



Integrating Incremental Conductance with Cuckoo Search Approach for Enhanced Maximum Power Point Tracking Efficiency in Solar Energy Systems

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ABSTRACT

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Solar panels usually encounter problems in delivering peak power when sunlight conditions are rapidly changing with low irradiance levels. Traditional Maximum Power Point Tracking (MPPT) methods generally have slow convergence speeds and low precision. To enhance the efficiency of solar energy systems, a hybrid Cuckoo Search–Incremental Conductance algorithm (CSA–INC) is proposed. It combines the strengths of the global optimization capability of the Cuckoo Search Algorithm with the fast dynamic response of the incremental conductance method. Simulation results under varying irradiance conditions show that the CSA–INC algorithm yields an impressive efficiency of 99.73%. This represents significant progress, resulting in reliable and efficient solar energy conversion under rapid weather changes and low-light conditions. Thus, it indirectly promotes the better utilization of renewable resources and supports the sustainable energy development goals.

1. INTRODUCTION

Photovoltaic systems are continuously advancing as a result of innovations in photovoltaic (PV) cell designs, improved energy conversion efficiencies and PV array architectures, deployment of advanced power-electronic interfaces, and use of effective control methods for Maximum Power Point Tracking (MPPT) [1, 2]. Nevertheless, environmental variations decrease their performance, leading to the destabilization of credible operation at large scales [3].

The characteristics of PV panels are nonlinear and time-varying current–voltage (I–V) [4–6]. These characteristics depend on the fluctuations of incident irradiance and temperature levels, which are considered difficult to predict [7]. Thus, there is a necessity for selecting a suitable control method to dynamically adjust system parameters to extract optimum output power from the system during variable environmental circumstances [8].

Since the output power of the PV panels depends on environmental factors, every unique pairing of irradiance and temperature results in a specific Maximum Power Point (MPP) [9]. A wide range of techniques has been developed to identify the MPP, differing in their circuit complexity, cost, accuracy, sensor requirements, and ease of practical deployment [10–12]. Conventional techniques, such as open-circuit voltage [13], short-circuit current [14], incremental conductance (INC) [15, 16], perturb and observe (P&O) [17–19], and hill climbing [20, 21], are straightforward to implement but often exhibit slow convergence, steady-state

oscillations, and limited adaptability to rapid environmental changes.

In an effort to circumvent these limitations, some researchers explored the use of promising soft computing and metaheuristic techniques to identify MPP. Techniques such as Fuzzy Logic Control (FLC) [22, 23], Bat Algorithm (BA) [24, 25], Particle Swarm Optimization (PSO) [26, 27], Genetic Algorithm (GA) [28, 29], and Gravitational Search Algorithm (GSA) [30, 31] bring to the fore more serious search abilities and adaptability. These techniques, however, rarely come without a computational price to pay, fine synthesis of parameters, and in some cases, the solution gets stuck in a local optimum problem.

Another promising technique in this domain is the Cuckoo Search Algorithm (CSA) [32–34], which handles the nonlinear characteristics of PV systems and quickly converges in continuous changing conditions. However, the CSA suffers from steady-state oscillations and lower accuracy at low irradiance levels.

Several studies were conducted on both conventional and intelligent methods; however, none have combined fast response, global optimization, and consistent accuracy under rapidly changing environmental conditions. Traditional approaches are basically hindered by oscillation and slow adaptation, whereas metaheuristics generally lie in the domain of high computational complexity and sometimes do not provide the level of accuracy that has been relied upon in practical applications.

This paper introduces a hybrid control strategy based on the

proposed CSA-INC algorithm, in which the CSA undertakes the global search while INC produces a fast response that can increase the tracking speed, stability, and accuracy under changing conditions. The effectiveness of the proposed algorithm was verified in the MATLAB/Simulink environment.

2. SYSTEM OVERVIEW

Sunlight and air temperature are major inputs for the PV module. The output parameters of the panel, namely voltage (V_{PV}), current (I_{PV}), along with irradiance (G) and temperature (T), are continuously monitored by the control unit [35]. These inputs are fed to different tracking algorithms. Three different approaches are evaluated:

- (i) The conventional INC method
- (ii) The CSA algorithm
- (iii) The proposed hybrid CSA-INC algorithm

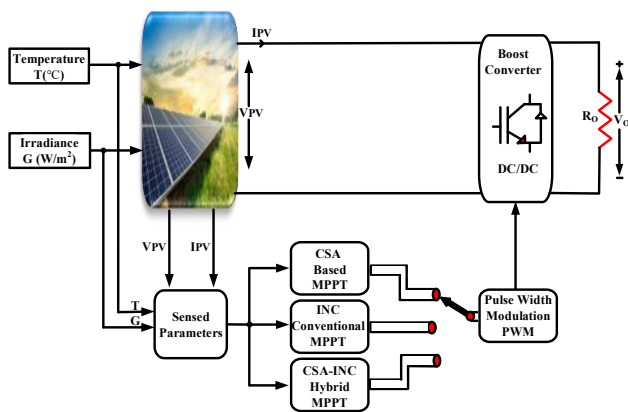


Figure 1. A solar photovoltaic system integrated with a load through a Maximum Power Point Tracking (MPPT) controller

Note: PV: photovoltaic; V_o : output voltage; R_o : load resistance; DC/DC: Direct Current to Direct Current; V_{PV} : voltage; I_{PV} : current

The proposed CSA-INC algorithm embeds the global search capability of CSA with the fast response provided by INC. The algorithm provides an optimal operating duty cycle as a control signal. This signal is then fed to a Pulse Width Modulation (PWM) controller, which subsequently drives the switching action of the Direct Current to Direct Current (DC-DC) boost converter. The boost converter works as an interface between the PV array and the electrical load to adjust the output voltage (V_o) and current to make the PV array operate close to its MPP. Finally, load resistance (R_o) represents the end-use device or system that actually consumes the harvested energy. The overall system configuration is shown in Figure 1.

