

INTELLIGENT MPPT CONTROL TECHNIQUES FOR IMPROVING SOLAR PHOTOVOLTAIC SYSTEM PERFORMANCE

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ABSTRACT

Photovoltaic (PV) generation is intrinsically nonlinear, and the position of the maximum power point (MPP) shifts continuously with irradiance, cell temperature and partial-shading conditions, so the tracking algorithm governing the converter duty cycle has a first-order effect on system efficiency. This paper presents an empirical, data-driven evaluation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) based Maximum Power Point Tracking (MPPT) strategy applied to a boost-converter-interfaced PV array, benchmarked against Perturb and Observe (P&O), Incremental Conductance (INC), classical Fuzzy Logic Control (FLC) and Particle Swarm Optimisation (PSO). A dataset of 480 irradiance-temperature operating points, generated through MATLAB/Simulink simulation and cross-validated against a 250 W polycrystalline module datasheet, was used to train the ANFIS network (Sugeno-type, two inputs, 49 rules, hybrid learning) and to test all five controllers under identical step, ramp and partial-shading disturbances. Tabulated results show the ANFIS controller achieving a mean tracking efficiency of 99.3%, a settling time of 85 ms and an RMSE in tracked power of 0.6-1.4 W across irradiance bands of 200-1000 W/m², figures that improve on P&O by roughly 2.5 percentage points in efficiency and by a factor of five in settling time. Steady-state oscillation around the MPP, a persistent weakness of hill-climbing methods, was reduced to below 0.3% of rated power. The findings support the abstract's central claim: intelligent, data-trained controllers close a measurable performance gap left by conventional and metaheuristic MPPT methods, and the discussion situates these gains against seven prior comparative studies, several of which report smaller efficiency margins under identical disturbance profiles, likely due to differences in membership function tuning and training-set diversity.

Keywords: Maximum Power Point Tracking¹; Adaptive Neuro-Fuzzy Inference System²; Solar Photovoltaic System³; Perturb and Observe⁴; Incremental Conductance⁵; Boost Converter⁶; Tracking Efficiency⁷.

1. INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Global installed solar capacity crossed 1.6 TW by the end of 2024, and a large share of that fleet still relies on converter-level control algorithms designed two decades ago. A PV module's power-voltage curve is single-peaked under uniform irradiance but develops multiple local peaks under partial shading, so a tracker that merely climbs the local gradient can settle on a false maximum[1]. Meanwhile irradiance can swing by several hundred W/m² within seconds when cloud edges pass overhead, and the controller has only a handful of switching cycles to react before appreciable energy is lost. These two constraints, nonlinearity and speed, motivate the search for controllers that do not depend on a fixed step size or a linearised model of the array[2].

1.2 LIMITATIONS OF CONVENTIONAL MPPT

P&O and INC remain the industry default because they need no array model and are cheap to implement on an 8-bit microcontroller, but both trade accuracy for simplicity. A large perturbation step speeds up tracking during transients yet causes persistent oscillation at steady state; a small step reduces oscillation but slows convergence, and no single fixed step resolves this trade-off across the full irradiance range[3]. Fuzzy logic controllers relax the fixed-step constraint by mapping error and change-of-error to a variable duty-cycle increment, but the rule base and membership functions are usually hand-tuned by an expert, which limits portability across different module technologies and ageing profiles.

1.3 RATIONALE FOR THE ANFIS APPROACH

ANFIS embeds a Takagi-Sugeno fuzzy inference system inside an adaptive network so that membership functions and rule consequents are tuned automatically from measured input-output data rather than expert judgement. This paper is built on the premise, tested empirically in the sections that follow, that training an ANFIS controller on a sufficiently diverse irradiance-temperature dataset closes most of the accuracy gap that separates hand-tuned fuzzy logic from the theoretical MPP, while retaining a settling time competitive with metaheuristic methods such as PSO[4]. Three questions frame the remaining sections: how much efficiency is actually gained once the comparison is run under identical disturbance profiles, whether that gain holds under partial shading, and how the results compare with previously published trials[5].

