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Hybridization of PSO-SSA for photovoltaic system MPPT under dynamic irradiance and temperature

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Abstract

Maximum Power Point Tracking (MPPT) has become an important area of research to optimize the power generated by photovoltaic (PV) systems, particularly under various configurations such as series and parallel. Conventional methods, including Perturb and Observe (P&O) and Incremental Conductance (InC), often fail under dynamic or partial shading conditions, while metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Salp Swarm Algorithm (SSA) provide global optimization but still suffer from slow convergence and power oscillations. This study proposes a hybrid MPPT approach by combining PSO and SSA to overcome these limitations. The algorithm was implemented in MATLAB/Simulink and tested under 96 scenarios covering series and parallel configurations with irradiance and temperature variations that change both suddenly (< 1 s) and gradually (> 1 s). Simulation results demonstrate that the hybrid PSO–SSA consistently achieves faster convergence compared to standalone PSO or SSA, with an average convergence time of 0.286 s in the series configuration (25–36% faster) and 0.282–0.284 s in parallel configuration, while achieving comparable power output to PSO. Overall, the proposed hybrid PSO–SSA algorithm provides a faster, more adaptive, and robust MPPT strategy under realistic PV operating conditions, contributing to reducing energy losses in fluctuating environments.

1. Introduction

Solar energy has become one of the fastest-growing renewable energy sources in the world. This growth is driven by the decline in photovoltaic (PV) installation costs and global policies to reduce dependence on fossil fuels. PV systems are capable of converting light energy into electrical energy directly, but their efficiency is strongly influenced by environmental factors such as solar irradiance and temperature. These factors cause the maximum power point (MPP) to change dynamically. Therefore, the existence of a Maximum Power Point Tracking (MPPT) algorithm is very important for PV systems to operate at their optimum point. Currently, MPPT remains an active research area, particularly for dynamic scenarios and partial shading conditions that often occur in real PV systems [1] [2] [3].

Due to these two conditions, most PV systems lose significant energy and their efficiency drops between 20% and 70% [4]. Direct connection between the PV system and the load will make the power transfer less optimal due to the characteristics of the current-voltage relationship (I-V curve) of the PV output which is non-linear, resulting in a unique MPP on the power-voltage curve (P-V curve). This situation becomes more complex under varying irradiance and temperature conditions, because in the end the current-voltage curve of a PV system depends on both conditions. When the current-voltage curve of a PV system changes, the location of its MPP will also change [5]. To achieve optimal power transfer from a PV system, an MPPT technique is required. MPPT is a real-time tracking method that maintains operation at the MPP under changing environmental conditions. The current-voltage curve and MPP location of a PV system are not static data that can be obtained from datasheets, nameplates, or other tables. Instead, determining the current-voltage curve and MPP would require continuous sweeping experiment of the load impedance, which is impractical in real-time operation. Therefore, MPPT can only track MPP by implementing a trial-and-error strategy. MPPT changes the output voltage (thus changing the output current according to the current-voltage curve) by changing the load impedance seen by the PV system. This impedance variation is achieved by changing the duty cycle of the DC-DC converter installed at the output of the PV system.

Conventional MPPT methods such as P&O (Perturb and Observe) and InC (Incremental Conductance) are still widely used, but their performance often declines under dynamic conditions or partial shading because they are easily trapped in local MPP [6]. Metaheuristic-based algorithms such as PSO (Particle Swarm Optimization), SSA (Salp Swarm Algorithm), Grey Wolf Optimization (GWO), Simulated Annealing (SA), Cuckoo Search (CS), Ant Colony Optimization (ACO), and Genetic Algorithm (GA) offer global solutions, but still have limitations, such as slow convergence and power oscillation under changing environmental conditions. Most previous studies have focused only on irradiance variations or compared one algorithm with another, without simultaneously considering both irradiance and temperature changes under rapid and gradual conditions [6] [7] [2]. Several previous studies have improved MPPT performance in various aspects. One critical issue arises in the case of partial irradiance, namely when several solar panels in one PV system receive non-uniform sunlight due to the appearance of clouds or because they are covered by the shadow of trees and buildings [2] [8] [6] [7] [5] [9]. In this case, the current-voltage curve formed produces several local MPPs. The next aspect that plays a significant role is the problem that arises when there is a rapid change in lighting conditions (sudden condition change), which occurs instantaneously in simulation or within less than one second in practice [8] [7] [4] [2] [5]. Another aspect is the problem that occurs when there is a gradual change in irradiance conditions, which is more realistic with a time scales ranging from one second to one minute or longer [4]. Some studies have raised the use of one metaheuristic method [2] [4] [10] [11], while others discuss the comparison of several metaheuristic methods in MPPT [8] [6] [7] [9]. From various previous studies, the problem of partial shading in PV systems, metaheuristic MPPT algorithms, comparison and combination of several methods for MPPT, and changing irradiance conditions have been discussed.

To address these limitations, this study developed a hybrid PSO and SSA-based MPPT algorithm. This combination is designed to utilize the advantages of PSO in exploitation speed and the advantages of SSA in exploration capabilities, so that the MPPT system can find the global MPP faster and be more resilient under dynamic environmental conditions. The PSO–SSA hybrid algorithm was applied to a multi-panel PV system (series and parallel configurations) and evaluated through MATLAB/Simulink simulations under 96 scenarios covering various irradiance and temperature conditions, with changes occurring both rapidly (sudden change—under one second) and slowly (gradual changes—more than one second). Therefore, the combined advantages of PSO and SSA are expected to enhance MPPT performance.

Based on the background described above, the research problems are formulated as follows:

1. How to design and develop a PSO-SSA hybrid algorithm for MPPT optimization that can adapt to rapid and gradual changes in irradiance and temperature under real-operating conditions.
2. How to simulate a multi-panel PV system in MATLAB/Simulink to evaluate the performance of the proposed MPPT method.
3. How to analyze and compare simulation results to determine the advantages of PSO, SSA, and hybrid PSO-SSA methods.

Patel and Agarwal (2008) conducted a study on MPPT, which proposed an improved MPPT algorithm to prevent the system from being trapped at local MPPs under partial irradiance conditions. The algorithm was formulated based on several critical observations of PV characteristics and the behavior of local and global MPP under partial shading. In order to increase the MPP tracking speed, a controller was created that was able to handle feedback input using the reference voltage from the algorithm. The result was an increase in the MPP tracking speed up to five times faster when compared to the conventional MPPT controller [5].

Mirjalili et al. (2017) created an approach to metaheuristic techniques, called SSA. In their study, two algorithm optimization schemes were proposed for solving single- and multi-objective problems , namely SSA and Multi-objective Salp Swarm Algorithm (MSSA). The results on mathematical functions show that SSA is able to improve the performance of the initial random solution effectively and achieve rapid convergence. The results on MSSA show that the algorithm can provide an approximation value to the optimal solution with a high convergence rate and wide coverage [10].