3. SINGLE-DIODE EQUIVALENT CIRCUIT MODEL

The single-diode equivalent circuit is one of the most widely used models for simulating the current-voltage (I-V) characteristics of PV modules, as illustrated in Figure 2 [36-38]. This model captures the electrical behavior of a solar cell using a simplified circuit comprising a light-generated current source, a diode, a series resistance, and a shunt resistance. The photocurrent source (I_{ph}) produces current in proportion to incident solar irradiance. It is connected in parallel with a diode that represents the nonlinear characteristics of the p-n junction. The single-diode model is chosen because it provides a good balance between computational simplicity and modeling accuracy. While more complex models (e.g., double- or triple-diode models) can capture additional physical effects, they require more parameters, which are often difficult to measure or estimate reliably. The single-diode model represents a good compromise between precision and computation demand for large-scale system studies and control design, such as maximum power extraction. In the equation below, (I_s) is the saturation current of the diode, (V_o) denotes the terminal output voltage of the PV module, and the series resistance (R_s) accounts for the internal ohmic losses. The shunt resistance, denoted as (R_{sh}), models leakage currents, while (K_{VT}) denotes the thermal voltage factor, which, unless otherwise specified, is taken as 26 mV at 300 K and depends on temperature. Individual cells in practical PV arrays are interconnected for higher output power. Cells connected in series per string (S_{CPS}) increase the overall voltage, while the cells grouped into parallel strings (PS) boost the current available. By combining both series and parallel configurations, large PV arrays can be designed to meet particular demands for voltage and current. The total output current of the PV module (I_T) is calculated using Eq. (1), which has been derived based on Kirchhoff's Current Law:

$$I_T = I_{ph} - I_s \left[\exp \left(\frac{V_o + I_T R_s}{K_{VT}} \right) - 1 \right] - \frac{V_o + I_T R_s}{R_{sh}} \quad (1)$$

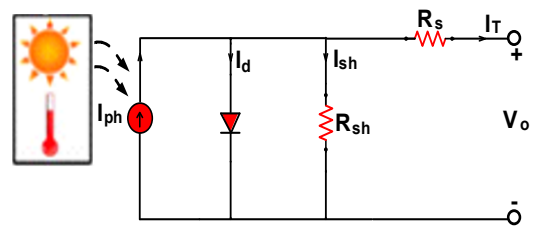
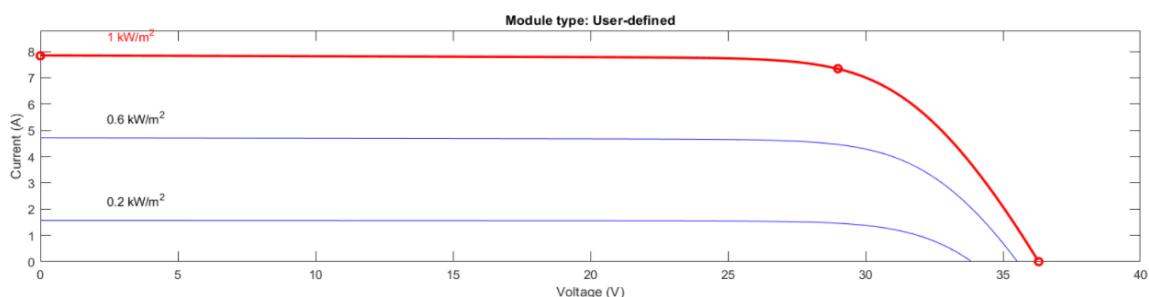
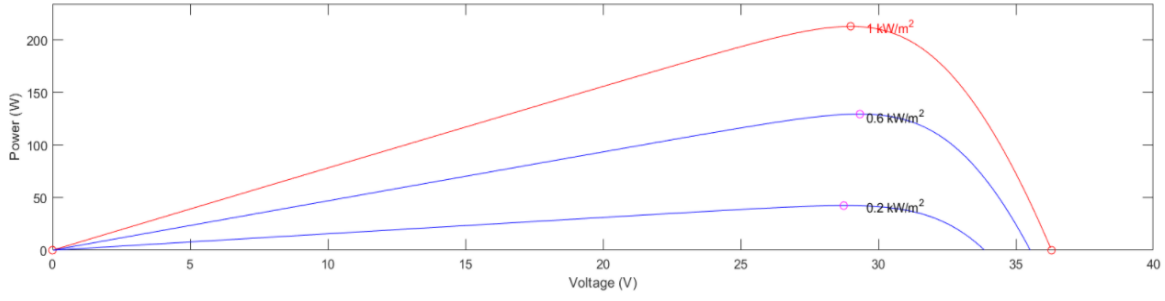


Figure 2. Diagram of the single-parameter model

Note: photocurrent source (I_{ph}); saturation current (I_s); series resistance (R_s); shunt resistance (R_{sh}); diode current (I_d); shunt resistance current (I_{sh}); total current (I_T)



(a) I-V characteristics



(b) P–V characteristics

Figure 3. Current–voltage (I–V) and power–voltage (P–V) characteristics of a photovoltaic (PV) array at varying irradiance levels

The total output current is the light-generated current reduced by the diode current and the current lost through the shunt path. The resistive elements further influence the relationship between voltage and current, as illustrated in Figure 3.

In high irradiance conditions, I_{ph} becomes dominant, and the module is able to provide high output currents. Nevertheless, when the diodes are under low irradiance or high temperature, the saturation current (I_s), series resistance (R_s), and shunt resistance (R_{sh}) become more prominent, resulting in a significant difference from the ideal I–V curve. Hence, this gives a reason for the drop in PV performance in the mentioned conditions. Given the Boltzmann's constant ($K_B = 1.38 \times 10^{-23}$ J/K), the major factor influencing PV array performance is the diode ideality factor (A). The modules' ratings are calculated based on the Standard Test Conditions (STCs) (1000 W/m², 25 °C), which involve the operating temperature (T in Kelvin) and the electron charge ($q = 1.6 \times 10^{-19}$ C). The I_{ph} is calculated using Eq. (2), which considers the irradiance–temperature relationship.

$$I_{ph} = \frac{G_i}{G_s} [I_{sc,ST} + K_{sc} (T - T_r)] \quad (2)$$

where, G_i is the solar irradiance that the PV surface is receiving, G_s is the standard irradiance level, and $I_{sc,ST}$ is the short-circuit current under STCs, and K_{sc} is the temperature coefficient indicating the short-circuit current's dependence on temperature. The reference temperature (T_r) is used as a standard for measuring the effects of temperature on PV modeling. The diode's reverse saturation current (I_{rs}) is a temperature-dependent parameter that is computed as depicted in Eq. (3), where it doubles exponentially with every 10 °C increases in temperature. This behavior contributes to the non-standard conditions I–V curve predictions being less accurate. The coefficient (K_{ov}) is a scale factor of the open-circuit voltage drop with temperature, expressed in volts per Kelvin. It basically tells us how much voltage is being lost because of the increasing noise from the heat. Both parameters are necessary in order to achieve correct simulation and performance evaluation of PV modules subjected to different environmental conditions.

