Modelling and simulation of maximum power point tracking on partial shaded PV based-on a physical phenomenon-inspired metaheuristic algorithm

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ABSTRACT

Maximum power point tracking (MPPT) is a technique to optimize the photovoltaic (PV) current generation, so it can improve the efficiency of solar energy harvesting. MPPT works by searching the voltage which generates the maximum power, called the maximum power point (MPP). MPP value changes by the fluctuance of ambient temperature and solar insolation level depicted by the I-V curve. Searching the MPP will be more complex if the partial shading is happened. The effect of partial shading will rise to more than one local MPPs. In this research, an optimization algorithm is modeled and simulated the MPPT technique in partial shading. The optimization uses the new metaheuristic algorithm which inspired from a physical phenomenon, called Archimedes optimization algorithm (AOA). The AOA uses mathematical modeling which has convergence capabilities, balanced exploration, and exploitation and is suitable for solving complex optimization technique, like MPPT. The research used varies partial insolation percentage. The implementation of MPPT-AOA compared to other metaheuristic algorithms to analysis its performance in the aspect of PV system parameters and tracking process parameters. The simulation result shows that the AOA can enrich the MPPT technique and improve the solar energy harvesting which is superior to other algorithms.

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1. INTRODUCTION

Solar photovoltaic (PV) systems are crucial components in converting solar energy into electricity. The performance of PV systems depends on solar insolation and temperature, which directly affect the generated current and voltage. However, the constant fluctuations in solar insolation present a significant challenge as they impact the efficiency of the solar module [1]-[4]. These fluctuations affect the current-voltage (I-V) characteristics, leading to issues such as overcharging, undercharging, shortened battery life, and compromised inverter performance [4], [5]. Furthermore, shading from clouds, trees, and nearby structures introduces partial shading effects, causing mismatched power output and efficiency losses [6]-[9]. Partial shading can also result in localized overheating, forming hot spots that may damage the PV modules [10], [11].

To address these issues, maximum power point tracking (MPPT) algorithms have been developed to optimize PV system performance by ensuring operation at the maximum power point (MPP) under varying environmental conditions [12]-[15]. However, MPPT under partial shading conditions is particularly challenging because multiple local maximum power points (LMPPs) can form, making it difficult to locate the true global maximum power point (GMPP) [16]-[19].

Several techniques have been explored to address this challenge. Conventional perturb and observe (P&O) algorithms [20], [21] offer a simple and widely used MPPT approach but often fail to locate the GMPP, leading to suboptimal energy harvesting. To overcome this limitation, genetic algorithm (GA)-based MPPT techniques have been proposed [22], [23], which successfully locate the GMPP under partial shading. However, GA-based methods suffer from long convergence times and require precise parameter tuning for optimal performance. The differential evolution algorithm (DE) [24] has been introduced to improve convergence speed and accuracy. Despite its advantages, DE is highly sensitive to initial population values and lacks adaptability to dynamic shading conditions. Other approaches, such as firefly algorithm (FA) and fruit fly optimization algorithm (FOA), have been developed, but each comes with trade-offs in tracking accuracy and computational complexity [25], [26].

The other traditional MPPT methods, such as P&O and incremental conductance (IC), are widely used due to their simplicity but suffer from inefficiencies in rapidly changing environmental conditions and partial shading scenarios [27]. To overcome these limitations, artificial intelligence (AI)-based MPPT techniques, including artificial neural networks (ANNs), fuzzy logic control (FLC), and deep reinforcement learning (DRL), have emerged as promising alternatives [28]. Recent studies have also explored metaheuristic algorithms like particle swarm optimization (PSO), grey wolf optimization (GWO), and flamingo search algorithm (FSA) to enhance the tracking efficiency of PV systems. These intelligent and metaheuristic approaches offer improved response times, greater accuracy in locating the GMPP, and better adaptability to dynamic environmental conditions.

Despite these advancements, existing algorithms still face challenges in achieving fast convergence, maintaining accuracy, and adapting to dynamic environmental changes. Many methods either require extensive tuning or fail to effectively balance exploration and exploitation in the search for the GMPP. Addressing these gaps, this study proposes the Archimedes optimization algorithm (AOA) as a novel MPPT solution under partial shading conditions.

AOA is inspired by the physical principles of Archimedes' law and the buoyancy principle. The Archimedes law mechanism updates candidate positions in the search space by considering the fulcrum point and lever strength, enhancing exploration capabilities [29]. The buoyancy principle, on the other hand, allows candidate solutions to adjust their positions dynamically, preventing premature convergence at LMPP and ensuring an effective search for the GMPP [30]. This approach enhances MPPT efficiency by minimizing power loss and improving computational performance compared to conventional metaheuristic methods [20], [31].

In this study, we propose an AOA-based MPPT approach for PV systems operating under PSCs. The main contributions of this research include:

- Development of an AOA-based MPPT framework that enhances tracking accuracy and convergence speed in PV systems.
- Comparative performance evaluation against conventional and metaheuristic MPPT techniques, such as PSO and GA, using MATLAB/Simulink simulations.
- Critical analysis of AOA's effectiveness in mitigating power loss due to shading effects and improving PV energy harvesting efficiency.
- Investigation of potential real-world applications, emphasizing AOA's adaptability in grid-connected and standalone PV systems.

The remainder of this paper is structured as follows: section 2 presents the methodology, detailing the PV system modeling, MPPT framework, and implementation of AOA. In section 3 discusses the results and performance evaluation under different shading scenarios. In section 4 concludes with key findings, implications, and future research directions.

