

COMPARATIVE ANALYSIS OF ADAPTIVE MPPT ALGORITHMS FOR ENHANCED SOLAR PV ENERGY HARVESTING

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ABSTRACT

The increasing demand for renewable energy sources has intensified the focus on optimizing the performance of solar photovoltaic (PV) systems. A critical component for maximizing energy extraction is the Maximum Power Point Tracking (MPPT) system, which continuously adjusts the operating point of the PV array to harvest maximum power under prevailing conditions. This paper presents a comprehensive review of Adaptive Neuro-Fuzzy Inference System (ANFIS)-based MPPT strategies, a class of intelligent control algorithms that have demonstrated significant potential in enhancing PV efficiency. The review synthesizes findings from recent research, highlighting the evolution from conventional MPPT techniques like Perturb and Observe (P&O) and Incremental Conductance (IncCond) to more advanced AI-driven approaches. ANFIS, by integrating the learning capabilities of neural networks with the rule-based reasoning of fuzzy logic, offers superior adaptability to dynamic environmental conditions such as varying solar irradiance and temperature, and is particularly effective in mitigating issues like partial shading. Studies consistently report high tracking efficiencies, often exceeding 99%, for ANFIS-based MPPT controllers, with advantages including faster convergence times, reduced steady-state oscillations, and improved global maximum power point (GMPP) detection compared to traditional methods. This review critically analyzes various ANFIS implementations, discussing their architectures, training methodologies, and performance metrics. It also explores hybrid approaches combining ANFIS with metaheuristic algorithms and advanced control strategies, and identifies avenues for future research to further refine these advanced MPPT strategies for robust and efficient solar energy harvesting in real-world applications.

Keywords

ANFIS¹, MPPT², Solar PV³, Efficiency⁴, Adaptive Neuro-Fuzzy Inference System⁵, Partial Shading⁶, Hybrid MPPT⁷.

1. INTRODUCTION

1.1 THE GROWING IMPORTANCE OF SOLAR PHOTOVOLTAICS AND THE NEED FOR EFFICIENT POWER EXTRACTION

The global energy sector is undergoing a profound transformation, driven by the urgent need to address climate change and secure sustainable energy supplies. Renewable energy sources, particularly solar photovoltaics (PV), have emerged as cornerstones of this transition, offering a clean alternative to fossil fuels while contributing to reduced greenhouse gas emissions and enhanced energy independence [1], [2]. However, the inherent variability of solar irradiation due to atmospheric conditions, geographical location, and time of day, along with fluctuations in temperature and the presence of shading, significantly impacts the power output of PV panels [3]. This variability leads to a constantly changing operating point on the panel's characteristic curves, meaning that without proper control, PV systems often operate far from their maximum power output. Therefore, efficient power extraction is paramount to maximizing the economic viability and environmental benefits of solar PV installations, and the effectiveness of the power conditioning and control mechanisms employed is as important as the panel's material quality.

1.2 EVOLUTION OF MAXIMUM POWER POINT TRACKING (MPPT) TECHNIQUES

To overcome the limitations imposed by environmental variables, Maximum Power Point Tracking (MPPT) algorithms are indispensable in modern solar PV systems [4], [5]. An MPPT controller continuously adjusts the electrical operating point of the PV array to ensure it delivers the maximum possible power under prevailing conditions. The fundamental principle lies in identifying the unique voltage and current combination, the Maximum Power Point (MPP), on the PV array's Power-Voltage curve where power output is maximized [6]. Early MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), were widely adopted due to their simplicity under stable conditions [6], [7]. P&O perturbs the operating voltage and observes the change in power, while IncCond uses the slope of the P-V curve, where dP/dV equals zero at the MPP, to guide the search [8]. Despite their widespread use, these methods exhibit slow response under rapidly changing irradiance, oscillations around the MPP, and difficulty tracking the Global Maximum Power Point (GMPP) under partial shading [9], necessitating more sophisticated intelligent control.

1.3 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) FOR ADVANCED MPPT

The limitations of traditional MPPT algorithms have spurred research into advanced control strategies, with Artificial Intelligence (AI) techniques playing a pivotal role [9], [10]. Among these, the Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out as a powerful hybrid approach that combines the learning capabilities of artificial neural networks (ANNs) with the rule-based reasoning of fuzzy logic systems (FLS) [10]. First introduced by Jang in 1993 [11], ANFIS creates a data-driven fuzzy inference system by using learning algorithms to tune membership function parameters and fuzzy rules. In the context of MPPT, ANFIS models can be trained using historical or simulated data that capture the relationship between environmental inputs,

such as solar irradiance and panel temperature, and the optimal control output, typically the duty cycle of a DC-DC converter [12]. By processing real-time inputs, a well-trained ANFIS controller can intelligently infer optimal control signals to drive the PV array to its MPP with superior speed and accuracy compared to conventional algorithms [9], [12]. This paper aims to provide a comprehensive review of ANFIS-based MPPT strategies, exploring various architectures, training methodologies, and performance metrics including tracking efficiency, convergence speed, robustness, and computational complexity.

