Comparative Study Between Conventional and Metaheuristic MPPT Algorithms Under Varying Irradiance conditions

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Abstract **-** This study conducts a comprehensive comparison of Maximum Power Point Tracking (MPPT) algorithms to enhance the efficiency of photovoltaic (PV) systems under variable irradiance conditions. Amidst growing reliance on renewable energy sources, optimizing PV array performance is crucial for maximizing energy harvest. We examine four MPPT methods: the conventional Perturb and Observe (P&O) and Incremental Conductance (INC), alongside metaheuristic Particle Swarm Optimization (PSO) and Cuckoo Search Algorithm (CSA). Through simulation and analysis on Matlab/Simulink, we assess each algorithm's convergence time, efficiency, computational cost, and suitability for different irradiance conditions. Our findings reveal that metaheuristic algorithms, PSO and CSA, exhibit superior performance in terms of faster convergence and higher efficiency, highlighting their potential for improving PV system operation in dynamic environmental conditions. This comparative study aims to guide researchers and practitioners in selecting appropriate MPPT algorithms, balancing complexity and performance to enhance solar energy systems.

Keywords **–** Boost, CSA, DC-DC, MPPT, P&O, PSO, PV.

I. INTRODUCTION

The urgency to transition towards renewable energy sources is more pronounced than ever against the backdrop of escalating global energy demands and the critical need to mitigate climate change [1]. Among renewable energy sources, solar power stands out due to its abundant availability and sustainability, positioning photovoltaic (PV) systems at the forefront of this transition. These systems, which convert sunlight directly into electricity, are pivotal in harnessing solar energy. However, their efficiency and output are directly influenced by various factors, including changing weather conditions, temperature fluctuations, and the inherent variability of solar irradiance. To counteract these challenges and optimize the energy harvest from PV systems, Maximum Power Point Tracking (MPPT) technologies are employed [2].

Significant advancements in the field of MPPT have been documented extensively in the literature. For example, Esram and Chapman [3] in their seminal work provided a foundational comparison of MPPT techniques that has influenced subsequent research in the field. Additionally, Patel and Agarwal [4] address the challenges and solutions for MPPT in varying irradiance conditions, further emphasizing the importance of robust MPPT algorithms.

MPPT algorithms play a critical role in enhancing the efficiency of PV systems by dynamically adjusting the electrical operating point of the modules or arrays to their maximum power point (MPP) [5]. The MPP is where a PV system's power output is at its peak for a given set of environmental conditions. However, with the continuous variation in solar irradiance and temperature throughout the day, the MPP also shifts, necessitating sophisticated algorithms that can track these changes accurately and swiftly to maintain optimal performance.

Building upon the research conducted by Salas et al. [6] in "Review of the Maximum Power Point Tracking Algorithms for Stand-Alone Photovoltaic Systems," this paper presents a comparative study of four MPPT algorithms, each representing a unique approach to tracking the MPP under variable irradiance conditions. The traditional Perturb and Observe (P&O) method, and the Incremental Conductance (INC) algorithm represent the conventional spectrum of

MPPT techniques. Meanwhile, recent innovations introduce metaheuristic algorithms like Particle Swarm Optimization (PSO) and Cuckoo Search Algorithm (CSA), showcasing their potential in handling complex environmental variations [7].

The primary objective of this study is to evaluate and compare these four algorithms across various performance metrics, leveraging the insights to assess convergence speed, overall efficiency, computational demand, and adaptability to fluctuating irradiance conditions. Through detailed simulation and analysis, we aim to build on the groundwork laid by these studies, providing a nuanced understanding of the applicability of each MPPT method in different PV system configurations and environmental scenarios.

By offering comprehensive insights into the capabilities and performance of conventional and metaheuristic MPPT algorithms, this study aspires to inform researchers, system designers, and practitioners in the field of renewable energy. It guides them in selecting the most appropriate MPPT strategies to enhance the efficiency and reliability of PV systems, crucial for advancing solar energy technologies and making solar power a more viable and competitive option in the global energy landscape [8].

II. MATERIALS AND METHODS

A) Solar PV Module

The photovoltaic module is constituted of solar cells mounted in series or in parallel, generating a direct electric current when illuminated by sunlight. An equivalent circuit has been developed to represent the single diode solar cell model as shown in Fig.1. It shows a current source, a diode, a series resistance and a shunt resistance [9].

The load current is given as:

$$I = I_{Ph} - I_S\left(exp\frac{q(V+R_SI)}{NKT} - 1\right) - \frac{(V+R_SI)}{R_{Sh}} \quad (1)$$

I_{Ph} and I_S are the Photocurrent and the reverse saturation current of the diode, respectively. q is the elementary charge, V is the voltage across the diode, K is the Boltzmann's constant, T the junction temperature, N the ideality of the diode, R_S and R_{Sh} are the series resistance and the shunt resistance, respectively [10].

