside that range.

Modules also degrade over the years, shifting their characteristics, which means periodic retraining is necessary in long-term deployments. These requirements

make ANN MPPT more suited to large installations where the cost of training and maintenance can be spread across a significant installed capacity [7], [8].

### COMPARATIVE ANALYSIS

The four methods are compared across six performance criteria in Table 1. Efficiency

figures are approximate values drawn from published experimental and simulation studies under Standard Test Conditions (STC: irradiance 1000 W/m<sup>2</sup>, cell temperature 25°C). The intent is not to pick a winner but to show where each technique sits relative to the others [4]–[9].

*Table 1:-Performance Comparison of MPPT Techniques*

Technique	Efficiency	Tracking Speed	Complexity	Hardware Cost	Partial Shading	Oscillation at MPP
Perturb & Observe (P&O)	~97%	Moderate	Low	Low	Poor	High
Incremental Conductance (INC)	~98%	Moderate	Moderate	Moderate	Poor	Low
Fuzzy Logic Control (FLC)	~99%	Fast	High	Moderate	Moderate	Very Low
Artificial Neural Network (ANN)	~99.5%	Very Fast	Very High	High	Good	Negligible

From Table 1, a consistent pattern emerges: each step up in algorithmic sophistication yields roughly one additional percentage point of tracking efficiency, but also brings higher implementation cost and complexity. The jump from P&O to INC is the easiest to justify the hardware cost increase is modest, the efficiency gain is real, and the reduction in steady-state oscillation is measurable. The jump from INC to FLC or ANN is larger, and whether it is worth making depends on the scale and operating environment of the installation.

### Efficiency across Different Irradiance Conditions

Under steady irradiance at STC, the efficiency differences between the four methods are relatively small. All four are within a few percent of each other, and in a well-designed system the choice of MPPT algorithm is not the dominant

factor. The picture shifts noticeably under variable irradiance the kind that occurs on partly cloudy days when irradiance can swing by 300–400 W/m<sup>2</sup> within a few seconds.

Under these dynamic conditions, P&O is most vulnerable. As described in Section 3.1, the algorithm can briefly track away from the MPP when irradiance rises rapidly. Measured efficiency in such scenarios has been reported as low as 91–95% in published studies. INC handles moderate irradiance changes better, but still shows transient undershoot with abrupt steps. FLC and ANN both maintain efficiency above 97% in most published test scenarios, owing to their ability to respond to the magnitude and rate of change of the input rather than just its current value. Table 2 summarises approximate efficiency ranges reported across several studies [4]–[14].



**Table 2:-Tracking Efficiency - Steady vs. Variable Irradiance Conditions**

MPPT Technique	Efficiency at STC (%)	Efficiency under Variable Irradiance (%)
Perturb & Observe (P&O)	96.5 – 97.5	91.0 – 95.0
Incremental Conductance (INC)	97.0 – 98.5	94.5 – 97.0
Fuzzy Logic Control (FLC)	98.0 – 99.0	97.0 – 98.5
Artificial Neural Network (ANN)	99.0 – 99.5	98.0 – 99.5

### **Behaviour under Partial Shading**

Partial shading where one or more modules in an array receive less irradiance than the rest creates multiple local power maxima on the P-V curve. P&O and INC are both local search algorithms: they climb toward the nearest peak and have no mechanism for detecting that a higher peak might exist elsewhere on the curve. In worst-case shading configurations, these methods can settle at a local maximum that is 20–30% below the true global maximum.

FLC performs somewhat better in shaded conditions if its rule base was designed

with this scenario in mind, but it is still fundamentally a local technique. ANN-based methods, provided they were trained on data that includes representative shading patterns, can often predict the global MPP location directly and avoid the local trap entirely [8].

This distinction becomes increasingly important as PV systems are installed in urban environments where shading from adjacent buildings, trees, and rooftop equipment is common. Table 3 provides a concise guide to which technique is most appropriate for different application scenarios.

**Table 3:-Technique Suitability by Application Type**

Technique	Small Off-Grid Systems	Medium Rooftop	Large Grid-Connected	Partial Shading Sites
P&O	Most suitable	Acceptable	Not recommended	Not recommended
INC	Good	Most suitable	Acceptable	Limited
FLC	Not cost-effective	Good	Good	Good
ANN	Not cost-effective	Acceptable	Most suitable	Most suitable

**DISCUSSION**

The comparison in Tables 1–3 suggests a fairly clear decision framework, though the right choice ultimately depends on how the system will be used and what budget is available for the control electronics.

For small off-grid systems rural water pumps, standalone lighting, remote sensor nodes P&O is hard to beat on cost grounds. The oscillation loss of 3–5% at rated power is a known and accepted trade-off when the entire system budget is constrained. Adding the hardware needed for FLC or ANN on a system that might have a total panel capacity of 100–300 W would not recover its cost in additional energy yield within any reasonable payback period.

Medium-scale rooftop installations in the 5–50 kW range are where INC tends to justify itself. At this scale, the improved steady-state accuracy and better transient tracking begin to matter economically, and the higher ADC resolution and processing power needed are standard in modern microcontrollers at negligible added cost. Over a 20-year system life, the extra one to two percent annual yield from INC over P&O is a real number worth capturing.

Large ground-mount and rooftop installations above 100 kW, and particularly those connected to the grid, are the environment where FLC and ANN show their value most clearly. India's solar capacity has grown substantially the country crossed 70 GW of installed solar by late 2023 [1] and at these scales, even a 0.5% improvement in annual energy yield represents significant revenue.

The decreasing cost of digital signal processors and embedded computing platforms has largely removed the cost objection to deploying FLC or ANN-based MPPT in new inverter designs [15].

One factor not captured in the efficiency tables is integration complexity. P&O and INC have long deployment histories and well-characterised stability margins when connected to standard boost or buck-boost converters. FLC and ANN controllers require careful validation on the actual hardware, since a rule base or neural network trained on one module type may not transfer well to another without retuning. For any installation using these advanced methods, hardware-in-the-loop testing before commissioning is strongly recommended [12].

Looking ahead, the most interesting development in this space is the emergence of hybrid architectures that combine a local tracker like INC with a global search routine that activates only when shading is detected. This gives the efficiency benefits of a simple local algorithm under normal conditions and the global tracking capability of a more complex method when it is actually needed. Reinforcement learning-based controllers that adapt online to the specific operating history of an installation are also being studied, though they remain primarily in the research phase [8].

**CONCLUSION**

This paper has reviewed and compared four widely used MPPT techniques Perturb and Observe, Incremental Conductance, Fuzzy Logic Control, and Artificial Neural Network-based MPPT across six performance dimensions. The central finding is that no single technique is universally optimal. Each occupies a distinct position in the trade-off space between cost, complexity, and tracking performance.

P&O remains the default choice for small, cost-sensitive systems where its simplicity and proven reliability outweigh its efficiency limitations. INC offers a meaningful improvement in steady-state

accuracy and transient tracking at modest additional implementation cost, making it the better default for medium-scale systems. FLC and ANN deliver the highest tracking efficiency and the best dynamic response under variable irradiance and partial shading, and they are increasingly practical in large-scale installations where DSP and microcontroller costs have dropped substantially.

From an Indian perspective, the variability introduced by the south-west monsoon season makes the choice between these algorithms a real engineering decision rather than a textbook exercise. Systems in Karnataka and other monsoon-affected states could see measurable yield improvements from deploying FLC or ANN over INC, particularly in the June–September period. Quantifying this improvement under Indian climatic data is an extension of this work that the author intends to pursue.

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