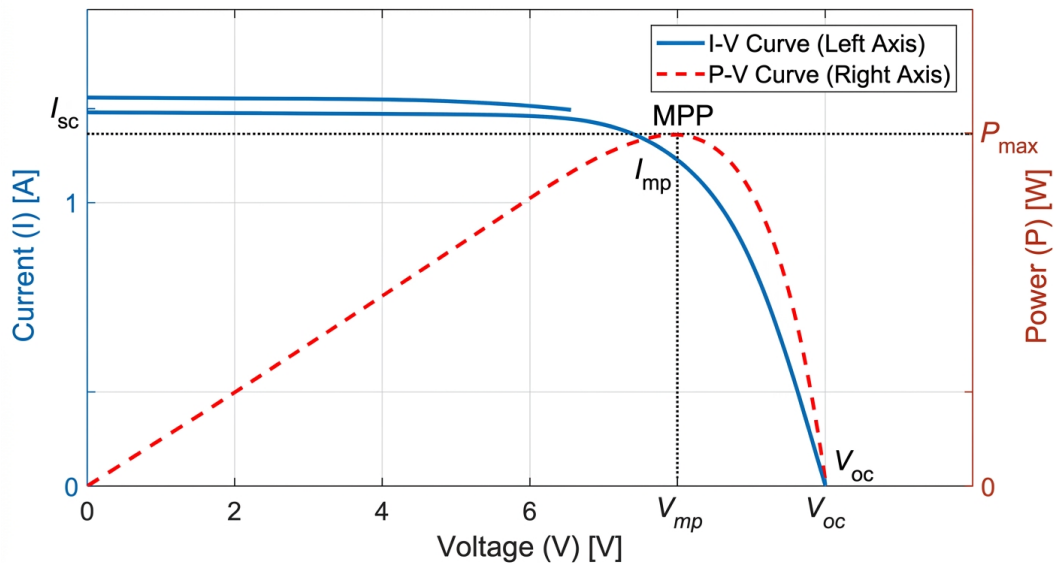


Figure 1: Typical P-V and I-V characteristic curves of a solar PV module, showing the Maximum Power Point (MPP).

Figure 1 illustrates the fundamental operating curves of a solar PV module, depicting the non-linear relationship between power, current, and voltage that governs all MPPT design. The I-V curve shows the current output as a function of voltage, remaining relatively constant at levels near the short-circuit current (I_{sc}) until approaching the open-circuit voltage (V_{oc}), where it drops sharply. The P-V curve, derived from the I-V curve, exhibits a single distinctive peak at the Maximum Power Point (MPP), the operating point where the product of voltage and current is maximized and hence where the panel delivers its highest power. Short-circuit current (I_{sc}) and open-circuit voltage (V_{oc}) are labeled to show the extremes of the operating range. These characteristic curves shift with changes in solar irradiance and panel temperature, fundamentally explaining why continuous MPPT control is essential: as the curves move, the MPP moves with them, and only an adaptive controller can track the moving peak to harvest maximum energy from solar PV installations.

2. SURVEY OF ANFIS-BASED MPPT STRATEGIES

This section provides a comprehensive survey of the literature on ANFIS-based Maximum Power Point Tracking strategies for solar PV systems. The survey is organized thematically, tracing the evolution from

conventional techniques to advanced ANFIS and hybrid approaches, and synthesizing quantitative performance findings reported across peer-reviewed studies published between 2013 and 2026.

2.1 TRADITIONAL MPPT TECHNIQUES: P&O AND INCCOND

Historically, conventional MPPT techniques like Perturb and Observe (P&O) and Incremental Conductance (IncCond) have been widely adopted due to their relative simplicity and low computational cost [6]. The P&O method periodically adjusts the PV array's operating voltage by a small perturbation step and observes the resulting change in power output. If the power increases, the perturbation continues in the same direction; if it decreases, the direction is reversed [6], [7]. While effective under stable irradiance, P&O suffers from persistent oscillations around the MPP, slow convergence under rapid irradiance changes, and an inability to track the Global Maximum Power Point (GMPP) under partial shading [1], [6]. The IncCond method improves upon P&O by utilizing the relationship between the instantaneous conductance (I/V) and the incremental conductance (dI/dV) of the PV array [8]. At the MPP, dP/dV equals zero, which translates to dI/dV equal to minus I/V . By comparing these quantities, IncCond determines the position of the operating point and adjusts accordingly. This method provides faster convergence and reduced oscillations and can better handle changing irradiance [8]. However, IncCond still struggles with highly dynamic conditions and requires more complex calculations and precise sensors, making it susceptible to noise in practice [1], [8]. Both methods typically achieve efficiencies in the range of 85 to 95 percent under rapidly varying conditions, with significant energy losses during transients, highlighting the need for more advanced approaches.