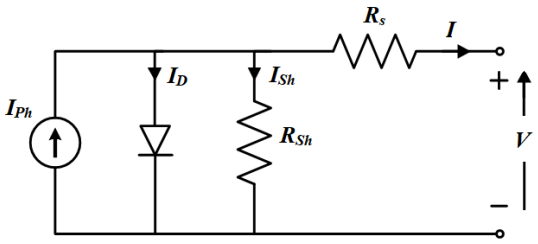

Fig. 1. Single diode solar cell model.

B) DC-DC Boost Converter

A PWM DC-DC boost converter, as shown in Fig. 2, has its output voltage V0 always higher than the input voltage Vi. Hence the name, it 'boosts' the input voltage. The boost converter consists of an input capacitor Cin, an inductor L, a power MOSFET, a diode D, a filter capacitor Cout and a load resistance RL. The MOSFET which is considered as a switch is turned ON and OFF at the switching frequency fs=1/T with the ON duty ratio D = t_{on}/T where ton is the time interval where the MOSFET is ON [11].

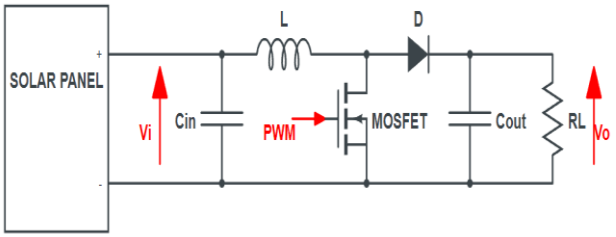

Fig. 2. DC-DC boost converter.

C) Perturb and Observe

The Perturb and Observe (P&O) method, often used as a benchmark in photovoltaic system comparisons, is a traditional MPPT technique. It operates by incrementally adjusting the voltage of the PV module and observing changes in power output to locate the MPP. The process involves small perturbations in voltage followed by an evaluation of whether these adjustments lead to an increase or decrease in power output, guiding the system toward optimal performance, see Fig. 3. Renowned for its simplicity and straightforward implementation, but it tends to oscillate around the MPP and may not converge quickly, especially under variable environmental

conditions, which can impact its efficiency. Despite these limitations, P&O is well-suited for applications in stable environments where minor fluctuations in efficiency are permissible [12].

```
1. Initialize:
Set initial duty cycle D = Dstart
Apply duty cycle D and stabilize the system
Measure initial voltage Vpv and current Ipv
Calculate initial power Pprev = Vpv * Ipv
Set step size ΔD
2. Loop Forever:
Perturb the duty cycle:
  D = D + ΔD
  Apply new duty cycle D and allow system to stabilize
Measure new voltage Vpv and current Ipv
Calculate new power Pnew = Vpv * Ipv
Compare power outputs:
  if Pnew > Pprev then
    if ΔD was positive then
      Continue increasing duty cycle
    else
      Continue decreasing duty cycle
  else
    if ΔD was positive then
      Change direction: ΔD = -ΔD
    else
      Change direction: ΔD = -ΔD
3. Update previous power:
    Pprev = Pnew
```

Fig. 3. P&O pseudocode.

D) Incremental Conductance

Incremental Conductance (INC) is an advanced MPPT algorithm that computes the derivative of the power with respect to voltage and compares it with the instantaneous conductance (I/V) to track the MPP. Unlike P&O, which relies on perturbations, INC directly calculates the slope of the power curve to make decisions, allowing for a more precise tracking under rapidly changing conditions[13]. The INC algorithm reduces oscillations around the MPP and improves convergence time, especially in dynamic weather. It operates on the principle that at the MPP, the derivative of power with respect to voltage is zero, and away from the MPP, this derivative is negative on the left of the MPP and positive on the right. This method continuously adjusts the duty cycle of the converter to match the incremental conductance to the instantaneous conductance, ensuring maximum power extraction [13][14].

```
1. Initialize:
Set initial duty cycle D = Dstart
Apply duty cycle D and stabilize the system
Measure initial voltage Vprev and current Iprev
Calculate initial power Pprev = Vprev * Iprev
Set step size ΔD
2. Loop Forever:
Measure new voltage V and current I
Calculate new power P = V * I
Calculate incremental conductance dI/dV and compare it to -I/V
if (I/V) == (dI/dV) then
  // MPP is reached, no change in duty cycle
else if (I/V) > (dI/dV) then
  // Operating point is left of the MPP
  Increase duty cycle: D = D + ΔD
else
  // Operating point is right of the MPP
  Decrease duty cycle: D = D - ΔD
3. Update previous measurements:
  Vprev = V, Iprev = I, Pprev = P
```

Fig. 4. INC pseudocode.

