Volume 10, Issue 3, March – 2025 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar098

Binary Search Algorithm for Solar Photovoltaic under Dynamic Changing Irradiance Conditions

Meng Chung Tiong; Thomas Shan Yau Moh; Ling Ai Wong; Jonny Ti Siong Tie

School of Engineering and Technology, University of Technology Sarawak, Sibu, Sarawak, Malaysia

Publication Date: 2025/03/19

Abstract: This paper presents a study in maximum power point tracking (MPPT) algorithm in solar photovoltaic (PV) using Binary Search Algorithm (BSA). With the increasing popularity in solar power generation, the effort of extracting maximum power from the installed capacity remains a challenge. This study aims to identify the performance of the Binary Search Algorithm under constant irradiance conditions and dynamic change irradiance conditions. A simulation model of BSA was developed and implemented using DC/DC boost converter in MATLAB Simulink. For the purpose of comparison, the performance of the BSA was evaluated together with another well-established algorithm, Particle Swarm Optimization (PSO). Both algorithms were evaluated under 10 constant irradiance test cases and 6 dynamic changing irradiance test cases. The BSA has shown its capability in tracking for maximum power under both constant and dynamic changing irradiance conditions. For most of the cases, the BSA was able to achieve the maximum power operating point with efficiency up to 99%. It was found that both BSA and PSO were having the tendency to experience premature convergence, which leads to slight power losses during the operation.

Keywords: *Maximum Power Point Tracking, Solar Photovoltaic, Binary Search, Particle Swarm Optimization.*

How to Cite: Meng Chung Tiong; Thomas Shan Yau Moh; Ling Ai Wong; Jonny Ti Siong Tie (2025) Binary Search Algorithm for Solar Photovoltaic under Dynamic Changing Irradiance Conditions. *International Journal of Innovative Science and Research Technology*, 10(3), 317-322. https://doi.org/10.38124/ijisrt/25mar098

I. INTRODUCTION

In recent years, solar energy has emerged as a pivotal resource in the global shift towards renewable energy. By 2022, solar energy constituted approximately 31% of the total global renewable energy capacity, making it the second most installed renewable source after hydropower [1]. This share rose to 37% by the end of 2023, positioning solar energy as the dominant contributor to global renewable power capacity [2]. Solar photovoltaic (PV) technology has gained popularity as a renewable energy source due to its inexhaustible solar supply, environmental benefits, and minimal maintenance requirements [3].

However, compared to other non-renewable energy sources, PV system is currently a more expensive energy generation system. The primary causes are seasonal fluctuations and constantly shifting weather patterns, which have an impact on how much solar energy the solar panels receive [4]. Furthermore, external factors such as temperature and variations in solar radiation cause the output voltage and current to have non-linear characteristics. Additionally, external factors such as temperature fluctuations and variations in solar radiation leads to non-linear power-voltage (P-V) characteristics. These complexities often result in multiple peaks in the P-V curve, further reducing system performance. The inherent nonlinearity of PV cells, coupled with these environmental factors, limits their conversion efficiency to a range of 12–25%, which is significantly lower than other energy generation systems [4], [5].

To address the low conversion efficiency and nonlinearity behavior of the output I-V, maximum power point tracking (MPPT) controller is integrated into PV system in order to maximize the energy yield. MPPT controllers dynamically adjust the operating point of the PV system to align with its Maximum Power Point (MPP), thereby optimizing energy yield under varying climatic conditions [3]. Numerous studies have been conducted on different kinds of MPPT algorithms to track MPP from PV systems, each with merits and cons. Numerous factors, including hardware implementation, convergence speed, sensor requirements, complexity, popularity, cost, and effectiveness, vary among the algorithms. Selecting an appropriate MPPT algorithm can significantly improve output power and efficiency while reducing the overall system cost [4].

This study investigates the performance of three MPPT techniques: particle swarm optimization (PSO), binary search algorithm (BSA), and direct control strategy. The performance of these algorithms is evaluated under both constant and dynamically changing irradiance conditions using simulation and real-time testing.