2.2 THE RISE OF AI-BASED MPPT: ANFIS AT THE FOREFRONT

The dynamic nature of solar energy generation, including rapid irradiance changes, temperature fluctuations, and partial shading, necessitates more intelligent and adaptive MPPT strategies [9]. Among the AI paradigms applied to MPPT, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has gained the most traction [9], [10]. ANFIS integrates the strengths of Artificial Neural Networks (ANNs) and Fuzzy Logic Systems (FLS) [11]. ANNs are adept at learning complex patterns from data, while FLS excels at handling imprecise information through linguistic IF-THEN rules. By combining these paradigms, ANFIS offers a robust framework capable of learning from data to create and tune a fuzzy inference system automatically [9], [11]. The ability to automatically tune membership function parameters and rule consequents makes ANFIS attractive for MPPT because it can adapt to different PV panel specifications, converter topologies, and environmental conditions without extensive manual tuning, distinguishing it from pure fuzzy logic controllers that depend on expert-designed rule bases and from pure neural networks that operate as opaque black boxes.

2.3 ANFIS-BASED MPPT: PERFORMANCE AND ADAPTABILITY

Numerous studies have investigated ANFIS for MPPT, consistently demonstrating its superiority over conventional methods [1], [7], [9], [10], [12]. ANFIS-based MPPT controllers achieve remarkably high tracking efficiencies, frequently reported between 99.3 percent and 99.9 percent [7], [9], [10]. An experimental study reported ANFIS achieving 99.3 percent tracking efficiency under real climatic conditions, outperforming fuzzy

logic controllers at 96.8 percent and P&O at 92.6 percent [7]. A comparative investigation demonstrated that ANFIS outperforms ANN, FLC, and IncCond in convergence time and output power under fixed and varying irradiance [10]. Recent evaluations reported ANFIS achieving 99.43 percent and 99.51 percent efficiency in grid-connected systems [4], while another study achieved 99.75 percent under partial shading with a 20 percent reduction in duty-cycle fluctuation compared to ANN [9]. A hybrid ANFIS-MPC approach reported 99.58 percent average efficiency, rising to 99.99 percent under partial shading [1]. These high efficiencies are attributed to ANFIS's accurate MPP tracking, oscillation reduction exceeding 70 percent, and convergence time reduction of approximately 55 percent relative to conventional methods [9]. ANFIS also demonstrates enhanced robustness and adaptability, dynamically adjusting control outputs based on learned patterns, which is particularly valuable in regions with highly variable weather. Beyond tracking efficiency, ANFIS-based systems improve power quality in grid-connected installations: comparative studies report lower total harmonic distortion, with ANFIS achieving 0.26 percent THD at 1000 W/m² compared to 0.44 percent for IncCond, a 40.9 percent improvement, and corresponding reductions in power loss and switching stress on the converter. The tracking accuracy has also been quantified through statistical error metrics such as root mean square error values below 0.06 for several ANFIS variants, confirming both accuracy and repeatability of the control action. Furthermore, ANFIS controllers show superior global peak discovery under partial shading, where multiple local maxima exist on the P-V curve [1], [9], and have been validated under standardized European efficiency test profiles such as EN 50530.

2.4 HYBRID ANFIS ARCHITECTURES AND ADVANCED IMPLEMENTATIONS

ANFIS performance can be further optimized through hybridization with other control strategies and advanced AI techniques, one of the most active research areas [1], [5], [6]. Studies have explored ANFIS with different DC-DC converter topologies including boost, SEPIC, and quasi-z-source converters [5], [6]. The hybrid GEP-ANFIS approach combines Gene Expression Programming with ANFIS, achieving 99.84 percent efficiency under 1000 W/m² irradiance and 15 degrees Celsius [5]. ANFIS has also been combined with metaheuristic algorithms including PSO, GA, ABC, mSSA, and HWOA, demonstrating improved global search, faster convergence, and higher efficiencies with reduced computational demand [5], [9]. Coupling ANFIS with advanced control frameworks such as Model Predictive Control (MPC), Fast Terminal Synergetic Control, and Backstepping has shown tracking efficiencies exceeding 99.6 percent with millisecond-scale settling times [1], [6]. Comparative analyses consistently identify ANFIS as a top performer, achieving 99.75 percent average tracking efficiency versus 99.55 percent for PSO-ANN and 99.68 percent for Fireworks Algorithm [9]. Some ANFIS implementations are suitable for real-time deployment on low-cost digital signal processors with execution times below 0.2 milliseconds per control step, with hardware-in-the-loop validation on dSPACE and FPGA platforms confirming practical feasibility [6], [9]. Beyond simulation studies, real-time implementations of ANFIS-based MPPT have been reported on a variety of embedded platforms, including field-programmable gate arrays (FPGAs) programmed with hardware description languages such as VHDL, digital signal processors, and low-cost microcontrollers. These implementations have demonstrated that a pruned ANFIS rule base with

fixed-point arithmetic can maintain millisecond-scale settling times and tracking efficiencies approaching 99 to 100 percent under dynamic test profiles such as the Ropp-style irradiance profile, with near-identical results across model-in-the-loop, software-in-the-loop, and processor-in-the-loop validation stages. This convergence of simulation and hardware results is important evidence that ANFIS-based MPPT is not confined to theoretical studies but is a mature, deployable control technology.