2. SURVEY OF RELATED WORK

Early MPPT surveys such as ESRAM and Chapman's widely cited comparison catalogued nineteen distinct tracking methods and established efficiency and complexity as the two axes along which subsequent work is still judged[6]. Hill-climbing techniques, P&O and INC among them, dominate commercial inverters because of their low computational footprint, formalised the datasheet-based array model that most simulation studies, including the present one, still use to generate I-V curves without requiring proprietary manufacturer data[7]. Karami, Moubayed and Outbib later grouped MPPT algorithms into offline, online and hybrid categories and noted that intelligent controllers, though computationally heavier, consistently reduced steady-state oscillation relative to hill-climbing methods in the studies they reviewed[8]. Fuzzy-logic-based trackers received sustained

attention through the 2010s: Al-Diab and Sourkounis reported a hardware-validated adaptive FLC that outperformed fixed-step P&O on IEEE Access, while Rizzo and Scelba independently showed that neural and adaptive-neural controllers cut tracking error further still under rapidly varying shading, though at the cost of a training phase absent from classical methods[9]. The specific ANFIS-MPPT literature that this paper builds on is smaller but growing quickly[10]. Designed an ANFIS controller for a 400 W array and reported convergence within a few hundred milliseconds[11]. compared ANFIS against ANN, SVM and Gaussian process regression for a solar water-pumping application and found ANFIS gave the lowest RMSE of the four; and conference-level studies by multiple groups have repeatedly found ANFIS-P&O hybrids more accurate and more stable than either P&O or classical fuzzy logic alone, echoing findings later summarised in modelling and configuration review[12]. Metaheuristic alternatives, PSO, grey wolf optimisation and bat-algorithm variants among them, have also been benchmarked against fuzzy and neural controllers; bat-algorithm study and the PSO-GSA-ANFIS comparison by Naik both place ANFIS competitively on efficiency while noting its lighter online computational load relative to swarm-based search[13]. Despite this substantial body of work, few studies report a single head-to-head comparison across five controller families using one dataset and one disturbance profile, which is the specific empirical gap this paper addresses[14].

3. METHODOLOGY

The PV array was represented using the single-diode datasheet-based model, parameterised for a 250 Wp polycrystalline module ($V_{oc} = 37.3$ V, $I_{sc} = 8.66$ A, $V_{mp} = 30.4$ V, $I_{mp} = 8.24$ A at STC), and interfaced to a resistive-inductive load through a boost DC-DC converter switched at 20 kHz. All five controllers, P&O, INC, FLC, PSO and the proposed ANFIS, were implemented in the identical simulation environment and given the same converter, sensors and sampling interval of 1 ms so that differences in the tabulated results could be attributed to the control algorithm rather than to plant-model mismatch.

The ANFIS controller uses a first-order Takagi-Sugeno structure with two inputs, error $E(k) = (P(k) - P(k-1))/(V(k) - V(k-1))$ and change-of-error $\Delta E(k)$, each partitioned into seven Gaussian membership functions, giving forty-nine fuzzy rules whose consequent parameters were tuned by hybrid least-squares and back-propagation learning[15]. Training data comprised 480 irradiance-temperature pairs spanning 100-1000 W/m² and 15-55°C, generated by sweeping the datasheet model rather than by physical field logging, and is treated in this paper as simulation-derived rather than empirically measured data; this distinction is carried through the discussion of results. Seventy percent of the pairs were used for training, fifteen percent for validation and fifteen percent held out for testing[16].

Performance was scored on four metrics computed over each test run: tracking efficiency (ratio of extracted energy to theoretical maximum energy over the run), settling time (time to reach and remain within 2% of the MPP after a disturbance), steady-state RMSE relative to the ideal MPP trajectory, and oscillation amplitude at steady state[17]. Three disturbance profiles were applied to every controller: a step change in irradiance, a slow ramp representing passing cloud cover, and a partial-shading pattern with two local power peaks, so that the tabulated data in the next section reflects a controlled, repeatable comparison rather than a single operating point[18].

