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Performance analysis on convergence of particle swarm optimization and incremental conductance MPPT method for NTR 5E3E PV module

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ABSTRACT

Particle swarm optimization (PSO), a technique in Artificial Intelligence, is one of the MPPT methods used to optimize the output of a Photovoltaic (PV) system. The PSO is well known for its convergence in Maximum Power Point Tracking (MPPT). However, no comprehensive study has been conducted on the performance of the PSO and incremental-conductance (INC) MPPT combination for the NTR 5E3E PV module. This study aims to provide a detailed performance analysis of the convergence of PSO and INC combination compared to PSO MPPT during maximum power (MP) tracking on NTR 5E3E PV module. This research work studies the relationships among PV parameters and other parameters affected during the implementation of PSO-INC MPPT. The study found that, in terms of efficient power and time consumption during the Maximum Power (MP) tracking process, the PSO-INC MPPT combination provides the highest average peak power at the shortest time compared to standalone PSO. The efficiency of PSO-INC Average Power is near 98.9% to 99.93%, compared to PSO MPPT, which is between 95.7% and 99.3%. The PSO and INC MPPT were tested on a boost converter without altering the specific electrical component characteristics to ensure accurate output during testing. Furthermore, a boost converter is sufficient to meet the overall requirements for the research work and simulation testing. The characteristics of the PSO and INC MPPT are observed using MATLAB/Simulink. This research assesses the robustness of the PSO-INC combination, advancing hybrid MPPT technology by demonstrating its performance.

1. Introduction

Renewable energy sources, such as wind and solar, have become increasingly important for sustainable energy solutions [1]–[3]. The implementation of PV systems enables the harvesting of electrical energy from solar irradiance. These plentiful and clean energy sources play a key role in lowering carbon emissions, minimizing pollution in the environment, and tackling global issues like resource shortages and climate change [4], [5]. The source of solar energy offers a solution to reduce the greenhouse effect compared to the conventional use of electrical energy from the power system [4]. A typical PV system consists of a PV panel, MPPT, and a converter device that work together to maximize the PV panel's power. To ensure the optimal utilization of PV panels, a maximum power point tracker (MPPT) is employed in conjunction with the converter device [6]. This research work utilizes a boost converter, PSO, and INC as an MPPT controller for the PV system. The utilization of PSO offers the benefit of rapidly achieving maximal power and efficiently tracking multiple peaks within the PSO search space [7]. PSO is not a complex algorithm; only a few parameters require adjustment, including the inertia weight value from the PSO MPPT. The PSO MPPT equation consists of velocity and position updates; it leads to local and global power convergence. The PSO MPPT maintains a swarm of individuals (called particles), where each particle represents a candidate solution. Particles follow a simpler behaviour, emulate the success of neighbouring particles, and their own achieved successes [8]. The PSO MPPT is part of the soft-computing method; the MPPT technique can be categorized into three groups, which are the conventional method, the PV array characteristic method, and the soft computing method [1], [3], [4]. Soft computing methods are the most popular category due to their simplicity and low setup cost. The research on PSO and INC MPPT previously focused on convergence speed, parameter tuning, and the efficiency of the converged Power. However, there was no in-depth study focusing on a specific PV module and applying varying irradiance to the PV panel. This work aims to provide an in-depth analysis of PV power, convergence speed, and the parameters involved in the PSO-INC MPPT using the NTR 5E3E PV module. Since the NTR 5E3E PV module is widely utilized, it is necessary to conduct an in-depth analysis of the PSO and INC MPPT combination. Providing a detailed Maximum Power (MP) track from the MPPT based on irradiance readings for the NTR 5E3E PV module is part of this study's target. This will provide a detailed power analysis of varying irradiance from 100W/m2 to 1000W/m2. The test also included dynamic irradiance testing, which will provide detailed convergence and power tracking during rapid fluctuations in irradiance.

2. Method

2.1. Impedance Matching Process for Maximum Power Point Tracking

The impedance-matching process for the MPPT is a crucial technique, as it allows maximum power to be transferred to the load or battery from the solar panels [9]. Since a DC-DC converter is required for MPPT, a boost converter is chosen to convert the MPPT output. This research utilizes a boost converter since it provides the overall requirements needed for this research work. DC-DC converters are widely used for maximum power tracking, where each converter adjusts its duty cycle to track the maximum power from the PV panel [10]. This study used the NTR 5E3E PV Module for maximum power tracking, as shown in Table 1. The NTR 5E3E PV module was selected for testing due to its widespread availability, proven reliability, and suitability for typical environmental conditions in the region [11]. This module's performance characteristics, such as its power rating of 173.5W [11], efficiency, and durability, closely reflect real-world deployment scenarios in Malaysia, where similar modules are commonly used for residential and small-scale commercial solar installations. By using the NTR 5E3E, the study ensures that the results and insights are practically relevant and applicable to actual off-grid and grid-connected PV systems, providing valuable data for future research that may involve real-world implementation.

Table 1. NTR 5E3E PV module parameter [12]

Parameters	Value
Open circuit voltage, V_{oc}	44.4V
Short circuit current, I_{sc}	5.4A
Maximum Voltage, V_{mp}	35.4V
Maximum Current, I_{mp}	4.9A
Maximum Power, P_{mp}	173.5W

[a] The Parameters were simulated by using MATLAB/Simulink Software

The NTR 5E3E PV module needs to be connected to the boost converter. Due to the ability to store energy in an inductor, the boost converter produces a regulated high DC output for the load. Current affects the voltage drop across the inductor. Through the transfer and regulation of energy, this configuration maximizes system performance [8]. The relationship of the boost converter formula, such as duty cycle (D), input voltage (V_{in}), and output voltage (V_{out}), is given below. This equation relationship from (1), (2) and (3) is used for the converter to track MP from the PV panel [13].

$$(V_{out}/V_{in}) = (I_{in}/I_{out}) = 1/(1-D) \tag{1}$$

$$R_{eq} = R_L \,(1-D)\, 2 \tag{2}$$

$$D = 1 - \,(R_{eq}/R_L)^{1/2} \tag{3}$$

where R_{eq} is Equivalent resistance and R_L is Load Resistance [6]. To track the MP by using the MPPT, the P_{max} at each level of irradiance value needs to be identified through the simulation, together with the V_{max} and I_{max} which will then allow the value of R_{eq} and D to be calculated manually. The Boost converter operating region can cover irradiance values from 100 to 1000 W/m². R_{eq} is the resistance value at MP while R_L is the resistance value that can cover the tracking process for all the D required. Table 2 shows the R_{eq} and D value for different levels of irradiance from 100 to 1000W/m 2 for the NT5E3E PV panel.

Table 2. Duty Cycle value for irradiance of 100-1000W/m2

Irradiance	V_{max}	I_{max}	P_{max}	R_{eq}	D
1000W/m ^{2}	35.4	4.9	173.5	7.22	0.6532
900W/m ^{2}	35.4	4.409	156.1	8.03	0.6342
800W/m ^{2}	35.4	3.911	138.4	9.03	0.612
700W/m ^{2}	35.4	3.406	120.6	10.39	0.584
600W/m ^{2}	35.4	2.896	102.5	12.23	0.544
500W/m ^{2}	35.4	2.381	84.3	14.87	0.5023
400W/m ^{2}	35.4	1.863	65.95	19	0.437
300W/m ^{2}	35.4	1.341	47.47	26.4	0.337
200W/m ^{2}	32.57	0.879	29.1	37	0.215
100W/m ^{2}	23.52	0.416	9.78	58.32	0.014

[b.] The PV Parameters collected while adjusting the R_{eq} of the system

Based on the calculated value from Table 2, the load resistor must be bigger than 58.32 ohms in order to track the maximum power for each irradiance value. Therefore, the R_L values are set at 60 Ω. Based on the duty cycle calculated, it is obvious that the range of duty cycle (D) is below 0.7. Based on this requirement, the MPPT can be implemented by using the PSO and INC MPPT method. The operating region of a boost converter is the range of input voltage, output voltage, and load current conditions that allow the converter to operate efficiently [7]. Based on the given information of R_L and D the operating region of the boost converter can be identified by using the inclination angle (Θ_I) formulae as shown in (4) [14].

$$\Theta_I = tan^{-1}[1/\,(1-D)^2 \;\; R_L\,] \tag{4}$$

where θ_I is an inclination Angle, D for duty cycle, and R_L are Load Resistance. Duty cycle (D) is the ratio of the time the switch in the boost converter is in conducting mode to the total time of one switching cycle [13]. It is a critical parameter because it directly affects the boost converter's output voltage. A duty cycle of 1 would, in theory, mean the output voltage approaches infinity because the switch is always on, which is not feasible in practical applications [7].