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II. MAXIMUM POWER POINT TRACKING ALGORITHM

A. Particle Swarm Optimizaiton

Particle swarm optimization (PSO) is first suggested by Kennedy and Eberhart [5]. It is a swarm-based stochastic algorithm that takes advantage of animal social behavior principles such as fish schooling and bird flocking. PSO views every possible solution to a problem as a particle traveling through the issue space at a specific speed, similar to a flock of birds [5]. The algorithm executes the optimization by a swarm of individuals also known as particles, whereby each particle is equivalent to a potential solution. The particles with a certain velocity move through the search space just like a flock of birds. After all particles have been moved, the next iterations occur whereby each particle emulates the success of neighboring particles and their own achieved success to determine the next movement. In this algorithm, the movement of the particles obey the mathematical equation below:

$$x_i^{k+1} = x_i^k + \Phi_i^{k+1}$$

The velocity component of the particles can also be calculated by the equation below;

$$\Phi_i^{k+1} = \omega\Phi_i^k + c_1 r_1 \left\{P_{besti} - x_i^k\right\} + c_2 r_2 \left\{G_{best} - x_i^k\right\}$$

Where ω is the inertia weight, C_1 and C_2 represent the acceleration coefficient, r_1, r_2 ε U(0,1), P_{besti} is the best position of the individual particle I and G_{besti} is the best known position achieved in the entire population.

Known for its robustness, simplicity, effectiveness, and popularity as a swarm optimization technique, PSO has consistently been utilized for MPPT in PV systems and is recognized as one of the most effective algorithms for handling non-linear optimization problems [6-8]. By dispersing search particles across the search space, PSO evaluates the fitness of various positions efficiently, and through successive iterations, these particles converge toward the optimal point with the highest fitness, representing the maximum power operating point. Studies by various researchers have highlighted PSO's effectiveness in identifying the MPP even in complex scenarios, such as partial shading conditions with multiple maxima [9], [10].

B. Binary Search Algorithm

Binary Search Algorithm (BSA) is a search algorithm that is utilized in computer science application to search for a specific target in an arranged dataset [11], [12]. This search algorithm is also known as half interval search because of its property that removes half of the elements in the dataset after each search iteration.

The binary search algorithm operates by repeatedly dividing a sorted dataset in half to efficiently locate a target value [12]. The search begins by comparing the target value with the middle element of the dataset. If the target matches the middle element, the search terminates successfully. If the target is less than the middle element, the algorithm discards the upper half of the dataset, as the target cannot reside there. Conversely, if the target is greater than the middle element, the lower half is discarded. The algorithm then repeats the process on the remaining subset, comparing the target to the new middle element. This continues until the target is found or the search space is exhausted, indicating that the target is not present in the dataset.

In the context of MPPT, the binary search algorithm is applied to optimize the power output of a photovoltaic (PV) system. Here, the PV output power serves as the target value, while the PV voltage represents the position in the search space (array) [11]. Unlike traditional search problems, the target value in MPPT is not predefined because the maximum power point (MPP) of the system is initially unknown. As a result, the algorithm dynamically updates its target value during operation. This adaptive approach ensures that the search continuously progresses toward the MPP, updating its goal with each iteration until the optimal power output is identified.

III. DIRECT CONTROL STRATEGY

The Proportional-Integral (PI) controller has been widely used in traditional Maximum Power Point Tracking (MPPT) control schemes because of its ease of use, low maintenance costs, and efficiency in linear systems. However, because photovoltaic (PV) cells have nonlinear characteristics and are highly susceptible to unpredictably changing environmental conditions, such as temperature and sunlight, PI controllers are not well suited for MPPT applications. These factors make it challenging for PI controllers to maintain optimal performance in PV systems, as they struggle to adapt to the dynamic and nonlinear nature of the system [13], [14].