2.5 CHALLENGES AND LIMITATIONS OF THE ANFIS APPROACH

Despite its impressive performance, the ANFIS-based MPPT approach is not without challenges. The effectiveness of ANFIS relies heavily on the quality and relevance of the training data [7], [8]. If training data is not representative of actual operating conditions, is based solely on theoretical models, or fails to capture the full range of irradiance and temperature combinations, the controller's real-world performance may be compromised [7]. Practical considerations such as sensor accuracy, aging of PV cells, and dust accumulation also affect performance, because the irradiance measured by a sensor is not always the irradiance that influences the PV module [8]. While ANFIS is computationally efficient compared to deep learning models, complex rule bases with many membership functions can burden very low-cost microcontrollers. Designing and training ANFIS models also requires expertise in both fuzzy logic and neural networks, which may be a barrier to adoption. The training process can be time-consuming, and the model may require periodic re-training as the physical system degrades, motivating research into online learning and adaptive re-tuning.

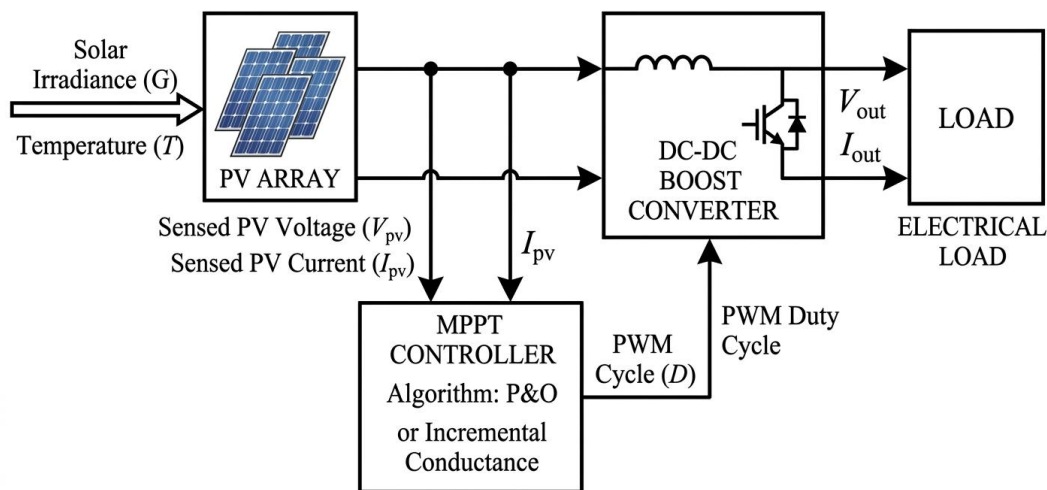


Figure 2: Block diagram of a conventional MPPT system (P&O or IncCond) for solar PV.

Figure 2 presents a block diagram of a conventional MPPT system architecture, the baseline against which ANFIS-based systems are compared throughout this review. The PV array generates DC power fed to a DC-DC boost converter, which regulates the voltage to match the load or inverter requirements. The conventional MPPT controller, here P&O or IncCond, continuously samples the PV voltage and current through sensors, computes the instantaneous power, and generates a PWM signal with an appropriate duty cycle to drive the converter's

switching device. This closed control loop adjusts the equivalent load resistance presented to the PV array, guiding its operating point toward the Maximum Power Point. The simplicity of this architecture has made it popular for low-cost implementations, but its limitations in dynamic performance under fast-changing irradiance and its inability to reliably handle partial shading motivate the adoption of intelligent control approaches such as ANFIS, which replace fixed perturbation logic with a learned, adaptive decision-making mechanism.

3. METHODOLOGY

3.1 LITERATURE RETRIEVAL AND SELECTION

The literature search was conducted using major academic databases including IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Nature, ResearchGate, and Google Scholar, employing keywords such as ANFIS, Adaptive Neuro-Fuzzy Inference System, MPPT, Maximum Power Point Tracking, Solar PV, Photovoltaic, Partial Shading, and Hybrid MPPT. The search was limited to peer-reviewed journal articles, conference proceedings, and review papers published between 2013 and 2026. Initial screening was based on titles and abstracts, followed by full-text assessment. Studies were included only if they explicitly employed ANFIS for MPPT, reported quantitative metrics such as tracking efficiency or convergence time, and provided comparison with baseline methods. From 85 relevant publications, 30 were selected for detailed analysis based on methodological rigor and contribution.