Table 3. The Operating Region of the Boost Converter for MPPT

Irradiance, W/m^2	Unused Operating Region	1000	900	800	700	600	500	400	300	200	100
Duty Cycle	1	0.6532	0.6342	0.612	0.584	0.544	0.5023	0.437	0.337	0.215	0.014
Inclination Angle, θ	90 (θ max)	7.8900	7.099	6.314	5.5010	4.583	3.8503	3.01	2.172	1.55	0.9822 (θ min)

c. The Operating Region collected while adjusting the R_{eq} of the system

Inclination angle (θ_I) represents the angle in a graphical representation of the boost converter's performance, potentially relating to the efficiency, output voltage, or another performance metric as a function of the duty cycle. Based on Table 3, the calculated duty cycle was within the MPPT operating region. The duty cycle values decrease from 0.6532 (7.89 degrees) down to 0.014 (0.9822 degrees), with corresponding reductions in the inclination angle. This suggests a decrease in the converter's output capability or efficiency as the duty cycle is reduced. The inclination angles of 7.89 and below indicate that as the duty cycle drops, the output voltage decreases while the converter continues to operate efficiently within a certain range. Fig. 1 shows the operating region of the boost converter for MPPT.

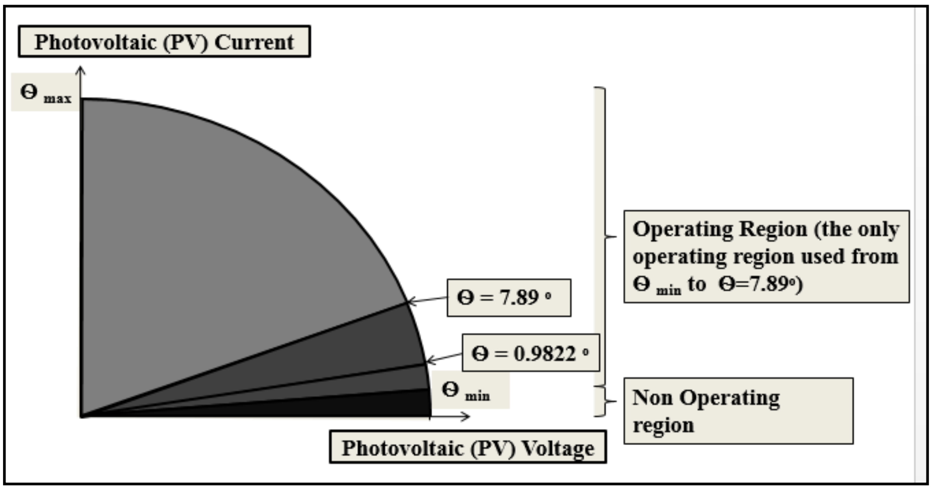

Fig. 1. The operating region of the boost converter for the MPPT process [7]

2.2. Particle Swarm optimization MPPT method applied to a PV system

The PSO algorithm is a meta-heuristic approach that facilitates the global optimization of multipole functions [15], [16]. PSO algorithm based on swarm intelligence is a soft computing method which collects multiple PV powers for optimization purposes. In the PSO, every particle has three parameters: its direction, velocity, and current position. Each particle's position ($pXid$) when alliteratively updating its position is based on both the optimal value ($gBest$) for the entire population and the particle's present historical optimal value ($pBest$). The velocity update formula in (5), (6), (7) and the position update formula in (8) are given as follows [2], [4], [15], [16]:

- Velocity update

$$a = (c1 * (pBest - pXid) * r1); \tag{5}$$

$$b = (c2 * (gBest - pXid) * r2); \quad (6)$$

$$c = psoweight * pVid + (a + b); \quad (7)$$

- Position update

$$pXid' = pXid + c; \quad (8)$$

Where the current particle velocity is $pVid$, particle velocity update is c, inertia weight is $psoweight$, influence of individual learning rate is $c1$, influence of social learning rate is $c2$, the best position found by the particle is $pBest$, the best position found by the swarm is $gBest$, the randomness to particle movement is $r1$ and $r2$, the current particle position is $pXid$ and particle position update is $pXid'$. Due to the preset parameters, the standard particle swarm algorithm is more sensitive to the initial conditions. The learning factors $c1$ and $c2$ can affect the speed ($pVid$) of particles moving to the individual optimal position ($pBest$) and the global optimal position ($gBest$), and the inertia weights ($psoweight$) reflects the degree of the algorithm's inheritance of particle speed, which has a large impact on the algorithm's search ability. PSO will continuously recalculate the particle's position update ($pXid'$), ($pBest$) and $gBest$ to provide the latest MP update during the iteration process. The criterion for convergence is either finding the best solution or completing the maximum number of iterations possible.

2.3. Incremental Conductance MPPT method applied for PV system

The INC MPPT method is the conventional way to track maximum power from the PV panel, using the current and previous voltage and power readings to determine MP. This is similar to the ability to track peak power using the perturb-and-observe (P&O) MPPT method; however, the INC MPPT depends on the slope of the PV curves to track the MP, whereas P&O perturbs the voltage and observes the power output. Fig. 2 shows the steps taken by INC MPPT to track MP.

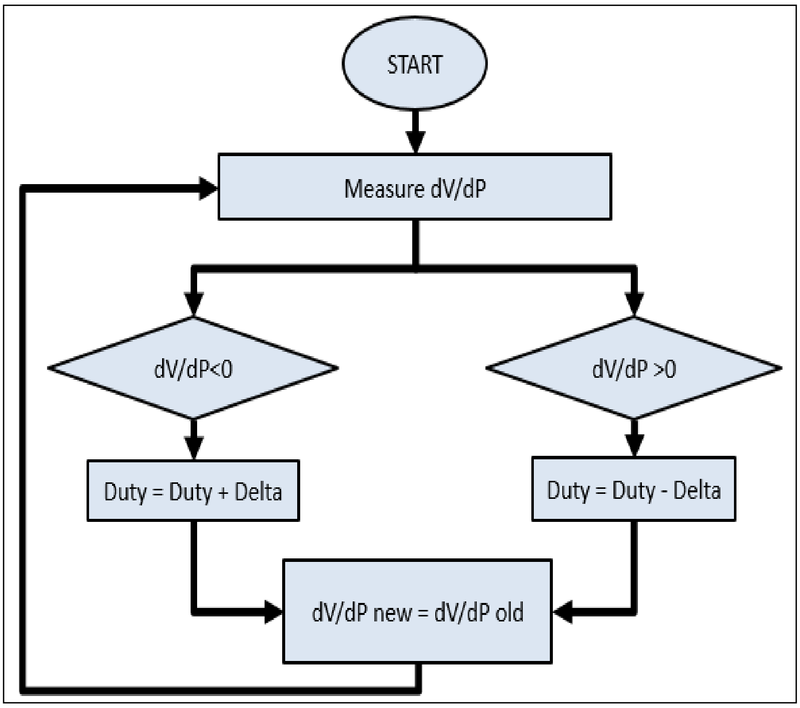

Fig. 2. The steps taken by INC MPPT to track MP

Based on Fig. 2, the dV/dP is analyzed before the slope value is identified, where the value of D will be added or substituted by a fixed delta value depending on the PV curve slope. The tracking process is illustrated in Fig. 3, where the PV curves must have a near-zero slope to reach the MP. If the slope is positive or negative, it will tend to move towards the MP point.