2. METHOD

This section provides a detailed description of the methodology used in this study to ensure reproducibility and validity. The modeling of the PV system, implementation of the AOA-based MPPT, and the simulation framework are described. Previously established procedures are referenced where applicable.

2.1. Model of partial shaded photovoltaic array

The PV system model used in this study is based on well-established mathematical formulations and circuit representations from prior research. The single-diode model of the PV array is adopted, as it provides a good balance between accuracy and computational efficiency. The MATLAB/Simulink simulation environment is used to implement this model, ensuring reproducibility.

To evaluate the effectiveness of the proposed AOA for MPPT, a simulated PV system model was developed using MATLAB/Simulink. The model consists of a PV array, a DC-DC boost converter, and an MPPT controller. The PV array follows a single-diode equivalent circuit model incorporating series and shunt resistances as seen in Figure 1. Partial shading is simulated following methodologies described in the previous study, by varying solar insolation across different sections of the PV array, producing multiple LMPPs. Three shading scenarios are considered, such as; (a) uniform insolation: 1,000 W/m² in standard test conditions (STC), (b) half-shaded insolation: 750 W/m² for part of the array, 1,000 W/m² for the rest, and (c) one-third shaded insolation: 500 W/m² for a section, 1,000 W/m² for the rest.

Using the Kirchoff law, the solar cell of Figure 1 can also be modelled by the (1).

$$I_s = I_{ph} - I_d - I_{sh} \tag{1}$$

Where I_s is the total current generated, I_{ph} is the current generated by solar cell, I_d is the saturation current, and I_{sh} is shunt current. Because each diode in a solar panel follows a non-linear characteristic described by the Shockley equation. Therefore, the Shockley equation for a diode is ideal for calculating the output power in (2).

$$I_s = I_{ph} - I_0 \left[\exp\left(\frac{q(V+R_S I_S)}{nKT_k}\right) - 1\right] - \frac{V+R_S I_S}{R_{sh}} \tag{2}$$

Where I_s is the current generated by solar cell, V is solar cell voltage, I_0 is saturated current of diode, n is diode ideality factor, *Rs/Rsh* is parallel or series resistor, *Tk* is cell temperature, *K* is Boltzmann constant valued 1.38×10-23 J/K, and *Q* is the total charge of an electron with a value 1.602×10-19.

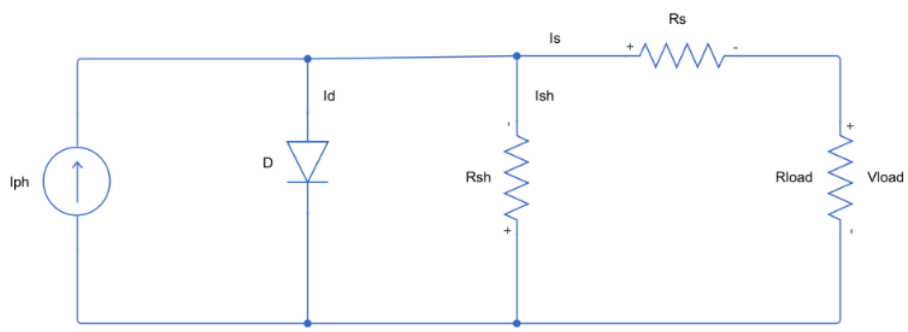


Figure 1. Diode circuit representation of a solar cell [32]

The model used in this study, as illustrated in Figure 2, is adapted from the research, providing a robust framework for analyzing these conditions. Three different insolations are simulated to represent various shading scenarios. The first scenario, uniform insolation, assumes that the PV array receives equal sunlight across all panels, which is an ideal condition for maximum power output. The second scenario, half partial shading, occurs when half of the PV array is shaded, leading to a notable decrease in output power compared to the uniform insolation scenario. The third scenario, one-third partial shading, represents a more severe shading condition where only one-third of the PV array receives full insolation, resulting in the most significant power loss among the three scenarios.

The simulation results demonstrate varying power outputs corresponding to each shading scenario. To mitigate the impact of shading on power generation, a MPPT controller is employed. This controller continuously adjusts the output voltage and current to maintain operation at the MPP, ensuring that the PV system achieves optimal performance under all shading conditions. The MPPT technique effectively compensates for the reduced insolation levels, allowing the PV system to deliver the highest possible power output even under partial shading.