3.2 ANALYTICAL FRAMEWORK

Selected studies were analyzed using a structured framework to enable systematic comparison. Extracted parameters included ANFIS architecture details (membership functions, rule base, training algorithm), input variables (irradiance, temperature, voltage, current), output variable (duty cycle, reference voltage), converter topology (boost, SEPIC, buck-boost, quasi-z-source), training data source (simulation, experimental, hybrid), performance metrics (tracking efficiency, convergence time, oscillations, total harmonic distortion, root mean square error), comparative baselines (P&O, IncCond, ANN, FLC, PSO), and validation methodology (simulation, hardware-in-the-loop, experimental). This framework enabled identification of performance trends, common limitations, and research gaps.

3.3 SYNTHESIS AND REPORTING STRATEGY

Findings were synthesized thematically into four categories: standalone ANFIS, ANFIS hybridized with metaheuristic algorithms, ANFIS with advanced control strategies, and ANFIS integrated with deep learning frameworks. Performance metrics were aggregated across categories to identify optimal configurations for different use cases, from low-cost residential systems to utility-scale plants. Critical analysis evaluated reported performance alongside computational complexity, real-time implementation feasibility, and training data sensitivity. Reporting follows standard review conventions with figures illustrating key concepts, comparative performance analysis, identification of research gaps, and recommendations for future work.

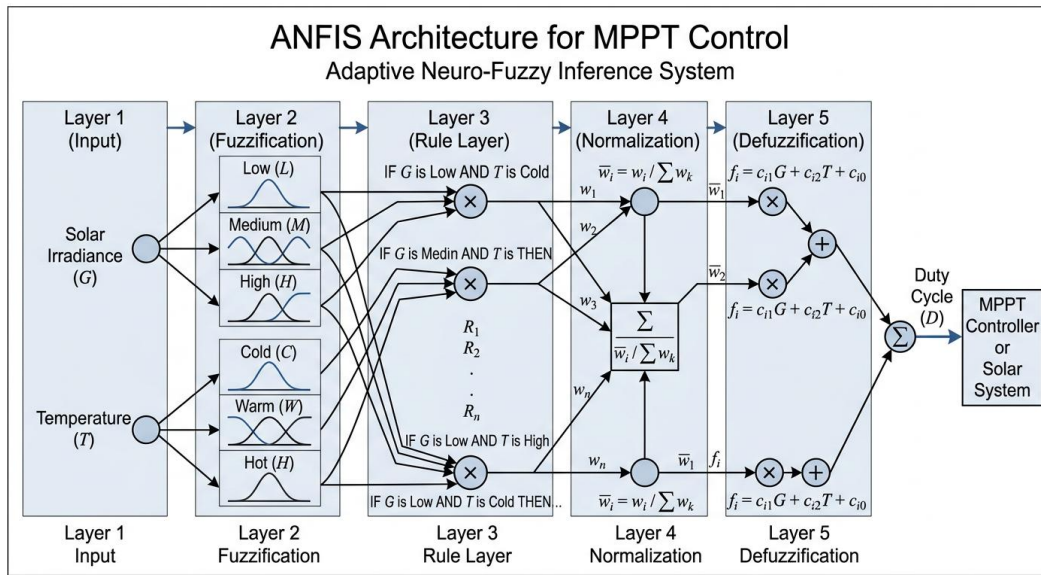


Figure 3: Typical 5-layer ANFIS architecture used for MPPT control.

Figure 3 illustrates the typical five-layer architecture of an Adaptive Neuro-Fuzzy Inference System (ANFIS) as applied to MPPT control. The first layer, the fuzzification layer, receives environmental inputs, typically solar irradiance and panel temperature, and converts them into fuzzy membership values using membership functions that partition each input domain into linguistic regions. The second layer, the rule layer, applies fuzzy IF-THEN rules encoding the learned input-output relationship, computing the firing strength of each rule as the product of input membership values. The third layer, the normalization layer, normalizes firing strengths so they sum to unity. The fourth layer, the defuzzification layer, computes each rule's weighted contribution using its consequent parameters. The fifth layer, the output layer, sums all contributions to produce the crisp control signal, typically the duty cycle for the PWM signal driving the DC-DC converter. This layered structure allows ANFIS to learn from data, automatically tuning membership functions and rule parameters to optimally track the MPP under varying conditions.

