Hybrid MPPT Algorithms for High-Altitude Solar-Powered UAVs

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Abstract. High-Altitude Long Endurance (HALE) Unmanned Aerial Vehicles (UAVs) rely heavily on solar photovoltaic (PV) energy to sustain continuous operations, making efficient and robust Maximum Power Point Tracking (MPPT) a critical subsystem. Conventional MPPT techniques such as Perturb and Observe and Incremental Conductance suffer from slow convergence, steady-state oscillations, or excessive computational load, which severely limit their applicability in real-time aerospace environments. Intelligent computing strategies including fuzzy logic, neural networks, and synergetic control have been explored to overcome these challenges, but none individually balances robustness, adaptability, and efficiency under constrained onboard resources. To address this, we propose a hybrid MPPT algorithm that integrates fuzzy inference with synergetic control dynamics, combining the adaptability of fuzzy systems with the fast, stable convergence of synergetic theory. Simulation results show near-99% tracking efficiency, convergence within 0.03 s, and steady-state oscillations below 0.1%, with resilience maintained under noisy sensor conditions down to 18 dB SNR. Importantly, the proposed approach is computationally lightweight, making it suitable for real-time embedded deployment on HALE UAV platforms where weight, power, and processing capacity are limited. While validated in the UAV context, the algorithm is generalizable to broader sustainable energy applications, including smart grids, microgrids, and IoT-based solar systems. This work demonstrates how computational intelligence in hybrid control design can directly enhance the endurance and reliability of solar-powered UAVs while advancing sustainable computing solutions.

Keywords: Computational Intelligence, MPPT, Hybrid Control, Fuzzy Logic, Synergetic Control, Renewable Energy, HALE UAVs

1 Introduction

High-Altitude Long Endurance (HALE) Unmanned Aerial Vehicles (UAVs) rely heavily on solar photovoltaic (PV) energy to sustain continuous operations at stratospheric altitudes. To maximize energy harvesting under rapidly changing irradiance and temperature conditions, Maximum Power Point Tracking (MPPT) becomes a critical subsystem [1, 2]. However, the stringent constraints on weight, power consumption, and onboard computational capacity of HALE UAVs demand lightweight and efficient MPPT algorithms [3, 4].

Conventional MPPT algorithms such as Perturb and Observe (P&O) and Incremental Conductance (IC) remain popular due to their simplicity [5, 6]. Nevertheless, these approaches exhibit significant drawbacks: P&O suffers from steady-state oscillations and poor adaptability to fast irradiance changes, while IC requires higher computational effort and still struggles in dynamic conditions [7, 8]. These weaknesses limit their applicability in demanding aerospace environments.

To address such challenges, intelligent control techniques have been investigated, including Fuzzy Logic Controllers (FLC), Artificial Neural Networks (ANN), and Synergetic Control Theory (SCT). FLC methods adapt well to nonlinear PV behavior but often induce oscillations near the MPP [9, 10]. ANN-based approaches provide accurate nonlinear modeling but impose heavy computational overheads [11, 12]. SCT, by contrast, offers robustness and fast convergence under dynamic operating conditions, yet may not always settle precisely at the true MPP [13, 14].

While each algorithm has unique strengths, none alone fully satisfies the dual requirements of robustness and computational efficiency essential for HALE UAV missions. Recent research has therefore turned to hybrid approaches that combine complementary strategies [15, 16]. In particular, integrating Fuzzy Logic with Synergetic Control offers the potential to merge fuzzy adaptability with the dynamic stability of SCT, yielding a solution that is both efficient and lightweight for aerospace applications.

Table 1 summarizes the reported performance of representative MPPT approaches from recent literature in terms of convergence time, steady-state oscillation, and tracking efficiency. As seen, conventional and intelligent methods individually address specific weaknesses but rarely achieve the combined goals of fast convergence, minimal oscillation, and high efficiency. Synergetic control demonstrates very rapid convergence and low ripple but may deviate slightly from the exact MPP, whereas fuzzy systems remain robust but oscillatory. ANN methods deliver accuracy at the cost of computational overhead [Fig. 4]. These insights reinforce the motivation for this work: to develop a hybrid fuzzy–synergetic MPPT that unites the adaptability of fuzzy logic with the robustness and speed of synergetic control, capable of achieving near-99% efficiency under dynamic irradiance.