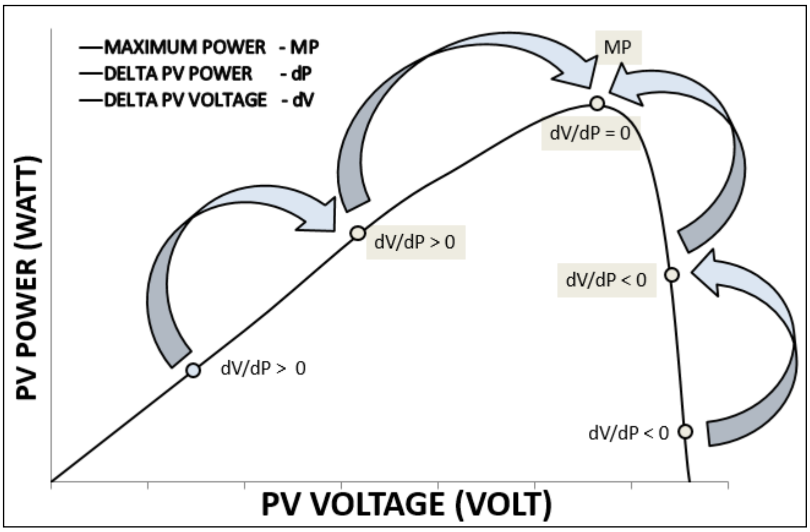

Fig. 3. The movement of INC MPPT towards the PV curve

2.4. Combinations of PSO and INC MPPT

PSO in the traditional sense significantly randomize the initialization of particle positions, causing system oscillations, while the actual algorithms have issues like control lag misclassification [15], [16]. In contrast, the PSO MPPT performs well in global optimization seeking, according to some application studies conducted recently. To resolve the trade-off between tracking speed and tracking accuracy, some researchers, both domestically and internationally, have attempted to integrate the PSO algorithm with conventional MPPT methods [15]. There are several improvements to the PSO algorithm to ensure the possibilities of using a DC-DC converter for the PV system [17]. The inertia weight, individual learning rate, and social learning rate of the PSO algorithm are set to 0.6, 1.5, and 2.5, respectively.

Using a random number generator as the initial search space to track maximum power, the swarm size is set to 20. In this study, the parameters for Particle Swarm Optimization (PSO), specifically, the inertia weight (0.6), influence of individual learning rate (1.5), influence of social learning rate (2.5), and swarm size (20) were selected through an iterative trial-and-error process, guided by heuristic principles and empirical testing. The aim was to optimize the Maximum Power Point Tracking (MPPT) performance for the boost converter system [18]. The inertia weight was chosen to balance exploration and convergence, thereby reducing oscillations around the maximum power point (MPP) in a dynamic photovoltaic (PV) environment [18]. The cognitive and social learning factors were fine-tuned to enhance convergence speed while ensuring accuracy, and preliminary simulations demonstrated their effectiveness [19]. The swarm size was determined to provide an appropriate balance between thorough searching and computational efficiency. To validate these selections, a sensitivity analysis was performed by slightly varying each parameter. The study revealed minimal impact on both convergence speed and MPPT stability, confirming the robustness of the chosen configuration [19]. Overall, these parameters were derived from systematic simulations, ensuring stable, efficient, and practical tuning tailored for PV MPPT applications using the boost converter [20]. The PSO algorithm's iteration depends on the swarm size. If the swarm size is bigger, the iteration process loops more. The value of swarmsize is set to 20 to ensure a better searching process for the maximum power and to prevent premature convergence [5]. The combination of PSO and INC MPPT was first introduced by Abdulkadir and Yatim, who found that the proposed hybrid method can track the global maximum point with ease and has faster response time and better dynamic response than the plain PSO method alone [21]. Fig. 4 shows the SIMULINK script on swarm process of the PSO-INC MPPT, where the particles hold the value of I, P and V in array form, and the value of a, b, and c is the PSO formula, while the dV, dI, $dVnew$, $dInew$, $dVold$ and $dIold$ hold the value of the current, new and previous voltage and current reading.

```
particles(iter, 3) = P;
particles(iter, 7) = V;
particles(iter, 9) = I;

a = (c1 * (pBest(1,1) − particles(iter, 1)) * r1);
b = (c2 * (gBest(1,1) − particles(iter, 1)) * r2);
c = psoweight * pVid + (a + b);

if(c > vMax)
  c = vMax;
elseif(c < vMin)
  c = vMin;
end

dV = particles(iter, 7) − Vold;
dI = particles(iter, 9) − Iold;

if (dI/dV) > −(Iold/Vold)
  particles(iter, 1) = particles(iter, 1) − c;
else
  if(dI/dV) < −(Iold/Vold)
  particles(iter, 1) = particles(iter, 1) + c;
  end
end


pXid = particles(iter, 1);
Vold = particles(iter, 7);
Iold = particles(iter, 9);
```

Fig. 4. The Combination of the PSO-INC MPPT script

The flowchart in Fig. 5 illustrates the PSO-INC MPPT algorithm's control process, which begins by including a header file and, if enabled, initializing the system. The initialization stage sets up the algorithm.