Elgweal et al. (2019) made a comparison between the Fuzzy Logic Control (FLC) and P&O methods in a scientific paper. The study was conducted to compare the two MPPT methods under Standard Test Condition (STC), and found the advantages of FLC compared to P&O. One of the advantages of FLC is that it is able to achieve a power efficiency of 98.43%, while the P&O method achieves a power efficiency of 98.11%. In addition, FLC produced significantly smaller oscillations around the MPP than the P&O method [12].

Jamaludin et al. (2021) published a scientific paper proposing a metaheuristic algorithm for MPPT. In their study, a duty-cycle-based direct MPP tracking method was proposed that takes inspiration from the optimization algorithm in the field of biology known as SSA. The main objective is to improve the tracking capability of MPPT control in PV systems to achieve optimal power transfer under changing environmental conditions. The performance of the proposed SSA was tested under transitions between uniform and partial irradiance conditions, with a focus on convergence speed, tracking accuracy, minimization of initial power oscillations, and steady-state oscillations around the MPP. The simulation results show the superiority of the proposed SSA in tracking performance, with low oscillations around the MPP under stable irradiance conditions [4].

Xu and Yu (2018) conducted research on the convergence of the PSO method. In their study, two PSO variants were analyzed, namely Standard PSO (SPSO) and Quantum-behaved PSO (QPSO). The results showed that SPSO can achieve a global maximum in probability. Moreover, the analysis demonstrated that QPSO can also be classified as a global convergence algorithm. However, SPSO was found to be simpler and more effective algorithm without special implementation [11].

Bollipo et al. (2021) conducted a study discussing the comparison between classical, intelligent, optimal, and combined MPPT methods. Their results showed that classical MPPT tend to fail under partial shading conditions. Intelligent or even combined techniques are needed to achieve optimal MPPT performance under such conditions. However, the study also highlighted that advanced MPPT techniques, including intelligent, optimal, and combined methods, involve higher computational complexity, which can lead to slower processing cycles when implemented in hardware [1].

Lyden et al. (2021) wrote a scientific paper on the combination of SA algorithms with conventional P&O to be applied to MPPT. This approach was intended to obtain the advantages of both algorithms. The results of simulations and experiments successfully validated that the combination of the two algorithms was able to exceed the performance of both SA and P&O individually on MPPT. Drastically changing environmental conditions, especially partial shading conditions, produce several local MPPs, which have been successfully overcome by using a combination of SA and P&O, especially to prevent MPPT from being trapped at local MPPs [2].

Wan et al. (2019) conducted a study on MPPT combining SSA with GWO. This study aimed to overcome the problem of partial shading in PV systems with an algorithm inspired by nature, and focused on high convergence speed and accuracy. The proposed SSA-GWO hybrid MPPT control system demonstrated improved performance and effectiveness under both static and dynamic partial shading conditions compared to conventional MPPT methods [8].

Kermadi et al. (2019) published a scientific paper discussing a combined algorithm for MPPT on PV systems under complex partial shading conditions. The study developed a combination of adaptive P&O and PSO on MPPT using the Search-Skip-Judge (SSJ) mechanism to minimize the area in the power-voltage curve that is the object of tracking. Furthermore, the performance of PSO was improved by preventing particles from re-exploring previously searched regions, thereby reducing unnecessary particle movements and accelerating the convergence process. Simulation results show that the proposed approach was able to achieve global MPP faster. In addition, the results of the study also guarantee that tracking on the global MPP will occur even under complex partial shading conditions [6].

Jamaludin et al. (2021) conducted a study aimed at improving MPPT performance focused on PV systems under slowly changing irradiance. The algorithm used is a combination of conventional Hill Climbing (HC) with the metaheuristic SSA. The proposed algorithm combination has succeeded in overcoming varying irradiance conditions that occur. The conventional HC algorithm always fails to track global MPP when partial irradiance occurs, but always succeeds in tracking global MPP under conditions of slow changes in irradiance. The opposite occurs with the SSA method. By combining SSA and HC in MPPT, the advantages of both methods are obtained, so that they can always succeed in tracking global MPP under both slow and rapid irradiance changes [7].

Hasan et al. (2022) published a scientific paper to compare two methods. In this study, a comparison of the ACO and PSO methods were carried out on MPPT for PV systems. The results of the experiment showed that ACO achieved higher efficiency, with an improvement of 1.58% compared to PSO; however, ACO exhibited slower tracking performance [9].

Kacimi et al. (2023) published research on the combination of three MPPT methods. The study proposed a hybridization of three MPPT methods consisting of InC, PSO, and MPC. In their study, the PV system was connected to a boost converter and directly used to generate three-phase AC electricity through an inverter. In its application, the MPC method was employed to minimize the difference between the reference and predicted power, while the combination of InC and PSO was used to maximize power to the boost converter input. With this approach, the results of an effective control mechanism are obtained to track MPP with very minimal oscillation [13].

In 2022, Bonthagorla and Mikkili conducted research on the optimal configuration of solar panel arrays to optimize power transfer under partial shading conditions using power-loss mitigation techniques. The study demonstrated the occurrence of local MPP, and evaluated several configurations, including series, series-parallel, bridge-link, honeycomb, total-cross-tied, and triple-tied. These techniques focus on physical configuration rather than MPPT algorithms. The results indicated that the total-cross-tied configuration has a higher probability of achieving maximum power compared to other configurations [14].

In 2021, Roy et al. analyzed the performance of Artificial Neural Network (ANN) algorithms on MPPT. The evaluated ANN algorithms included Levenberg-Marquardt (LM), Bayesian regularization (BR), and Scaled Conjugate Gradient (SCG). In their study, 70% of the data was used for training, 15% for validation, and the remaining 15% for testing. The results showed that the SCG-based algorithm outperformed the LM and BR algorithms [15].

Ali et al. (2020) conducted research investigating several MPPT techniques under uniform and variable irradiance conditions. After a comprehensive assessment of online, offline, and hybrid MPPT optimization methods, this study concluded that most conventional MPPT algorithms are effective for tracking the global MPP under normal irradiance conditions, but fail to obtain accurate global MPP under rapidly changing and partial irradiance conditions. Hybrid optimization algorithms can quickly and accurately track global MPP under partial shading and rapidly changing irradiance conditions. However, these algorithms are complex and difficult to implement using embedded technology [16].