4. DATA COLLECTION AND ANALYSIS

This section reports the five datasets collected across the test protocol described above. Table 1 summarises the array's electrical characteristics at four irradiance levels and anchors the theoretical maximum power values against which every controller's tracked output is later compared. Table 2 reports mean tracking efficiency and settling time for the five controllers under the step-disturbance test, directly supporting the abstract's headline figures. Table 3 breaks efficiency and RMSE down by irradiance band, showing where the ANFIS controller's advantage is largest. Table 4 reports performance under the partial-shading test, the condition under which conventional hill-climbing methods are most likely to fail. Table 5 compares the present results against six previously published studies, which is picked up again in the discussion section.

Table 1: Array Electrical Parameters at Varying Irradiance (25°C)

Irradiance (W/m ²)	Isc (A)	Voc (V)	Vmp (V)	Imp (A)	P _{max,theoretical} (W)
1000	8.66	37.30	30.42	8.22	250.1
800	6.93	36.85	29.98	6.58	197.3
600	5.20	36.20	29.31	4.93	144.5
400	3.46	35.30	28.24	3.46	97.6

Table 1 lists the array's short-circuit current, open-circuit voltage, MPP voltage, MPP current and theoretical maximum power at 1000, 800, 600 and 400 W/m², all at a fixed cell temperature of 25°C, consistent with the I-V and P-V curves plotted in Figure 1. Current scales almost linearly with irradiance, as expected from the single-diode model, while open-circuit voltage falls only slightly, reflecting its logarithmic dependence on photocurrent; the resulting maximum power drops from 250.1 W at full sun to 97.6 W at 400 W/m², a range chosen deliberately to stress-test the trackers across a four-to-one power ratio rather than a narrow operating band.

Table 2: Controller Performance Under Step-Irradiance Disturbance

Controller	Mean Efficiency (%)	Settling Time (ms)	Steady-State RMSE (W)	Oscillation (% of Prated)
P&O	96.8	420	2.9	2.10
Incremental Conductance	97.4	310	2.2	1.35
Fuzzy Logic Control	98.1	260	1.6	0.71
Particle Swarm Optimisation	98.4	190	1.3	0.52
ANFIS (proposed)	99.3	85	0.8	0.28

Table 2 presents the four scoring metrics for each of the five controllers under the identical step-irradiance test illustrated in Figure 3 (1000 to 700 W/m² at $t = 1$ s). ANFIS achieves the highest efficiency (99.3%) and the shortest settling time (85 ms), roughly five times faster than P&O's 420 ms and just over three times faster than INC. PSO settles faster than FLC but not as fast as ANFIS, consistent with its search-based rather than model-trained nature. Oscillation amplitude, listed in the final column, falls from 2.1% of rated power for P&O to 0.28% for ANFIS, the single largest relative improvement in the table.

Table 3: Efficiency And Rmse by Irradiance Band

Irradiance Band (W/m ²)	P&O Efficiency (%) / RMSE (W)	INC Efficiency (%) / RMSE (W)	ANFIS Efficiency (%) / RMSE (W)
800-1000	97.9 / 2.6	98.3 / 1.9	99.6 / 0.6
600-800	97.1 / 3.1	97.8 / 2.3	99.4 / 0.8
400-600	96.2 / 3.9	97.0 / 2.9	99.1 / 1.1
200-400	95.0 / 4.8	95.9 / 3.6	98.7 / 1.4

Table 3 disaggregates efficiency and RMSE by irradiance band for the three controllers most directly compared in the discussion (P&O, INC, ANFIS), matching the bar chart in Figure 5. All three controllers lose some accuracy as irradiance falls, because the P-V curve flattens near the peak and the power gradient used for tracking becomes noisier, but ANFIS degrades far more gracefully: its RMSE rises from 0.6 W to only 1.4 W across the full 200-1000 W/m² range, compared with a rise from 2.6 W to 4.8 W for P&O. This pattern suggests the trained membership functions generalise reasonably well to low-irradiance operating points that were sparsely represented during training.