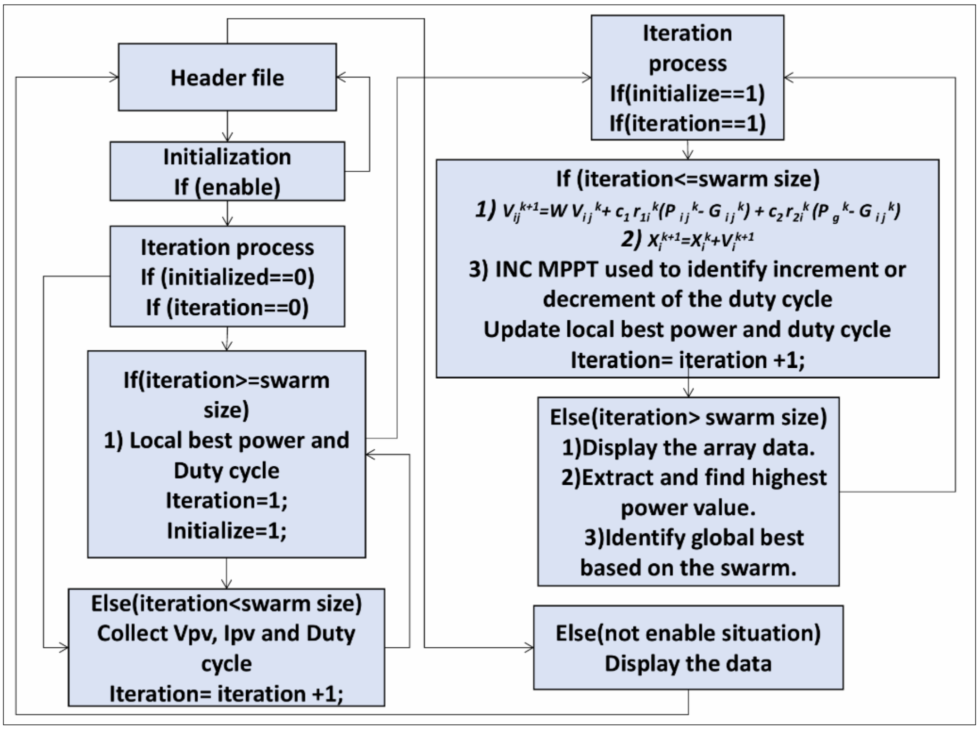

Fig. 5. PSO-INC MPPT process flow

The "Iteration process" block is central, managing the swarm's movement within the search space. Initially, if the system hasn't been initialized, the algorithm collects PV voltage (V_{PV}), PV current (I_{PV}), and duty cycle values for each particle until the iteration count reaches the swarm size. After this initial data collection, the local best power and duty cycle for each particle are set, and the "initialize" flag is set to 1 to indicate data is ready for the PSO iteration. For each subsequent iteration, the algorithm updates each particle's velocity and position based on the PSO equations, where W is inertia weight, C_1 and C_2 are acceleration coefficients, r_1 and r_2 are random numbers, P is particle, G is global, V is velocity and X is position. Additionally, an Incremental Conductance (INC) MPPT technique is employed to fine-tune the duty cycle, incrementing or decrementing it based on the PV system's operating point relative to the MPP. This step updates the local best power and duty cycle. The algorithm iterates until the number of iterations exceeds the swarm size; it displays the particle data, extracts the highest power value, and identifies the global best operating point based on the swarm, ultimately converging towards the MPP. If initialization is not enabled at all or there is a system error, it will go the "Else (not enable situation)" which is the display the data. Fig. 6 illustrated the operation of a PSO-INC MPPT for photovoltaic (PV) systems. The core principle is to use a swarm of particles to navigate the PV power-voltage curve and identify the maximum power point (MPP). Each particle represents a potential operating point, influenced by its individual best position ($Pbest$) and the swarm's global best position ($Gbest$). This iterative process enables the algorithm to converge to the MPP, where the slope of the power-voltage curve (dV/dP) approaches zero, indicating the peak power output. Furthermore, by monitoring dV/dP, the algorithm can adjust its search behaviour. When $dV/dP$is positive, indicating that increasing voltage leads to increasing power, the algorithm continues searching towards higher voltages. Conversely, when dV/dP is negative, signifying a decline in power with increasing voltage, the algorithm adjusts its search towards lower voltages. This adaptive approach, combining PSO's exploration capabilities with INC's precise MPP tracking, enhances the algorithm's robustness and efficiency in dynamic operating conditions [17].

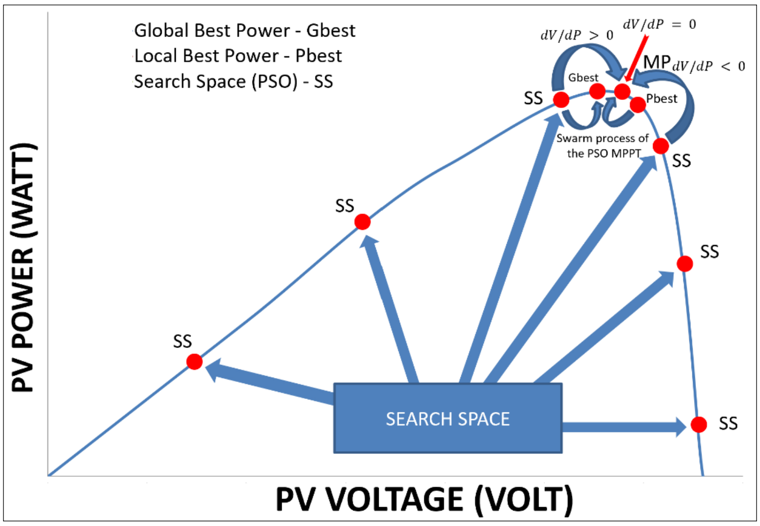

Fig. 6. The MP tracking of PSO-INC MPPT

3. Results and Discussion

This section is divided into three subsections, which are performance analysis based on varying solar irradiance, performance analysis based on fluctuating solar irradiance, and the analysis of the PSO-INC MPPT approach in relation to the existing research work

3.1. The MPPT performance based on varying solar irradiance for the PV Panel

The results were obtained from simulating a photovoltaic (PV) module using MATLAB Simulink. The PV module parameters were taken from the NTR 5E3E model. The tests focused on Maximum Power Point Tracking (MPPT) techniques, using both Particle Swarm Optimization (PSO) and a combination of PSO and Incremental Conductance (INC). The irradiance was fixed at 100 W/m² increments for each test, allowing direct comparison between the simulated values and those calculated from Table 2. Each test lasted 1 second. This section also discusses the efficiency of the PSO-INC MPPT convergence and compares it to the standard PSO MPPT.

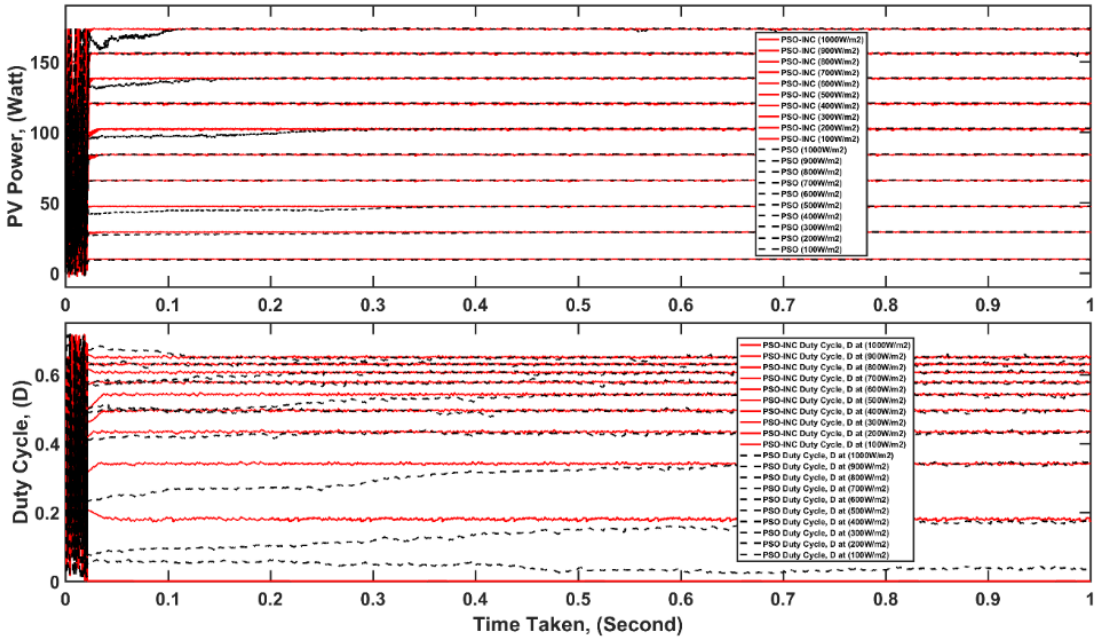

Fig. 7. MP track by PSO-IC and PSO MPPT under varying irradiance levels from 100W/m2 to 1000W/m2 for NTR 5E3E PV Module

The proposed method, combining PSO and INC, was tested through simulation and implemented in hardware to assess its effectiveness in real-life situations. The simulation software used for these tests is MATLAB's SIMULINK. The proposed method was examined under two categories of irradiance conditions: constant and dynamic/fluctuating. This testing was conducted to ensure the method can operate effectively under extreme conditions during MP identification. Fig. 7 illustrates the MP tracking process for both the PSO-INC and PSO MPPT techniques under varying levels of irradiance, while Table 4 summarizes the performance parameters of the MPPT.

Analyzing the performance results of the PSO-INC and PSO MPPT methods for the NTR 5E3E PV module at varying irradiance levels provides valuable insights into their efficiency, speed, and energy harvesting capabilities under different environmental conditions. Here is a detailed discussion of the data. In terms of Maximum Power Output (Watts), both PSO-INC and PSO MPPT achieve their highest power outputs at 1000 W/m², with PSO-INC slightly outperforming PSO MPPT in some instances. Both algorithms effectively track the Maximum Power Point (MPP) under high irradiance, although PSO-INC shows marginally higher power output at certain levels. This suggests that PSO-INC may have a slight advantage in optimal power extraction under stable, high-irradiance conditions. Regarding Average Power (Watts), the average outputs closely follow the maximum power trends but are slightly lower. This reflects real-world operational conditions, where the algorithm occasionally converges to or fluctuates around the MPP. The similarity in performance indicates that both methods are stable and effective in consistently extracting near-optimal power across different irradiance levels. When examining convergence speed, PSO-INC demonstrates significantly faster convergence times, typically ranging from 0.004 to 0.0559 seconds, compared to PSO MPPT, which has times ranging from approximately 0.005 seconds to as high as 0.759 seconds. The faster convergence of PSO-INC suggests it adapts more quickly to changes in irradiance, which is crucial in dynamic outdoor environments. Faster convergence and higher efficiency in maximum power point tracking (MPPT) algorithms can significantly benefit larger photovoltaic (PV) farms and grid-connected systems by maximizing energy extraction, especially under rapidly changing environmental conditions, such as cloud cover or shading [22]. Improved convergence speed reduces the time the system operates below its optimal power point, thus increasing overall energy harvest and enhancing the plant's profitability [23]. Higher MPPT efficiency ensures that a greater portion of available solar energy is converted into usable electrical power, which is critical at a large scale, as even minor percentage improvements can lead to substantial energy gains.