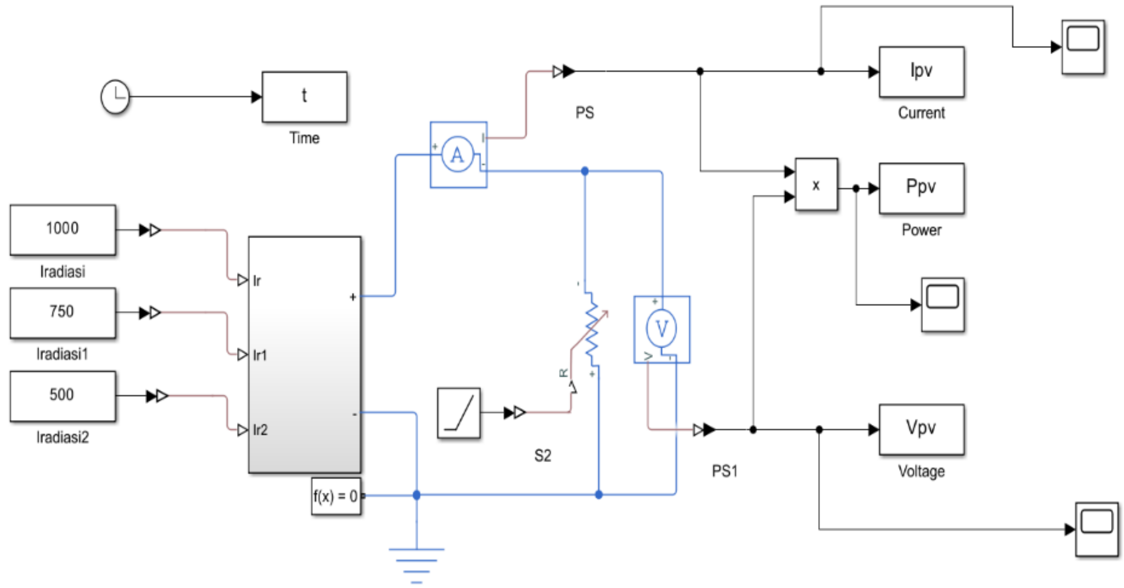


Figure 2. Model of partial shaded PV array

2.2. MPPT framework

In this study, the modeling of MPPT is carried out using a comprehensive approach that integrates various algorithms for optimizing power output from PV systems, as shown in Figure 3. The MPPT model is implemented within the Simulink environment of MATLAB, where the algorithm is designed to continuously track and adjust the operating point of the PV system to ensure it operates at its MPP.

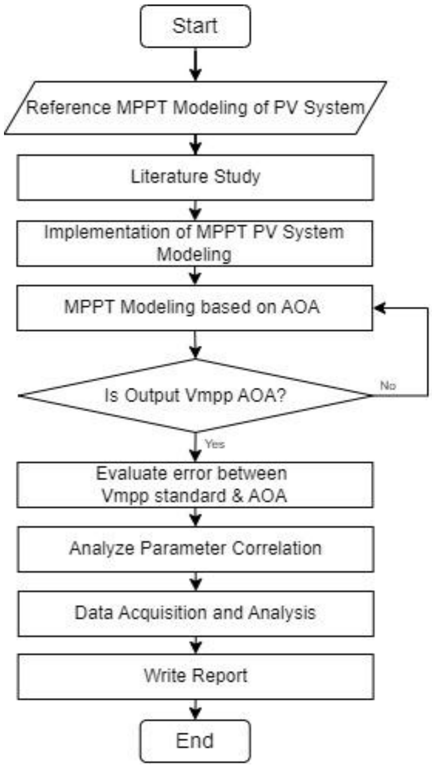


Figure 3. Flowchart diagram illustrating the research model

A key component of this study is the MPPT controller, which ensures that the PV system operates at the GMPP under shading conditions. The AOA-based MPPT is implemented and compared against conventional PSO-based MPPT. The research process begins with a comprehensive literature review to identify research gaps and define the MPPT model for partial shading conditions. Following the model development, simulations are conducted to test the MPPT model under different shading conditions to determine the maximum voltage achievable. The performance of the AOA-based MPPT model is then compared to standard values derived from characteristic P-V and I-V curves. If the standard MPP voltage from the P-V and I-V curves is higher than that obtained by the AOA-based MPPT model, parameter adjustments and further iterations are carried out to refine the model. If the AOA-based MPPT model successfully tracks a higher maximum voltage, the results are analyzed and discussed in the final report. A visual representation of this methodology is provided in a flowchart, as illustrated in Figure 3, to ensure clarity in the research process. The AOA-based MPPT implementation follows the systematic approach outlined in Algorithm 1. This algorithm leverages the AOA to dynamically track the global maximum power point by treating voltage values as search agents that explore the solution space based on buoyancy principles.

Algorithm 1. AOA-based MPPT implementation
```
Begin
   Initialize population of search agents (voltage values)
   Define maximum iterations and convergence criteria
   Evaluate initial power output for each agent
   Identify the best agent corresponding to the highest power (initial GMPP)

   While stopping condition not met do
      Compute density and volume update for each search agent
      Adjust search agent positions based on Archimedes' principle
      Evaluate new power outputs for updated agents
      Update the best solution if a higher power output is found
      Adapt exploration and exploitation balance dynamically
   End While

   Return best voltage corresponding to the GMPP
End
```

This pseudocode outlines the step-by-step execution of the AOA-based MPPT technique, ensuring a balance between exploration, such as searching for new potential solutions and exploitation, such as refining known good solutions.

2.3. Archimedes optimization algorithm

AOA is a metaheuristic algorithm that is an efficient optimization control algorithm with balanced convergence, exploration, and exploitation capabilities, which are considered suitable for solving complex optimization problems. AOA is based on a physics principle, namely the Archimedes principle, which states that when an object is submerged in a fluid, either entirely or partially, the fluid will exert an upward force on the object that is equal to the weight of the fluid pushed out by the object. When an object is immersed in the fluid, it will experience an upward force called buoyant force, which has the same magnitude as the weight of the fluid pushed out by the object [33]. As shown in Figure 4, AOA serves as the core technique for the MPPT model, utilizing several key algorithmic parameters such as X_i, den_i, vol_i, and acc_i.