$$I_{rs} = \frac{I_{sc,ST} + K_{sc}(T - T_r)}{\exp(V_{oc,ST} + K_{ov}(T - T_r)/AK_{VT}) - 1} \quad (3)$$

where, $V_{oc,ST}$ denotes the voltage at no load at the standard conditions. The temperature–intensity relations defined by these coefficients are important for precise PV modeling since

they control the reverse saturation current, which is the main performance factor of the PV cell.

$$I_s = I_{rs} \cdot \left(\frac{T}{T_r}\right)^3 \cdot \exp\left[\frac{qE_g}{AK_B} \left(\frac{1}{T_r} - \frac{1}{T}\right)\right] \quad (4)$$

The diode saturation current (I_s) is expressed as a function of temperature and energy, as presented in Eq. (4). The cubic term $(T/T_r)^3$, along with the exponential component, signifies its large variation, nonlinear increase with temperature. The increase of (I_s) with temperature is not a simple rise but rather an exponential climb that affects the I–V characteristics of the PV device. The electrical and material properties of the 1Soltech 1STH-250-WH module were employed for precise simulation and parameter extraction [37-40], with the PV parameters as listed in Table 1.

Table 1. Parameters of solar-powered

Photovoltaic Parameters	Values
P_S	1
S_{CPS}	1
P_{MP}	213.15 W
V_{oc}	36.3 V
I_{sc}	7.84 A
V_{MP}	29 W
I_{MP}	7.35 A
I_{ph}	7.865 A
I_s	$2.9273e^{-10}$ A
A	0.98119
n_s	60
n_p	1
R_s	0.3938 Ω
R_{sh}	313.0553 Ω

4. STANDARD BOOST CONVERTER

The boost converter acts as a bridge between the PV array and the load and increases the low PV voltage to a stable level. It is evidenced by Figure 4 that it gets its control from a PWM signal, which is responsible for the switching of the Insulated Gate Bipolar Transistor (IGBT). The MPPT controller is constantly monitoring the PV voltage (V_{PV}) and current (I_{PV}), computing the power, and then making a comparison with the previous point. It will then set the highest possible duty cycle and will forward it to the PWM generator for the adjustment of the IGBT switching to ensure that power extraction is at its maximum. This is a closed-loop control which allows the

MPPT technique to keep on adjusting the converter and thus the PV array is always at or very close to the MPP [41–42]. In order to have a power flow that is stable, the single-stage boost converter (SBC) is designed with certain passive components of utmost importance. The input capacitor (C_i), which is connected in parallel with the PV array, serves as a DC link for voltage stabilization, energy delivery support, and energy transfer prevention during those times when there is a change in the amount of light or load. The inductor (L) keeps energy when the IGBT is on and gives it away when it is off; the diode (D) prevents reverse current. The output capacitor (C_o) eliminates voltage ripples, thus providing a stable power supply to the load (R_o). The converter scheme is depicted in Table 2 and Figure 4, with voltage and current relationships expressed in Eqs. (5) and (6).

$$V_o = \frac{V_{PV}}{1 - D} \quad (5)$$

$$I_o = \frac{I_{PV}}{1 - D} \quad (6)$$

By means of these equations, it is demonstrated that the duty cycle change brings about a shift in the voltage and current of the PV module, thereby directing it to the most power output area. Provided that there are no losses, the equivalent resistance of the load is represented by Eq. (7):

$$R_o = \frac{V_o^2}{P_{PV}} \quad (7)$$

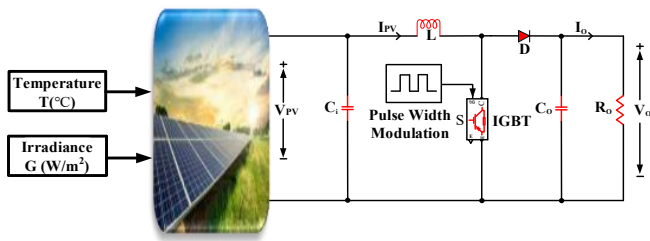


Figure 4. Relation of a photovoltaic system with a boost converter and power optimization control

Table 2. Parameters of the standard boost converter

Single-Stage Boost Converter Parameters	Values
Inductor, L	6 mH
Capacitor, C_i	21 μ F
Capacitor, C_o	30 μ F
Output load resistance, R_o	37 Ω
Switching frequency, f_s	26 kHz

As shown by Eq. (8), the voltage gain (A_v) is defined as the ratio of the output voltage (V_o) to the input voltage (V_{PV}).

$$A_v = \frac{V_o}{V_{PV}} = \frac{1}{1 - D} \quad (8)$$

The output voltage can be made to greatly surpass the PV input voltage by varying the duty cycle. In this paper, the boost converter is configured to give an output voltage of around double the MPP voltage of the PV array, thus increasing the efficiency of power and energy transfer [43]. Tracking efficiency (η) refers to the proportion of power taken out of the power available at the maximum level, which is presented in

Eq. (9):

$$\eta = \frac{\text{Power Tracking } (P_o)}{\text{Maximum Power } (P_{in})} \times 100\% \quad (9)$$

5. MAXIMUM POWER POINT TRACKING

The I–V characteristics of PV modules are nonlinear and vary depending on the irradiance and temperature. To ensure maximum power output, MPPT controllers monitor the voltage and current, perform power calculations, and modify the duty cycle of the DC–DC converter to follow the MPP [44–46].

MPPT techniques are divided into two main groups, which are classical methods and intelligent methods. Classical methods, including P&O, INC, and hill climbing, are simple and cheap [47, 48]. P&O has a problem with oscillations and loses its accuracy under fast changes [48, 49]. On the other hand, INC ensures stability but at the same time may lose some precision during small changes in irradiance [50].