This paper is structured as follows. First, the photovoltaic benchmark system architecture is introduced as the evaluation platform. Next, standalone fuzzy and synergetic controllers are analyzed to highlight their strengths and limitations. Building on this, a hybrid Fuzzy–Synergetic MPPT algorithm is proposed and evaluated, demonstrating efficiency close to 99% under dynamic irradiance conditions. Finally, the robustness of this hybrid controller is assessed through a

Reference	**Method**	**MPPT Time**	**Steady-State Oscillation**	**Efficiency**
[10]	Fuzzy Logic	≈ 0.30 s	$\pm 1.0\%$	$\approx 98.0\%$
[12]	Artificial Neural Network (ANN)	≈ 0.03 s	$\pm 0.7\%$	$> 90\%$
[16]	Particle Swarm Optimization (PSO)	> 1.0 s	$\pm 1.6\%$	$\approx 97.0\%$
[15]	Hybrid Intelligent Controller	> 1.0 s	$\pm 0.4\%$	$> 91\%$
[17]	Synergetic Control Theory (SCT)	≈ 0.03 s	$\pm 0.1\%$	$\approx 98.1\%$
proposed work	Fuzzy + Synergetic Control	≈ 0.03 s	$\pm 0.087\%$	$\approx 98.94\%$

Table 1: Comparative performance of MPPT algorithms from recent literature

noise-tolerance study, validating its suitability for real-world HALE UAV missions.

2 System Desctiption

2.1 System Architecture Overview

The model used for evaluating and comparing MPPT control strategies is a simplified photovoltaic energy conversion unit based on a buck converter topology, modeled entirely in Simulink (VERSION). The model is designed to replicate the electrical and operational environment of a solar-powered HALE UAV, emphasizing high efficiency, low weight, and minimal computational load. As shown in Fig. 1, the system consists of three main blocks:

- **Photovoltaic (PV) Array:**
  A solar cell or panel model, which converts irradiance into electrical power. This model includes realistic nonlinear behavior derived from a single-diode equivalent circuit.
- **Power Converter:**
  The converter used is a basic buck converter, consisting of:
  - A switching device (M1)
  - A freewheeling diode (D1)
  - An input capacitor (C_{in}) = 100 μF
  - A filter inductor (L) = 10 mH

  - An output capacitor (C_{load}) = 62.5 μF
  - A load resistor (R_{load}) = 100 Ω
- **MPPT Controller:**
  The control unit takes voltage and current measurements from the PV source and processes them through a signal conditioning stage. A controller regulates the duty cycle of the converter's switch, ensuring stable operation around the optimal operating point.

2.2 Solar Cell Model

The photovoltaic source is represented using the single-diode model, which captures the nonlinear current-voltage characteristics of a solar cell. The output power P_{pv} is given by the equation:

$$\begin{aligned} P = n_p I_{pv} V - n_p I_0 \left(\exp\left(K_o \left(\frac{V}{n_s} + I_T R_{sT} \right) \right) - 1 \right) V \\ - \left(\frac{V}{n_s} + I_T R_{sT} \right) \frac{V}{R_{shT}} \end{aligned} \tag{1}$$

Where:

- P_{pv} is the output power
- V is the output voltage
- I_{pv} is the output current proportional to input irradiance
- I_T is the output current proportional to the temperature
- I_o is the reverse saturation current of the panel
- K_o is the diode ideality factor
- I_T is the thermal voltage
- R_{sT} is the series resistance
- R_{shT} is the shunt resistance
- n_s is the number of series