Hanzaei et al. (2020) conducted a study reviewing several MPPT techniques related to input variables, including irradiance and temperature. The review was scheme-based, where previous MPPT studies were categorized and analyzed for each scheme. Subsequently, the advantages and key limitations of the presented MPPT schemes were compared and discussed. The study concluded that although many MPPT methods have been proposed, selecting the most suitable MPPT technique requires careful consideration of the advantages and limitations of each method [17].

Oufettoul et al. (2023) conducted a study analyzing the performance of solar panel module positioning in a series under partial shading conditions. The results showed that standard solar panel modules produced more power when arranged in a landscape configuration compared to a portrait configuration. The performance difference reached 1010 Wh for a simple PV system. Furthermore, the study also provided recommendations for optimal orientation and design of standard and advanced solar modules, particularly for installations in arid and densely populated urban areas with limited sunlight [18].

Toodeji and Aghaei (2021) designed a control strategy for a modular MPPT-based residential PV system operating under partial irradiance conditions. The results showed that the proposed PV system can be easily maintained and expanded, even by lay users. Furthermore, any module failure in the proposed PV system can be tolerated without affecting the normal operation of the other solar panel modules [19].

Xu et al. (2021) conducted a study on a grid-connected PV system with a single-phase configuration to implement the MPPT algorithm based on the Golden Section Search (GSS). In the study, an MPPT solution for grid-connected photovoltaic systems was proposed that combines the GSS, P&O, and INC methods to simultaneously achieve faster convergence and smaller oscillations, converging to the MPP by repeatedly narrowing the search interval according to the golden ratio. Simulation and experimental results have verified the feasibility and effectiveness of the proposed MPPT technique. The technique allows the system to find the MPP in 0.036 s and recover the shifted MPP in about 0.03 s under transient conditions, achieving an overall MPPT efficiency of 98.99% [20].

In 2024, Xu and Zhong conducted research on a simplified PSO-based MPPT algorithm by combining the concept of natural selection with conductivity changes. Simulation results in the study showed that under static partial shading conditions, the algorithm (NSNPSO-INC) achieved an efficiency of 99.9%, with a convergence rate 68.18% faster than conventional PSO and more stable performance than traditional INC. Under dynamic partial shading conditions, NSNPSO-INC adapted quickly, increasing the convergence rate by 93.33% compared to conventional PSO. Experimental results further confirmed that NSNPSO-INC achieved the fastest settling state, with a convergence rate increase of 85.52% compared to traditional PSO. The algorithm was able to maintain a stable power output of about 550 W even under cloudy conditions, significantly improving the PV energy conversion efficiency [21].

Riquelme-Dominguez and Martinez (2022) evaluated several MPPT algorithms using state-space models under different dynamic testing procedures. To test the flexibility of the proposed technique, three well-known P&O algorithms were compared. The tests focused on the MPP drift phenomenon under varying irradiance conditions. The experiments demonstrated that incorporating additional power measurements midway through the MPPT period helps avoid MPP drift under all conditions, with minimal implementation costs [22].

Xia et al. (2024) conducted a study to improve the performance of MPPT in PV systems based on ACO and fuzzy logic under partial shading conditions. In the study, an MPPT method was created in the form of a combination of ACO and fuzzy logic, called Ant-Fuzzy Optimization (AFO). The results of the study demonstrated the feasibility and effectiveness of AFO in its application. Both simulation and experimental prototypes showed that AFO can extract MPP quickly and accurately, with an accuracy of up to 98.7%. In addition, AFO exhibited fast dynamic response characteristics, reaching a steady state in 0.9 seconds, thus providing a reliable solution for optimizing the PV system output power [23].

Padmanaban et al. (2021) conducted a study on combining ANN with Newton-Rhapson algorithm (ANN-NR) to mitigate harmonics that occur in inverters from PV system applications. The proposed technique was tested through simulations of the developed inverter, and the results confirmed that the algorithm is more efficient and provides highly accurate voltage firing angles. Multiple iterations improved the ability of the method to handle local optima. The developed algorithm was further validated through an experimental implementation on a proposed H-bridge inverter. The proposed SHE-PWM algorithm was shown to be suitable for grid-connected and FACTS applications [24].

Rao et al. (2021) conducted a study aimed at producing a DC-DC converter design with an improved P&O algorithm applied to PV applications. In the study, an improved P&O algorithm was introduced to increase the power extracted from a solar panel array source. To validate the converter performance, operating mode principle, steady-state and efficiency surveys, and comparative evaluations with other converters were conducted. A prototype was developed with a 20 V DC input, 200 V AC output, 200 W power rating, and 50 Hz operating frequency to validate the mathematical analysis and effectiveness of the proposed structure. The efficiency of the proposed converter was reported to exceed 95% across various power levels [25].

From the studies reviewed, issues related to partial shading in PV systems, metaheuristic algorithms, comparison and combination of MPPT methods, and changing irradiance conditions have been discussed. However, existing studies rarely consider irradiance and temperature variations simultaneously, under both fast and slow dynamic change scenarios.

This study investigates MPPT optimization in photovoltaic systems under dynamic irradiance and temperature conditions using a combination two metaheuristic algorithms: PSO and SSA. The environmental conditions discussed are more general and realistic, involving both irradiance and temperature variations under rapid (sudden change—under one second) and gradual (slow change—more than one second) dynamics.

Therefore, the main novelty raised in this study is about the combination of PSO with SSA and more realistic environmental conditions. The realistic conditions referred to rapid and gradual changes in irradiance and temperature, under both uniform and partial shading scenarios. Various irradiance change scenarios are modelled, including cloud movement, shadows from trees and buildings, surface obstruction by objects, and gradual dust accumulation on solar panels. These scenarios are implemented for both rapid and slow transitions to reflect real field conditions, where partial shading frequently occurs. In addition, realistic temperature variations scenarios are considered, including temperature differences between solar panels. In this study, PSO and SSA are integrated in the MPPT framework to exploit the advantages of each algorithm. The proposed MPPT system is designed to detect operating conditions in real-time and determine the best method, with a focus on convergence speed, guaranteed global MPP tracking, and high output efficiency.

2. Research Method

This research adopted a quantitative approach using modeling and simulation methods to test the proposed hypotheses.