Smart MPPT techniques, such as fuzzy logic, neural networks, genetic algorithms, and particle swarm optimization, are intelligent strategies that provide great adaptability and global search, particularly in partial shading with multiple peaks [49, 51–53]. However, these techniques have high computational requirements, need accuracy tuning, and demand additional sensors. The selection of an MPPT method is a compromise among cost, complexity, speed, and accuracy [50]. Efram et al. [2] have categorized more than 19 methods, all of which have particular advantages. The latest advancements are mainly directed towards the use of the adaptive step-size and hybrid MPPT approaches. These advancements are expected to enhance tracking precision, minimize oscillations, and increase response speed during rapid condition changes [54]. In practice, the MPPT controller adjusts a boost converter to keep the PV module at its MPP while ensuring stable power delivery [43, 51].

5.1 Incremental conductance

INC is a widely used classical MPPT algorithm that determines the optimum operating voltage of a PV module by comparing:

- Instantaneous conductance: $-I/V$, which is the negative ratio of current to voltage, and
- Incremental conductance: dI/dV , which is the rate of change of current with respect to voltage [15, 16, 48–50].

At the MPP, the slope of the PV power–voltage (P–V) curve is $dP/dV = 0$. Mathematically:

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = I + V \frac{dI}{dV} = 0 \quad (10)$$

Which simplifies to:

$$\frac{dI}{dV} = -\frac{I}{V} \quad (11)$$

where, I is the module output current (A), and V is the module output voltage (V). The operating conditions of the INC algorithm are as follows:

- If $dI/dV > -I/V$, then $dP/dV > 0$ (Eq. (12)) \rightarrow the

operating point is to the left of the MPP, and the terminal voltage must be increased.

- If $dI/dV < -I/V$, then $dP/dV < 0$ (Eq. (13)) → the operating point is to the right of the MPP, and the terminal voltage must be decreased.
- When $dI/dV = -I/V$, the system has reached the MPP, and no further adjustment is required.

By continuously applying these conditions, INC guides the PV system toward the exact MPP [43-46].

$$\frac{dP}{dV} \geq 0 = \frac{dI}{dV} > -\frac{I}{V} \quad (12)$$

$$\frac{dP}{dV} \leq 0 = \frac{dI}{dV} < -\frac{I}{V} \quad (13)$$

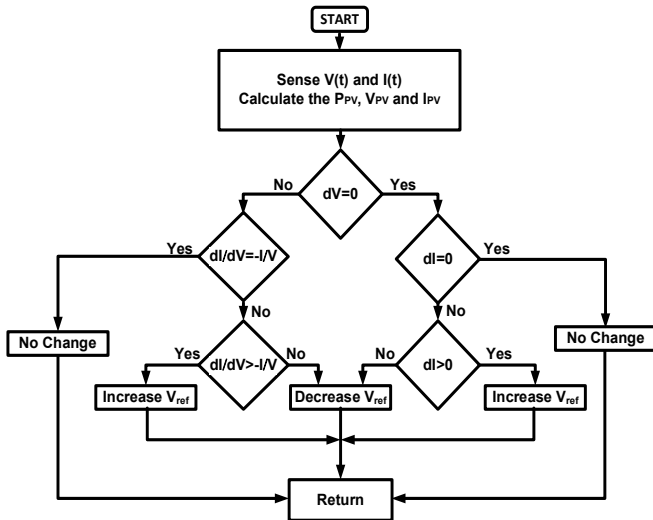


Figure 5. Flowchart of the incremental conductance Maximum Power Point Tracking (MPPT)

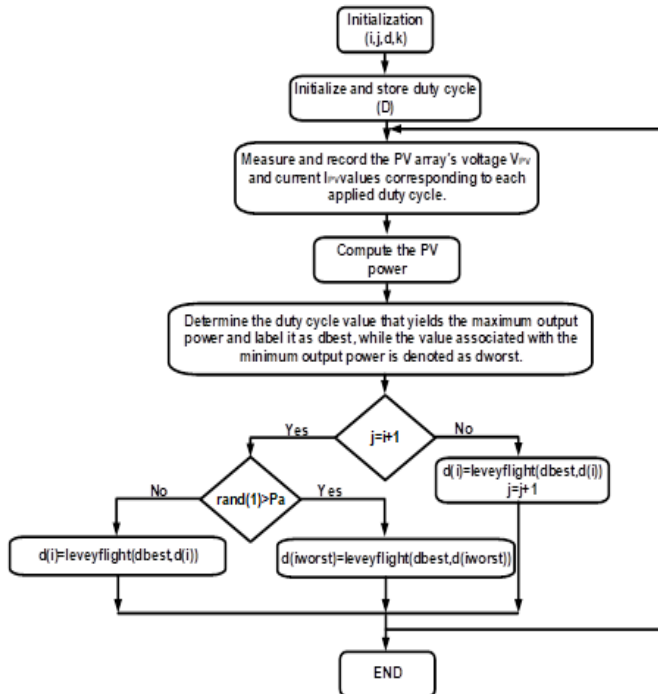


Figure 6. Flowchart of the Cuckoo Search Algorithm Maximum Power Point Tracking (MPPT) algorithm

The flowchart of the operational sequence of the INC algorithm is depicted in Figure 5. The controller samples PV

voltage and current to calculate instantaneous and incremental conductance. The reference voltage (V_{ref}) is then updated in the following manner:

- Allow V_{ref} to go up if the operating point is on the left side of MPP,
- Allow V_{ref} to go down if the point is on the right side of MPP,
- Maintain V_{ref} at the same level when MPP is reached.

Such a mechanism gives the INC algorithm the capability to steadily and precisely approach the MPP compared to the already mentioned methods, particularly P&O, when there is a quick change in irradiance.

5.2 Cuckoo Search Algorithm

CSA, a nature-inspired metaheuristic, is employed in MPPT to address the drawbacks encountered in classical MPP methods, even under tough environmental conditions [55]. The “cuckoo brood parasitism” concept is the basis of CSA, which employs global search with a population-based approach to locate the real MPP. This technique proves to be effective in partial shading situations where the traditional ones, like P&O or INC, might not work at all [56].

The CSA algorithm considers different duty cycles by resorting solely to the power output generated from the solar PV modules, i.e., PPV, thus pointing out:

- d_{best} : the duty cycle arc with the highest power,
- d_{worst} : the arc with the lowest power.

Additionally, candidate solutions are revived through Lévy flight-driven random walks, which allow both local refinement and global exploration.

$$d(i) = dbest + \alpha \cdot Lévy(\lambda) \quad (14)$$

where, $d(i)$ is the current duty cycle, α is the step-size scaling coefficient, $Lévy(\lambda)$ is the Lévy distribution function with λ controlling step length.