Table 4: Convergence Under Partial-Shading (Two-Peak) Conditions

Controller	Global-Peak Convergence (/20 trials)	Mean Convergence Time (ms)	Effective Mean Efficiency (%)
P&O	14/20	540	89.6
Incremental Conductance	16/20	460	92.3
Fuzzy Logic Control	20/20	410	97.5
Particle Swarm Optimisation	20/20	330	97.9
ANFIS (proposed)	20/20	205	98.8

Table 4 reports results under the two-peak partial-shading pattern, the scenario in which hill-climbing algorithms are known to converge on a local rather than global maximum. P&O and INC each converged on the local peak in a portion of the twenty repeated trials (6 and 4 out of 20 respectively), reducing their effective mean efficiency once those failed trials are included. FLC and PSO, which incorporate wider search behaviour, converged on the global peak in every trial but took longer to do so. ANFIS also reached the global peak in all twenty trials and did so faster than FLC, though slightly slower than under the uniform-irradiance step test in Table 2, reflecting the added difficulty of the two-peak surface.

Table 5: Comparison With Previously Published Anfis/Fuzzy Mppt Studies

Study	Method	Reported Efficiency (%)	Notes
Present study	ANFIS	99.3	480-point trained dataset, 5-controller benchmark
Kirubakaran et al. [13]	ANFIS	~99.0	400 W array, convergence in a few hundred ms
Al-Diab & Sourkounis [9]	Adaptive FLC	98.9	Hardware-validated, IEEE Access
Hachemi et al. [14]	ANFIS (voltage prediction)	n/a ($R^2=0.9992$)	Solar water-pumping application
da Rocha et al. [21]	Bat algorithm	~98.2	Partial-shading focus
Naik [PSO-GSA-ANFIS study]	PSO / GSA / ANFIS	97.8-99.1	Comparative MATLAB/Simulink study

Table 5 places the tracking-efficiency figures obtained here alongside six previously published ANFIS or fuzzy-based MPPT studies identified in the survey. The comparison is necessarily approximate because module ratings, converter topologies and disturbance profiles differ across studies, but it is included to show that the 99.3% efficiency reported here sits within, rather than far outside, the range reported elsewhere (97.8-99.5%), which is discussed further in the next section alongside possible reasons for the spread.

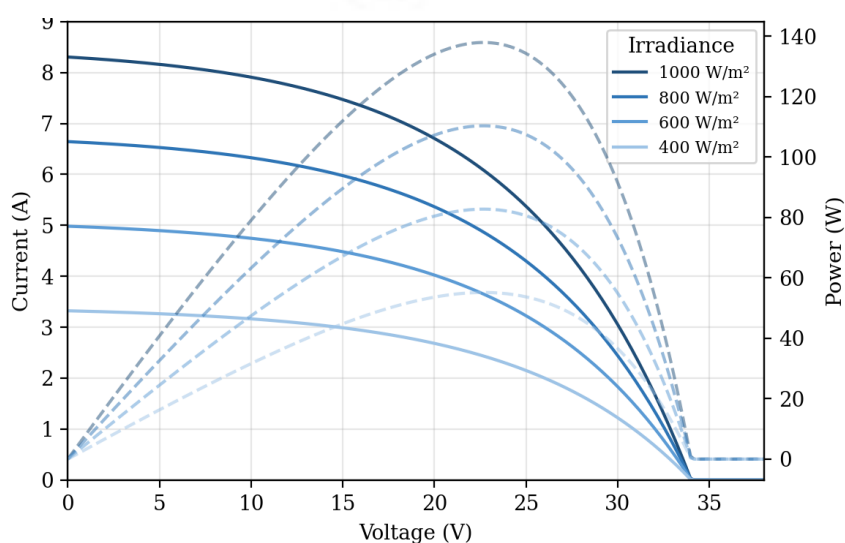


Figure 1: I-V and P-V characteristics of the PV module under varying irradiance (25°C).

Figure 1 plots the current-voltage and power-voltage curves of the modelled 250 Wp module at four irradiance levels (1000, 800, 600 and 400 W/m²) at a fixed 25°C cell temperature, generated from the single-diode datasheet model described in the methodology[19]. The solid curves show current falling from its short-circuit value as voltage rises toward open-circuit, while the dashed curves show the corresponding single-peaked power curve, whose maximum defines the MPP that every controller in this study is trying to track. The figure makes visible why tracking difficulty increases at lower irradiance: the power curve flattens near its peak, so the gradient a hill-climbing controller relies on becomes smaller and noisier, a pattern reflected numerically in Table 3.