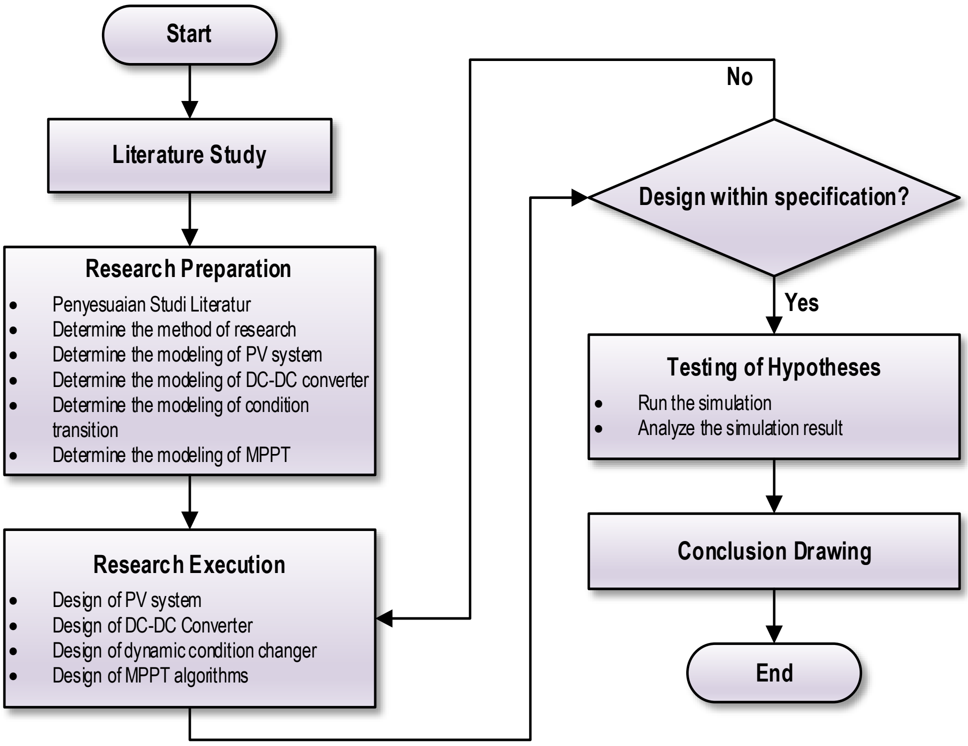

Figure 1. Flowchart of Research Method

As shown in Figure 1, this research began with a literature study, followed by the research preparation stage. Next, the research execution stage was conducted and might be repeated if defects or errors were identified in the process. The subsequent stage involved hypotheses testing, where the developed model was evaluated through simulations and the results were analyzed. The final stage consisted of drawing conclusions and providing recommendations to address the formulated research problems and determine the overall success of the study.

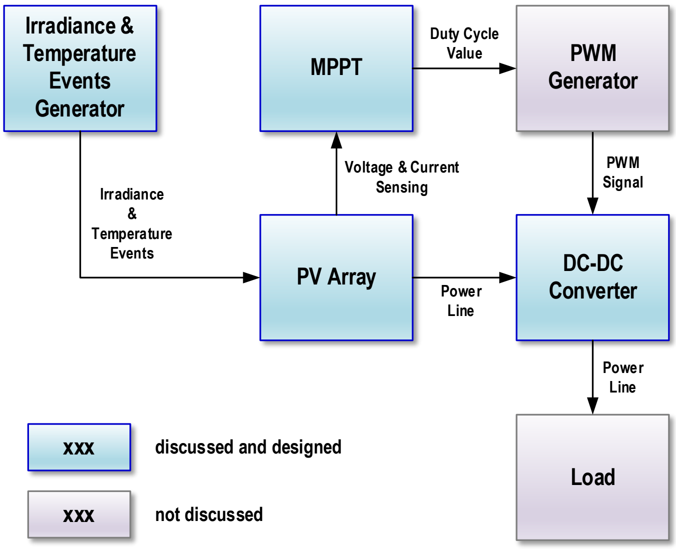

Figure 2. Block Diagram of the Research Design

In general, the simulation design in this study was divided into six main blocks, as shown in Figure 2. The system included a PV model subjected to simulated changes in radiance and temperature generated by an event generator. The PV system supplied power to a DC-DC converter (buck-boost converter), which delivered energy to the load in the form of an electric battery. Voltage and current sensors were installed at the PV output and provide input signals to the MPPT. Based on the measured voltage and current, the MPPT algorithm generated a duty-cycle command for the PWM generator. The PWM generator produced switching signals according to the duty-cycle value, which were used to control the DC-DC converter. Of the six main blocks in the diagram, the PWM generator and electric battery are not discussed in this study.

2.1 Design of PV System

Several design scenarios were carried out, including the selection of solar panel modules and the type of installation configuration. The types of installation of several solar panel modules included series installation, parallel installation, and a combination of the two, resulting in three configuration types. The specifications of each solar panel module are made the same. The number of solar panel modules was limited to a maximum of eight units. All of these configurations were determined in the subsequent stages of the study.

The PV module used in this study was the AxunTek Solar Energy AR931200132, with the specifications listed below:

1. Open-circuit voltage: 26.6 V.
2. Short-circuit current: 2.01 A.
3. Voltage and current at the maximum power point: 17.9 V and 1.77 A, respectively.
4. Temperature coefficient of open-circuit voltage: -0.39%/K.
5. Temperature coefficient of short-circuit current: 0.016716%/K.
6. Number of cells: 49.
7. Configuration: 40 strings in parallel and 10 strings in series.

2.2 Design of DC-DC Converter

In the design of DC-DC converter, a buck-boost converter type was selected. Several parameters were determined, including the inductor inductance value, capacitance value, and capacitor voltage, which were adjusted according to resistance (impedance) of the electric battery load. In addition, the PWM frequency and duty cycle limit were also determined for application in the MOSFET switching process.

The buck-boost converter used in the series and parallel configurations operated at a PWM frequency of 200 kHz, with special distinctions between the two configurations as follows:

1. The main inductor for the series configuration was set to 7.5 μH, while that for the parallel configuration was set to 10 μH.
2. The input capacitor for the series configuration was set to 20 μF, while that for the parallel configuration was set to 470 μF.
3. The output capacitor for both configurations was set to 10 μF.
4. The output load for both configurations was set to 5 Ω.

With this setup, the buck-boost converter response time in the series configuration was below 2 ms, while that in the parallel configuration was below 1 ms. Therefore, the MPPT period was set to 2 ms for a fair comparison. All buck-boost converter inputs exhibited ripple in both voltage and current, resulting in power ripple. For the series configuration, the maximum power ripple was 550 W, whereas for the parallel configuration, it was supressed to as low as 150 W.

2.3 Design of Dynamic Condition Changer

The irradiance (G) conditions were generated using the following eight scenarios:
1. Uniform shading conditions with sudden change.
2. Uniform shading conditions with gradual change.
3. Uniform shading conditions with a sudden transition to partial shading conditions.
4. Uniform shading conditions with a gradual transition to partial shading conditions.
5. Partial shading conditions with sudden change.
6. Partial shading conditions with gradual change.
7. Partial shading conditions with a sudden transition to uniform shading conditions.
8. Partial shading conditions with a gradual transition to uniform shading conditions.

