High-Efficiency MPPT for PV Systems Based on PSO-Tuned Variable Step-Size Incremental Conductance

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Abstract: This work proposes a new method for maximum power point tracking (MPPT) for PV systems that combines particle swarm optimization (PSO) with an adaptive variable step-size (VSS) Incremental conductance (IncCond) algorithm which is able to achieve a higher tracking speed, stability and efficiency. This new step-size perturbation is dynamically determined by choosing an optimal scaling factor from a pre-trained PSO-based lookup table including only the voltage and current values. This reduces the need for computation and environmental sensors, providing a fast, accurate, and computationally efficient solution. In this context, PSO is employed for determining the appropriate scaling factor as per the available level of irradiance and so it increases the effectiveness of the VSS IncCond-based MPPT method. Extensive simulations were carried out under standard test conditions, abrupt changes in irradiance and real-world solar irradiance conditions. The obtained results confirm that the proposed method surpassed four other existing approaches, attaining an average tracking efficiency of 99.6% and an average tracking time of 0.007 seconds, and a minimal oscillation level in comparison with conventional and intelligent MPPT algorithms including fuzzy logic, ANN-based, and traditional incremental conductance methods. It has also proven to be highly adaptable and easy to implement, which is particularly important for real-time embedded PV applications in dynamic environments.

Keywords: Photovoltaic (PV) system, Maximum power point tracking (MPPT), Particle swarm optimization (PSO), Incremental Conductance (IncCond), Boost converter variable step-size (VSS).

1. Introduction

As non-renewable energy sources like oil, coal, and natural gas continue to be consumed at a rapid rate, concerns about environmental and energy-related challenges are becoming more urgent (Drucker & Gueron 2019; Wang et al., 2019). Solar energy has emerged as a key clean, sustainable option. Solar power is plentiful and critical for life; without it, life would be impossible (Zhang et al., 2019; Liu et al. 2021a; Liu et al. 2021b).

Recent progress in photovoltaic (PV) generation has been swift. Now, solar energy is a top subject in renewable research. With innovative technology, solar cells and PV systems are viewed as useful ways of producing energy.

The International Energy Agency (IEA) states that world energy use is increasing (Liu et al., 2021a; Ma et al., 2021; Li et al., 2022). PV systems have become common because they make little noise, have a long lifespan, do not create pollution once implemented, and require no fuel (Gao et al., 2022a; Gao et al., 2022b; Ma et al., 2020). These gains make solar energy reliable and sustainable, making people use it for cleaner solutions. Photovoltaic (PV) systems are used in water pumps, power support (Sousa & Vilela, 2014), communication (Boonkajay & Adachi, 2017), home systems, big power plants and space vehicles (Zaouche et al., 2017). However, even with their potential, PVs seem costly, so research focuses on reducing those costs. One key area is power electronics, which helps obtain the most power out of PV systems (Baba et al., 2020). With Maximum Power Point Tracking (MPPT), one can pull most energy out of PV systems even when a change takes place (Lyden & Haque, 2015).

Many MPPT algorithms have come out over the years. They differ regarding their control mechanisms, their level of precision, how fast they respond, what sensors they need, how easy they are to use, how much they cost, and how well they adjust to changes in the environment. Generally, these MPPT techniques can be split into direct and indirect methods (Ibrahim et al., 2020). In summary, the perturb and observe (P&O) and incremental conductance (IncCond) algorithms both have pros and cons; however, efforts are underway for improving their practical performance and strengthening their ability to be deployed in the real world. These upgrades are important as PV systems are becoming essential in the move to renewable energy.

Traditional Maximum Power Point Tracking (MPPT) methods struggle to balance the perturbation step size, which impacts how quickly the system reacts and how steady it remains. Small steps slow reaction times, but big steps cause more fluctuation when the system should be stable. To fix this, scientists developed MPPT

https://doi.org/10.24846/v35i2y202608

algorithms that adjust to fast-changing irradiation. These applications react faster and oscillate less when things are steady. One popular method is the adaptive variable step-size (VSS) algorithm (Thangavelu et al., 2017). Such methods figure out the perturbation step size by analysing things like power-to-voltage slope (dP/dV) (Pandey et al., 2008), the derivative of the power-to-duty cycle (dP/dD) (Liu et al., 2008), and the power-to-current tangent (dP/dI) (Mei et al., 2011). Choosing the correct scaling factors is very important, but it can be difficult. A fixed scaling factor might work well in certain irradiation conditions, but it may not work in other conditions. An adaptive method, such as that in (Loukriz et al., 2016), was proposed for addressing this issue, but it has its own limitations.