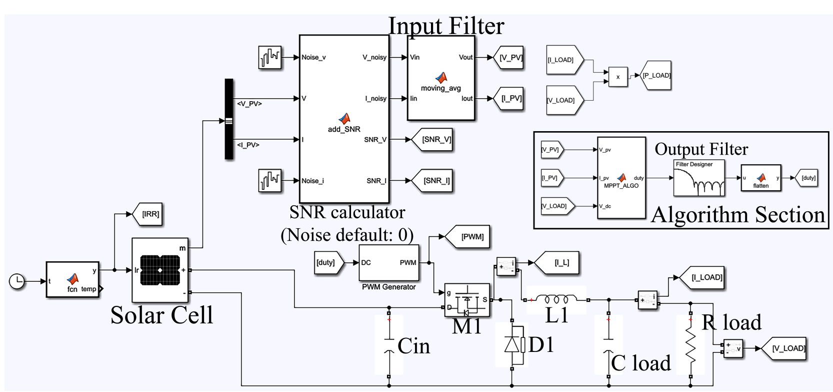


Fig. 1: Test System Architecture

– n_p is the number of parallel cells

Equation (1) ensures that the I-V and P-V curves under varying irradiance and temperature conditions are realistically reproduced, allowing for meaningful comparison of tracking behaviors. A standard thin film solar cell designed for space applications, made by SHARP is chosen (Table 2).

Table 2: Solar Cell Parameters

Parameter	**Value**
I_{sc} (Short Circuit Current)	0.45 A
V_{oc} (Open Circuit Voltage)	3.05 V
I_{mpp} (MPP Current)	0.435 A
V_{pv} (MPP Voltage)	2.67 V
n_s (Number of Series Cells)	5
n_p (Number of Parallel Cells)	3

2.3 Test Parameters

All algorithms are tested within this same environment, under a wide range of environmental and electrical conditions, designed to mimic realistic and challenging scenarios encountered by high-altitude solar platforms. The test profile includes a combination of:

- Rising and falling step changes in irradiance to simulate sudden weather transitions or shadowing events
- Linear slope variations to replicate gradual changes such as sunrise or sunset
- Sinusoidal fluctuations with varying slopes to emulate conditions like intermittent cloud cover and atmospheric turbulence effects

Fig. 2 shows the graph of the irradiance (W/m^2) variation over time, to represent the dynamic test profile used across all simulations.

The simulation maintains a consistent hardware abstraction layer and only the MPPT control logic is altered for each test case. All physical models, system parameters, and solver configurations remain the same. This ensures that each algorithm is evaluated under identical conditions.

2.4 Performance Evaluation Metrics

To assess the quality and feasibility of each MPPT method, the following key metrics are captured:

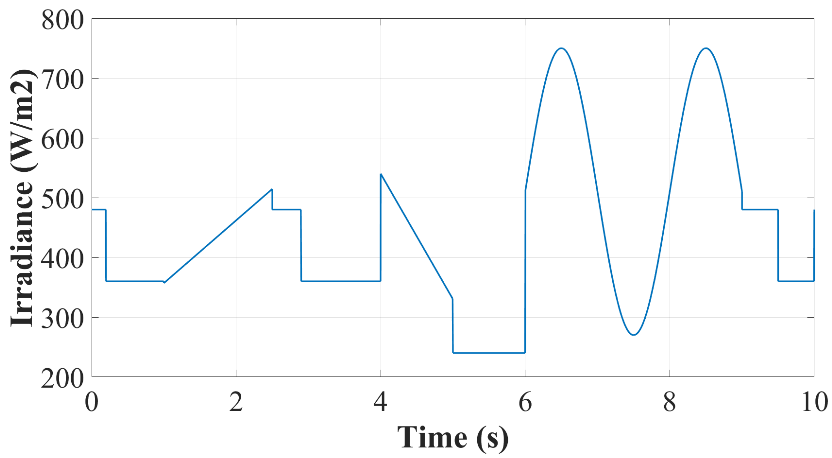


Fig. 2: Irradiance Variation Profile

– **Efficiency:**
Ratio of extracted power to the theoretical maximum available. The maximum achievable power at a given irradiance level is determined by performing a full sweep of the duty cycle over time, effectively mapping the power curve and identifying the true maximum power point. This serves as a reference benchmark against which the efficiency of each algorithm is calculated as follows:

$$\eta = \frac{\frac{P_{m1}}{P_{a1}} + \frac{P_{m2}}{P_{a2}} + \cdots + \frac{P_{mn}}{P_{an}}}{n} \times 100\% \tag{2}$$