The algorithm is characterized by high computational efficiency, low execution time, and low hardware resource requirements. Thus, it is an ideal choice for PV systems with limited processing capacity [56]. The literature indicates its faster convergence and better power tracking accuracy over traditional MPPT methods [57]. Figure 6 presents the flowchart of the MPPT based on CSA. It assesses the prospective duty cycles, selects the best and worst solutions, and modifies them through Lévy flight exploration.

Despite being quite effective, CSA does have its handcuffs like the steady-state oscillations, the parameter setting sensitivity, and the possibility of early convergence to local optima [56]. These problems are related to the accuracy versus response speed dilemma that is typical in bio-inspired algorithms.

In real implementation, the CSA-based MPPT is normally combined with a DC–DC boost converter to ensure that the PV system operates close to the global MPP even during fluctuations in irradiance and temperature [55, 56]. The simulation results, particularly in MATLAB/Simulink, always prove the effectiveness of CSA, especially when the partial shading is present [57].

Both INC and CSA are intended to track the MPP, while they use different strategies for their operation. INC is considered to be a simple solution to the problem that needs very little computation and a fast reaction to slight irradiance variations. However, it has low accuracy and makes steady-

state oscillations around the MPP.

5.3 Hybrid Cuckoo Search Algorithm–Incremental Conductance algorithm

Even though CSA is more computationally intensive, it efficiently manages to deal with nonlinear PV behavior and partial shading PV modules through its ability to perform a global search for MPP. On the downside, the method can be influenced by parameter variability and oscillations at steady state [58]. All these issues make the hybrid CSA–INC algorithm attractive, as a combination of global searching by CSA and fast local tracking by INC results in better MPPT performance.

The hybrid CSA–INC algorithm combines the latter’s rapid convergence with the former’s global search for the purpose of achieving efficient and adaptive MPPT for PV systems. By employing random walks and Lévy flights, CSA enables the following: global search through long jumps, thus avoiding local optima, and local refinement through short steps [59].

The effectiveness of the CSA method during partial shading is due to this dual search strategy, which prevents conventional

tracking techniques from being trapped in several local maxima. The general update rule for generating new duty cycles is:

$$x_i^{(t+1)} = x_i^t + \alpha \cdot Lévy(\lambda) \quad (15)$$

where, x_i^t denotes the solution at iteration t . This allows CSA to efficiently search the duty cycle space and move toward the global MPP. The step-size factor (α) balances exploration and exploitation:

- A large α may overshoot the optimal region.
- A small α can cause early convergence to local optima.

In practice, α is tuned based on convergence and irradiance changes. Smaller values of α improve precision near the MPP, while larger ones boost exploration during shading or sudden conditions. In the hybrid method, CSA performs global exploration to locate potential MPP regions, then INC takes over for precise local tracking.

- CSA → Explores the duty cycle space broadly.
- INC → Refines and stabilizes the MPP within the identified region.

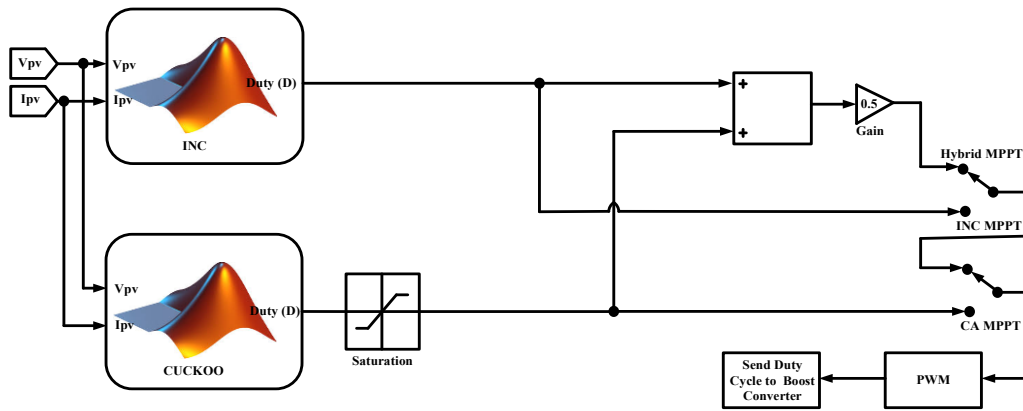


Figure 7. Hybrid Cuckoo Search Algorithm–incremental conductance-based Maximum Power Point Tracking (MPPT) control strategy implemented in the boost converter system

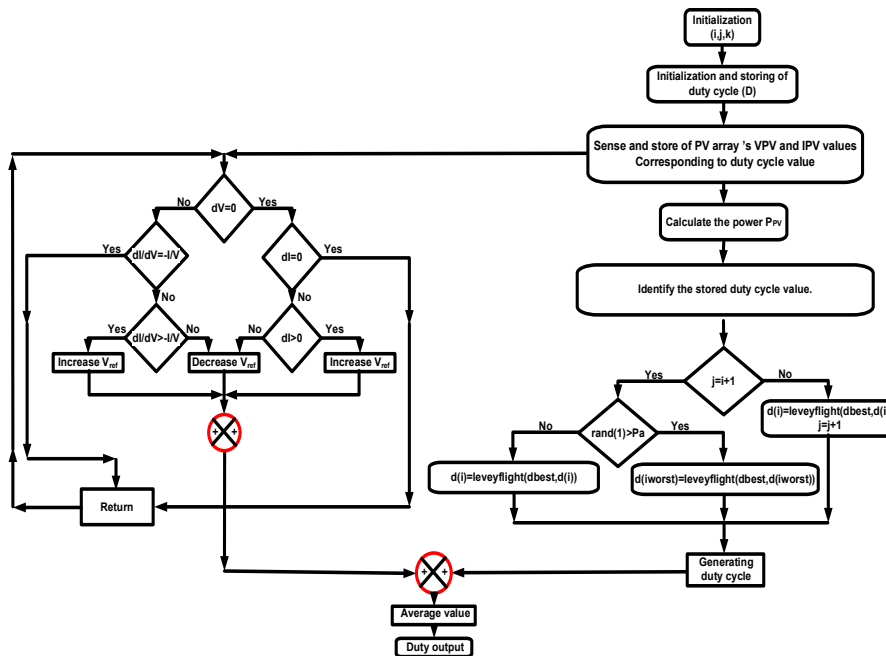


Figure 8. Flowchart of the proposed incremental conductance and Cuckoo Search Algorithm