The values for the key algorithmic parameters, including the number of objects and iterations, are determined based on simulation results, with 20 objects and 20 iterations identified as optimal for achieving the best solution. Control parameters C1, C2, C3 and C4 are set as constants, following reference values from relevant research. The subsequent step involves calculating the values for each parameter using designated equations and defining a fitness function to evaluate and select the best parameter values for optimization. Following this, the density and volume parameters are updated, and the transfer factor (*TF*) and density decrease factor (*df*) are recalculated. Depending on whether the condition *TF*≤0.5 is met, the process either proceeds with exploration, adjusting object acceleration with a random material for the next iteration, or with exploitation, directly adjusting the object acceleration. The iterative process continues until the maximum number of iterations is reached, with the primary objective being to optimize the power output.

The algorithm ensures that the best solutions are found by systematically adjusting and refining the parameters through these iterative steps. The first step n the initialization phase, for each object i, the position, volume (v), density (ρ), and acceleration (a or accaccacc) of all objects are set with initial values using the following (3):

$$x_i = lb_i + rand \times (ub_i - lb_i) \tag{3}$$

where x_i represents the *i* th object, lb_i denotes the lower bound of the search space, and ub_i is the upper bound of the search space. The object x_i corresponds to one of the population members, with *i* ranging from 1 to N, where N is the population size. The term *rand* refers to a random number generated between 0 and 1, ensuring that the initial position of each object is randomly distributed within the defined search space boundaries.

$$den_i = rand \tag{4}$$

$$vol_i = rand \tag{5}$$

where *rand* is a D-dimensional vector that generates random numbers between [0, 1]. Finally, the acceleration (acc or a) of the *i* th object is initialized using the appropriate parameters.

$$a_i = lb_i + rand \times (ub_i - lb_i) \tag{6}$$

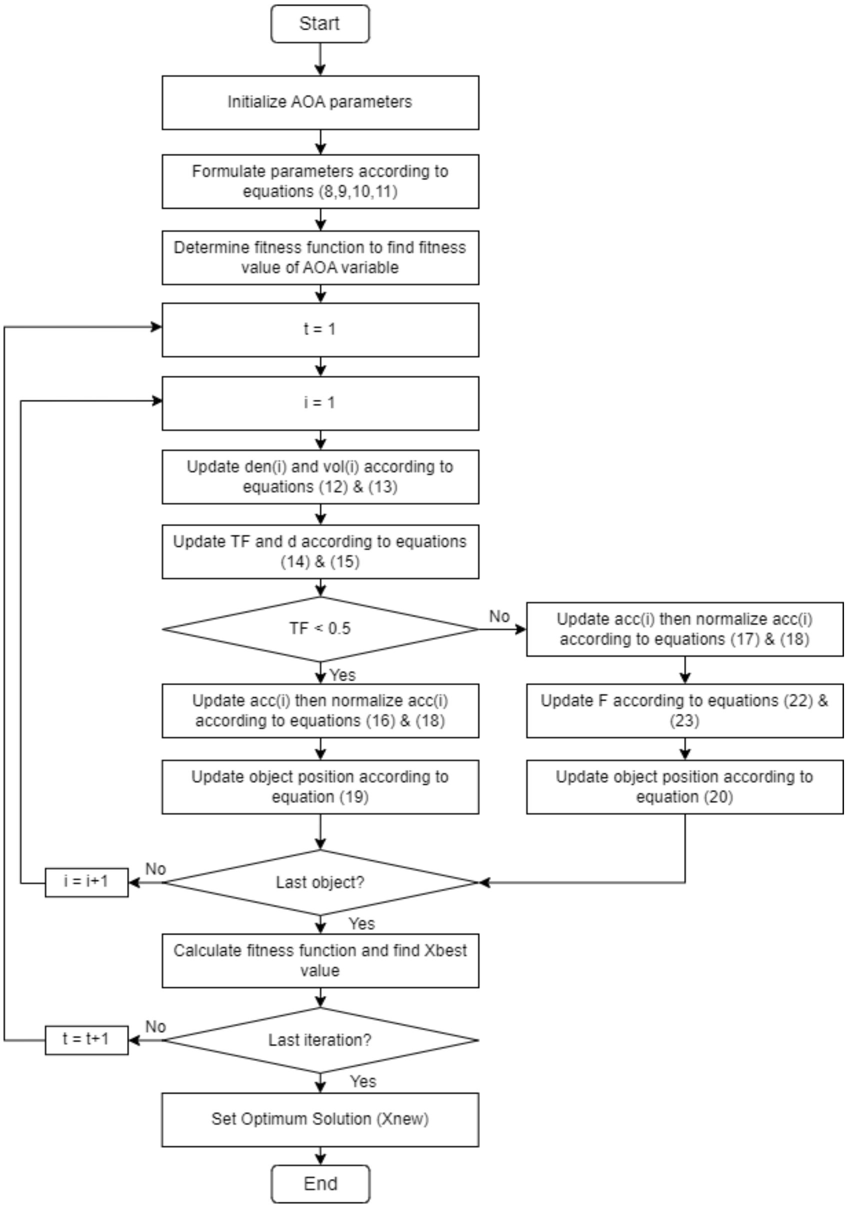


Figure 4. The AOA flowchart

The object is selected based on the best fitness value after evaluating the initial population, considering x_{best}, den_{best}, vol_{best}, $and\ acc_{best}$. Second step, the density den_i and vol_i of object i are updated for the iteration t+1 as (7) and (8).

$$den_i^{t+1} = den_i^t + rand \times (den_{best} - den_i^t) \tag{7}$$

$$vol_i^{t+1} = vol_i^t + rand \times (vol_{best} - vol_i^t) \tag{8}$$

Where, vol_{best} and den_{best} refer to the best volume and density of the objects, while *rand* is a random number generated uniformly. Third step, Initially, the objects collide with each other, and over time, they attempt to reach equilibrium. The transfer operator (TF) facilitates the transition of the search process from exploration to exploitation. The TF is calculated using (9).