Amir et al. (2017) investigated the use of two different scaling factors for handling different irradiation levels - high and low. This added some flexibility, letting the system react to changing irradiation conditions. But, even with its positive aspects, this approach might not make the system work optimally for all the different irradiation levels encountered in the real world. In short, the scaling factor is very important for any adaptive voltage - and the current-source maximum power point tracking (MPPT) method. It changes how well the system works. Picking the right scaling factor is key to getting the most out of MPPT, as it affects how well the system can grab and use solar power. Still, finding the best scaling factor that can change with different irradiation conditions is still a big problem for those working in this area.

A new method, called Variable Step-Size (VSS) incremental conductance (IncCond), was created by Ye et al. (2022). It uses an adaptive scaling factor to make maximum power point tracking (MPPT) work better. This method guesses the irradiation levels based on a model, so the scaling factor can be changed as needed. Still, there are certain issues: many tests are needed to find the best scaling factor, and complex calculations are needed to figure out the irradiance level correctly.

This paper introduces a new technique related to maximum power point tracking (MPPT). It uses particle swarm optimization (PSO) to figure out the best scaling factor. This factor is based on the current and voltage readings taken at two points by using the variable step-size (VSS) incremental conductance (IncCond) method. To deal with a power output that fluctuates and long wait times for solutions, which can happen because PSO searches randomly, a lookup table was set up. This table keeps track of the optimal configurations, so that they could be used right away during MPPT.

This approach simplifies the process by eliminating the need for extensive simulations and complicated state estimations.

MPPT efficiency depends not only on the steady-state accuracy but also on cumulative energy harvesting, which is affected by transient tracking speed and oscillation losses. Conventional MPPT methods are prone to energy losses under a rapidly changing irradiance. Therefore, an optimized variable step-size MPPT is essential, and the proposed PSO-tuned Incremental Conductance method directly addresses this challenge.

This remainder of this paper is organized as follows. Section 2 introduces the proposed Maximum Power Point Tracking (MPPT) method, explaining its design and how it works. Section 3 provides an extensive validation of the proposed method against state-of-the-art methods in different operating situations, which includes nominal testing conditions, step and ramp variations of irradiance, and real irradiance profiles. Finally, Section 4 concludes this paper, outlining its key findings and contributions and also future possible research directions

2. Proposed MPPT Algorithm

The technique proposed by this paper initially employs particle swarm optimization (PSO) to calculate the optimal scaling factor (OSF) that should be applied to the current irradiance levels. Subsequently, it utilizes the variable step-size incremental conductance (VSS IncCond) approach to determine the maximum power point (MPP). This begins by outlining the OSF estimation technique implemented via PSO, followed by the process of applying the VSS IncCond MPPT algorithm by using the determined OSF.

2.1 PSO Algorithm Design and Implementation

The Particle Swarm Optimization (PSO) algorithm works in a way which is similar to how fish swim in schools or birds flock together while searching for food. It achieves this by relying on three main factors: the velocity of each particle, a particle`s individual experiences, and the experiences of neighboring particles. These components collaborate to guide the movement of the particle and help it find the best solution within the search area (Ibrahim et al., 2023).

The algorithm updates each particle's position using a velocity equation:

$$v_i^{(k+1)} = \omega v_i^{(k)} + c_1 r_1^{(k)} [P_{best_i}^{(k)} - x_i^{(k)}] + c_2 r_2^{(k)} [G_{best_i}^{(k)} - x_i^{(k)}] \quad (1)$$

This equation includes the following elements: the inertia weight (ω), which helps maintain the particle's current motion; the cognitive coefficient (c_1), which represents the particle's tendency to move towards its best-known position; and the social coefficient (c_2), which encourages the particle to align with the best position found by the entire swarm. Random values (r_1 and r_2) ranging from 0 to 1 introduce variability, ensuring a thorough exploration of the search area. The velocity equation defines how the particle adjusts its speed and direction based on these factors.