The value of dG / dt for each scenario—either sudden (assumed to occur in less than one second) or gradual (assumed to occur in one second or more)—was defined as follows:
1. For sudden change, the simulation lasted 1.55 s, with irradiance change starting at 0.5 s and ending at 0.55 s, and temperature change starting at 0.6 s and ending at 0.65 s.
2. For gradual change, the simulation lasted 3.55 s, with irradiance change starting at 0.5 s and ending at 2.5 s, and temperature change overlapping from 0.6 s to 2.6 s.

The temperature change condition (T) was created using the following scenarios:
1. No temperature change.
2. Temperature changes following irradiance change with delay of 0.1 s and proportional related to the irradiance change.

All of these scenarios were implemented in a Simulink function and could be combined as required.

2.4 Design of MPPT Algorithm

The MPPT algorithms to be tested include the following:
1. PSO algorithm.
2. SSA algorithm.
3. A combination of the PSO and SSA algorithm.

For the combined algorithm, its ability to recognize changes in irradiance and temperature conditions was specifically evaluated. If a mismatch occurred or the system experienced difficulty determining the appropriate control action, additional sensors—namely, an irradiance sensor and a temperature sensor—were considered.

The PSO and SSA algorithms were implemented in two MATLAB functions. The combination process was performed using an interleaving strategy, in which both methods were alternately executed at each iteration. This approach was adopted because changes in environmental conditions could not be identified at the initial moments. Identification of new condition types can only be performed after the overall condition change process has occurred.

3. Results and Discussion

3.1 Simulation Division

The simulation process was divided into the following phases:
1. Two configuration types were considered, namely series and parallel;
2. Each configuration included two major dynamic plans, namely irradiance change and irradiance-temperature change;
3. Each plan consisted of eight scenarios; and
4. Each scenario was evaluated using three MPPT methods, namely PSO, SSA, and the hybrid PSO+SSA method.

Therefore, the total number of simulations conducted is 96. Under these conditions, it is impractical to present all dynamic conditions and simulation results graphically. Hence, only several representative examples of dynamic conditions and simulation results are presented. Figure 3 shows the examples of irradiance and temperature dynamic conditions in Scenario 3 for both irradiance and temperature changes.

3.2 Examples of Simulation Result

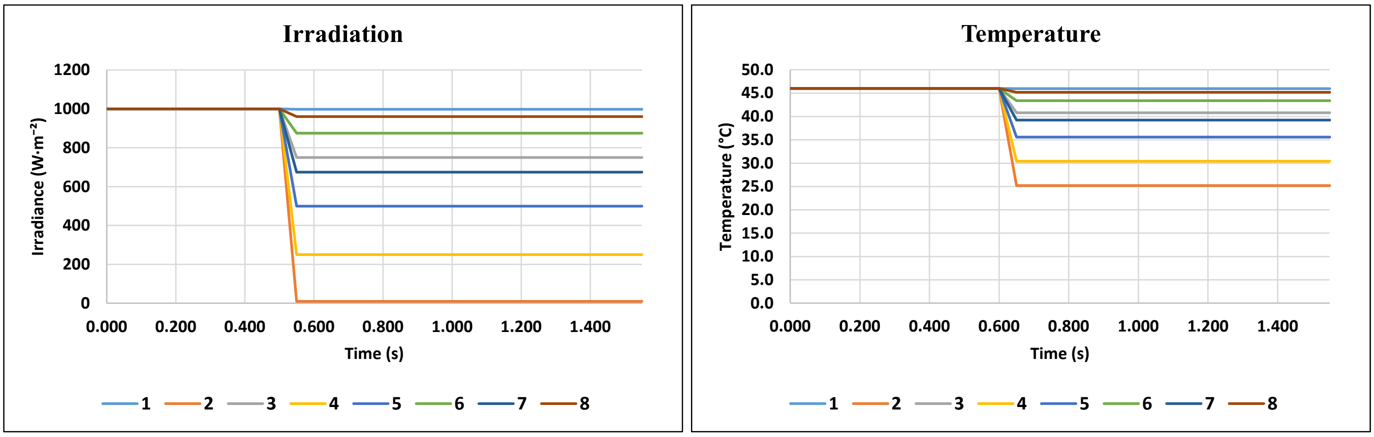

Figure 3. Example of Irradiance and Temperature Dynamic Condition in Scenario 3 for Both Irradiance and Temperature Change

Figure 4 shows the example of irradiance and temperature dynamic conditions in Scenario 6 for irradiance change.

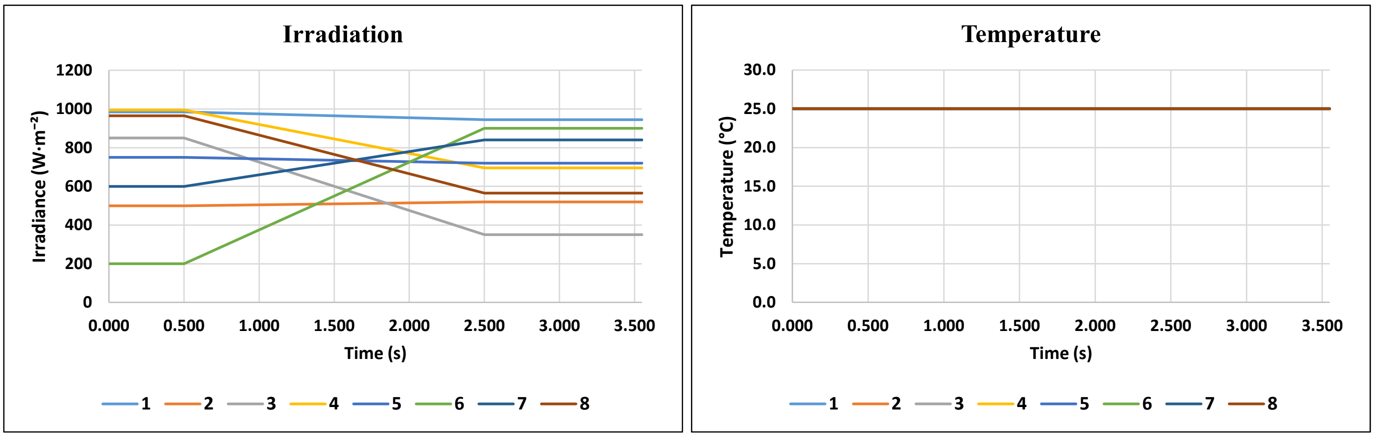

Figure 4. Example of Irradiance and Temperature Dynamic Condition in Scenario 6 for Irradiance Change

Figures 5, 6, and 7 show the examples of the power profile comparison of three MPPT methods, i.e., PSO, SSA, and the PSO+SSA hybrid, respectively, under the series configuration in Scenario 1 with irradiance change only. From the graphics, it can be determined visually that the hybrid PSO+SSA method has achieved the fastest convergence time.