Table 3. Comparative summary of Maximum Power Point Tracking (MPPT) methods

Method	Advantages	Limitations	Complexity
Perturb and observe (P&O)	Simple, low-cost, easy to implement	Oscillations; poor performance in fast changes	Low
Incremental conductance (INC)	Better stability, responsive to variations	Struggles with small irradiance changes	Moderate
Fuzzy logic	Handles uncertainty, good adaptability	Requires a rule-based tuning; tuning is complex	Moderate
Particle swarm optimization (PSO)	Global optimization is good under shading	High computation; risk of local optima	High
Cuckoo Search Algorithm (CSA)	Fast convergence, global search capability	May oscillate; reduced accuracy at low irradiance	High
Proposed Cuckoo Search Algorithm–Incremental Conductance (CSA–INC)	Combines INC stability with CSA optimization, fast, accurate, robust	Added design complexity vs. single methods	Moderate–High

Figures 7 and 8 illustrate the proposed control strategy of the hybrid CSA–INC MPPT for solar energy systems, showing the integration of both algorithms and how the average duty cycle controls the boost converter via PWM. As a result, the combination of the two methods allows efficient performance and adaptive MPPT, while also exceeding the performance of individual methods in varying situations. The hybrid method overcomes the weaknesses of each standalone approach through:

- INC alone can get trapped in local optima under partial shading. This limitation is addressed by CSA's global search.
- CSA by itself may converge slowly or oscillate, but INC enhances speed and stabilizes the operating point.

Combining CSA's global search with INC's precision, the hybrid CSA–INC algorithm offers:

- Faster convergence to the exact MPP extraction,
- Improved tracking under rapid environmental changes,
- Reduced steady-state oscillations, and
- Stable performance even in low irradiance.

Table 3 provides a comparative overview of various MPPT techniques. The hybrid CSA–INC method offers a well-balanced solution and effectively maximizes energy extraction in scenarios where individual algorithms may underperform.

6. SIMULATION RESULT

The effectiveness of the proposed CSA–INC algorithm was assessed under varying irradiance conditions of 200, 600, and 1000 W/m². As depicted in Table 4, the hybrid approach consistently demonstrated superior performance over standalone INC and CSA methods in terms of power tracking accuracy, voltage regulation, and overall efficiency across all scenarios. The discussion focuses on the performance trends

observed rather than isolated numerical results.

The hybrid CSA–INC approach outperforms standalone INC and CSA methods in terms of convergence speed and enhanced operational stability. At an irradiance level of 1000 W/m², the hybrid algorithm achieved the highest output power of 212.5 W, approximately 123% higher than INC (95.33 W) and marginally outperforming CSA (212.2 W), as depicted in Figures 9 and 10. Under 600 W/m², the proposed hybrid algorithm yielded 128.3 W, representing a 46% improvement over INC (87.89 W) and exhibiting greater voltage stability compared to CSA (127.4 W). Even at low irradiance (200 W/m²), where MPPT effectiveness typically declines, the hybrid algorithm delivered a 33% increase in performance relative to INC.

Therefore, the hybrid approach has kept the PV voltage closer to the theoretical MPP for the entire tested irradiance range. At 1000 W/m², the hybrid converged at 88.6 V, representing a 49% improvement over the INC approach at 59.4 V and very similar to CSA at 88.6 V, as observed in Figures 11 and 12. At an irradiance level of 600 W/m², the hybrid system sustained a voltage of 68.9 V, which was around 21% greater than the voltage (57.0 V) measured by the INC technique. Such advantages signify lower overshoot and excursion, which in turn means better energy delivery stability.

The analysis of efficiency clearly showed that the proposed algorithm is the best choice. It reached 99.73% at 1000 W/m², which is 1.1% better than INC and 0.07% better than CSA. For 600 and 200 W/m², a 0.6% and 0.4% improvement over INC was recorded. The oscillations were less and the efficiency steady over the different irradiances, as shown in Figures 13 and 14.

In Table 5, the CSA–INC algorithm reveals an efficiency of 99.73%, thus surpassing the majority of contemporary hybrid MPPT techniques. This underlines its importance and considerable promise for future photovoltaic applications.

Table 4. Simulation results of Maximum Power Point Tracking (MPPT) algorithms under different irradiance levels

Irradiation Values W/m ²	MPPT Methods	Maximum Power P _{in} (W)	Power Tracking P _o (W)	Voltage V _o (V)	Current I _o (A)	Efficiency (η)
1000	INC	96.62	95.33	59.39	1.605	98.67
	CS	212.9	212.2	88.6	2.395	99.66
600	Hybrid	213	212.5	88.66	2.396	99.73
	INC	89.15	87.89	57.03	1.541	98.58
	CS	128.8	127.4	68.66	1.856	98.95
200	Hybrid	129.4	128.3	68.91	1.862	99.18
	INC	31.28	30.46	33.57	0.9074	97.4
	CS	42.46	41.41	39.14	1.058	97.52
	Hybrid	41.77	40.74	38.83	1.049	97.53