Once the velocity is determined, the particle's position is updated by using another equation that combines its existing position with the newly calculated velocity (Ibrahim et al., 2023):

$$x_i^{(k+1)} = x_i^{(k)} + v_i^{(k+1)} \quad (2)$$

The goal is for each particle to constantly change its position, using its own best position (P_{best}) and the best-known position of the swarm (G_{best}) as reference points. Through this repeated process, the swarm gradually approaches the optimal solution.

In essence, the PSO algorithm ensures that each particle learns from its own successes as well as those of its neighbours, making it a powerful and efficient optimization technique.

To help a particle stay on a steady path in a given direction, the inertia weight $\omega(t)$ is essential. It significantly influences how the particle swarm optimization (PSO) algorithm converges. By gradually reducing $\omega(t)$ over time, the algorithm cleverly shifts from a wide-ranging exploration at the beginning to a more concentrated exploitation as it moves forward. This thoughtful approach enhances the optimization process, leading to more effective solutions. In this sense, exciting possibilities are on the horizon.

To enhance the quality of the attained solutions, it is customary to initiate the inertia weight with a relatively high value, subsequently employing a gradual reduction throughout the iterative process. A widely accepted methodology is to adopt a linear decrease, which can be articulated using the following formula:

$$\omega(t) = \omega_{\max} - \frac{t}{t_{\max}} \left(\omega_{\max} - \omega_{\min} \right) \quad (3)$$

In this equation, ω_{max} represents the initial maximum inertia weight, ω_{min} is the minimum value the inertia weight can reach and t_{max} denotes the maximum number of iterations allowed.

This approach to gradually reducing parameters ensures a seamless shift from exploration to convergence. It is fascinating how the social coefficient (c_2) and the cognitive coefficient (c_1) significantly influence particle behaviour.

For example, if c_1 is bigger than c_2, particles usually focus on their own best positions (P_{best}), which lets them explore on their own. But, if c_2 is bigger, the particles usually move toward the best global position (G_{best}), encouraging teamwork. By changing these values, particle swarm optimization (PSO) can be adjusted as it goes on, achieving a desirable equilibrium between exploration and exploitation. This makes it a useful way for handling different search problems.

To better regulate swarm behavior, the cognitive and social acceleration coefficients c_1 and c_2 are dynamically changed throughout the search. As iterations go on, one coefficient is usually increased while the other is decreased, balancing exploration (looking for new areas) and exploitation (improving the promising solutions). The cognitive coefficient, c_1 has a low value in the beginning and goes up over time. This pushes the particles to explore more later on. On the other hand, the social coefficient, c_2 has a high value in the beginning and goes down over time. This ensures that the particles focus on their own learning first and later prioritize working together.

By using the two varying coefficients below, the algorithm adjusts the weight of the personal best solutions (P_{best}) versus the global best solution (G_{best}). This helps optimize both the exploration and convergence phases, allowing the swarm to find a better overall solution more efficiently.

$$c_1(t) = c_{1,\max} - \frac{t}{t_{\max}} \left(c_{1,\max} - c_{1,\min} \right) \quad (4)$$

$$c_2(t) = c_{2,\max} - \frac{t}{t_{\max}} \left(c_{2,\max} - c_{2,\min} \right) \quad (5)$$

As detailed previously, the scaling factor M (within the variable step-size method) denotes particle position in the context of the PSO algorithm. The output power of the PV array acts as a fitness function, thereby guiding the optimization process. The flowchart of the proposed PSO algorithm is illustrated in Figure 1 and its essential steps are summarized as follows:

Step 1: Parameter Selection

The variable step-size MPPT technique uses five particles (or scaling factors, M). This number strikes a balance between accuracy and how fast the calculations are made. The number five might seem an arbitrary choice, but this is what ensures an optimal implementation

Step 2: PSO Initialization

In the PSO setup phase, particles start from positions which were initially set. The scaling factor (M) goes from 0.1 to 10. To space out five values evenly in that range, the following formula is employed:

$$\frac{i-1}{n-1}\times\left(M_{\max}-M_{\min}\right) \tag{6}$$

This way, the values of M are spread out proportionally. This is a simple idea, but implementing it well is significant for desirable consequences. It should be carefully observed how things begin. This is essential for the algorithm to work well.