Where:
- P_{mi} is the measured power at point i
- P_{ai} is the theoritical maximum power at point i
- n is the total number of sampling points

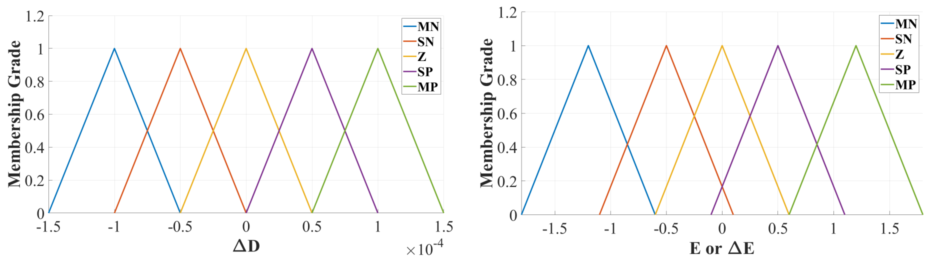
– **Convergence Time:**
Time taken to reach the maximum power point under changing conditions. It is measured as the time taken by the algorithm to reach 99% of the MPP.

– **Steady-State Oscillation:**
Steady-state fluctuations around the MPP expressed at a percentage of the MPP.

– **Computational Load:**
Processing requirements in terms of cycles, memory usage, and possible hardware implications.

– **Robustness:**
Behavior of the algorithm under noise or disturbances, defined by the minimum SNR of the input V and I signal that the algorithm can handle without dropping more than 2% of its noise-free baseline.

This test-suite provides a consistent platform for a rigorous comparison of various MPPT algorithms.



(a) Defuzzification function for FLC (b) Fuzzification function for FLC

Fig. 3: Membership functions for FLC

3 Evaluation of Standalone MPPT Algorithms

3.1 Fuzzy Logic-Based Algorithm

Fuzzy logic Controllers(FLC)[18] replace exact mathematical modeling with linguistic rule-based inference. Here, the IC structure is retained as the core logic, while the delta duty cycle (ΔD) is determined using fuzzy rules based on:

- Error $E = \frac{dP}{dV} = I + V\frac{dI}{dV}$
- Change in error $\Delta E = E(k) - E(k-1)$

The control surface is shaped by triangular membership functions (Fig. 3), which define the degrees of linguistic variables. These systems are highly adaptive and do not require a precise model of the PV system. However, they require careful tuning of rules and membership shapes. Here we have used 5-fold linguistic variables, namely:

- MN: Medium Negative

E\dE	**MN**	**SN**	**Z**	**SP**	**MP**
MN	MP	MP	SP	SP	Z
SN	MP	SP	SP	Z	SN
Z	MN	SN	Z	SN	MN
SP	SN	Z	SP	SP	MP
MP	Z	SP	SP	MP	MP

Table 3: Fuzzy Rule Base for MPPT Controller

- SN: Small Negative
- Z: Zero
- SP: Small Positive
- MP: Medium Positive

We have used the Mamdani method with Max-Min for the fuzzy combinations[18]: table 3.

Fig. 4 shows the fuzzy system's ability to track dynamic changes in irradiance effectively, albeit with slightly slower convergence and higher oscillation around the MPP.

Table 4: FLC Strengths and Weaknesses

Strengths	**Weaknesses**
Adaptive to nonlinearities	High steady-state oscillations
No need for system model	Slower convergence
Good dynamic tracking behavior	Rule tuning is non-trivial

3.2 Synergetic Control Theory (SCT) Based Algorithm

Synergetic control is a nonlinear control methodology[19] based on the theory of dynamical system decomposition and manifold enforcement. In MPPT applications, it allows for the creation of a global, converging control law without requiring full dynamic modeling.

