

# Fuzzy Logic Enhanced PI Controller with Arithmetic Optimization for Real-Time MPPT in PV Systems

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## Abstract

This study introduces a real-time Maximum Power Point Tracking (MPPT) technique for photovoltaic (PV) systems that uses a dSPACE real-time platform and is created by merging fuzzy logic control, a proportional-integral (PI) controller, and the Arithmetic Optimization Algorithm (AOA). The proposed hybrid method uses the adaptive characteristics of fuzzy logic to control nonlinearity and the corrective accuracy of the PI controller to maintain system stability even as the AOA dynamically optimizes controller parameters to achieve rapid convergence and more effectively tracking efficiency under various irradiance and temperature conditions. The dSPACE technology enables rapid development and real-time validation, hence ensuring practical usability and resilience of the suggested controller. Experimental results confirm that, as compared to conventional methods, the combined fuzzy-PI-AOA approach improves MPPT accuracy, reduces oscillations around significantly increases the PV energy extraction system's total efficiency at the maximum power point.

**Keywords:** Maximum Power Point Tracking (MPPT), Photovoltaic (PV), Proportional-Integral (PI), Arithmetic Optimization Algorithm (AOA)

## 1. Introduction

The environmental advantages of photovoltaic (PV) systems and dropping installation prices have driven research as global demand for renewable energy increases [1,2]. To optimize energy accumulation, efficient Maximum Power Point Tracking (MPPT) algorithms must address the nonlinear characteristics of PV modules influenced by temperature, irradiance, and other variables [3]. Motivating the study of improved control techniques, conventional MPPT approaches could exhibit low efficiency in dynamic conditions, oscillations, and slow convergence [4].

Though simply and explicit to use, conventional PI-based MPPT controllers are constrained by set gain values that do not sufficiently respond to changing system dynamics [5]. Moreover, conventional optimization techniques utilized to modify PI parameters lacked real-time responsiveness or global optimality [6]. These difficulties draw attention to the requirement of complex and adaptable control systems able to attain exact MPPT under changing environmental conditions [7,8].

This paper offers a hybrid MPPT control approach integrating fuzzy logic control, a PI controller, and the Arithmetic Optimization Algorithm (AOA) to get around these constraints. Though the PI controller guarantees precise error correction, fuzzy logic offers adaptive ability to decide to manage the nonlinearities and uncertainties natural to PV systems. In dynamically changing the fuzzy-PI controller parameters in real-time, the AOA effectively balances rapid tracking and low steady-state error. Real-time validation of the proposed

control strategy is provided using a dSPACE platform renowned for its rapid execution and exact simulation-to-hardware deployment capabilities. Through providing a practical environment to assess the results and dependability of the hybrid controller under actual operating situations, the dSPACE system supports rapidly prototyping, real-time modification, and hardware-in-the-loop testing.

This paper's primary contributions include the development of an AOA-tuned fuzzy-PI MPPT controller, real-time execution on a dSPACE system, and thorough comparison of conventional MPPT techniques. The following is the remainder of the paper is structured: The system modelling and control design are presented in the second part, the third section details the AOA algorithm integration, the fourth section discusses the dSPACE experimental setup and results, and the final section concludes the results and makes recommendations for further lines of inquiry.

## 2. Related works

Tukeman [9] maximized the power output of photovoltaic (PV) systems, intelligent MPPT algorithms such as the real-time Estimate-Perturb-Perturb (EPP) method have been developed. The EPP technique effectively manages PV system performance by dynamically adjusting voltage and current using a digital controller. A boost DC-DC converter extracts low DC voltages from the PV array, while an inverter converts the high DC voltage into AC power for residential or grid use. A 1 kW prototype using this algorithm, supported by a DSP controller, showed promising results under rapidly changing environmental conditions compared to other hill-climbing MPPT methods. Additionally, fuzzy logic controllers (FLCs) further enhance MPPT efficiency when optimized using genetic algorithms (GAs), which efficiently handle complex multivariable design problems. These GAs optimize the FLC's membership functions and rules. The FLC and PV model were implemented using MATLAB/Simulink, accounting for irradiance and temperature effects. Simulation results demonstrated improved output power and current performance under dynamic conditions.