Step 3: Fitness Evaluation

The main goal of the PSO-based MPPT method is to obtain the highest power possible from a PV setup. The algorithm determines output power by measuring PV voltage and current. Then, it uses this power as a fitness value for evaluation.

Step 4: Updating the Local and Global Best Values

Every particle keeps track of the best position it has found so far. This is called (P_{best}). The particle with the best fitness is labeled (G_{best}) indicating that it is the top solution overall.

Step 5: Updating Velocity and Position

After checking all the particles, the algorithm changes each particle's speed and location using certain formulas. This makes sure they move toward a better solution.

Step 6: Convergence Determination

The algorithm decides when to stop by looking at two things: (1) if a particle's speed gets too low, or (2) if it reaches the maximum number of iterations. If either one happens, the calculation stops, and the best solution is chosen.

Step 7: Re-initialization

Given that the global MPP position may fluctuate because of altering irradiance conditions, the PSO algorithm is designed to reinitialize itself. Equation (7) helps identify

environmental changes: furthermore, it restarts the optimization process. This, in turn, ensures a precise tracking of the new MPP:

$$\frac{P_{PV}-P_{PV,old}}{P_{PV,old}} > \Delta P\,(\%) \tag{7}$$

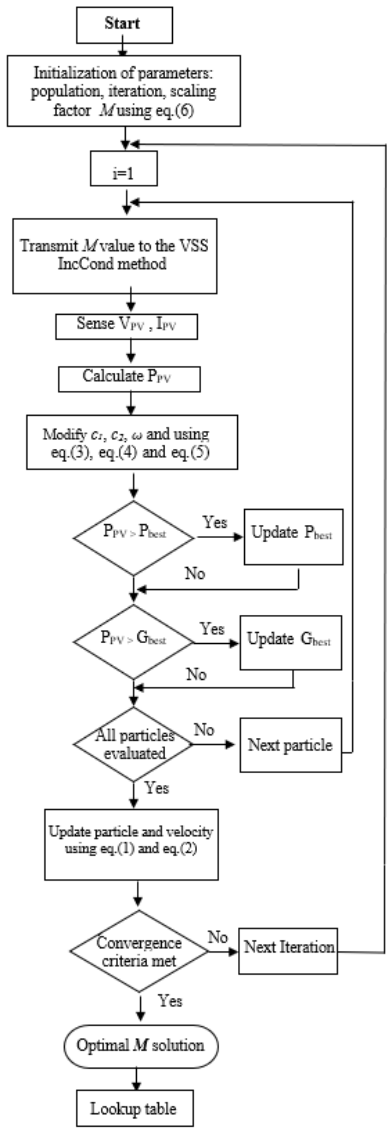


Figure 1. Flowchart of the enhanced PSO algorithm

2.2 The Proposed PSO-Assisted VSS IncCond MPPT Algorithm

The traditional Variable Step-Size (VSS) Incremental Conductance (IncCond) MPPT algorithm is recognized for its merits: an elevated tracking speed and accuracy and minimal tracking losses. However, its dependence on a fixed scaling factor constrains its efficacy when irradiance levels fluctuate (equation (1)). To address this limitation, this study proposes a PSO-assisted VSS IncCond MPPT algorithm. The process begins with the generation of a random population of candidate solutions, each evaluated for its fitness P_{PV} via a solar PV system model developed in Simulink. A PSO process is applied to the initial population in order to yield a subsequent generation of solutions. This iterative optimization persists until the criteria for discerning the optimal solution are fulfilled. Figure 2 illustrates the flowchart of the proposed PSO-Assisted VSS IncCond MPPT Algorithm.

Although PSO effectively converges towards a global optimal solution, its stochastic nature can initially cause notable power output oscillations. The phenomenon under discussion is illustrated, showing the PSO process that begins with a diverse array of solutions. This process progressively converges towards an optimal outcome, resulting in unique scaling factors, denoted as M, for each irradiance condition.