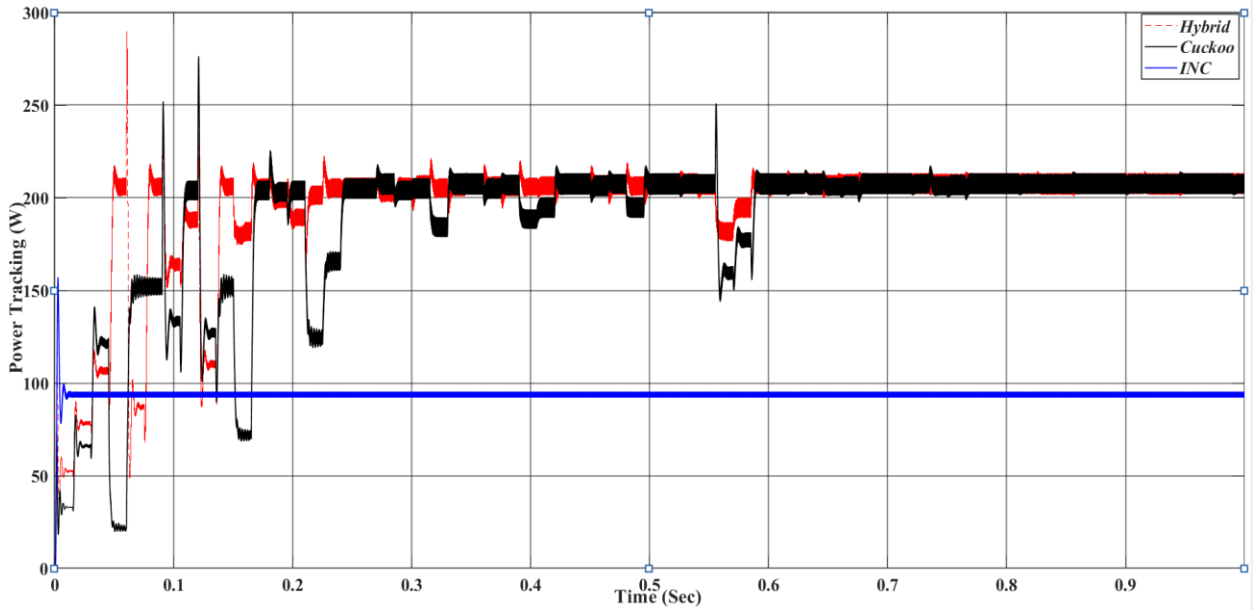


Figure 9. Power tracking performance at irradiance level 1 KW/m²

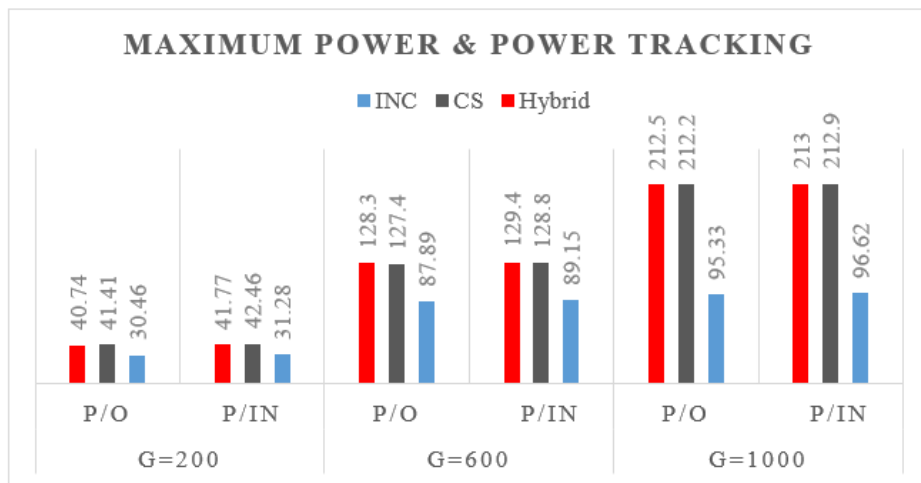


Figure 10. Simulation results of Maximum Power Point Tracking (MPPT) algorithms under varying irradiance levels (200, 600, and 1000 W/m²)