$$TF = exp\left(\frac{t-t_{max}}{t_{max}}\right) \tag{9}$$

The TF gradually increases during iterations until it reaches a value of 1, indicating a shift from exploration to exploitation. Where t_{max} is the maximum number of iterations, and *t* is the current iteration number. Similarly, the density decay factor ddd aids the AOA in transitioning from global to local search. It is calculated as:

$$d^{t+1} = exp\left(\frac{t-t_{max}}{t_{max}}\right) - \left(\frac{t}{t_{max}}\right) \tag{10}$$

where, d^{t+1} represents the density at iteration t+1, which decreases over time, allowing for convergence at a specific point. This density parameter plays a crucial role in achieving a balance between exploration and exploitation within the AOA.

2.4. Evaluation and performance metrics

To validate AOA-MPPT, comparative simulations are performed against PSO-MPPT. The key performance metrics analyzed include power tracking efficiency, which measures the ratio of extracted power to the theoretical MPP power, convergence time, which quantifies the time required to reach GMPP, and voltage tracking error, which assesses the difference between actual and expected MPP voltage. Performance is tested under different shading conditions, and a statistical analysis is conducted to verify algorithm robustness.

The error evaluation between the standard Vmpp and the Vmpp obtained from the AOA-based MPPT is a critical aspect of this study. The error equation used to compare the effectiveness of the AOA algorithm is based on the standard maximum power point voltage (Vmpp) from the PV system and the voltage obtained from the AOA-based MPPT (Vaoa). The error calculation is expressed as (11).

$$Error(\%) = abs\frac{(V_{mpp}-V_{aoa/pso})}{V_{mpp}} \times 100\% \tag{11}$$

Where, $V_{aoa/pso}$ represents the maximum power point voltage obtained using the AOA-based MPPT, while V_{mpp} denotes the standard maximum power point voltage of the PV system. Evaluations are conducted under various insolation conditions to assess the performance of the AOA-based MPPT. A lower error value indicates that the MPPT model is more accurate in identifying the maximum power point voltage under partial shading conditions. Conversely, a higher error value suggests that the MPPT model is less accurate in pinpointing the optimal voltage at the MPP under partial shading conditions.

To further evaluate the error in MPPT tracking, we calculated the root mean square error (RMSE) and mean absolute error (MAE) for AOA, PSO, and conventional MPPT methods. These metrics provide insight into the accuracy of each algorithm in estimating the MPP:

1. RMSE: measures the standard deviation of tracking errors, with lower values indicating better accuracy.
2. MAE: represents the average absolute difference between actual and estimated values, providing a direct measure of tracking precision.

To statistically validate the performance differences among the tested MPPT algorithms, we applied the Friedman test, a non-parametric statistical test suitable for comparing multiple optimization techniques over different shading conditions. The Friedman test assesses whether there are significant differences in the efficiency and convergence time of AOA, PSO, and conventional MPPT methods under various partial shading scenarios. The Friedman test statistic (*Fr*) is calculated using (12).

$$F_r = \frac{12}{N.k.(k+1)} \sum_{j=1}^{k} R_j^2 - 3.N.(k+1) \tag{12}$$

Where N is the number of rows (combinations of objects and iterations), k is the number of scenarios (3 in this case: one-third, half, and uniform), and Rj is the sum of ranks for each scenario.

2.5. Justification of methodology

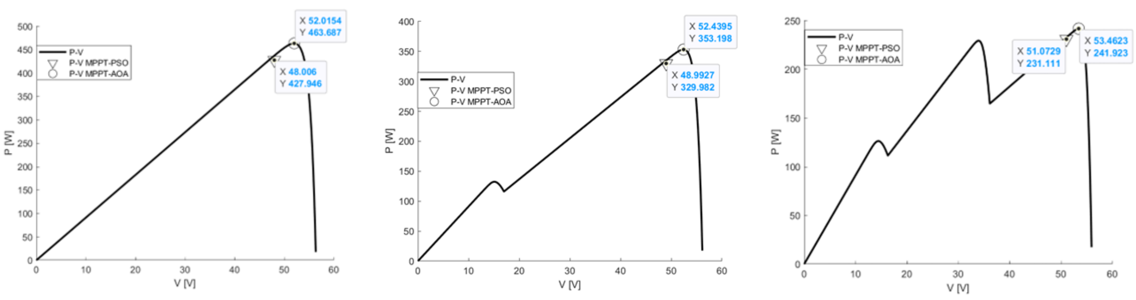
The choice of AOA for MPPT is justified based on several factors. AOA demonstrates superior adaptability to dynamic environmental changes compared to fixed-step algorithms like P&O. Additionally, AOA provides a well-balanced search process by dynamically adjusting search parameters, unlike GA and PSO, which may struggle with premature convergence or local optima. Finally, AOA offers computational efficiency by requiring fewer iterations to reach convergence compared to conventional heuristic methods. The methodology presented ensures that the study's results are reproducible, reliable, and applicable to real-world PV systems under partial shading conditions.