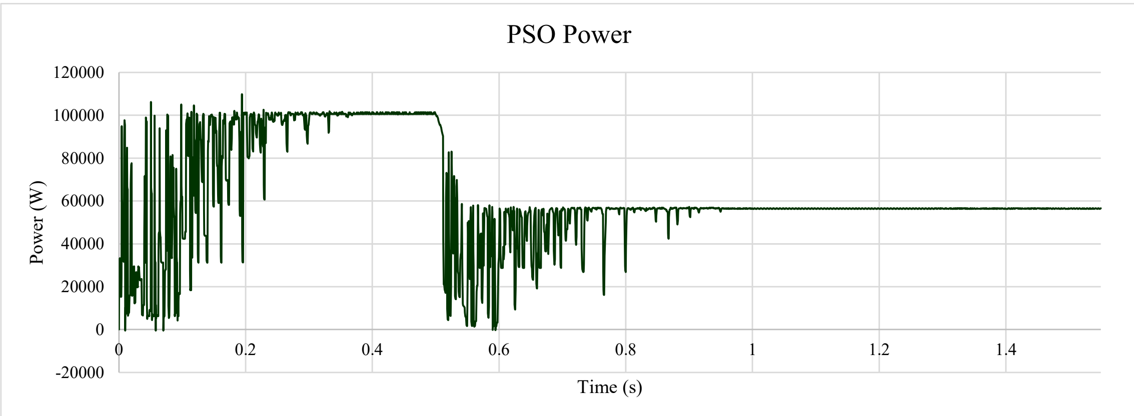

Figure 5. Power Profile of PSO-based MPPT Method Under Series Configuration in Scenario 1 Involving Irradiance Change Only

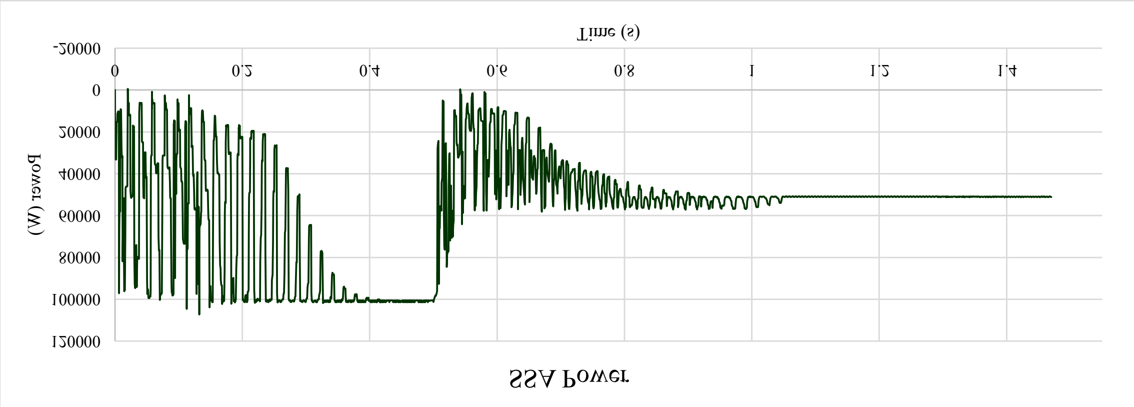

Figure 6. Power Profile of SSA-based MPPT Method Under Series Configuration in Scenario 1 of Involving Irradiance Change Only

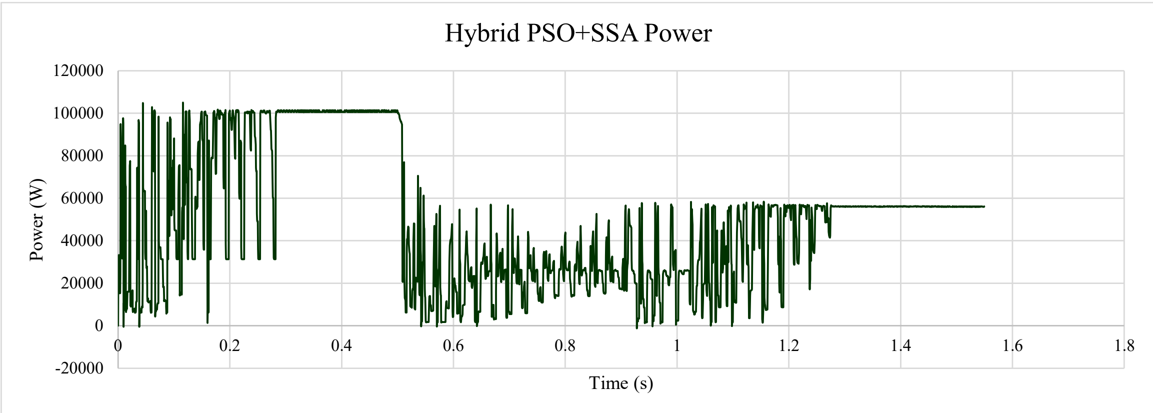

Figure 7. Power Profile of PSO+SSA-based MPPT Method Under Series Configuration in Scenario 1 Involving Irradiance Change Only

3.3 Resumes of All Simulation

For all 96 simulation results, summaries of convergence time and achieved power are provided for each simulation. Both convergence time and achieved power are divided into two categories: static and dynamic parts. All summarized result is presented in Tables 1, 2, 3, and 4.