Tabla 4. The Operating Region of the boost converter for MPPT (The Parameters of the PSO-INC and PSO MPPT due to varying Irradiance).

MPPT	Performance Parameters	Varying Irradiance, W/M^2									
		1000	***900***	***800***	***700***	***600***	***500***	***400***	***300***	***200***	***100***
PSO-INC	Maximum Power, Watt	173.459649	156.093253	138.477597	120.628210	102.567553	84.323185	65.939027	47.487775	29.106260	9.857338
	Average Power, Watt	171.760000	154.460000	137.165800	119.396900	101.364900	83.465000	65.341070	47.083900	28.904000	9.773100
	Convergence Time	0.005200	0.004200	0.055914	0.295700	0.044000	0.039000	0.039000	0.027310	0.005601	0.004200
	Efficiency	98.997118	98.949391	99.108237	99.002405	98.892585	99.009490	99.076679	99.186644	99.326460	99.929448
	Energy (Wh)	0.000248	0.000180	0.002130	0.009807	0.001239	0.000904	0.000708	0.000357	0.000045	0.000011
	c	0.000007	0.000005	0.000060	0.000277	0.000035	0.000026	0.000020	0.000010	0.000001	0.000000
PSO	Maximum Power	173.459374	156.089645	138.477580	120.215738	102.567012	84.323189	65.939111	47.478824	29.102302	9.576124
	Averange Power	171.096000	154.262800	136.544400	119.516800	100.498060	83.595300	65.479500	46.135300	28.380000	9.360100
	Convergence Time	0.143355	0.005000	0.021915	0.298300	0.417000	0.051000	0.219013	0.686000	0.759000	9.667958
	Efficiency	98.614409	98.823062	98.659249	99.101824	98.046888	99.164057	99.286581	97.188329	97.525773	95.706544
	Energy (Wh)	0.006813	0.000214	0.000831	0.009903	0.011641	0.001184	0.003984	0.008791	0.005983	0.025137
	Capacity(Ah)	0.000192	0.000006	0.000023	0.000280	0.000329	0.000033	0.000113	0.000248	0.000184	0.001069

[a] The PV Parameters collected from Simulation

Furthermore, rapid and accurate MPPT can enhance grid stability by providing consistent, high-quality power output and reducing fluctuations that may impact grid performance [18]. Overall, these advantages lead to improved system performance, increased economic returns, and more reliable integration into the power grid. The longer convergence times of PSO MPPT at certain levels may limit its real-time effectiveness and increase the possibility of tracking errors during rapid irradiance fluctuations. In terms of efficiency, PSO-INC maintains an efficiency range of approximately 98.9% to 99.93%.

The Particle Swarm Optimization (PSO) Maximum Power Point Tracking (MPPT) technique shows slightly lower efficiencies, generally ranging between 95.7% and 99.3%. Both PSO-INC and PSO MPPT are highly efficient, but PSO-INC slightly outperforms PSO MPPT, especially under moderate irradiance levels. This suggests that PSO-INC offers improved precision in tracking the Maximum Power Point (MPP). Regarding energy harvested (Wh), the amount of energy accumulated over a short period varies, with PSO-INC typically capturing slightly more energy at higher irradiance levels. This aligns with its higher power outputs and faster convergence rate. The marginally higher energy yields observed with PSO-INC indicate its potential for more effective energy harvesting under real-world conditions. The PSO-INC method can be effectively integrated into grid-connected photovoltaic (PV) systems to enhance overall efficiency and stability. Unlike traditional Particle Swarm Optimization (PSO) methods for Maximum Power Point Tracking (MPPT), which primarily rely on stochastic optimization to locate the maximum power point, PSO-INC combines the strengths of both PSO and the Incremental Conductance (INC) technique [24]. This hybrid approach utilizes PSO's global search capability along with INC's rapid convergence in changing conditions, allowing for more precise and faster tracking of the maximum power point, especially during dynamic environmental changes such as rapid fluctuations in irradiance or temperature, which are common in grid-connected environments. In practical terms, PSO-INC can be incorporated into the inverter control system of a grid-connected PV setup [25]. It continuously optimizes the operating point in real-time, ensuring maximum power extraction with minimal oscillations. This optimization not only maximizes energy yield but also stabilizes the voltage and current fed into the grid, thereby improving power quality. Furthermore, PSO-INC's adaptability makes it suitable for various PV module types, including monocrystalline, polycrystalline, and thin-film, by fine-tuning its algorithm parameters to match different electrical characteristics [26]. Its broad applicability across diverse module configurations and environmental conditions can significantly enhance the efficiency and reliability of large-scale grid-connected PV systems. This positions PSO-INC as a more impactful and scalable solution compared to PSO MPPT alone [27]. Overall, it highlights the potential of PSO-INC as an advanced MPPT strategy that can adapt to varied operational scenarios while delivering superior performance. The capacity values (Ah) are pretty low (on the order of a few milliamps to Ah), which is expected due to the brief sampling period (approximately 0.02 seconds). These values reflect instantaneous current capability rather than total stored charge. While useful for understanding instantaneous current behavior, PSO-INC again shows marginally higher capacity across most irradiance levels. In summary, based on speed and responsiveness, PSO-INC significantly outperforms PSO MPPT in convergence speed, which is crucial for accurately capturing dynamic changes in irradiance conditions typical of outdoor environments. In terms of power and efficiency, both methods are effective, with PSO-INC slightly leading in maximum power, average power, and overall efficiency. The marginal differences suggest that both algorithms are suitable for practical implementation, but PSO-INC may be preferred when rapid response is a priority. The energy and capacity metrics support the conclusion that PSO-INC can harvest slightly more energy across different irradiance levels, making it advantageous for maximizing energy output, especially under fluctuating sunlight conditions. For practical deployment, the faster convergence of PSO-INC suggests it would perform better in environments with rapid changes in irradiance, such as during cloud cover or at sunrise/sunset. The high efficiencies indicate operational stability, but real-world testing over longer periods is necessary to account for variability and potential noise. While both algorithms perform well, the choice between them may depend on factors such as hardware complexity, computational resources, and specific operational demands.

3.2. The MPPT performance based on fluctuating solar irradiance for the PV Panel

The dynamic irradiance test will instantly alter irradiance during the photovoltaic (PV) power-tracking process. The PV power will directly respond to these changes in irradiance. Each irradiance value will change every 0.2 seconds. For the 1st pattern of irradiance set in the simulation system, the values are 600, 750, 700, and 500W/m^2. The 2nd pattern consists of 600, 700, 900, and 700W/m^2. During each change in irradiance, an analysis will be conducted to demonstrate the effectiveness of the proposed Maximum Power Point Tracking (MPPT) method. Fig. 8 and Fig. 9 illustrate the performance of the proposed MPPT method during the first and second irradiance tests. The comparative performance assessment of the PSO-INC and PSO MPPT methods across two distinct irradiance patterns reveals significant differences in their ability to extract maximum power under varying environmental conditions.