Typically, PI-based MPPT control schemes use two independent control loops: one for voltage control and another for current control. The voltage control loop adjusts the operating voltage of the PV system based on a reference voltage generated by the MPPT algorithm [15]. The output of this loop serves as the reference signal for the current control loop, which aims to minimize the tracking error and achieve the maximum power point (MPP). The final output of the PI controller is a duty cycle value that determines the operation of the power converter [16]. While this approach has been effective in some cases, it requires careful tuning of the PI controller coefficients, which can be time-consuming and complex.

An alternative to the PI-based control scheme is the direct control MPPT strategy, where the duty cycle for the power converter is generated directly by the MPPT algorithm, bypassing the need for a PI controller. This method simplifies the control structure, reduces computational time, and eliminates the need for tuning PI coefficients [17]. The direct control strategies maintain optimal tracking performance while offering a more streamlined and efficient approach. Overall, the direct control strategy represents a significant advancement in MPPT technology, offering a simpler and

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar098

more robust solution compared to traditional PI-based methods [18].

IV. METHODOLOGY

MATLAB Simulink was used to create a simulation model that included a PV string coupled to a DC/DC boost converter and an MPPT controller. Three series-connected 245 W multicrystalline PV modules, model MYS-60P/B3/CF-245, produced by Malaysia Solar Resource (MSR), were linked to the PV string. Using the methodology presented in [19], the PV module was mathematically simulated. The PV module's mathematical model was analysed to ensure that it would have the same properties as those listed in the manufacturer's data sheet.

The study's MPPT algorithms were included into the MPPT controller, which modifies the duty cycle of the DC/DC boost converter to regulate the PV system's operating point. The PV system in MATLAB Simulink was build and used to simulate both of the study's algorithms. For both approaches, a sample period of 0.05 s was used to guarantee that the search agents had reached their steady state during the sampling procedure [20]. The MPPT algorithm also directly calculated the power converter's switching duty cycle using a direct control technique, which streamlines system design while preserving the optimal tracking outcome [21].

To evaluate the effectiveness of the two algorithms, simulations were conducted under two distinct scenarios: ten conditions with constant irradiance and six conditions involving rapid changes in irradiance. For performance comparison, the maximum power points (MPP) identified by both algorithms were measured against the theoretical MPP. This theoretical value was determined by sweeping the PV string's operating point across its entire range, starting from zero operating voltage (short-circuit current) up to the open-circuit voltage.

A. Particle Swarm Optimization

In this research, the PSO MPPT algorithm utilized three search particles. The parameters selected for the algorithm were set as follows: $C_1 = 1.2$, $C_2 = 1.6$ and $\omega = 0.4$. These values were derived from a previous study referenced as [22], which served as the basis for their adoption in this work.

B. Binary Search Algorithm

In the implementation of the BSA, the search boundaries were initially set to cover a broad range, ensuring the algorithm could effectively identify the maximum power operating point. Additionally, two predefined thresholds were established: one to minimize steady-state oscillations at the maximum power point (th_{osc}) and another to allow the algorithm to widen the search boundaries during significant weather fluctuations (th). These thresholds were set at 0.003 and 0.05, respectively. Furthermore, the constant value was selected as u = 0.05.

V. RESULT AND DISCUSSIONS

The performance of BSA and PSO for MPPT under varying irradiance condition is evaluated using static and dynamic test cases. The results are as shown in Table 1 and Table 2, where BSA demonstrated higher efficiency in most scenarios, with notable exceptions that highlight critical algorithmic limitation.

A. Constant Irradiance Conditions

Table 1 Constant Irradiance Condition

Irradiance (G)	Maximum Output Power (W)				Efficiency, η (%)	
	Theoretical	PSO	BSA		PSO	BSA
1000	735.8	735.3	735.3		99.93	99.93
900	659.0	658.9	658.4		99.98	99.91
800	582.6	582.5	579.4		99.98	99.45
700	506.3	411.4	495.0		81.26	97.77
600	430.5	430.4	429.2		99.98	99.70
500	355.3	355.2	319.8		99.97	90.01
400	280.7	276.8	278.4		98.40	99.18
300	206.9	206.8	206.8		99.95	99.95
200	134.5	125.7	102.0		93.46	75.84
100	64.3	32.5	62.8		50.50	97.76

The results presented in Table 1 demonstrate the performance of two optimization algorithms, PSO and BSA, in tracking the MPP under constant irradiance conditions. Overall, BSA exhibits superior performance compared to PSO across most irradiance levels, achieving higher efficiency in tracking the MPP. However, there are specific scenarios where both algorithms face challenges, leading to suboptimal performance.