Table 1. Simulation Result for Irradiance Only in Series Configuration

Scenario	Method	Change (s)		Sim Time (s)	1st Conv		Meta Before Change Stop (s)			Meta After Change Stop (s)			Last Power (W)
		Start	Stop		Time (s)	Power (W)	Start	Conv	Total Time	Start	Conv	Total Time	
1 sudden uni-uni	PSO	0.5	0.55	1.55	0.377	100550	0.512	0.955	0.443				56627
	SSA	0.5	0.55	1.55	0.417	100587	0.507	1.047	0.541				51709
	PSOSSA	0.5	0.55	1.55	0.283	100780				0.921	1.275	0.354	55554
2 gradual uni-uni	PSO	0.5	2.5	3.55	0.376	100560	2.485	2.791	0.306				66572
	SSA	0.5	2.5	3.55	0.434	100714	2.343	2.847	0.505				65391
	PSOSSA	0.5	2.5	3.55	0.283	100916	2.328	2.581	0.253				61097
3 sudden uni-part	PSO	0.5	0.55	1.55	0.376	100560				0.988	1.397	0.409	50656
	SSA	0.5	0.55	1.55	0.434	100714	0.506	1.047	0.541				48193
	PSOSSA	0.5	0.55	1.55	0.283	100764	0.508	0.788	0.281				48396
4 gradual uni-part	PSO	0.5	2.5	3.55	0.377	101156	2.110	2.485	0.375				44352
	SSA	0.5	2.5	3.55	0.434	100714	2.342	2.865	0.523				48162
	PSOSSA	0.5	2.5	3.55	0.283	100916	2.106	2.359	0.252				50932
5 sudden part-part	PSO	0.5	0.55	1.55	0.377	57646	0.512	0.921	0.408				46651
	SSA	0.5	0.55	1.55	0.453	56795	0.524	1.065	0.540				46369
	PSOSSA	0.5	0.55	1.55	0.282	57496				0.930	1.192	0.262	46910
6 gradual part-part	PSO	0.5	2.5	3.55	0.377	57646	1.906	2.281	0.374				53188
	SSA	0.5	2.5	3.55	0.453	56795	2.108	2.595	0.487				58111
	PSOSSA	0.5	2.5	3.55	0.283	56306	1.886	2.167	0.281				55796
7 sudden part-uni	PSO	0.5	0.55	1.55	0.410	57649	0.512	0.920	0.408				100576
	SSA	0.5	0.55	1.55	0.452	56192	0.506	1.046	0.540				100966
	PSOSSA	0.5	0.55	1.55	0.282	57592	0.506	0.730	0.224				101146

8	PSO	0.5	2.5	3.55	0.376	55709	2.451	2.757	0.307				100565
gradual	SSA	0.5	2.5	3.55	0.453	55350	2.361	2.865	0.504				100578
part-uni	PSOSSA	0.5	2.5	3.55	0.283	55337	2.094	2.403	0.308				100043

Table 2. Simulation Result for Irradiance Only in Parallel Configuration

Scenario	Method	Change (s)		Sim Time (s)	1st Conv		Meta Before Change Stop (s)			Meta After Change Stop (s)			Last Power (W)
		Start	Stop		Time (s)	Power (W)	Start	Conv	Total Time	Start	Conv	Total Time	
1	PSO	0.5	0.55	1.55	0.410	100912				0.988	1.397	0.408	56751
sudden	SSA	0.5	0.55	1.55	0.416	100870	0.506	1.065	0.558				52979
uni-uni	PSOSSA	0.5	0.55	1.55	0.282	100998				0.898	1.328	0.430	56894
2	PSO	0.5	2.5	3.55	0.410	100912				2.519	2.927	0.409	66907
gradual	SSA	0.5	2.5	3.55	0.416	100870	2.361	2.865	0.505				66839
uni-uni	PSOSSA	0.5	2.5	3.55	0.282	100998	2.343	2.595	0.252				66345
3	PSO	0.5	0.55	1.55	0.410	100912				0.988	1.396	0.408	66024
sudden	SSA	0.5	0.55	1.55	0.416	100870	0.506	1.065	0.558				65746
uni-part	PSOSSA	0.5	0.55	1.55	0.282	100998	0.508	0.788	0.280				60886
4	PSO	0.5	2.5	3.55	0.410	100912	2.144	2.553	0.409				66693
gradual	SSA	0.5	2.5	3.55	0.416	100870	2.361	2.883	0.523				69390
uni-part	PSOSSA	0.5	2.5	3.55	0.282	100998	2.389	2.641	0.252				69567
5	PSO	0.5	0.55	1.55	0.410	76411	0.546	0.920	0.374				69814
sudden	SSA	0.5	0.55	1.55	0.470	76432	0.524	1.101	0.576				69652
part-part	PSOSSA	0.5	0.55	1.55	0.282	76561	0.522	0.774	0.252				65485
6	PSO	0.5	2.5	3.55	0.410	76411	1.872	2.315	0.443				74794
gradual	SSA	0.5	2.5	3.55	0.470	76432	2.018	2.595	0.577				74085
part-part	PSOSSA	0.5	2.5	3.55	0.282	76561	1.964	2.217	0.253				74559
7	PSO	0.5	0.55	1.55	0.410	76411	0.512	0.920	0.408				100893
sudden	SSA	0.5	0.55	1.55	0.470	76432	0.524	1.101	0.576				100892
part-uni	PSOSSA	0.5	0.55	1.55	0.282	76561	0.506	0.758	0.252				100638
8	PSO	0.5	2.5	3.55	0.410	74129	2.246	2.621	0.375				100889
gradual	SSA	0.5	2.5	3.55	0.470	74123	2.343	2.739	0.396				100892
part-uni	PSOSSA	0.5	2.5	3.55	0.282	74150	2.397	2.649	0.252				101038

Table 3. Simulation Result for Irradiance-Temperature in Series Configuration

Scenario	Method	G Change (s)		T Change (s)		Sim Time (s)	1st Conv		Meta Before Change Stop (s)			Meta After Change Stop (s)			Last Power (W)
		Start	Stop	Start	Stop		Time (s)	Power (W)	Start	Conv	Total Time	Start	Conv	Total Time	
1	PSO	0.5	0.55	0.6	0.65	1.55	0.343	88016				0.988	1.261	0.273	53006
sudden	SSA	0.5	0.55	0.6	0.65	1.55	0.453	88033	0.506	1.047	0.541				29623
uni-uni	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	87881				0.926	1.273	0.347	53359
2	PSO	0.5	2.5	0.6	2.6	3.55	0.343	88316	2.485	2.825	0.341				61872
gradual	SSA	0.5	2.5	0.6	2.6	3.55	0.452	88526	2.343	2.829	0.487				57883
uni-uni	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.282	87793	2.367	2.619	0.252				59902
3	PSO	0.5	0.55	0.6	0.65	1.55	0.339	88565				0.988	1.359	0.370	45963
sudden	SSA	0.5	0.55	0.6	0.65	1.55	0.453	88384	0.506	1.046	0.540				44983
uni-part	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	88134	0.508	0.788	0.280				46024
4	PSO	0.5	2.5	0.6	2.6	3.55	0.343	88316	1.974	2.383	0.409				45552
gradual	SSA	0.5	2.5	0.6	2.6	3.55	0.452	88526	2.306	2.829	0.523				41226
uni-part	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.282	87793	2.425	2.761	0.337				43838
5	PSO	0.5	0.55	0.6	0.65	1.55	0.478	52872	0.580	1.023	0.442				44797
sudden	SSA	0.5	0.55	0.6	0.65	1.55	0.471	51444	0.524	1.083	0.558				41843
part-part	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.282	52739				0.932	1.195	0.262	44765
6	PSO	0.5	2.5	0.6	2.6	3.55	0.479	52877	1.906	2.281	0.374				48821
gradual	SSA	0.5	2.5	0.6	2.6	3.55	0.470	51351	1.892	2.415	0.523				47611
part-part	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.282	52866	1.880	2.161	0.280				52987
7	PSO	0.5	0.55	0.6	0.65	1.55	0.478	52872	0.580	0.988	0.408				88320
sudden	SSA	0.5	0.55	0.6	0.65	1.55	0.471	51444	0.524	1.083	0.558				88549
part-uni	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.282	52739	0.508	0.732	0.224				88545
8	PSO	0.5	2.5	0.6	2.6	3.55	0.343	49614	2.417	2.757	0.341				88302
gradual	SSA	0.5	2.5	0.6	2.6	3.55	0.471	49863	2.469	2.973	0.505				88032
part-uni	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.339	49481	2.002	2.311	0.309				86516