E) Particle Swarm Optimization

Particle Swarm Optimization is an MPPT algorithm inspired by social behavior patterns, commonly used in photovoltaic systems to find the MPP in a collaborative manner. Each "particle" in the swarm represents a potential solution, i.e., a particular duty cycle setting for the PV system's power converter. Particles adjust their position (duty cycle) by considering their personal best performance and the best-known positions of their neighbors, converging on the optimal solution through iterative cooperation and information sharing. The PSO method stands out for its robustness against rapidly changing atmospheric conditions and its ability to escape local maxima, providing efficient tracking of the MPP without requiring the direct calculation of the power-voltage curve gradient [15].

The movement of these particles is defined as follows:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

$$V_i^{k+1} = wV_i^k + c_1 r_1 \left(Pbest_i - X_i^k\right) + c_2 r_2 (Gbest_i - X_i^k) \quad (3)$$

where X is the position of the particle; i the particle number, k the number of iterations; V the velocity; w the inertial weight; c_1 and c_2 the particle acceleration coefficients; P_{best} and G_{best} are the best local position and the best global position respectively; r_1, $r_2 \in [0.1]$ are uniformly distributed random coefficients [16].

1. Initialize:
   For each particle *i* in the swarm:
      Set initial position *X(i)*
      Set initial velocity *V(i)*
      Apply *X(i)* as duty cycle, measure power output to define fitness
      Set P_{best}(i) to initial position *X(i)*
      Set initial G_{best} to the position of the best particle
   Define *w*, c_1, c_2
2. Loop until convergence criteria met:
   For each particle i in the swarm:
      Generate random coefficients r_1, r_2 within [0, 1]
      Update velocity using Eq. (2)
      Update position using Eq. (3) as duty cycle.
      Measure new power output as fitness
      If new fitness > fitness(P_{best}):
         Update P_{best} to *X(i)*
      If new fitness > fitness(G_{best}):
         Update G_{best} to *X(i)*
3. Check for convergence

Fig. 5. PSO pseudocode.

F) Cuckoo Search Algorithm

Cuckoo Search Algorithm (CSA) is an optimization algorithm inspired by the brood parasitism of some cuckoo species. It utilizes a combination of Lévy flights and the discovery of the best solution to achieve efficient global search. In this context, for MPPT in PV systems, each cuckoo's egg in a nest represents a set of parameters (the duty cycle) that could potentially yield the maximum power output. The search is driven by generating new solutions ($X^{(t+1)}$) through Lévy flights, which allow for a random walk with step sizes drawn from a heavy-tailed probability distribution (Lévy(λ)) [17].

$$X^{(t+1)} = X_i^t + \alpha \oplus Lévy(\lambda) \quad (4)$$

Where :

$$\alpha = \alpha_0(x_{best} + x_i) \quad (5)$$

$$Lévy(\lambda) \approx u = l^{-\lambda}, \qquad (1 < \lambda < 3) \quad (6)$$

X_i^t is samples/eggs, i is the sample number, t is the number of iteration and $\alpha > 0$ is the step size l is the flight length and λ is the variance. Since $1 < \lambda < 3$, thus u has an infinite variance [18].

1. Initialize:
   Set number of nests *N*
   For each egg *i* in the nest:
      Initialize position *X(i)*
      Evaluate power output to define fitness of *X(i)*
   Determine the best current position x_{best} based on the highest fitness
   Set step size scaling factor α_0 and Lévy variance parameter λ
2. Loop until convergence criteria met:
   For each egg i in the nest:
      Calculate step size α using Eq. (5)
      Generate new step based on Lévy distribution using Eq. (6)
      Update position of the egg using Eq. (4)
      Apply $X^{(t+1)}$ as duty cycle, measure new power output as fitness
      If new fitness is better than the fitness of the current egg:
         Replace egg with new solution
         If new fitness is better than the fitness of x_{best}:
            Update x_{best} to new solution
3. Check for convergence

Fig. 6 CSA pseudocode.

III. RESULTS AND DISCUSSION

The simulation study was conducted using Matlab/Simulink to meticulously evaluate the performance of four distinct MPPT algorithms, namely, Perturb and Observe, Incremental

Conductance, Particle Swarm Optimization, and Cuckoo Search. Within the Simulink environment, each algorithm was encapsulated in a dedicated Matlab function block whose primary output was the calculated duty cycle. This duty cycle was then dynamically fed into a PWM generator, ultimately controlling an Insulated Gate Bipolar Transistor (IGBT) that managed power flow through the boost converter circuit.