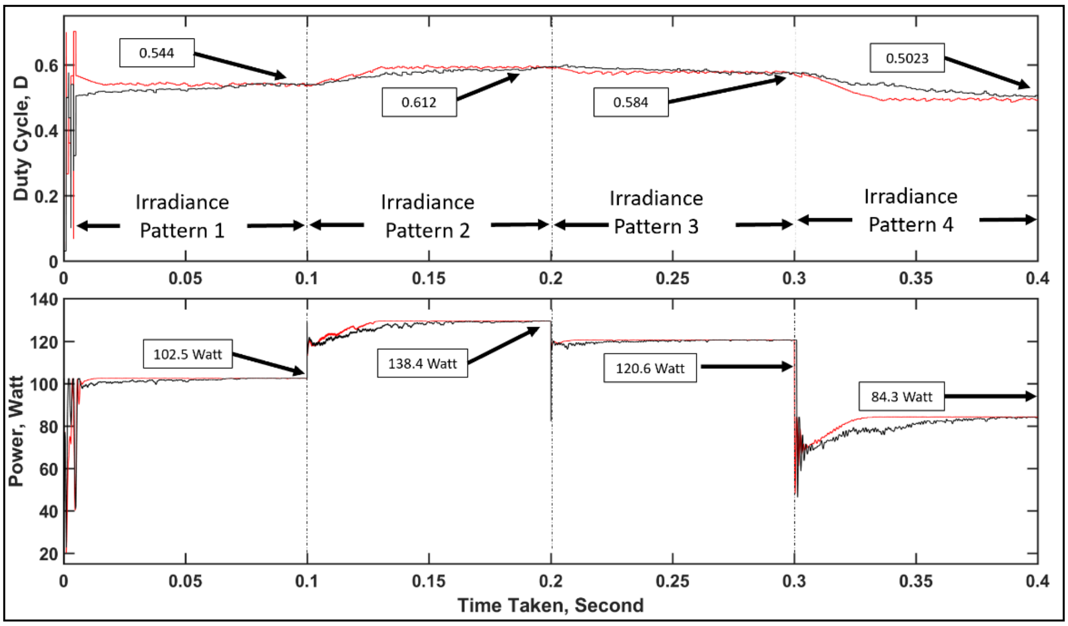

Fig. 8. The analysis on PV power collected for 1^{st} pattern of dynamic irradiance

In Pattern 1, both PSO-INC and PSO yield remarkably similar results, with maximum power outputs closely aligned at approximately 109.28 W for PSO-INC and 109.17 W for PSO. The average power values also show minimal variance, with PSO-INC averaging 107.76 W and PSO at 106.73 W. Their efficiencies are around 98.6%, indicating that both algorithms are highly effective in stable irradiance conditions. In contrast, Pattern 2 features a more dynamic or fluctuating irradiance environment. Here, PSO-INC slightly outperforms PSO, reaching a maximum power of approximately 124.98 W compared to PSO's 124.77 W. The average power also favours PSO-INC, with around 123.08 W versus PSO's 120.42 W. Notably, the efficiency of PSO-INC in Pattern 2 surpasses that of PSO, at 98.48% compared to 96.36%. This suggests that the hybrid PSO-INC method exhibits more stable convergence toward the maximum power point (MPP) under environmental variations. The slight advantage of the PSO-INC algorithm in extracting higher power and efficiency, particularly in the more unstable Pattern 2, highlights its robustness and adaptability in real-world conditions where irradiance levels can change rapidly or unpredictably. The results indicate that both algorithms are capable of achieving near-optimal power, but PSO-INC's mechanism, combining the global search capability of Particle Swarm Optimization (PSO) with the local refinement of Incremental Conductance (INC) offers a better balance between exploration and exploitation. This balanced approach likely contributes to improved convergence stability, reducing the likelihood of getting trapped in local maxima, especially under variable conditions. Overall, the data suggest that incorporating hybrid techniques like PSO-INC can lead to significant improvements in system performance, making it more suitable for practical applications where environmental factors are unpredictable and dynamic.

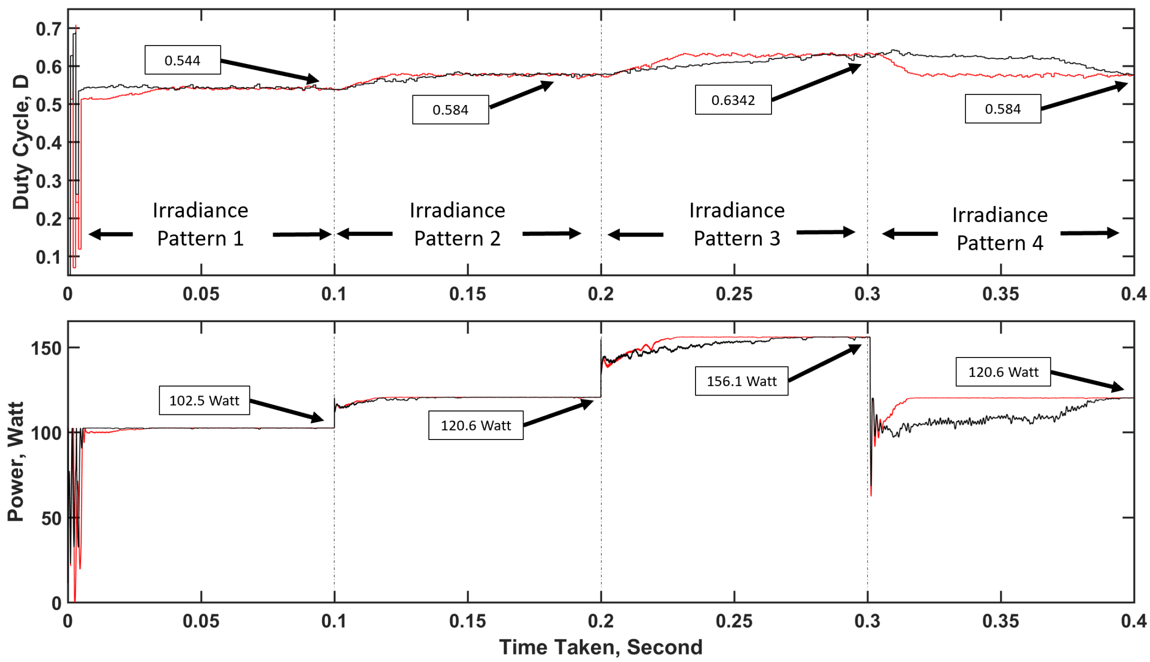

Fig. 9. The analysis of PV power collected for the 2nd pattern of dynamic irradiance

Table 5 summarizes the performance of PSO-INC and PSO during fluctuating solar irradiance. The comparison between the PSO-INC and PSO algorithms reveals significant differences in convergence time and root-mean-square (RMS) error under varying irradiance conditions.

Table 4. The Parameters of the PSO-INC and PSO MPPT due to Fluctuating Solar Irradiance

MPPT	Performance Parameters	Varying Irradiance							
		Pattern 1				*Pattern 2*			
PSO-INC	*Maximum Power*	109.281295				124.9793065			
	Average Power	107.7569				123.0845			
	Convergence Time	0-0.1s	0.1-0.2 s	0.2-0.3 s	0.3-0.4 s	0-0.1s	0.1-0.2 s	0.2-0.3 s	0.3-0.4 s
		0.02217	0.13926	0.219986	0.336179	0.047011	0.1232	0.23328	0.3139
	RMS Error	0.014146611				0.015394355			
	Efficiency	98.60507231				98.48390383			
PSO	*Maximum Power*	109.1772963				124.7720334			
	Average Power	106.7344				120.424			
	Convergence Time	0-0.1s	0.1-0.2 s	0.2-0.3 s	0.3-0.4 s	0-0.1s	0.1-0.2 s	0.2-0.3 s	0.3-0.4 s
		0.07727	0.1971	0.2735	0.3978	0.013321	0.160754	0.287759	0.398776
	RMS Error	0.022887619				0.036106037			
	Efficiency	97.66941356				96.35515142			

The PV Power collected during Simulating Fluctuating Irradiance on the PV system

The PSO-INC algorithm consistently converges faster, with total convergence times of approximately 0.8 seconds in both Pattern 1 and Pattern 2. In contrast, the PSO algorithm exhibits slightly longer convergence durations, also approaching 0.8 seconds. This indicates that PSO-INC is more efficient at rapidly locating the maximum power point, which is especially important for dynamic photovoltaic (PV) systems subject to rapid environmental changes. In terms of RMS errors, PSO-INC achieves lower values, ranging from 0.0141 to 0.0154, indicating greater accuracy in tracking the maximum power point than the PSO algorithm, which has RMS errors between 0.0229 and 0.0361. The lower RMS error of PSO-INC enhances its reliability for consistent maximum power point tracking, particularly under fluctuating irradiance conditions that can cause deviations in power output. Overall, these results highlight PSO-INC's superior performance in both convergence speed and tracking accuracy, making it well-suited for efficient, reliable maximum power point tracking (MPPT) in real-world applications.