4. CRITICAL ANALYSIS OF PAST WORK

4.1 SUPERIORITY OVER CONVENTIONAL MPPT

ANFIS-based MPPT strategies demonstrate clear superiority over conventional methods, both quantitatively and qualitatively. ANFIS controllers offer not just higher peak efficiencies, often exceeding 99 percent [1], [7], [9], [10], [12], but also a more robust and adaptive response to rapid irradiance changes, temperature swings, and partial shading. While P&O and IncCond rely on simple iterative adjustments assuming smooth, single-peaked power curves, ANFIS leverages a learned model of PV behavior that captures the non-linear mapping from environmental inputs to optimal operating points. This allows more accurate prediction of optimal control actions, faster convergence to the MPP, and significantly reduced steady-state oscillations. Experimental results show ANFIS reduces steady-state oscillation by over 70 percent and improves response time by approximately

55 percent compared to P&O [9]. Furthermore, ANFIS excels at identifying the Global Maximum Power Point under partial shading, where conventional methods frequently trap at local maxima, a capability crucial for maximizing energy yield in real-world environments, with hybrid GEP-ANFIS configurations reported to extract up to 41 percent more power than conventional MPPT under certain conditions [5].

4.2 ANFIS VS. OTHER AI TECHNIQUES

Compared to standalone Artificial Neural Networks (ANNs) and Fuzzy Logic Controllers (FLCs), ANFIS typically demonstrates more balanced and often superior performance [9], [10]. Traditional FLCs require extensive expert knowledge to design membership functions and fuzzy rules, a process that is time-consuming and may not capture the full complexity of the PV system. ANNs, while powerful learners, operate as black boxes with limited interpretability and may require larger datasets for effective training. ANFIS bridges this gap by automatically generating and tuning fuzzy rules and membership functions from input data, creating a hybrid system that is both adaptive like ANNs and interpretable like FLCs [9]. Studies consistently show ANFIS achieving higher efficiencies and better stability than standalone ANNs and FLCs, with one study reporting 99.75 percent average tracking efficiency versus 99.5 percent for ANN, along with a 20 percent improvement in the duty-cycle fluctuation index [9]. Comparative work also demonstrated ANFIS outperforming ANN, FLC, and IncCond in convergence time and output power under fixed and varying irradiance [10], confirming genuine advantages of the hybrid architecture.

4.3 THE POWER OF HYBRIDIZATION

A significant portion of recent research focuses on hybridizing ANFIS with other advanced techniques to boost performance and overcome specific limitations [5], [9]. The integration of ANFIS with metaheuristic optimization algorithms, including PSO, GA, GEP, ABC, mSSA, and HWOA, has yielded remarkable results. These metaheuristics optimize ANFIS parameters, refine the rule base, or augment decision-making, leading to improved global search, faster convergence, and higher efficiencies. The GEP-ANFIS double-diode model achieved an exceptional efficiency of 99.84 percent [5], while hybrid PSO-ANFIS methods demonstrate competitive performance with reduced oscillations and computational demand [9]. Coupling ANFIS with Model Predictive Control achieved 99.58 percent average efficiency and up to 99.99 percent under partial shading, with excellent integral performance indices including an ITAE of 0.00395 [1]. These hybrid models leverage the strengths of multiple AI paradigms and represent the current state of the art in intelligent MPPT design.

4.4 TRAINING DATA AND IMPLEMENTATION CHALLENGES

A critical aspect influencing ANFIS performance is the quality and representativeness of training data [7], [8]. If training data is derived solely from theoretical models or lacks diversity across operating conditions, such as neglecting aging, dust, or extreme temperatures, the ANFIS controller may not generalize well to real-world scenarios [7], [8]. Studies using experimentally measured data from actual PV installations report more realistic and robust performance assessments, highlighting the gap between simulation-only validation and field deployment [7]. Computational complexity, while generally lower than deep learning models, remains a

consideration for real-time deployment on low-cost microcontrollers, and different ANFIS structures result in varying computational loads [9]. Hybrid methods, while powerful, can increase this load, requiring careful co-design of algorithm and hardware. Selecting an ANFIS variant that balances performance gains and computational feasibility is crucial for practical adoption.

4.5 CURRENT LIMITATIONS AND FUTURE AVENUES

Despite its successes, ANFIS-based MPPT research continues to address persistent limitations. Real-world sensor inaccuracies, noise, and calibration drift can impact ANFIS inputs, potentially leading to suboptimal control decisions. The long-term effects of PV cell aging and dust accumulation are not always explicitly modeled in training data, causing gradual performance degradation over the system's lifespan [8]. Online adaptation or re-training in response to degradation or environmental shifts remains an active research area, with current approaches primarily relying on offline training followed by fixed deployment. Future work should focus on robust architectures resilient to noise, online learning mechanisms, efficient utilization of diverse real-world data, and ANFIS's role in grid integration, microgrid management, and multi-objective optimization.