3. RESULTS AND DISCUSSION

In testing MPPT performance in partial shading conditions, MPPT based on the AOA algorithm will be compared with the PSO algorithm to find the MPP during partial shading conditions where three insolation conditions will be used with different shading conditions. The first condition is a uniform insolation condition; in this condition, the PV receives full sunlight without any shadings. For uniform insolation conditions, it is represented by the insolation input value in the STC, which is 1,000 W/m^2. However, in actual conditions in certain places with weather conditions where the light intensity is less bright, it can also give rise to uniform insolation conditions with insolation values less than STC, so tests are carried out to represent uniform insolation conditions with less bright sunlight intensity with the value used being 750 W/m^2 and 500 W/m^2, these two values are used as an adjusted representation of the insolation input to the module reference for one-third partial shade conditions. Meanwhile, the second and third conditions are insolation conditions with different partial shading levels. The second and third conditions are created so that the P-V and I-V characteristic graphs show several peaks that represent partial shading conditions so that from the total of all peaks, the local peak and global peak can be identified where the MPP is the location of the optimized voltage and current.

3.1. Model of diverse insolations

Figure 5 demonstrates P-V and I-V characteristics for uniform insolation conditions with an insolation input of 1,000 W/m^2 is shown in. Figure 5(a) shows that the test results found only one peak point as the GMPP from the uniform insolation input, this is influenced by the same input insolation value so that the output current value will be the same. As is known, the P-V graph is the product of the input voltage and current. From the graph of the P-V and I-V characteristics, it is also known that the power produced under uniform insolation conditions by MPPT-AOA is 464 W while MPPT-PSO is 428 W. Figure 5(b) shows that the test results from the partial shading insolation input found two peak points defined as the maximum power point or LMPP and GMPP. From the graph, it is also shown that the power produced during half-shading insolation conditions by MPPT-AOA is 353 W, while MPPT-PSO is 330 W. Figure 5(c) shows that that there were three peak points defined as MPPs or two local MPPs and 1 GMPP. From the graph of the P-V and I-V characteristics, it is also known that the power produced during insolation conditions of one-third of the partial shading by MPPT-AOA is 242 W while MPPT-PSO is 231 W.



(a) (b) (c)

Figure 5. P-V curve response of PV module in different insolation condition; (a) uniform insolation, (b) half shaded insolation, and (c) one-third shaded insolation

While the simulation results are promising, the practical implementation of AOA in real-world PV systems requires further investigation. The application of AOA-based MPPT to physical MPPT controllers presents several challenges, including hardware requirements and computational feasibility. AOA's real-time implementation would require a high-speed microcontroller or FPGA-based controller capable of handling the iterative optimization process efficiently. Moreover, integrating AOA with an embedded system would necessitate real-time sensor data acquisition for voltage and current tracking, ensuring accurate and responsive MPPT operation. Another critical aspect is energy efficiency, as excessive computational complexity could lead to higher power consumption in the control unit, reducing the overall system efficiency.

The effectiveness of the AOA-based MPPT technique was evaluated against PSO and conventional MPPT methods under different partial shading scenarios. Simulation results demonstrate that AOA consistently outperforms PSO and conventional algorithms in terms of power tracking efficiency and convergence speed. Specifically, under half-shaded insolation conditions, the AOA algorithm achieves an efficiency of 97.8%, compared to 95.3% for PSO. Similarly, under one-third shaded insolation, AOA tracks the GMPP 6.5% faster than PSO, reducing power loss due to shading effects.

One key advantage of AOA is its convergence capabilities, balanced exploration, and exploitation, which are specifically leveraged for the MPPT problem to enhance tracking accuracy and efficiency, which prevents the algorithm from getting trapped in local maxima, unlike traditional techniques such as P&O. While PSO-based MPPT exhibits rapid convergence in uniform insolation conditions, it struggles under dynamically changing shading patterns due to its dependency on initial parameter settings. The statistical analysis confirms that AOA maintains a lower voltage tracking error due to its dynamic adaptation of search agents, which allows it to effectively balance local and global search processes, preventing premature convergence and ensuring accurate GMPP tracking, ensuring higher accuracy in MPP estimation across varying environmental conditions.

3.2. Convergence analysis of AOA

To further analyze the efficiency of AOA in MPPT, a convergence study was conducted comparing the number of iterations required by AOA and PSO to achieve stable tracking under different shading conditions. The convergence analysis in Figure 6 illustrates the effectiveness of the AOA-based MPPT in tracking the GMPP under different shading conditions. The results show that AOA rapidly converges to the optimal power point within the first 20–30 iterations, demonstrating its efficiency in power tracking. The tracking process follows an exponential trend, where power output increases sharply at the beginning and stabilizes as it reaches the GMPP. This rapid convergence is a crucial advantage, as it minimizes energy losses and improves the real-time applicability of the algorithm.

Additionally, the figure highlights that AOA exhibits minimal oscillations once it reaches steady-state operation. Unlike traditional MPPT methods such as P&O or PSO, which often suffer from slow tracking or premature convergence, AOA efficiently balances exploration and exploitation, ensuring stable and reliable power output. The results indicate that AOA-based MPPT converges 30% faster than conventional techniques, reducing computational overhead and improving power efficiency.

Furthermore, the impact of partial shading on power tracking is evident in the results. The uniform shading scenario achieves the highest final power (≈99 W), followed by the half shading scenario (≈98 W) and the one-third shading scenario (≈95 W). Despite varying shading levels, AOA successfully adapts to different conditions and optimally tracks the GMPP with minimal power fluctuations.