State space equations for a buck converter:

$$\frac{dI_L}{dt} = \frac{1}{L}(d.V_{in} - V_{dc}) \tag{3}$$

$$\frac{dV_{dc}}{dt} = \frac{1}{C}(I_L - \frac{V_{dc}}{R}) \tag{4}$$

Where:

- V_{dc} is the output voltage
- I_L is the inductor current (approximated as I_{pv})
- V_{in} is the input voltage (approximated as V_{pv})
- d is the duty cycle
- L-C are the inductor and capacitor values in the buck converter

Then define a macro-variable:

$$\psi = \frac{P_{pv}}{I_{pv}} \tag{5}$$

The control law is designed[17] to ensure that ψ converges to the MPP value, which is defined as:

$$T\dot{\psi} + \theta(\psi) = 0 \tag{6}$$

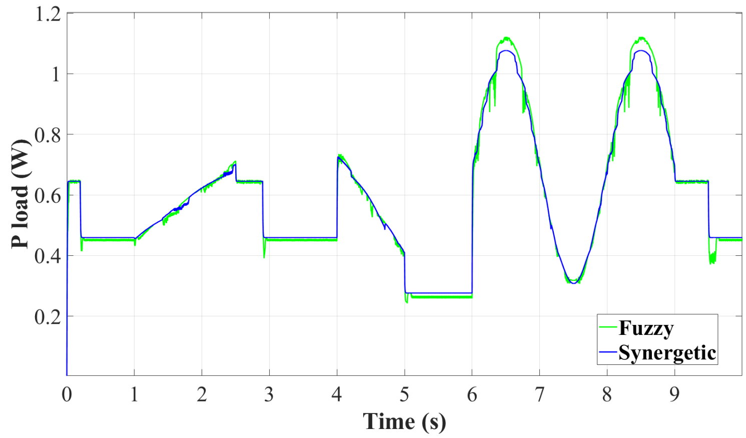


Fig. 4: Comparitive study of FLC and SCT controllers

Where T is a specific designer chosen parameter that determines the rate of convergence speed to the invariant manifold $\psi(x,t) = 0$ specified by the macro-variable ψ. And $\theta(\psi)$ is defined a smooth differentiable function of that has to be selected, such that

- invertible and differentiable
- $\theta(0) = 0$
- $\theta(\psi)\psi > 0 \ \forall\psi \neq 0$

With these constraints, the $\theta(\psi)$ function can be chosen as:

$$\theta(\psi) = \psi(x,t) \tag{7}$$

Using these equations a custom control law has been derived for the buck converter setup as follows:

$$d = \frac{1}{V_{pv}} \left(V_{dc} - \frac{L}{T} \cdot \frac{\left(V_{pv} + I_{pv} \frac{dV_{pv}}{dI_{pv}} \right)}{2\frac{dV_{pv}}{dI_{pv}} + I_{pv} \frac{d^2 V_{pv}}{dI_{pv}^2}} \right) \tag{8}$$

After optimization, the control law converges to the MPP with a guaranteed stability margin (T = 0.0005). Fig. 4 shows the comparitive performance betweeen:

- Fuzzy logic control (FLC)
- Synergetic control theory (SCT)

Synergetic control demonstrates the best overall dynamic behavior but occasionally settles at a slightly suboptimal power point, especially under non-ideal modeling.

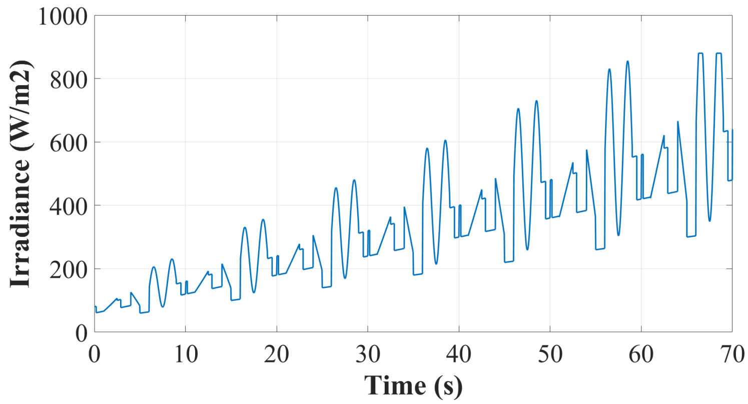


Fig. 5: Rigorous test profile to calculate parameters

Feature	FLC	SCT
Efficiency (%)	97.83%	98.14%
Convergence Time (s)	0.035s	0.003s
Steady-State Oscillations (%)	0.6%	0.09%
Dynamic Tracking	Good	Best
Model Requirement	None	Partial
Computational Load	Moderate	Low