Berrazouane and Mohammedi [10] produced to use the Cuckoo Search (CS) algorithm to manage an independent hybrid power system. The FLC regulates the power rates of the battery, PV system, and diesel generator using the battery state of charge (SOC) and net power flow as inputs. We adjusted the controller using weekly data on load, temperature, and solar irradiation. Levelized energy cost (LEC), excess energy (EE), and loss of power supply probability (LPSP) were all successfully decreased by the CS-based optimization. According to the results, when it came to adjusting the parameters of fuzzy systems, the CS algorithm performed more effectively than particle swarm optimization (PSO).

Hamed and El-Moghany [11] implemented using a photovoltaic module, stepper motor, sensors, I/O interface, and an expert fuzzy logic controller (FLC) on an FPGA platform. This setup ensures the solar panels continuously align with the sun throughout the day for maximum energy capture. The proposed sun tracking and MPPT controllers were modeled and tested using MATLAB/Simulink and validated in real-time implementation. Results demonstrated that both the tracking and MPPT controllers outperformed conventional controllers in terms of response time and efficiency, highlighting the effectiveness of intelligent control techniques in enhancing PV system performance.

Siano and Citro[12] proposed a multi-objective particle swarm optimization (MO-PSO) to optimize membership functions and rule sets. This approach enhances controller performance by ensuring low sensitivity to input voltage fluctuations, fast response during load transients, and robustness against component aging. Laboratory tests on a buck converter under varying voltage inputs, load conditions, and component tolerances confirmed the controller's effectiveness. Compared to a conventional PI controller, the optimized fuzzy controller showed superior voltage regulation and adaptability, demonstrating its suitability for dynamic and uncertain operating environments in power electronic systems.

Roshan [13] proposed a modeling and simulation approach for photovoltaic (PV) systems incorporating MPPT is presented to address the inherently low efficiency of PV systems. The research emphasizes the use of the Incremental Conductance (INC) MPPT technique, which efficiently monitors the maximum power point in a range of environmental conditions. The MATLAB-implemented simulation model provides relevant I-V and P-V characteristics by taking temperature and solar irradiance into account as input variables. The INC algorithm

enhances energy extraction by continuously adjusting the operating point, demonstrating improved performance in maintaining maximum power output across different operating scenarios.

### 3. Proposed Methodology

The suggested setup comprises a photovoltaic module combined with a boost converter whose duty cycle is regulated by a hybrid controller implemented on a dSPACE real-time platform. The MPPT algorithm utilizes PI controller combined with Arithmetic Optimization Algorithm (AOA) to guarantee mimics simple arithmetic operations to find the best solution by smartly balancing wide search and local refinement across optimization problems [14]. Figure 1 shows the flow of the suggested technique.

#### 3.1. PV Model

The research used a single-diode model because of its accuracy and ease of use. As shown in Figure 1, this method simulates the PV in an electric circuit as a DC source. As a result of solar radiation, the PV produces a current  $I_{ph}$ . The diode's current leakage at the p-n junction is represented by  $I_{sh}$ , while the resistance across the PV is shown by  $R_s$ . Two other resistances are also taken into consideration. The latter reduces the system's maximum power output.

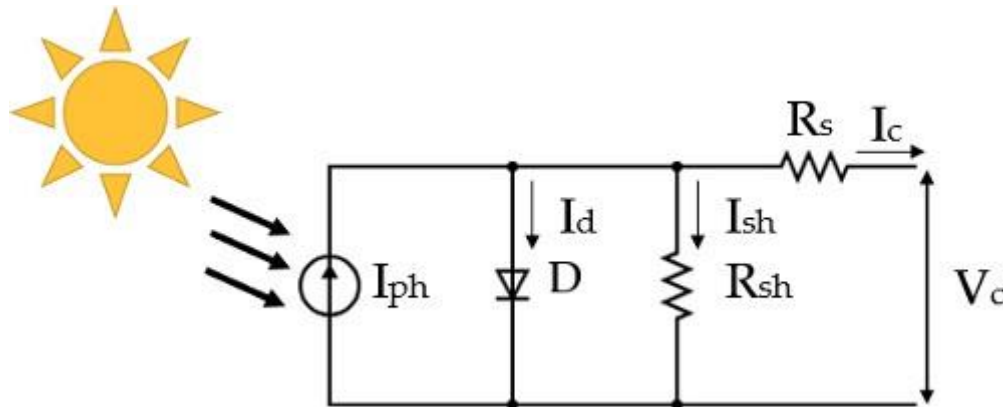


Figure 1. PV Model

Equation (1), where  $I_{sh}$  and  $I_c$  use the following equations to define, is given using Kirchhoff's current law:

$$I_c = I_{ph} - I_d - I_{sh} \quad (1)$$

$$I_c = I_{ph} - I_o \left( e^{\frac{q(V + R_s I_c)}{aKT_c}} - 1 \right) - \frac{V + R_s I_c}{R_{sh}} \quad (2)$$

The operating temperature, the fundamental charge and the Boltzmann constant, and the reverse saturation current are denoted by  $T_c$ ,  $K$ ,  $q$ , and  $I_o$ , respectively. Equation (3), where  $G/G_{SRC}$  represents the connection between the radiance under standard rating conditions (SRCs) and the actual solar radiation, also expresses the current that the PV produces. At SRC,  $T_{ref}$  is the PV temperature and  $I_{sc_{ref}}$  is the PV's short-circuit current. One component of the short-circuit current's thermal factor is  $kI_{ref}$ .

$$I_{ph} \frac{G}{G_{ref}} = \left( I_{sc_{ref}} + K_{I_{ref}}(T - T_{ref}) \right) \quad (3)$$

Equation (4) determines the output current ( $I_m$ ) and voltage ( $V_m$ ) of the whole PV panel, which is constructed in parallel with numerous components ( $N_p$ ) and series ( $N_s$ ). Thus, using the above formulas, the PVG's output current may be expressed as follows.

$$I_m = N_p I_c \quad (4)$$

$$V_m = N_s V_c \quad (5)$$

$$I_c = I_{ph} N_p - N_p I_o \left( e^{\frac{q(V+R_z I_c)}{aKT_c}} - 1 \right) - N_p \frac{V+R_z I_c}{R_{zh}} \quad (6)$$

### 3.2. Incremental Conductance

In contrast to the P&O algorithm, the IncCond tracking method is well-liked due to its precision and efficiency [15]. By assessing the voltage and current conditions and implementing increment/decrement modifications, it regulates the power converter's duty cycle,  $D$ , as shown in Figure 2. The authors of used an almost controlled step size in their experimental design and implementation of this approach. In addition to causing soft power oscillations in steady state, a small step-size number for a duty cycle also results in a slow dynamic response that is sensitive to external disturbances. Increasing the step size has the opposite effect, causing excessive power fluctuation in a steady state. Although the results in indicated satisfactory tracking precision, the lack of evaluation under external disturbances calls its robustness into question. In fact, most traditional MPPT algorithms use a fixed step size and therefore cannot deliver both rapid response and high steady-state accuracy at the same time. A variable step size one that decreases the perturbation magnitude as the operating point nears the target is necessary to achieve both fast dynamics and precise convergence.