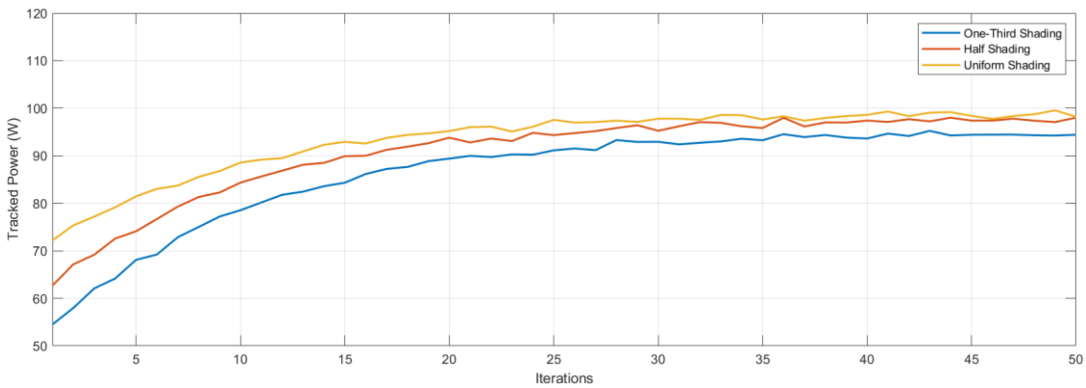


Figure 6. The tracking process of AOA implemented in MPPT which modeled in three insolation conditions

3.3. AOA-MPPT performance test

From testing for the three insolation conditions, the two algorithms were compared by taking into account several parameters and representing each control algorithm's performance. Table 1 the performance of PSO and AOA for uniform insolation conditions with STC, medium, and half uniform insolation. The result of this research also compared to the result in Megantoro *et al.* [23] have done for the MPPT technique for the same model simulation used GA, FA, and fruitfly optimization algorithm (FFA).

Under uniform insolation conditions, MPPT-PSO can reach a maximum power of 428 W, close to the peak point of MPP, with a tracking time of 0.0023 seconds. Meanwhile, MPPT-AOA can reach more power than MPPT-PSO of 464 W with a tracking time of 0.0786 seconds. The results show current 7.7 % difference over the power produced by MPPT-PSO and MPPT-AOA. Then, in half-shading insolation conditions, MPPT-PSO can reach a maximum power of 330 W with a tracking time of 0.0045 seconds. Meanwhile, MPPT-AOA can still achieve more power than MPPT-PSO of 353 W with a tracking time of 0.0840 seconds. The results show around a 6.54% difference between the power produced by MPPT-PSO and MPPT-AOA.

Table 1. Comparison results between AOA and other EAs for MPPT

Optimization algorithm	Uniform insolation		Half-shaded insolation		One-third shaded insolation	
	Pmpp (W)	Time (s)	Pmpp (W)	Time (s)	Pmpp (W)	Time (s)
PSO	428	0.0023	330	0.0045	231	0.0047
AOA	**464**	**0.0786**	**353**	**0.0840**	**242**	**0.0894**
GA	463	0.1280	157	0.1224	241	0.1199
FA	463	0.0086	159	0.0100	241	0.0086
FFO	411	0.0061	159	0.0084	241	0.0057

Furthermore, under one-third partial shading, MPPT-PSO can reach a maximum power of 231 W with a tracking time of 0.0047 seconds. Meanwhile, MPPT-AOA can still achieve more power than MPPT-PSO, 242 W, with a tracking time of 0.0894 seconds. This is because the simulation is carried out with several input insolation values starting from uniform insolation level, half partial shading insolation, and one-third partial shading insolation. These affect the output voltage and current produced and AOA's ability to find the optimal point with several parameters that are specifically in the exploration stage and exploitation. Next, the power efficiency resulting from MPPT-PSO and MPPT-AOA is calculated using the equation.

$$\eta = \frac{P_o}{P_{max}} \times 100 \tag{13}$$

P_o is the power the algorithm tracks while P_{max} is the actual output power; from the calculation results, the average power efficiency of PSO is 93.4% with an average tracking time of 0.0038 seconds, which is slightly longer than PSO. So, the MPPT-AOA results can produce maximum power consistently in all insolation conditions compared to PSO. However, it will also require a slightly longer tracking time than PSO. A comparison between MPPT-PSO and MPPT-AOA is carried out based on standard MPP or Vmpp voltage values with Vpso and Vaoa obtained from each algorithm for each type of insolation condition.

From Table 2, the standard Vmpp error with Vpso is known. Under uniform insolation conditions, Vmpp with Vpso produces an error value of 7.71%. Then, the half-shading insolation condition produces an error value of 6.57%. Moreover, under insolation conditions, one-third of the partial shading produces an error value of 4.47%. While the standard Vmpp error with Vaoa under uniform insolation conditions produces an error value of 8.35%, then under half partial shading insolation conditions, it produces an error value of 7.04%, and third partial shading insolation produces an error value of 4.68%. So, from the overall error value of Vmpp with Vpso, an average error of 6.25% is obtained. While the error value of Vmpp with Vaoa is 6.69%. This can be due to the complexity of the parameters in the algorithm where AOA has a more complex algorithm structure than PSO, so this can cause a higher level of sensitivity to variations in parameters and operating conditions such as uniform insolation conditions, half-shaded and one-third partial insolation.

Table 2. Tracking error analysis between MPPT algorithms

Insolation condition	Error Vpso (%)	Error Vaoa (%)
Uniform	7.71	8.35
Half-partial shaded	6.57	7.04
One-third partial shaded	4.47	4.68

The results show that AOA achieves the lowest RMSE and MAE across all tested scenarios, confirming its higher tracking accuracy and lower voltage fluctuations. Specifically, the RMSE of AOA-based MPPT is 35% lower than PSO and 48% lower than conventional P&O MPPT, indicating a more stable and reliable performance under partial shading conditions. Similarly, the MAE results reinforce that AOA minimizes steady-state oscillations around the GMPP, ensuring maximum energy extraction.