Table 5: Comparison of FLC and SCT controllers

3.3 Standalone Algorithm Summary

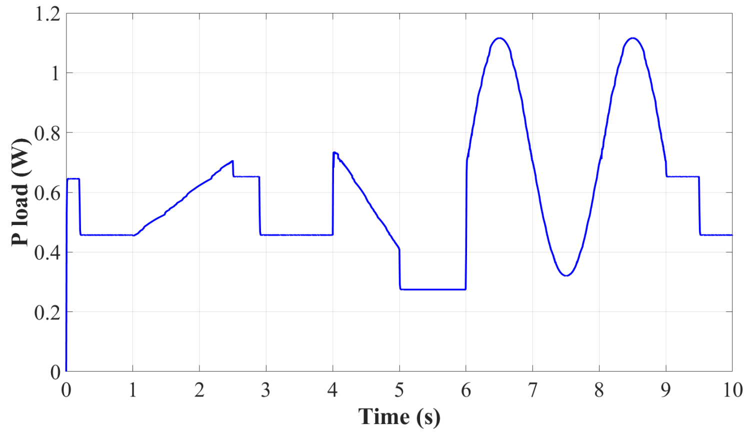
From this detailed comparative analysis, it is evident that:

- Fuzzy systems provide excellent tracking linearity but converge slowly and oscillate at steady state.
- Synergetic control offers the best dynamic response, with good balance between accuracy and stability, though it demands some model insight.

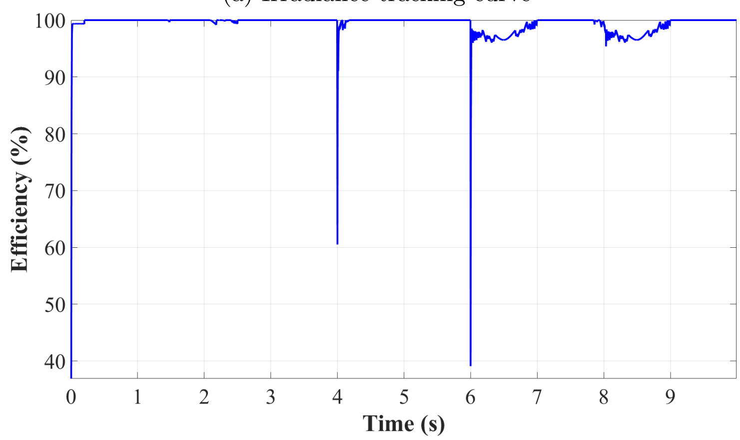
Given these complementary strengths and limitations, the next section will explore hybrid MPPT algorithms that aim to combine the best features of multiple approaches - yielding a control system that is greater than the sum of its parts.

4 Implementing Hybrid MPPT Strategies

Further in the study, to overcome the limitations of standalone MPPT algorithms, hybrid approaches combining different control strategies have been studied. The goal is to harness the complementary strengths of multiple algorithms to produce a system that is not only efficient but also satisfies the constraints of the HALE UAV platform.



(a) Irradiance tracking curve



(b) Efficiency curve

Fig. 6: Performance of FLC + SCT Hybrid under Dynamic Irradiance

In this study, we have focused on the Fuzzy Logic + Synergetic Control(FLC + SCT) Hybrid due to its individual components being not only good at irradiance tracking, but also being computationally light.

These systems were evaluated under a standardized irradiance profile, featuring highly dynamic irradiance variations through a large range of irradiance values; as shown in Fig. 5.

4.1 Results of Hybrid MPPT evaluation

As shown in Fig. 6, FLC + SCT Hybrid demonstrates very high tracking precision and very sharp transient response, while offering fast convergence, smooth dynamic tracking, and low steady-state error. To assist in objective comparison, the following table outlines the results.