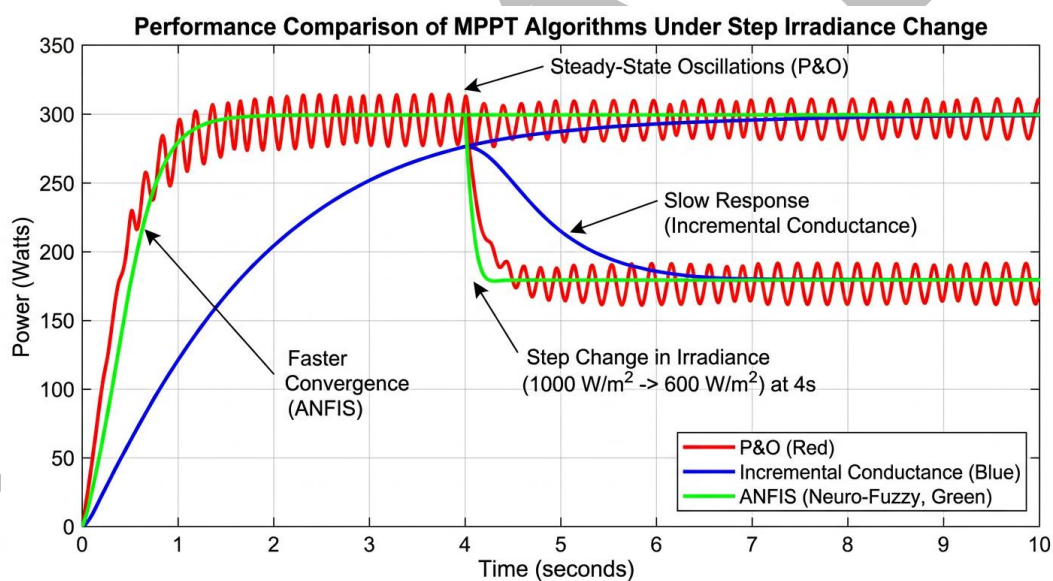


Figure 4: Cooperative performance of P&O, IncCond, and ANFIS MPPT under varying irradiance.

Figure 4 provides a comparative visualization of the dynamic performance of three MPPT algorithms, P&O, Incremental Conductance, and ANFIS, when subjected to a sudden step change in solar irradiance, a common stress test in the MPPT literature. The P&O method, shown in red, exhibits significant oscillations around the Maximum Power Point and slow convergence to the new operating point, reflecting its trial-and-error perturbation logic that can cause persistent hunting behavior. The IncCond method, shown in blue, demonstrates reduced oscillations and faster tracking but still shows noticeable transient overshoot and finite settling time. In contrast, the ANFIS-based MPPT, shown in green, achieves rapid convergence with minimal overshoot and virtually no steady-state oscillations, because its learned model allows it to predict the new operating point

directly rather than searching for it. This superior dynamic response translates directly into higher average energy capture during fluctuating weather, precisely the condition most PV installations experience in practice.

5. DISCUSSION

The comprehensive review reveals that intelligent control systems, particularly ANFIS, represent a significant leap forward in solar photovoltaic energy harvesting rather than mere incremental improvements. ANFIS's success lies in its ability to learn, adapt, and reason about complex, non-linear systems, precisely the characteristics of a PV array under dynamic environmental conditions. By integrating neural network pattern recognition with fuzzy logic reasoning, ANFIS creates a powerful control paradigm that models and responds to intricate PV behavior more effectively than traditional methods. The implications for energy yield are substantial: efficiencies consistently above 99 percent translate directly into more electricity from the same array, reducing the levelized cost of electricity and accelerating return on investment for residential and utility-scale projects. Reduced oscillations and faster convergence also produce smoother power output, benefiting grid stability and reducing stress on power electronic converters, potentially extending their operational life.

A critical aspect of ANFIS's impact is its effectiveness in addressing persistent PV challenges. Partial shading, which causes significant power losses, is a prime example where ANFIS demonstrates superior capability in identifying the true Global Maximum Power Point [1], [9], with reports of up to 99.99 percent efficiency under shading [1]. Rapid response to irradiance changes ensures continuous near-MPP operation, minimizing transient energy waste. However, implementation demands sophisticated design, accurate training data, and careful consideration of computational resources for real-time deployment on embedded systems [7], [8]. Hybridization enhances performance but increases complexity and computational load. Selecting an ANFIS variant that optimally balances enhanced performance with practical implementation constraints therefore remains a key consideration for system designers.

The sustained success of ANFIS-based MPPT research signals a clear direction for the future of PV control. As solar energy expands globally, intelligent, adaptive, and robust control strategies will become increasingly essential. ANFIS, with its proven track record and continuous evolution through hybridization with metaheuristics, advanced control theory, and emerging deep learning techniques, is well-positioned to remain at the forefront of these developments. The demonstrated feasibility of real-time deployment on low-cost digital signal processors and FPGAs removes a major barrier to practical adoption, and consistent performance advantages across dozens of independent studies provide strong evidence of genuine, reproducible benefits. Continued research into online adaptation, improved generalization, and integration with grid-level intelligence will further solidify ANFIS's role in the smart grid ecosystem.