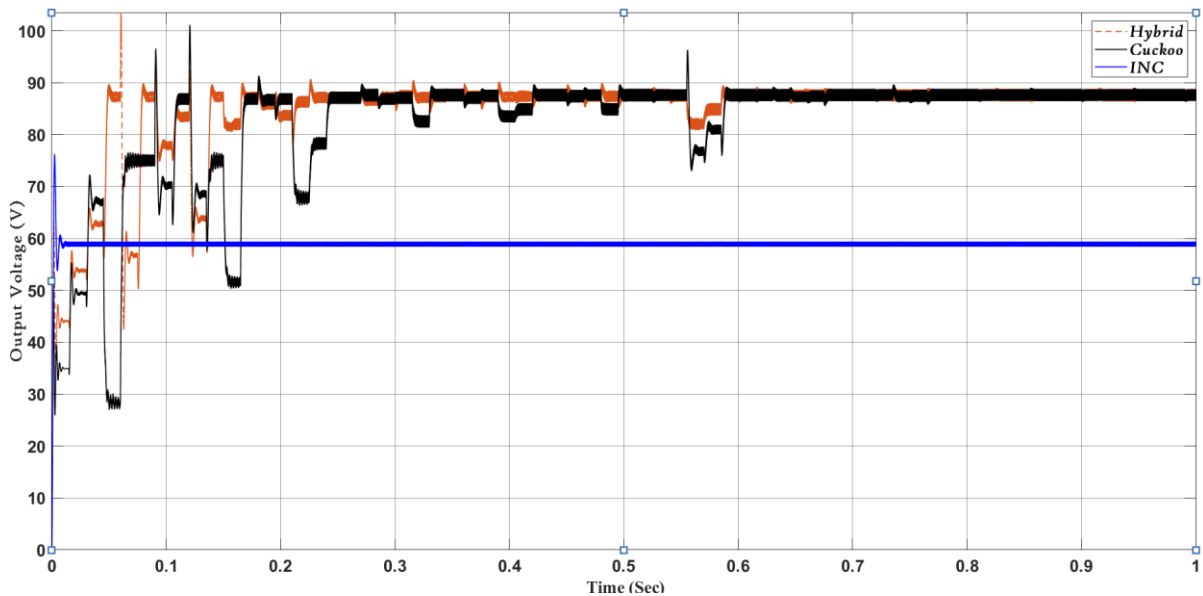


Figure 11. Voltage tracking performance at 1000 W/m²

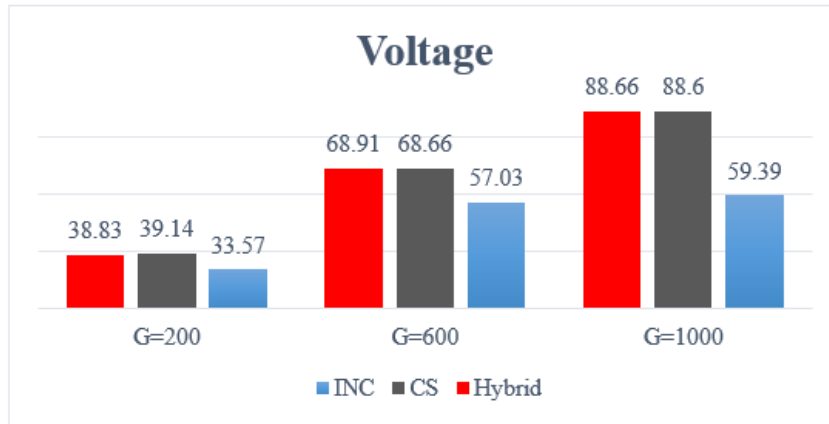


Figure 12. Maximum Power Point Tracking (MPPT) algorithm voltage comparison

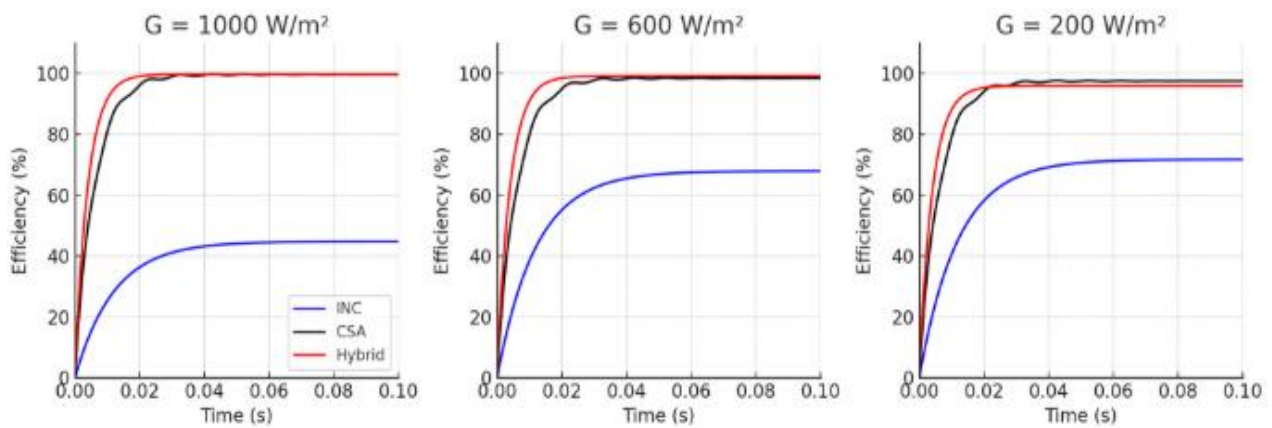


Figure 13. Efficiency of different irradiance levels

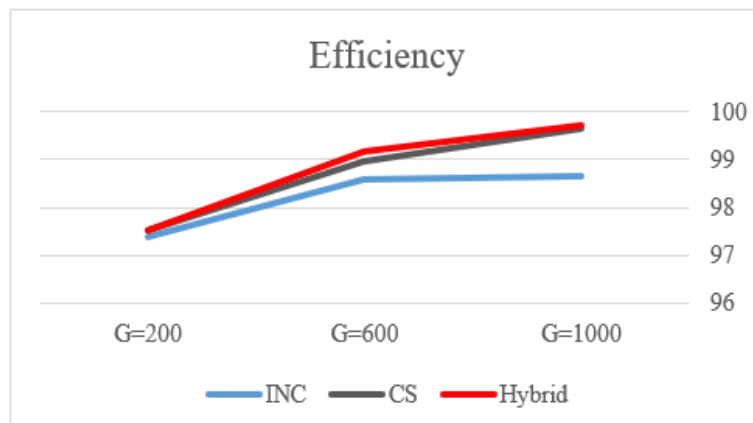


Figure 14. Efficiency of Maximum Power Point Tracking (MPPT) algorithms

Table 5. Comparative characteristics of various Maximum Power Point Tracking (MPPT) techniques, including the proposed method

Reference	Year	Method	Efficiency
[60]	2024	Hybrid Incremental Conductance+ Artificial Neural Network)	99.52%
[61]	2018	Hybrid Particle Swarm Optimization + Adaptive Neuro-Fuzzy Inference System	97%
[62]	2016	Hybrid Perturb-and-Observe + Adaptive Neuro-Fuzzy Inference System	85%
[63]	2018	Hybrid Fuzzy Logic Controller + Perturb and Observe, Fuzzy Logic Controller + Incremental Conductance	97%
[64]	2019	Hybrid Fuzzy Logic Controller + Incremental Conductance	95.3%
[65]	2022	Hybrid Fuzzy Logic Controller + Perturb and Observe	99.52%
Proposed	2025	Hybrid Incremental Conductance+ Cuckoo Search Algorithm	99.73%

7. CONCLUSION

The research presented here suggested a hybrid MPPT approach merging CSA's global search with INC's fine convergence, thus increasing the approach's capability to adapt and precisely extract MPP under changing light conditions. The results demonstrated that the integration of both heuristic and classical tracking methods enhances the stability and responsiveness of the PV systems. While CSA prevents the system from getting stuck in local optima, INC takes care of the accurate and fast convergence needed for effective MPPT.

The approach showed excellent performance in MATLAB/Simulink; however, it also has to cope with higher computational load and complications in real-time implementation. Moreover, there is still a necessity to perform thorough testing to find out the behavior of the hybrid approach under rapid irradiance changes. Future research could be directed toward hardware-in-loop (HIL) validation and embedded deployment for large-scale photovoltaic and grid-connected systems.

To sum up, the hybrid CSA-INC approach provides remarkable MPPT efficiency of 99.73%, indicating a progressive performance enhancement for solar energy systems. When the algorithm is coupled with hardware implementation, it will not only enhance the efficiency but also be adaptive to rapidly changing environmental conditions, partially shading, and work effectively in low irradiance. Thus, contributing to the transition to effective and adaptive MPPT development for renewable energy systems.

8. FUTURE WORK

The future direction of the hybrid CSA-INC algorithm may prioritize cutting down the computational demands for real-time implementation. This is achieved through real-time performance validation using HIL and microcontroller testing. In addition, the adoption of automatic tuning of critical parameters such as α and P_a to secure the reliable operation of the approach.

The above-said steps are crucial for the realistic development of the proposed algorithm using an actual embedded PV system. The mid-term targets are the incorporation of predictive models for the variations in solar radiation and temperature as well as the improvement of the performance in cases of partial shading and multi-peak P-V conditions.

Over the long term, the strategy for using the algorithm would be in microgrids and grid-connected PV systems. The focus should be on resilience, stability, and smart-grid compliance. Therefore, the algorithm will gradually shift from simulation to real-world application.

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