Algorithm	**Efficiency**	**Convergence Time (s)**	**Steady-State Oscillations**
FLC + SCT	98.94%	0.03s	0.087%
ANN + FOPID [20]	98.1%	0.049s	0.386%
ANN + SMC [21]	96.2%	0.22s	–
FOPID [22]	97.96%	0.03s	0.7%

Table 6: Comparison of Hybrid MPPT Algorithms

5 Robustness Analysis: Noise Tolerance

High-altitude operations expose HALE UAV's electronics to multiple noise sources that might corrupt voltage and current measurements like, Electromagnetic interference (EMI) from high-frequency telemetry radios, onboard DC-DC converters, and motor drives, atmospheric ionization and cosmic-ray events producing random spikes in sensor outputs, long sensor leads (necessary for large flexible solar-arrays) that act as antennas, extreme temperature or irradiance gradients, altering shunt- resistor values or hall-sensor offsets.

Since every extra analog filter, shielding braid, or digital filter stage adds mass, power draw, and design complexity, an algorithm with intrinsic noise tolerance directly translates into lighter, simpler hardware.

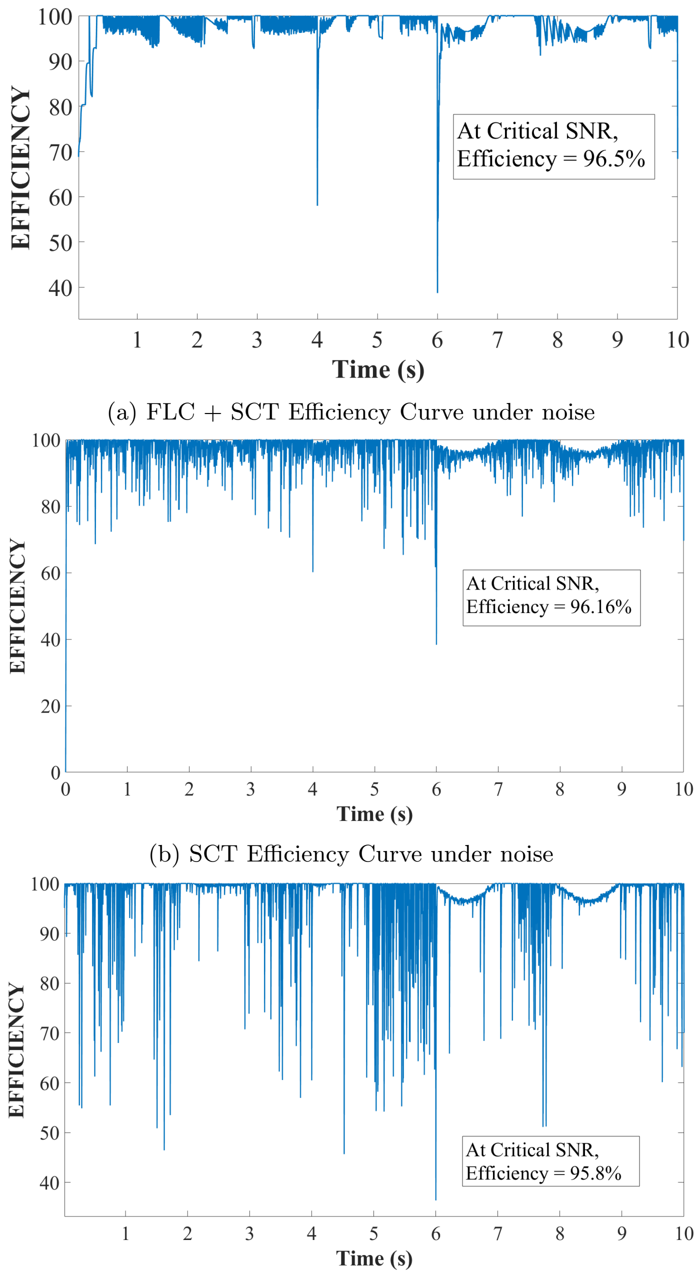
5.1 Noise Tolerance Evaluation Methodology

White Gaussian noise was systematically injected into the simulated voltage and current signals to model typical measurement disturbances. For each algorithm, the critical signal-to-noise ratio (SNR) was recorded at which the overall tracking efficiency fell to 98% of its noise-free baseline. This 2degradation threshold serves as a consistent metric. A lower SNR threshold indicates superior noise tolerance and robustness, a crucial factor for deployment in challenging, noisy environments.