In order to effectively address the challenges encountered during this optimization, a lookup table has been implemented for storing the optimal M values derived from the trained PSO. During MPPT, these values are retrieved directly, removing the need for real-time scaling factor computations. This ensures a consistent, high-speed tracking with fewer oscillations and a reliable performance in dynamic environments. The proposed algorithm is especially efficient and dependable. Subsequently, the variable step-size Incremental Conductance (VSS IncCond) MPPT method is employed, utilizing the selected M scaling factor. As the irradiance levels change, the system is structured so as to determine the new optimal scaling factor (OSF) (Figure 1). In this investigation, the OSF is established via a trained PSO algorithm involved in balancing the trade-offs between the scaling factors. The proposed approach features significant advantages; it includes rapid tracking speeds and minimal oscillations under static and dynamic environment conditions, thereby ensuring a dependable performance across diverse scenarios.

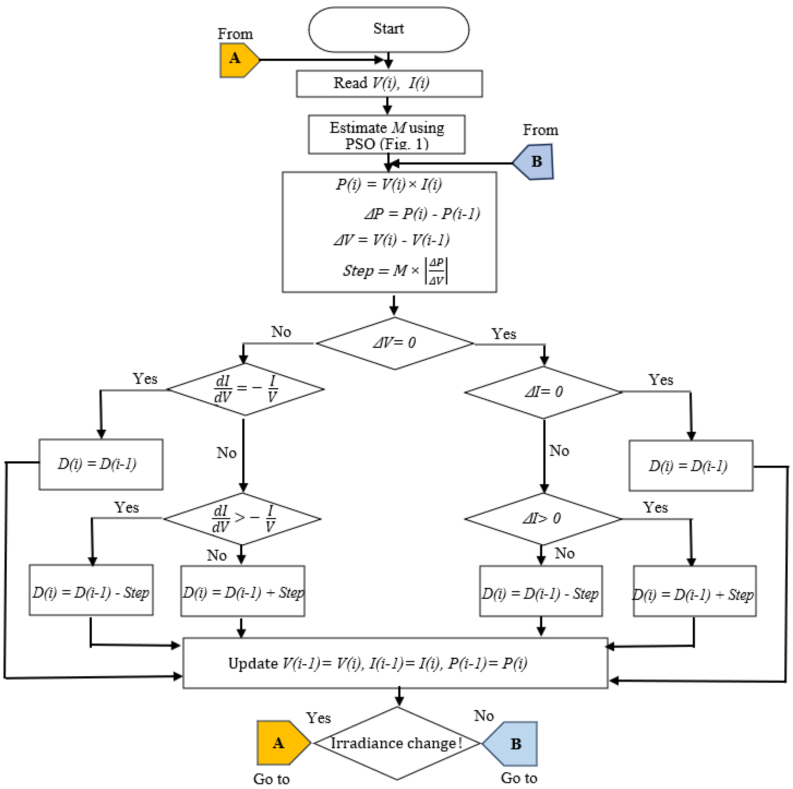


Figure 2. Flowchart of the proposed VSS-PSO algorithm

3. Results and Discussion

This study deals with the modeling and simulation of a stand-alone photovoltaic (PV) system in MATLAB/Simulink considering different MPPT methods under different conditions. This section introduces and describes the results of the simulations.

The performance of the proposed method is evaluated and compared with that of several existing approaches. Four full-scale simulation cases were analysed under the following conditions: Standard Test Conditions (1000 W/m², 25°C), Different Levels of Irradiance, and Actual Irradiance Profiles. Table 1 and Table 2 include the PV panel characteristics and the parameters of the boost converter, respectively. Figure 3 illustrates the block diagram of the simulated PV system.