To ensure fairness and accuracy in the comparative analysis, each algorithm was subjected to identical testing conditions, specifically set to an ambient temperature of 25°C and varying irradiance levels of 0.5 kW/m², 1 kW/m², and 0.8 kW/m². Consistency in the configuration was maintained by employing the same boost converter layout for all tests. This methodical approach not only allowed for the precise measurement of each MPPT technique's efficiency in harvesting solar energy but also provided a robust platform to benchmark the speed, stability, and tracking accuracy of the algorithms under fluctuating solar intensity scenarios.

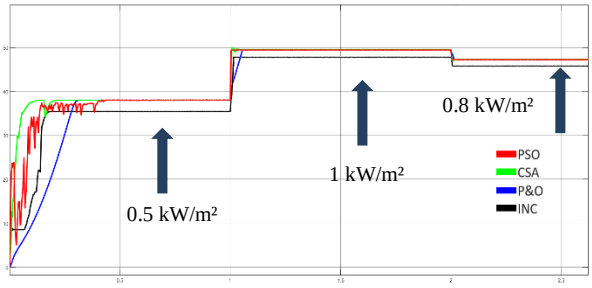

Fig. 7. Power output of P&O, INC, PSO and CSA.

Table 1. Results of the different responses

Algorithm	Convergence time (s)	Settling time (s)	Efficiency (%)	Error (%)
P&O	0.422	0.53	97.6	2.4
INC	0.129	0.19	91.2	8.8
PSO	0.083	0.22	99.6	0.4
CSA	0.027	0.17	99.4	0.6

Analyzing the results of the MPPT algorithms simulated in Matlab/Simulink, as shown in Fig. 7. and Table. 1, we observe that the P&O algorithm, with a convergence time of 0.422 seconds and a settling time of 0.53 seconds, demonstrates moderate efficiency at 97.6% and a higher error margin of 2.4%. The simplicity of P&O is a double-edged sword; its ease of implementation and minimal computational demand are offset by its susceptibility to oscillations and a propensity to misjudge the MPP under rapidly changing conditions. This can lead to a slower system response and less precision, as evidenced by the longer convergence and settling times.

However, the INC is exhibiting a faster convergence of 0.129 seconds and a settling time of 0.19 seconds, which is significantly quicker than P&O in finding and settling at the MPP. On the other hand, it shows a lower efficiency of 91.2% and a substantial error rate of 8.8%. The direct approach of INC to calculate the MPP can be highly effective in stable conditions but appears to struggle with accuracy due to its reliance on differential changes in voltage and current to guide its adjustments, resulting in a notable compromise in steady-state efficiency, its use would be perfect where a fast convergence and a relatively low computational cost is required.

In contrast, PSO and CSA show exceptional performance. PSO has the fastest convergence among traditional methods at 0.083 seconds, the highest efficiency at 99.6%, and the lowest error at 0.4%, albeit with a slightly longer settling time of 0.22 seconds. PSO's collaborative approach allows for rapid and precise MPP tracking, showcasing robustness against changing environmental conditions. The only minor trade-off is the marginally longer time it takes to fully stabilize at the MPP.

CSA stands out with the quickest convergence time at a mere 0.027 seconds and the shortest settling time at 0.17 seconds, while maintaining high efficiency at 99.4% and a low error percentage of 0.6%. CSA's use of Lévy flights introduces a powerful global search capability that rapidly converges to the MPP, efficiently exploiting the best solutions. This makes it highly suitable for dynamic conditions, though the complexity of its strategy might demand higher computational resources and could potentially result in unpredictability during the search process due to the infinite variance of the step sizes involved.

IV. CONCLUSION

In summary, the comparative analysis of MPPT algorithms reveals that PSO and CSA outperform P&O and INC in terms of efficiency and precision. While P&O is valued for its simplicity and INC for its quick convergence, PSO and CSA excel in environments with fluctuating solar conditions due to their sophisticated algorithmic nature.

PSO leverages the collective intelligence of a swarm, enabling rapid and accurate tracking of the maximum power point (MPP) by learning from both individual experiences and the group's collective insights. CSA, using Lévy flights, excels in exploring the solution space broadly and quickly, effectively escaping less optimal regions and converging on the MPP with remarkable speed. Both algorithms demonstrate a robust ability to adapt to changing conditions, maintaining optimal operation close to the MPP, which maximizes energy output and enhances system efficiency.

This analysis underscores the importance of choosing an MPPT algorithm that aligns with the environmental dynamics of the application, with PSO and CSA emerging as particularly effective for dynamic and complex scenarios.

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