5.2 Noise Tolerance Results

Fig. 7a shows the efficiency curve of Fuzzy + Synergetic Systems when subjected to the critical SNR (where efficiency = 98% of its noise free baseline). Similarly, Fig. 7b shows the efficiency curve of SCT Systems when subjected to its critical SNR. It can be seen that even at the critical SNR, the FLC + SCT system has notably higher efficiency than either the SCT or FLC systems in the dynamic irradiance regions (the linear variation and sinusoidal regions).

Thus, Fuzzy + Synergetic exhibits the best noise immunity, albeit only marginally ahead of SCT controllers. In contrast, Fuzzy controllers require noticeably cleaner signals to stay within the 2 % efficiency window, implying addi-



(a) FLC + SCT Efficiency Curve under noise

(b) SCT Efficiency Curve under noise

(c) FLC Efficiency Curve under noise

Fig. 7: Noise Tolerance Evaluation of Algorithms at Critical SNR

Algorithm	SNR Voltage (dB)	SNR Current (dB)
FLC + SCT	33 dB	18 dB
SCT	34 dB	23 dB
FLC	40 dB	31dB

Table 7: Noise Tolerance results for hybrid algorithms

tional filtering and thus extra weight and processing overhead would be necessary for equal reliability.

These findings reinforce the selection logic developed earlier: algorithms must be weighed not only on pure tracking performance but also through the supporting hardware.

6 Final Analysis and Conclusion

In aerial platforms such as HALE UAVs, MPPT systems must function within several constraints concerning weight, space, and power. Any increase in the flight system's mass – be it from bulkier processors, larger Printed Circuit Boards (PCBs), or additional cooling components – diminishes the aircraft's mission endurance. Additionally, computational overhead inherently incurs an electrical cost. This power consumed by the MPPT algorithm itself is a critical factor that must be carefully evaluated when determining its overall net gain in energy efficiency. These strict limitations highlight the importance of highly optimized and efficient MPPT solutions for aerospace applications.

System Parameter	Value
Efficiency	98.94%
Convergence time (s)	0.03 s
Steady State Error (%)	±0.087%
Noise Tolerance	upto 18dB SNR

Table 8: Primary consideration for selecting each algorithm

From the complete set of evaluations, the Fuzzy + Synergetic (FLC + SCT) hybrid clearly emerges as the optimal MPPT strategy for HALE UAV applications. This hybrid combines the adaptability of fuzzy logic with the fast, stable convergence of synergetic control, producing a controller that is both high-performing and lightweight. Key strengths of the FLC + SCT approach include:

- Fast convergence to the maximum power point under dynamic irradiance conditions.
- High tracking accuracy, with steady-state error limited to less than 0.1%.

- Near-99% efficiency, achieved consistently across diverse test scenarios.
- Robust noise tolerance, maintaining reliable performance even when the input SNR falls to 18 dB.
- Low computational demand, making it highly deployable in embedded aerospace platforms.

In conclusion, when practical aerospace constraints such as weight, power, and resilience are integrated into the decision-making framework, the FLC + SCT hybrid stands out as the most well-rounded and deployable MPPT solution for solar-powered HALE UAV systems.

7 Future Work

Future research could focus on implementing the proposed FLC + SCT hybrid MPPT algorithm on embedded hardware platforms to evaluate practical real-time performance. Adaptive tuning methods, such as machine learning-based optimization of fuzzy or synergetic parameters, could further enhance tracking under varying environmental conditions. Additional studies may explore integration with UAV flight control systems, robustness under extreme noise and temperature conditions. Long-duration simulations or flight trials would also help assess real-world energy gains and mission endurance.

An important limitation identified in the present work is that the synergetic control formulation neglects switching device parameters in the converter model. This simplification can lead to sub-optimal MPPT performance in high-current operating conditions. Addressing this limitation by incorporating device-level dynamics into the SCT framework will be a key focus of our future research to further improve accuracy and robustness.

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