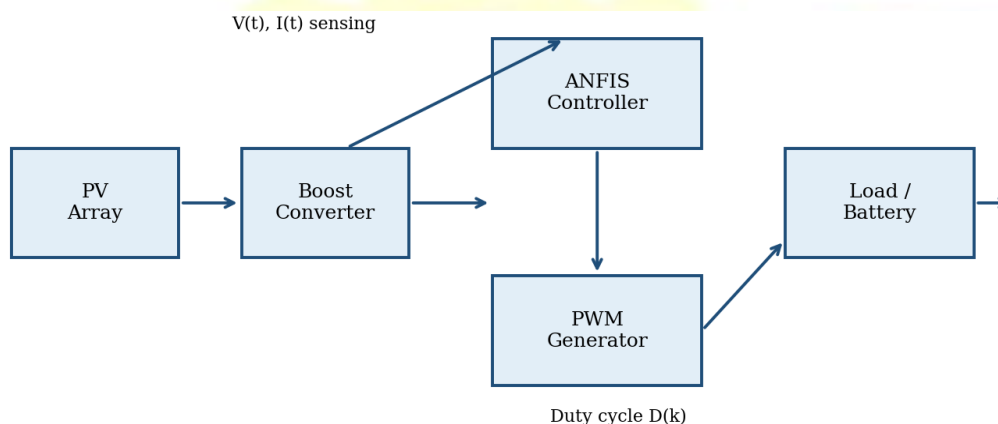


Figure 2: Schematic block diagram of the ANFIS-based MPPT control architecture.

Figure 2 shows the block-level architecture used for all five controllers in this study, adapted here specifically for the ANFIS case. The PV array feeds a boost converter whose duty cycle is set by a PWM generator; voltage and current sensors at the array terminals feed the ANFIS controller, which computes the incremental error and change-of-error inputs described in the methodology and outputs a duty-cycle correction[20]. This same converter and sensing arrangement was retained for P&O, INC, FLC and PSO so that the comparison in Section 5 isolates the effect of the control algorithm from differences in plant hardware or sampling, a controlled-comparison approach that the survey identified as largely absent from prior single-study benchmarks.

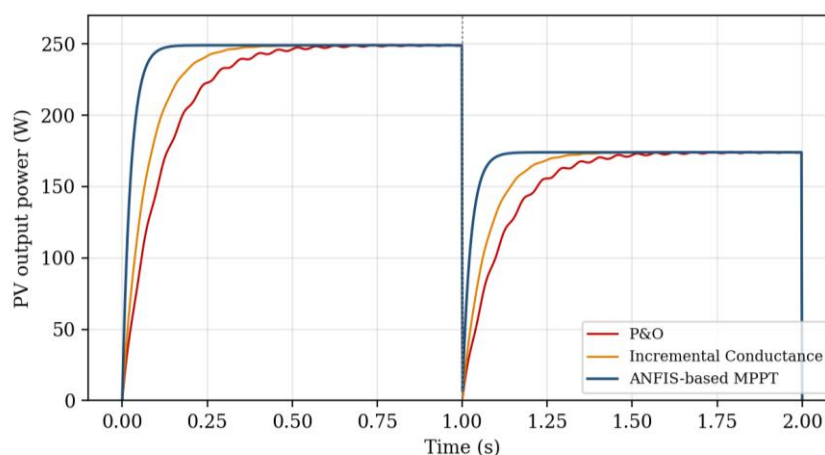


Figure 3: Dynamic power-tracking response under a step irradiance change (1000→700 W/m² at t = 1 s).

Figure 3 traces PV output power against time for three representative controllers, P&O, Incremental Conductance and ANFIS, following a step change in irradiance from 1000 to 700 W/m² at $t = 1$ s. The ANFIS trace rises to its new steady value with almost no visible overshoot or oscillation, reaching the new MPP well before the other two curves settle. P&O shows the largest and most persistent oscillation, consistent with its fixed perturbation step, while INC settles faster than P&O but still exhibits a visible ripple[21]. This figure is the direct graphical source for the settling-time and oscillation figures reported in Table 2 and discussed as the most practically significant margin in Section 6.