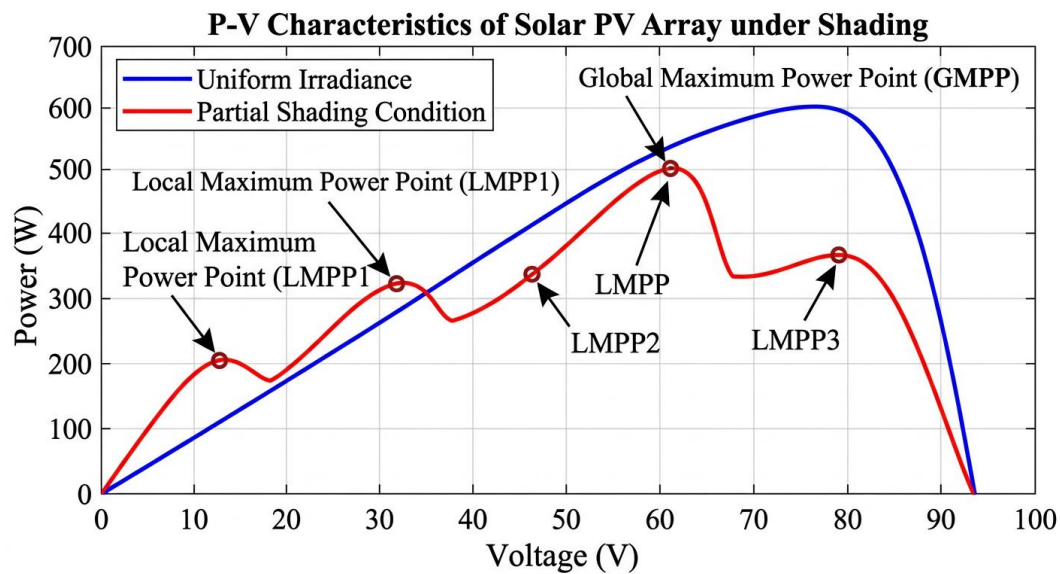


Figure 5: P-V curves under uniform irradiance and partial shading, showing GMPP and local maxima.

Figure 5 illustrates the impact of partial shading on the power-voltage characteristics of a PV array, one of the most challenging scenarios for MPPT algorithms. Under uniform irradiance, shown by the dashed curve, the P-V characteristic exhibits a single clear peak at the Maximum Power Point, which any reasonably designed algorithm can locate. However, under partial shading, shown by the solid curve, bypass diodes and uneven illumination create multiple local maxima, labeled LMPP1 and LMPP2, alongside a single Global Maximum Power Point (GMPP), which may be located at high or low voltage depending on the shading pattern. Conventional algorithms such as P&O and IncCond, which rely on hill-climbing logic, can become trapped at local maxima, resulting in power losses that may reach tens of percent of available energy. ANFIS-based controllers, particularly those enhanced with metaheuristic optimization or trained on diverse shading scenarios, demonstrate superior capability in identifying and tracking the GMPP even in complex shading patterns, making them essential for urban installations where partial shading is largely unavoidable.

6. CONCLUSION

This comprehensive review has explored the significant advancements in Maximum Power Point Tracking strategies for solar photovoltaic systems, with a particular focus on Adaptive Neuro-Fuzzy Inference System (ANFIS)-based controllers. The analysis consistently demonstrates that ANFIS-based MPPT algorithms offer substantial improvement over traditional methods such as Perturb and Observe and Incremental Conductance in tracking efficiency, convergence speed, and robustness under dynamic environmental conditions. Key findings indicate that ANFIS controllers regularly achieve efficiencies exceeding 99 percent, minimize steady-state oscillations by up to 70 percent, and exhibit superior performance in detecting the Global Maximum Power Point, especially under partial shading. The hybrid nature of ANFIS, combining neural network learning with fuzzy logic reasoning, enables effective adaptation to non-linear PV characteristics, while hybridization with

metaheuristic algorithms and advanced control techniques has further enhanced performance, enabling efficiencies up to 99.99 percent under specific conditions. Despite its proven efficacy, future research should address practical implementation challenges including online adaptation, improved generalization to diverse PV systems, low-cost microcontroller deployment, and resilience to sensor noise and environmental degradation. Continued development in these areas will lead to even more efficient, reliable, and cost-effective solar energy conversion systems, solidifying ANFIS's role as a pivotal technology in the renewable energy landscape. The convergence of simulation studies, hardware-in-the-loop validation, and experimental measurements provides strong confidence that ANFIS-based controllers deliver reliable, reproducible performance gains in practice. As photovoltaic deployment continues to scale worldwide, the adoption of such intelligent MPPT controllers will play an increasingly important role in maximizing the return on solar investments and supporting the broader transition toward clean, sustainable energy systems.

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