Table 1. Characteristics of the PV panel

Maximum Power, P_{MPP}	250.2 W
Maximum Voltage, V_{MPP}	30.7 V
Maximum Current, I_{MPP}	8.15 A
Open-circuit Voltage, V_{oc}	37.3 V
Short-circuit Current, I_{sc}	8.66 A
Temperature, STC	25°C

Table 2. Boost converter rating parameters

Capacitor, C_{in}	100μF
Capacitor, C_{out}	100μF
Inductor, L	3 mH
Switching frequency, f_s	20 kHz
Load Resistors	R_1 =20 Ω R_2 =30 Ω R_3 =40 Ω

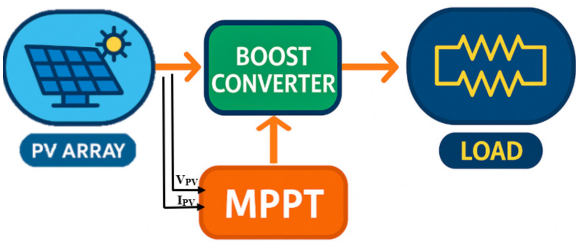


Figure 3. Block diagram of the simulated PV system

3.1 Case 1: Test Under Constant STC Irradiance and Constant STC Temperature

Figure 4 shows the real-time performance of five different MPPT algorithms under standard test conditions (1000 W/m² irradiance and 25°C temperature). The proposed method reaches the MPP (roughly 250 W) in 0.007 s with negligible oscillations, confirming its superior stability and effectiveness. The method proposed by Owusu-Nyarko et al. (2021) also provides a fast response but has some oscillations before settling down at 0.014 s. It can be observed that the method of Yang et al. (2017) guarantees a smooth adjustment trajectory and low power fluctuations but it takes much longer to reach the MPP (about 0.05 s). The method introduced by Zakzouk et al. (2016) achieves a reasonable accuracy, but with a tracking time of around 0.045 s it can also be considered moderate based on its fluctuations and stabilization properties. On the other hand, the method proposed by Liu et al. (2008) provides a tracking response with a tracking time of 0.03 s and the highest instability. As a conclusion, it is obvious that the proposed MPPT method performs better than the other four methods in terms of speed, accuracy and steady-state behavior under both transient and stable operating conditions.

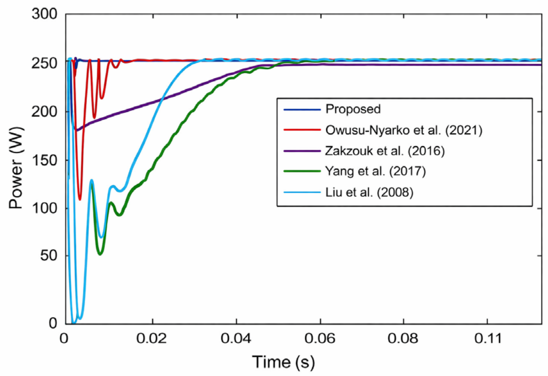


Figure 4. Simulation results for the proposed method and four existing MPPT techniques under stable irradiance conditions

3.2 Case 2: Test Under Sudden Changes in Irradiance While Maintaining a Constant STC Temperature

The dynamic response of the five MPPT algorithms under variable irradiance (1000, 800, 600, 400, and 200 W/m², as illustrated in Figure 5) is depicted in Figure 6. When the irradiance decreases stepwise, the performance of each algorithm is assessed by tracking speed, stability, and oscillatory behaviour. The proposed method achieves the fastest tracking time and smooth transitions at each irradiance level, with minimum oscillations for reaching the MPP for all levels of irradiance. Further on, although the method proposed by Owusu-Nyarko et al. (2021) also converges very fast, it has slightly larger initial overshoots than the proposed method. The approaches developed by Zakzouk et al. (2016) and Yang et al. (2017) feature slow dynamic responses and an oscillatory nature during low irradiance transitions. If the algorithm of Yang et al. (2017) is compared with the one of Zakzouk et al. (2016), it could be said that the former features high oscillations and a slow recovery under the step changes in irradiance, and the latter features a slow tracking dynamic and a low stability at a reduced power level. The method proposed by Liu et al. (2008) shows a similar performance to that of Zakzouk et al. (2016), exhibiting noticeable oscillations and a long settling time. To sum up, the fast response and stability criteria related to output power indicate that the proposed method is superior to the other methods across all the irradiance levels.