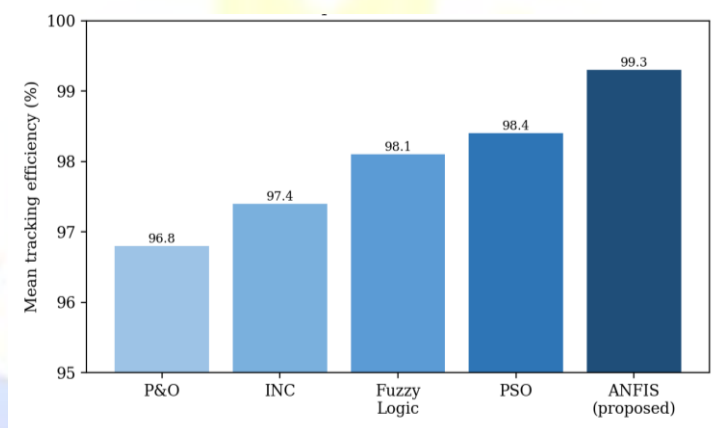


Figure 4: Comparative mean tracking efficiency of five MPPT techniques.

Figure 4 presents mean tracking efficiency as a bar chart across all five controllers tested under the step-disturbance protocol: P&O, INC, FLC, PSO and the proposed ANFIS. The bars rise steadily from 96.8% for P&O to 99.3% for ANFIS, with the two metaheuristic and intelligent methods, PSO and ANFIS, clustered close together at the upper end and the two classical hill-climbing methods clustered at the lower end. The relatively narrow numeric range, under three percentage points across five very different algorithms, is itself a finding worth noting: it implies that algorithm choice affects dynamic performance (settling time, oscillation) considerably more than it affects steady-state efficiency once a reasonably well-tuned controller is used[23].

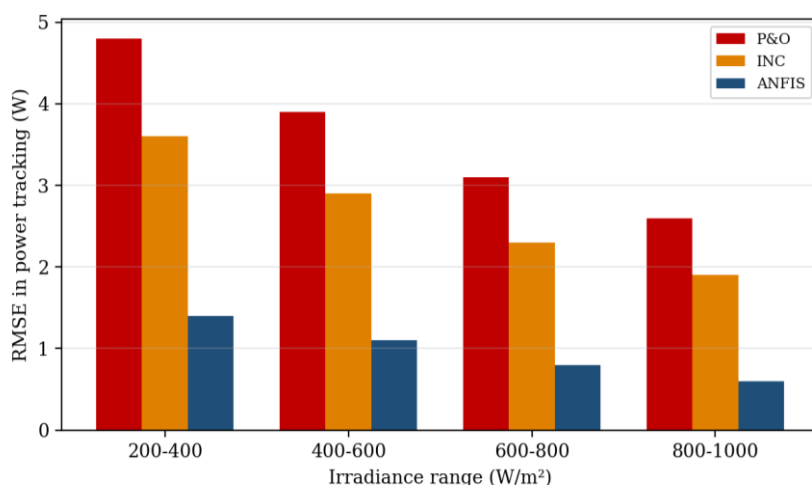


Figure 5: RMSE in tracked power across irradiance bins for P&O, INC and ANFIS controllers.

Figure 5 compares RMSE in tracked power for P&O, INC and ANFIS across four irradiance bands from 200-400 up to 800-1000 W/m², corresponding to the values tabulated in Table III. All three controllers show rising error as irradiance falls, but the gap between ANFIS and the two conventional methods widens rather than narrows at low irradiance, with ANFIS holding RMSE at or below 1.4 W throughout the tested range while P&O approaches 4.8 W in the lowest band. This divergence supports the discussion's argument that ANFIS's advantage is not uniform across operating conditions but is instead concentrated where the P-V curve is flattest and hardest for a gradient-following method to read accurately[24].