Table 4. Simulation Result for Irradiance-Temperature in Parallel Configuration

Scenario	Method	G Change (s)		T Change (s)		Sim Time (s)	1st Conv		Meta Before Change Stop (s)			Meta After Change Stop (s)			Last Power (W)
		Start	Stop	Start	Stop		Time (s)	Power (W)	Start	Conv	Total Time	Start	Conv	Total Time	
1	PSO	0.5	0.55	0.6	0.65	1.55	0.410	88317				0.988	1.465	0.476	53328
sudden	SSA	0.5	0.55	0.6	0.65	1.55	0.470	88321	0.524	1.101	0.576				47562
uni-uni	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	88337				0.900	1.330	0.430	53063
	PSO	0.5	2.5	0.6	2.6	3.55	0.410	88680	2.485	2.757	0.272				61886

2 gradual uni-uni	SSA	0.5	2.5	0.6	2.6	3.55	0.470	88323	2.288	2.775	0.487				59820
	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.283	88581	2.425	2.677	0.252				62055
3 sudden uni-part	PSO	0.5	0.55	0.6	0.65	1.55	0.410	88317				0.988	1.396	0.408	59108
	SSA	0.5	0.55	0.6	0.65	1.55	0.470	88321	0.524	1.101	0.576				59131
	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	88337	0.508	0.816	0.308				57662
4 gradual uni-part	PSO	0.5	2.5	0.6	2.6	3.55	0.410	88680	2.485	2.757	0.272				62736
	SSA	0.5	2.5	0.6	2.6	3.55	0.470	88323	2.343	2.829	0.486				62520
	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.283	88581	2.495	2.747	0.252				62708
5 sudden part-part	PSO	0.5	0.55	0.6	0.65	1.55	0.444	68359	0.546	0.920	0.374				62886
	SSA	0.5	0.55	0.6	0.65	1.55	0.452	68386	0.524	1.082	0.558				62980
	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	68412	0.526	0.778	0.252				61797
6 gradual part-part	PSO	0.5	2.5	0.6	2.6	3.55	0.444	68199	2.416	2.825	0.409				66802
	SSA	0.5	2.5	0.6	2.6	3.55	0.452	68178	2.360	2.919	0.559				66201
	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.283	68406	2.380	2.633	0.252				66626
7 sudden part-uni	PSO	0.5	0.55	0.6	0.65	1.55	0.444	68359	0.546	0.852	0.306				88494
	SSA	0.5	0.55	0.6	0.65	1.55	0.452	68386	0.506	1.065	0.558				88442
	PSOSSA	0.5	0.55	0.6	0.65	1.55	0.283	68412	0.506	0.758	0.252				88298
8 gradual part-uni	PSO	0.5	2.5	0.6	2.6	3.55	0.444	65997	2.178	2.553	0.375				88685
	SSA	0.5	2.5	0.6	2.6	3.55	0.452	66006	1.784	2.325	0.541				86690
	PSOSSA	0.5	2.5	0.6	2.6	3.55	0.283	66205	2.174	2.427	0.253				88098

3.4 Analysis of Simulation Result

The performance analysis of the MPPT methods (PSO, SSA, and hybrid PSO+SSA), based on Tables 1, 2, 3, and 4, can be divided into two configurations: series and parallel. The hybrid PSO–SSA algorithm was evaluated under various scenarios involving irradiance and temperature variations, including rapid and gradual changes, in both series and parallel configurations.

In the series configuration, PSO–SSA demonstrated superior convergence speed, with an average convergence time of 0.286 s, which is approximately 25% faster than PSO (0.374–0.387 s) and 36% faster than SSA (0.415–0.526 s). However, in terms of output power, PSO remained slightly superior, achieving 74,557 W under static conditions and 62,238 W under dynamic conditions, compared to PSO–SSA, which achieved 74,346 W (static) and 62,238 W (dynamic). This indicates that the hybrid PSO–SSA is primarily effective in accelerating adaptation to environmental changes, although PSO still achieves slightly higher output power in the series configuration.

In the parallel configuration, PSO–SSA again outperformed the other methods in terms of convergence speed (0.282–0.284 s), compared to PSO (0.366–0.419 s) and SSA (0.452–0.536 s). Regarding output power, PSO–SSA also achieved the highest performance, reaching 77,496 W, which is slightly higher than PSO (77,406 W) and SSA (77,029 W). These results indicate that the hybrid PSO–SSA provides optimal performance in the parallel configuration, both in convergence speed and power output.

A comparison with previous studies shows consistent findings. The SSA–GWO study [8] successfully improved MPPT accuracy under partial shading conditions, but its convergence speed was slower compared to PSO–SSA. Meanwhile, the PSO–InC method [13] demonstrated improved power stability compared to conventional algorithms but did not consider simultaneous variations in irradiance and temperature. Therefore, PSO–SSA not only overcomes the limitations of standalone PSO and SSA but also extends evaluation to more realistic dynamic operating scenarios.

Overall, these results confirm that PSO–SSA provides a significant contribution as a faster, more adaptive, and robust MPPT strategy under real PV system conditions, with strong potential to reduce energy losses in fluctuating field environments.

4. Conclusion

A novel PSO–SSA hybrid algorithm has been developed by combining the strengths of PSO and SSA to enhance real-time MPPT performance. The proposed method consistently demonstrates superior convergence speed, achieving an average of 0.286 s in the series configuration and 0.282–0.284 s in the parallel configuration, which is 25–36% faster than standalone PSO and SSA. In terms of power output, PSO–SSA provides comparable performance to PSO in the series configuration and slightly outperforms both PSO and SSA in the parallel configuration (77,496 W). Although the hybrid algorithm shows significant improvement in convergence time and robustness, further research is recommended to optimize its power output and validate its applicability under real PV system operating conditions.

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