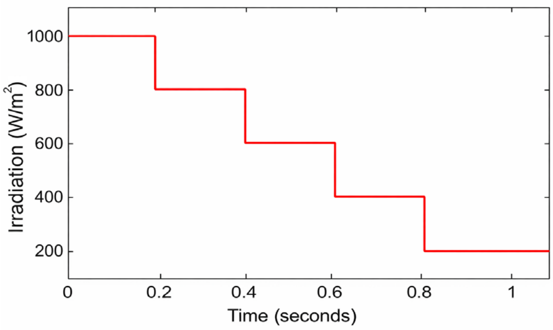


Figure 5. Step-change irradiance profile for the simulation: 1000W/m² to 200W/m² in 5 equal intervals of time at 25°C

Tables 3 and 4 present the PV output power summary and tracking efficiency summary during step changes in irradiance.

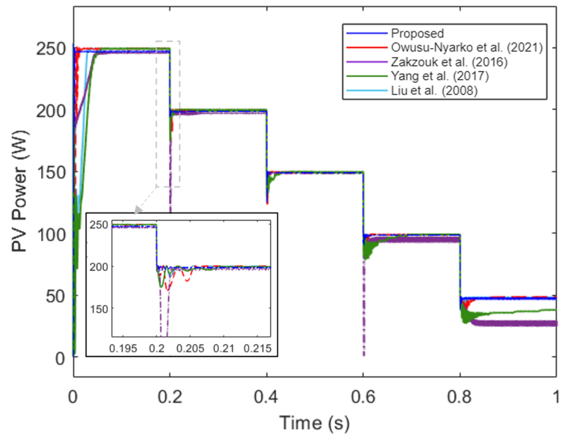


Figure 6. Simulation results for the proposed method and four existing MPPT techniques under step changes in irradiance

3.3 Case 3: Actual Irradiance Profiles

Actual irradiance conditions are analyzed for establishing the efficiency of the proposed method. It is important to note that this irradiance data was measured by a weather station, as reported by Ibrahim et al. (2023), using a sensor that measures the irradiance in cycles of 60 s, and then stores the data in a database for the same interval. Figure 7(a) highlights the rapid changes in irradiance that were measured for a ten-hour interval of a cloudy day in early June 2022. The responses of the photovoltaic (PV) system to instantaneous

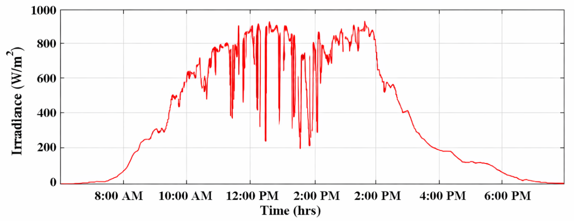
Table 3. PV Output Power Summary

Response time related to step changes in irradiance	PV array model output (W)	Owusu-Nyarko et al. (2021) (W)	Yang et al. (2017) (W)	Zakzouk et al. (2016) (W)	Proposed (W)
0-0.2 s	250	247.2	195.1	155.2	249.8
0.2-0.4 s	200	198.5	182.3	167.7	199.6
0.4-0.6 s	100	98.9	94.9	86.3	99.1
0.6-0.8 s	50	48.5	40.5	35.4	49.6
0.8-1 s	30	29.0	20.1	15.1	30.0

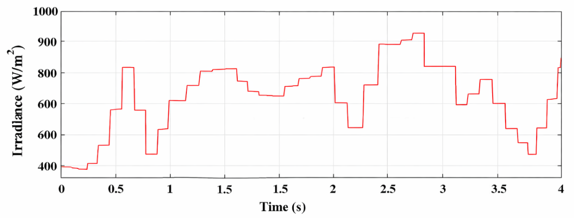
Table 4. Tracking Efficiency η_MPPT (%) Summary

Response time related to step changes in irradiance	Owusu-Nyarko et al. (2021) (%)	Yang et al. (2017) (%)	Zakzouk et al. (2016) (%)	Proposed (%)
0-0.2 s	98.88	78.04	62.08	99.92
0.2-0.4 s	99.25	91.15	83.85	99.80
0.4-0.6 s	98.90	94.90	86.30	99.10
0.6-0.8 s	97.00	81.00	70.80	99.20
0.8-1 s	96.67	67.00	50.33	100.00
Average Efficiency	98.14	82.42	70.67	99.60

changes in irradiance were simulated by taking 40 samples at equal time intervals from 10:55 AM to 11:15 AM. As shown in Figure 7(b), these data samples serve as the simulation's step-required input, allowing one to assume that variations did occur at intervals of 0.1 s.