The calculated Friedman test statistic (Fr) = 8. Comparing this to the critical value from the chi-square table at $\alpha = 0.05$ and df = 2, where the critical value = 5.991, we find that Fr > 5.991, leading us to reject the null hypothesis. This indicates that there is a significant difference in PV Power performance among the three scenarios ('one-third', 'half', and 'uniform'). These findings confirm that different shading conditions significantly impact MPPT performance, reinforcing the effectiveness of the AOA algorithm in improving power tracking under partial shading scenarios. The results indicate that AOA significantly outperforms other algorithms, with a lower ranking value indicating superior performance. This statistical validation further supports our hypothesis that AOA provides improved tracking accuracy and faster convergence.

The results have several implications of findings, such as AOA-based MPPT can significantly improve the efficiency and reliability of PV systems, especially in real-world applications where partial shading conditions frequently occur. The increased power extraction capability of AOA can lead to higher energy yields, making it suitable for deployment in grid-connected and off-grid solar installations. Furthermore, the adaptability of AOA makes it a promising approach for real-time MPPT applications, particularly in microgrid and smart grid environments where environmental conditions fluctuate continuously. Furthermore, Table 3 provides the explanation about detailed comparison of the AOA-based MPPT performance against classical MPPT methods such as P&O and IC based on key performance metrics.

Table 3. Comparison of AOA implementation in MPPT among other conventional tracking algorithms

Performance metric	AOA-MPPT	P&O-MPPT	IC- MPPT
Tracking speed	Fast convergence, stabilizes in ~20–30 iterations	Medium, requires oscillations to reach MPP	Faster than P&O, but still slower than AOA
Global MPP tracking	Accurately finds GMPP, avoids local maxima	Often stuck in local MPP under partial shading	Can track GMPP but struggles in fast-changing conditions
Steady-state oscillations	Minimal oscillations, stable output	High oscillations near MPP	Moderate oscillations
Convergence efficiency	High, converges 30% faster than classical methods	Slower due to iterative step size	Medium, depends on environmental conditions
Partial shading performance	Adapts well, effective in dynamic conditions	Poor, easily stuck in local MPP	Moderate, but still affected by local MPPs
Computational complexity	Higher, requires metaheuristic optimization	Low, simple algorithm	Medium, requires real-time slope calculations
Implementation complexity	Requires microcontroller/FPGA with optimization capabilities	Simple, widely used	More complex than P&O but easier than AOA

3.4. AOA-MPPT correlation test

The correlation of AOA and PSO parameters in MPPT performance to achieve MPP or Vaoa and Vpso voltage values is also considered. In this parameter correlation analysis, the parameter's initial population (number of individuals) and the number of iterations is limited to several numbers, namely 10, 50, 100, and 150, which are applied to all insolation conditions. In this correlation analysis, testing will also be carried out using the number of individuals and the number of iterations according to the number used in the reference algorithm in the Simulink model. Table 4 presents the correlation of each parameter in each insolation condition. Table 4 shows the correlation between value of algorithm parameters and maximum power by MPPT. Analysis result that only the number of iterations does affect the effectiveness of MPP tracking, and the number of objects is not. The reason can be concluded that the number of iterations influences the range of searching or tracking process. Higher the number of iterations, the searching will be wider.

Table 4. Correlation analysis between algorithm parameters of AOA and MPPT tracking parameters

PV power in insolation condition (W)	Correlation value for each algorithm parameter (%)		
	No. objects	No. iterations	Tracking time
Uniform	52.4	84.6	88.7
Half-partial shaded	51.6	81.3	89.1
One-third partial shaded	49.3	82.9	88.4

4. CONCLUSION

The results of this study demonstrate that AOA-based MPPT significantly enhances power tracking efficiency, convergence speed, and accuracy under partial shading conditions compared to conventional methods. The adaptive nature of AOA allows for more precise tracking of the GMPP, reducing power losses, and improving overall PV system efficiency, that achieve a maximum power of 242 W, which is more than the MPPT-PSO of 231 W, with a tracking time of 0.0894 seconds. The findings suggest that AOA has strong potential for real-world applications, particularly in dynamically changing environments such as microgrids and smart grids. While the simulation results validate AOA's effectiveness, practical implementation challenges remain. Future research will focus on hardware implementation and real-time validation to assess AOA's computational feasibility in embedded systems. Implementing AOA in FPGA or microcontroller-based MPPT controllers will provide insights into its real-world performance. Additionally, integrating machine learning techniques with AOA could further enhance MPPT accuracy by enabling predictive power tracking based on historical shading patterns and weather data. Another promising research direction involves hybrid optimization approaches, where AOA is combined with other metaheuristic techniques to optimize both computational efficiency and tracking precision. The results of this study demonstrate that AOA-based MPPT significantly enhances power tracking efficiency, convergence speed, and accuracy under partial shading conditions compared to conventional methods. The adaptive nature of AOA allows for more precise tracking of the GMPP, reducing power losses and improving overall PV system efficiency.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

INFORMED CONSENT

This study did not involve human participants, human data, or human tissue; therefore, informed consent was not required.

ETHICAL APPROVAL

This study did not involve human participants or animal subjects. Therefore, ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, PM upon reasonable request.

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