The result in Table 1 illustrates the behavior of both algorithms under varying irradiance conditions. For instance, when the irradiance is at 1000 W/m², both algorithms perform well, maintaining high efficiency and accurately tracking the MPP. Similarly, at 800 W/m², both BSA and PSO demonstrate strong performance, with BSA slightly outperforming PSO in terms of efficiency. However, as the irradiance decreases, the performance gap between the two algorithms becomes more apparent. At 500 W/m², BSA encounters a limitation due to its rapid convergence, causing it to miss the true MPP. In contrast, PSO struggles more significantly at 700 W/m², where its stochastic nature leads to premature convergence and a notable drop in efficiency.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar098

At even lower irradiance levels, such as 200 W/m², both algorithms face challenges in maintaining optimal performance. PSO, in particular, shows a more pronounced decline in efficiency compared to BSA, which still manages to perform relatively well despite the challenging conditions. This highlights the robustness of BSA in low-irradiance scenarios, where its deterministic approach allows it to maintain better accuracy compared to PSO. However, the performance of both algorithms at these lower levels indicates room for improvement, particularly in ensuring stable and accurate MPP tracking under all irradiance conditions.

These exceptional cases highlight the trade-offs between the two algorithms. While BSA's deterministic approach generally provides more accurate results, it can sometimes converge too quickly, missing the true MPP. On the other hand, PSO's stochastic nature allows for broader exploration of the search space, but it can also lead to instability and inefficiency in certain conditions.

B. Dynamic Chaning Irradiance Conditions

Table 2 Dynamic Changing Conditions

Irradiance Changes (From/To) (W/m^2)	Output power (W) (before irradiance changes)			Output power (W) (after irradiance changes)		
	Theoretical	PSO	BSA	Theoretical	PSO	BSA
800/1000	582.6	579.5	582.4	735.0	734.9	734.6
600/1000	430.4	430.3	429.2	735.0	734.7	734.9
300/1000	206.9	206.7	206.8	735.0	734.7	734.8
1000/800	735.0	734.8	734.8	582.6	582.5	581.9
1000/500	735.0	734.8	734.8	355.3	355.1	354.7
1000/200	735.0	734.8	734.8	134.5	125.6	127.1

In Dynamic Changing Condition, both BSA and PSO exhibit comparable performance in tracking the MPP. In most cases, BSA achieves values closer to the theoretical maximum, indicating its ability to more accurately track the MPP during irradiance transitions. However, there are instances where PSO slightly outperforms BSA, particularly in scenarios with moderate irradiance changes. This suggests that while BSA generally performs well, while PSO can occasionally achieve marginally better results in specific conditions.

In most cases, BSA achieves values closer to the theoretical maximum power output, demonstrating its ability to more accurately track the MPP during dynamic irradiance. This is particularly evident in scenarios involving extreme changes in irradiance, such as from 1000 W/m² to 200 W/m² and from 300 W/m² to 1000 W/m², where BSA outperforms PSO. These results highlight BSA's robustness and precision in handling significant shifts in irradiance, which is critical for maintaining stable power output in real-world applications where environmental conditions can change rapidly.

On the other hand, PSO occasionally outperforms BSA in scenarios with moderate irradiance changes. For example, in cases where the irradiance shifts from 1000 W/m² to 800 W/m² or from 1000 W/m² to 500 W/m², PSO achieves slightly better results compared to BSA. This suggests that PSO's stochastic nature, which allows for broader exploration of the search space, can be advantageous in conditions where the change in irradiance is less extreme. However, this advantage is limited to specific scenarios and does not consistently hold across all conditions.