(a)



(b)

Figure 7. Solar irradiance on a cloudy day: (a) a full-day profile; (b) measured irradiance scaled for the simulation (Ibrahim et al., 2023)

Figure 8 presents the comparative simulation results for the proposed method and four existing MPPT techniques in response to real-time irradiance changes.

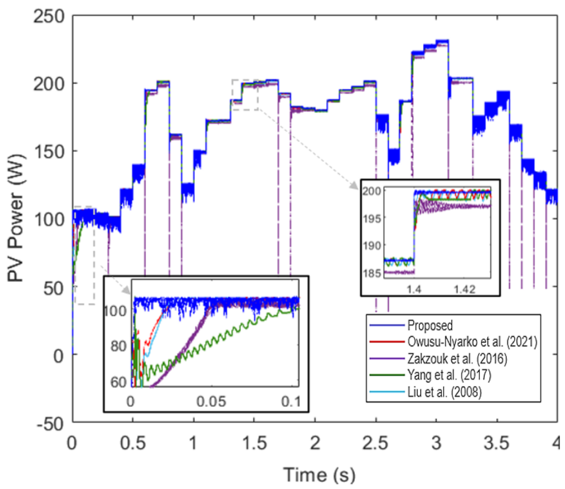


Figure 8. Simulation results for the proposed method and four existing MPPT techniques under real-time irradiance conditions

The methods proposed by Liu et al. (2008) and Owusu-Nyarko et al. (2021) exhibit rapid adjustments with relatively steady responses and minor oscillations, demonstrating both a high efficiency and a strong dynamic performance. The approach of Zakzouk et al. (2016) enables a reliable tracking but it features moderate oscillations and a slower settling time, indicating that it is less efficient than the other four approaches. On the other hand, the method of Yang et al. (2017) features certain instability issues. It often shows power fluctuations and long tracking times, which degrade its performance and efficiency. The proposed method features a quick tracking, almost no oscillations, and a good stability even when the irradiance level changes. It performs better than the methods of Zakzouk et al. (2016), Liu et al. (2008), and Yang et al. (2017), and it is comparable to, or slightly better than the method of Owusu-Nyarko et al. (2021). Furthermore, the effectiveness of the proposed approach significantly reduces energy losses and enhances the overall profitability of the PV system.

5. Conclusion

In this paper, an improved MPPT algorithm based on variable step-size (VSS) incremental conductance (IncCond) MPPT and particle swarm optimization (PSO) were applied for dynamically regulating and optimizing the scaling factor for PV systems. In contrast to the traditional VSS-based techniques that employ fixed or heuristically determined scaling factors, the proposed method determines these factors intelligently based on instantaneous voltage and current observations. An initial PSO-based lookup table was developed in order to avoid real-time optimization for a rapid convergence, stable oscillations, and a high tracking precision.

The proposed method was validated for four operating scenarios covering nominal test conditions, step and ramp changes in irradiance, and actual irradiance profiles. The simulation results showed that the proposed method significantly outperformed other state-of-the-art MPPTs like the fixed-step IncCond method, the VSS IncCond method utilizing fuzzy logic as well as other ANN-based and hybrid approaches. The proposed controller achieved the best average tracking efficiency (99.6%) and the quickest tracking time (0.007s), with perfect steady-state oscillations. This method is simple since it only needs voltage and current sensors and it is fairly easy to implement. This makes it good for low-cost embedded systems needing real-time speed. The obtained results show that the PSO-enhanced VSS IncCond algorithm is practical and can be scaled to autonomous and grid-connected solar power systems, especially when the environment changes or the loads shift. Future studies will involve hardware-in-the-loop testing as well as experimental validation using real photovoltaic systems in order to demonstrate their robustness under real-world conditions. These investigations will further confirm the real-world applicability and scalability of the proposed MPPT algorithm.

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