3.3. The analysis of the PSO-INC MPPT approach in relation to the existing research studies

Recent advances in photovoltaic (PV) maximum power point tracking (MPPT) techniques have shown that Particle Swarm Optimization (PSO) is highly effective in navigating the complex, nonlinear, and multi-peak power-voltage (P-V) characteristics of PV systems. This effectiveness is particularly noticeable under challenging environmental conditions, such as partial shading and rapid fluctuations in irradiance [3]–[5], [28]. The primary advantage of Particle Swarm Optimization (PSO) is its global exploration, which enables it to efficiently identify the global maximum power point (GMPP) even under varying shading conditions. PSO is known for its high convergence speed, robustness to nonlinearities, and adaptability to environmental changes. These qualities make PSO a superior alternative to traditional Maximum Power Point Tracking (MPPT) methods such as Perturb & Observe (P&O) and Hill Climbing (HC) [3], [28]. Despite its potential for compelling exploration, standard Particle Swarm Optimization (PSO) algorithms often experience steady-state oscillations around the maximum power point. This issue can lead to power losses and reduced system efficiency. Additionally, PSO performance is highly dependent on parameter tuning, including the inertia weight and acceleration coefficients. These parameters must be carefully calibrated to achieve a balance between exploration and exploitation, particularly in real-world applications [4], [5]. To address the limitations mentioned earlier, recent research has concentrated on combining PSO with local MPPT methods, particularly Incremental Conductance (INC), a well-established gradient-based approach recognized for its rapid, precise, and low-oscillation tracking under stable conditions [8], [21]. The Incremental Conductance (INC) method determines the Maximum Power Point (MPP) by analyzing the derivative of power in relation to voltage. When this derivative reaches zero, the system is at the MPP, which makes INC suitable for applications that require quick responses and minimal oscillations.

Table 5. The Summary on Research Study on INC, PSO, and PSO-INC MPPT for NTR 5E3E PV Module

Criteria / Method	Incremental Conductance (INC)	Particle Swarm Optimization (PSO)	Hybrid PSO-INC
Type of Approach	Classic gradient-based [29]	Metaheuristic (swarm optimization) [29]–[33]	Hybrid (global + local) [32], [34]
Search Nature	Local, gradient-based [29], [35]	Global exploration [29]–[33]	Global exploration + local refinement [4], [32], [34]
Convergence Speed	Faster in steady states [29], [35]	Very fast, especially with multiple peaks [29]–[33]	Faster overall, especially in complex, shading conditions [4], [32], [34]
Accuracy	High; accurate under steady uniform irradiance [29], [35], [36]	Very high, especially for multi-peak curves [4], [29]–[32]	Very high; combined methods improve accuracy [32], [34]
Robustness	Robust in steady conditions, struggles under shading [29], [35]	Robust against non-linearity and noise, yet oscillations occur [29], [32], [34]	Very robust, especially in partial shading [32], [34]
Oscillations Near MPP	Low steady oscillations [29], [35]	Oscillations unless parameters tuned [30]–[32]	Reduced oscillations, more stability [4], [32], [34]
Parameter Tuning	Moderate, needs tuning [29], [35]	Sensitive; optimization required [29], [32], [33]	Adaptive or self-tuning strategies [4], [32], [34]
Implementation Complexity	Moderate complexity [29], [35]	Slightly complex due to iterations [29]–[32]	More complex but higher performance [4], [32], [34]
Ideal Conditions	Steady, uniform irradiance [29], [35]	Challenging, rapid fluctuations, multi-peak [9], [29], [30]	Effective across challenging conditions [4], [29], [30]

However, a significant drawback of the INC method is its performance under partial shading or rapidly changing environmental conditions. In these situations, it can become trapped in local maxima, leading to unreliable tracking of the Global Maximum Power Point (GMPP), especially during dynamic shading or temperature fluctuations [8], [21]. Hybrid PSO-INC algorithms have been developed to leverage the complementary strengths of both methods. These approaches typically begin by using Particle Swarm Optimization (PSO) for global exploration, which effectively locates the general area of the Global Maximum Power Point (GMPP). This is followed by Incremental Conductance (INC) for precise local refinement, which minimizes oscillations and enhances tracking accuracy near the true GMPP [8], [21]. This hybridization reduces the search space for Particle Swarm Optimization (PSO), which accelerates convergence and enhances stability. As a result, it is better suited to real-world photovoltaic (PV) systems that experience variable shading patterns. Several studies indicate that hybrid PSO-Incremental Conductance (INC) systems perform better than standalone algorithms by achieving higher power extraction efficiency, faster convergence rates, and more stable operation during rapid environmental changes [8], [21]. Recent advancements involve hybridizing PSO with INC and utilizing sophisticated intelligent control strategies, as well as machine learning models, including unsupervised learning, to enhance the MPPT process [6]. These methods enable the system to adapt more effectively to unpredictable, fluctuating weather conditions, thereby improving power tracking accuracy. For example, unsupervised clustering algorithms can organize environmental data into homogeneous zones. This segmentation reduces the search space for Maximum Power Point Tracking (MPPT) algorithms, enabling them to converge more quickly to the Global Maximum Power Point (GMPP), even in the face of rapid changes in irradiance or temperature [6]. Furthermore, integrating hybrid PSO-INC strategies into larger renewable energy systems especially hybrid wind-solar systems has demonstrated potential in improving overall grid stability and optimizing the power output of each energy source [1]. In such scenarios, hybrid MPPT algorithms enhance the efficient use of solar and wind resources by accurately identifying their respective GMPPs and coordinating operations, thereby improving renewable energy integration and grid reliability [1]. Hybrid Maximum Power Point Tracking (MPPT) techniques that combine the strengths of Particle Swarm Optimization (PSO) for global search with Incremental Conductance (INC) for rapid local convergence are increasingly preferred for modern photovoltaic (PV) systems. These hybrid algorithms effectively address the slow convergence and oscillations often seen in traditional methods, demonstrating particular effectiveness in complex shading and fluctuating environmental conditions. Their ability to improve tracking speed, enhance accuracy, and maintain reliable operation in dynamic real-world environments makes them highly suitable for advancing renewable energy deployment, increasing system efficiency, and minimizing energy losses in PV installations [1], [3]–[6], [8], [21], [28]. Table 6 depicted the generally summarized research work on INC, PSO and PSO-INC MPPT while Table 7 summarize the recent research studies on PSO-INC, PSO-ANFIS, CPSO AND FUZZY-PSO MPPT. Numerous studies have consistently demonstrated the superior performance of Particle Swarm Optimization (PSO) over traditional maximum power point tracking (MPPT) techniques such as Perturb & Observe (P&O) and Incremental Conductance (INC), particularly under partial shading conditions (PSC) and dynamic irradiance. PSO-based MPPT techniques significantly outperform conventional methods in power extraction, convergence speed, and tracking accuracy. For instance, while P&O often converges to local maxima, PSO effectively identifies the global maximum power point (GMPP), achieving up to 360–365 W versus 220 W with P&O under shading [37]. Several studies report PSO achieving efficiencies up to 99.9% [14], [17], compared to 33.8–97.6% with P&O [38], [41]. Additionally, convergence times for PSO are generally faster, ranging from 0.018 s to 0.5 s, while P&O and INC can take up to 0.85 s or more [5], [7], [15], [39]. Another key advantage of PSO is its reduced power and voltage oscillations. For example, PSO achieves voltage ripple as low as 0.6%, while P&O shows up to 3.2% [37]. Studies also confirm that hybrid PSO methods lead to greater operational stability during environmental transients [15]. Numerous papers explore hybrid algorithms, combining PSO with INC [3], [5], [32], [39] or other metaheuristics like Gravitational Search (GSA) [4], Cuckoo Search (CS), and Memetic Algorithms [14]. These combinations exploit PSO's global search ability with the local fine-tuning of secondary techniques, leading to faster convergence, higher power output, and superior adaptability under shading and real-world fluctuations. Moreover, PSO-P&O-PI hybrid achieved 99.9% efficiency in 0.023 s [17]. Most studies emphasize PSO's robustness under partial shading, rapid irradiance shifts, and wind integration. Real-time validations, such as the hardware-implemented PSO memetic algorithm, confirm the practical viability of these advanced MPPT methods in real environments [14]. One notable study compared PSO to Grey Wolf Optimization (GWO), showing GWO slightly outperformed PSO with a power output of 190.12 W vs. 188.76 W, and faster convergence 2.8 s compared to 8.8 s, suggesting alternative algorithms may also hold promise.