The key observation from Table 2 is that BSA generally performs better in extreme irradiance changes, while PSO can achieve marginally better results in moderate changes. This indicates that the choice of algorithm may depend on the specific application and the expected range of irradiance fluctuations. BSA's deterministic approach makes it more reliable for handling large and rapid changes, whereas PSO's stochastic nature allows it to adapt more effectively in scenarios with smaller, more gradual changes.

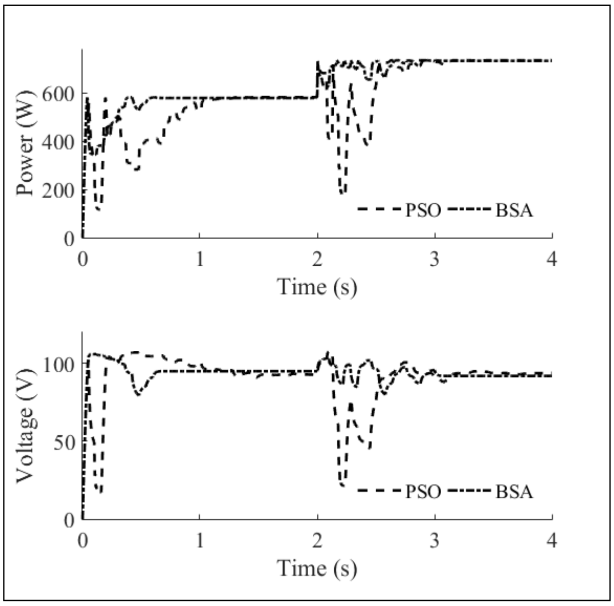

Fig 1 Tracking Performance of PSO and BAS under Dynamic Changing Condition from 800 to 1000 W/m^2

Figure 1 shows that BSA demonstrate a faster convergence speed compared to PSO. This is attributed to BSA's relatively simple search mechanism, which systematically narrows down the search space to locate the MPP. The structured nature of BSA allows it to make rapid and precise adjustments, enabling quicker stabilization at the MPP. This is particularly advantageous in dynamic environments where irradiance conditions change rapidly, as BSA can swiftly adapt to new conditions and maintain optimal power output.

In contrast, PSO's convergence is slower, as evident from the diagram. PSO relies on a stochastic exploration mechanism, where particles in the swarm explore the search space more randomly. While this approach can be effective in avoiding local maxima, it often results in a longer convergence time. The diagram shows that PSO takes more iterations to stabilize at the MPP compared to BSA, which can be a drawback in scenarios requiring rapid response to changing conditions.

In dynamic irradiance conditions, the faster convergence of BSA provides a significant advantage. The ability to quickly adapt to changing conditions ensures that the system maintains optimal power output with minimal delay. This is particularly important in real-time applications where rapid fluctuations in irradiance require immediate adjustments. While PSO's exploration can be beneficial in certain scenarios, its slower convergence makes it less suitable for environments with frequent and abrupt changes.

VI. CONCLUSION

In conclusion, this study highlights the comparative performance of the BSA and PSO algorithms in tracking the maximum power point (MPP) under both constant and dynamic irradiance conditions. BSA generally outperforms PSO, particularly in extreme and rapidly changing irradiance scenarios, due to its deterministic approach, faster convergence, and robustness in maintaining high efficiency. However, PSO demonstrates occasional advantages in moderate irradiance changes, leveraging its stochastic nature for broader exploration. Despite their strengths, both algorithms exhibit limitations in low-irradiance conditions, indicating a need for further refinement to ensure consistent and accurate MPP tracking across all scenarios. The choice of algorithm should therefore be guided by the specific application and expected irradiance variability, with BSA being more suitable for dynamic environments and PSO offering potential benefits in less extreme conditions.

ACKNOWLEDGMENT

The authors would like to thank University of Technology Sarawak for supporting this work under research grant ID UTS/Research/1/2022/13.

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