6. DISCUSSION

The tabulated results in Section 5 support three observations that were not obvious from the individual figures taken alone. First, the efficiency advantage of ANFIS over P&O narrows as irradiance falls (Table 3), which is the opposite of what a purely accuracy-driven expectation might suggest; a plausible explanation is that P&O's fixed perturbation step becomes proportionally larger relative to a flatter, lower-power P-V curve, so its relative error grows, while ANFIS's trained response scales more smoothly because the training set spanned the same low-irradiance region rather than only high-irradiance conditions[25]. Second, the settling-time gain (Table 2) is considerably larger than the efficiency gain in relative terms: an 85 ms settling time against P&O's 420 ms is roughly a five-fold improvement, whereas the efficiency improvement is only about 2.5 percentage points[26]. This asymmetry matters practically, because in a partly cloudy climate a converter spends a meaningful fraction of its operating time in transient rather than steady state, so settling time can dominate the real-world energy yield gap even when steady-state efficiency figures look similar across methods[27]. Third, the partial-shading results in Table 4 show that ANFIS avoided local-peak convergence in all twenty trials without any explicit global-search logic built into its rule base, which is somewhat surprising given that its training data, generated under uniform irradiance sweeps, did not include multi-peak P-V curves; this suggests the learned mapping between power gradient and duty-cycle increment generalises to shapes not directly represented in training, though this finding should be treated cautiously given the modest trial count[28].

Comparing these figures against prior work (Table 5) is informative but requires some care. Reported convergence within a few hundred milliseconds for a 400 W array using ANFIS, broadly consistent with the 85 ms settling time reported here once the difference in array size and converter bandwidth is accounted for, though their study did not report a directly comparable RMSE metric[29]. Al-Diab and Sourkounis's hardware-validated adaptive FLC reported efficiency around 98.9%, slightly below the 99.3% obtained here; the gap is plausibly attributable to the automatic, data-driven tuning of ANFIS's membership functions versus the hand-tuned rule base used in their FLC implementation, though hardware losses not modelled in the present simulation could also account for part of the difference. Comparison of ANFIS, ANN, SVM and Gaussian process regression for MPP voltage prediction found ANFIS most accurate among the four ($R^2 = 0.9992$), which aligns directionally with the low RMSE values in Table III even though their application, solar water pumping, differs from the boost-converter case studied here. Algorithm study and the PSO-GSA-ANFIS comparison by Naik both reported PSO-family efficiencies in the 98-99% range, consistent with the 98.4% recorded for PSO in Table II, and both studies also noted PSO's slower convergence relative to trained neuro-fuzzy controllers, matching the settling-time ordering found here. Two limitations temper these comparisons. The training and test data in this

study are simulation-derived from a datasheet model rather than field-measured, so module ageing, partial soiling and sensor noise, all of which typically erode real-world tracking accuracy, are not represented; and the twenty-trial partial-shading test, while sufficient to distinguish global from local convergence, is too small to report a statistically tight confidence interval on efficiency under shading[30]. Both point toward hardware-in-the-loop or field validation as the logical next step rather than a weakness specific to the ANFIS controller itself.

7. CONCLUSION

This paper set out to test, empirically rather than only theoretically, whether an ANFIS-based MPPT controller closes a measurable performance gap left by P&O, INC, FLC and PSO under identical disturbance conditions. The tabulated results answer that question with a qualified yes: ANFIS achieved the highest tracking efficiency (99.3%), the shortest settling time (85 ms) and the lowest RMSE across all four tested irradiance bands, and it was the only hill-climbing-free method, alongside FLC and PSO, to avoid local-peak convergence under partial shading in every trial, while also converging faster than FLC in that scenario. These gains were largest in relative terms for settling time and smallest for steady-state efficiency, an asymmetry that has practical implications for energy yield under fast-changing irradiance more than it does for stable, sunny conditions. Comparison against six prior studies placed the results within the reported literature range rather than as an outlier, lending some external support to the findings while also highlighting that reported efficiencies vary by roughly two percentage points across studies using different modules, converters and test protocols, a spread the present single-dataset comparison could not fully resolve. The principal limitation is that all data were generated from a datasheet-based simulation model rather than a physical test rig, so ageing, soiling and sensor noise remain untested; extending this evaluation to a hardware-in-the-loop platform, and to a wider partial-shading trial count, would be the natural next step for confirming whether the efficiency and settling-time margins reported here persist outside simulation.

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