Table 6. The Summary on Research Study on INC, PSO, and PSO-INC MPPT for NTR 5E3E PV Module

Paper Title	Max Power Output	Tracking Time	Efficiency	Notable Notes
Research of MPPT Control Method Based on PSO Algorithm [37]	360–365 W (PSO) vs 220 W (P&O)	~0.3 s	Higher than P&O	Less voltage volatility (0.6% vs 3.2%); needs better speed & hardware
Extraction of the Global Maximum Power for PV System under PSC Using an Improved PSO Technique [3]	1262–1352 W (PSO) vs 1150 W (P&O)	~0.3–0.5 s	Up to 99.6%	Hybrid PSO-INC improves GMPP tracking and stability
Comparative Assessment of P&O, PSO Sliding Mode, and PSO-ANFIS Controller MPPT for Microgrid Dynamics [8]	387 kW (PSO) vs 220 kW (P&O)	0.3–0.5 s	Higher than P&O	Hybrid PSO-ANFIS improves accuracy and adaptability
Synergistic Application of PSO and Gravitational Search Algorithm [5]	Up to 55.4 W	~0.04 s	Higher than P&O	Hybrid PSO-INC improves efficiency under complex shading
Comparison of MPPT optimization methods for P&O and PSO [38]	Up to 100% (PSO) vs ~33.8% (P&O)	Up to 2.8 s (PSO); 850 ms (P&O)	PSO higher under shading	PSO more robust in multi-peak environments
Dual-stage PV pumping system based on ANFTSMC and PI control enhanced by APSO optimization [39]	Up to ~55.4 W (PSO) vs ~20 W (P&O)	~0.3 s	Higher than P&O	Hybrid PSO-INC shows high efficiency with minimal oscillations
Differential flat & PSO based MPPT under partial shading [15]	Up to ~55.4 W (PSO) vs ~20 W (P&O)	0.3–0.5 s	Higher than P&O	Hybrid PSO-INC improves stability and accuracy
Efficient, intelligent PSO-P&O-PI MPPT under variable conditions [17]	~5994 W (PSO) vs 6000 W theoretical	~0.023 s	99.90%	Hybrid PSO with P&O and PI shows minimal oscillation and high energy yield
MPPT Using Improved Quantum-Behavior PSO [40]	~55.4 W (PSO) vs ~20 W (P&O)	0.3–0.5 s	Higher than P&O	Hybrid PSO-INC enhances tracking in multi-peak scenarios
Hybrid of Cuckoo Search and PSO (CSPSO) [32]	Up to ~394 W	0.11–0.32 s	Higher than PSO/CS alone	CSPSO reduces tracking time by 38–63%
In-Depth Comparison of PV Array Configurations Using P&O and PSO [7]	Up to ~55.4 W (PSO) vs ~20 W (P&O)	0.3–0.5 s	Higher in PSO-INC (up to 100%)	4S4P config most effective; PSO-INC best for accuracy
Hybrid P&O, PSO, and Fuzzy Logic MPPT [41]	99.5% (P&O-PSO-FL) vs 97.6% (P&O)	0.02 s (hybrid); 0.1 s (P&O)	99.50%	Best convergence and output stability with hybrid
PSO Memetic Algorithm for Tilt Angle MPPT [14]	99.9% efficiency	8.5 ms (PSO) vs hundreds ms (INC)	99.90%	Hardware-validated; robust, fast, and accurate
Deterministic PSO MPPT [42]	93.9% to 99.47%	0.25–4.5 s	Up to 99.47%	Eliminates steady-state oscillations; very stable
PSO-INC MPPT on NTR 5E3E PV Module	173.4596492 W around 99.93%	0.0042-0.2957	98.89% to 99.93%	Hybrid PSO-INC tested under varying irradiance value for NTR 5E3E PV module

This study presents a comprehensive analysis of the benefits of faster convergence and higher efficiency in Maximum Power Point Tracking (MPPT) algorithms for larger photovoltaic (PV) farms and grid-connected systems. By maximizing energy extraction, especially under rapidly changing environmental conditions such as cloud cover or shading, these improvements can significantly enhance overall system performance. Improved convergence speed reduces the time the system operates below its optimal power point, increasing energy harvest and profitability for the plant. Additionally, higher MPPT efficiency ensures that a larger portion of available solar energy is converted into usable electrical power. This is particularly critical at a large scale, where even small percentage gains can lead to substantial increases in energy production. Furthermore, rapid and accurate MPPT can enhance grid stability by providing consistent, high-quality power output, thereby reducing fluctuations that may impact grid performance. These advantages culminate in improved system performance, higher economic returns, and more reliable integration into the power grid. This study also examines the behavior of the Particle Swarm Optimization-Incremental Conductance (PSO-INC) MPPT method under various irradiance conditions, including both steady-state and dynamic, rapidly changing environments. Unlike previous research that often focuses solely on static conditions, this work emphasizes the algorithm's robustness and reliability in real-world scenarios where environmental factors fluctuate unpredictably. The detailed convergence data, including convergence speed, root mean square error (RMSE), and stability across multiple irradiance profiles, provide critical insights into the method's performance limits and adaptability. Such an in-depth examination is essential for informing the future deployment of MPPT algorithms in actual PV systems, helping to optimize system design, reduce transient losses, and ensure consistent energy harvesting, even under highly variable weather conditions. Moreover, the simulation setup and scripting were developed using a novel system configuration, ensuring that the results reflect realistic operating conditions. This approach effectively bridges the gap between laboratory research and practical implementation. Overall, this work contributes valuable knowledge towards developing resilient, high-performance MPPT solutions tailored for real-world applications in diverse environmental settings.

4. Conclusion

Based on the provided data, both the PSO-INC and PSO MPPT methods are highly effective in maximizing power extraction under varying irradiance conditions for the NTR 5E3E PV Module. The PSO-INC method consistently achieves a higher maximum and average power outputs across different patterns and illumination levels. In the first dataset, for instance, PSO-INC reaches a maximum power of approximately 173.46 W at 1000 W/m^2, while the PSO method achieves a similar, but marginally lower, power output. PSO-INC MPPT methods maintain efficiencies up to 99.9%, demonstrating their capability for high-precision maximum power point tracking (MPPT). The second dataset further confirms that PSO-INC generally outperforms PSO, particularly under challenging conditions such as Pattern 2, where power outputs from PSO-INC reach nearly 125 W compared to approximately 124.77 W from PSO at the same irradiance. Additionally, PSO-INC exhibits faster convergence than PSO, resulting in a quicker MPPT response, an important factor in environments with rapidly changing irradiance. Overall, the data suggest that PSO-INC offers significant improvements in power-tracking accuracy, efficiency, and dynamic response compared to the conventional PSO method. This makes PSO-INC a promising approach for optimal power extraction in variable outdoor conditions.

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Declarations

Author contribution. The first author focused on conducting the study and writing the manuscript. Meanwhile, the second author is responsible for supervising the research and correcting the manuscript.
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Conflict of interest. The authors declare no conflict of interest.
Additional information. The work was simulated using MATLAB/Simulink software, and the data are available.

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