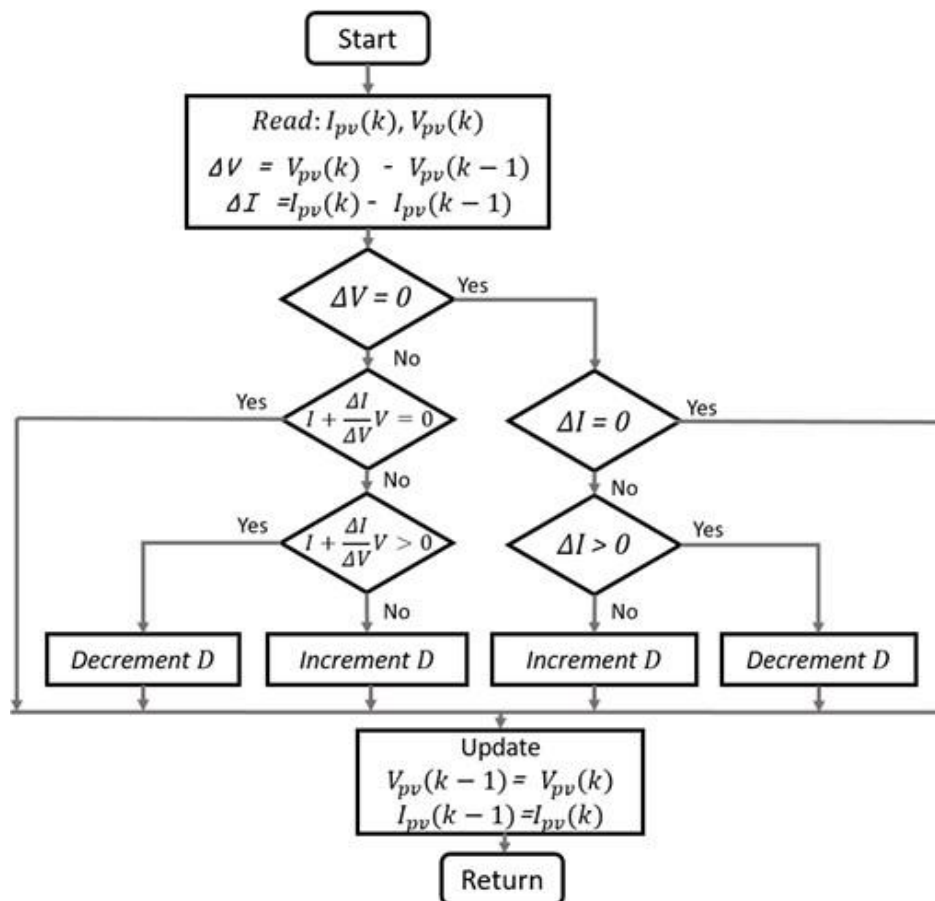


Figure 2: Flowchart of IncCond algorithm

### 3.3. Hybrid Fuzzy-ADSO controller

In this case, the MPPT algorithm incorporates fuzzy logic combined with PI-AOA to provide effective and dependable tracking of the largest power point under variable conditions solar environments.

#### 3.3.1. Fuzzy-PI-AOA Controller Overview

To ensure effective and reliable tracking of the highest power point possible under changing solar circumstances, the MPPT algorithm is based on fuzzy logic supplemented with AOA. The fuzzy logic controller

provides a human-experience-inspired, model-free control system that infers the duty cycle adjustment required for the boost converter.

i. Fuzzy Logic Control

An intelligent method to assess an MPPT algorithm based on fuzzy logic control (FLC) allows a PV system to reach its maximum operating power point. Using the system's mathematical model instead, it depends on human experience. Therefore, the proposed tracking method is developed using an adaptive, step-by-step search approach. Table 1 provides a summary of the MPP search rules, which are derived from the slope of the power–voltage curve ( $P_{pv} - V_{pv}$ ).

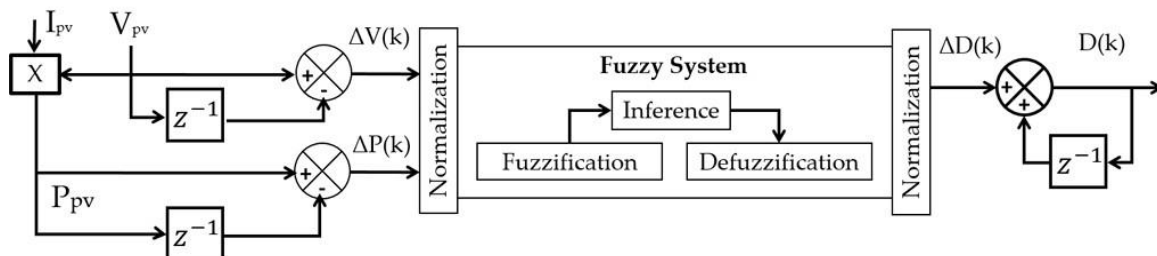
**Table 1: MPP Search Rules**

Case	$\Delta P$	$\Delta V$	Research Direction	Duty Ratio
1	+	+	Right direction	$D(k) = D(k-1) - \Delta D$
2	+	-	Right direction	$D(k) = D(k-1) + \Delta D$
3	-	-	Wrong direction	$D(k) = D(k-1) - \Delta D$
4	-	+	Wrong direction	$D(k) = D(k-1) + \Delta D$

The main components are fuzzification, inference, and defuzzification FLC control system, which is seen in Figure 3. The inputs, V and P, as stated in Equations (7) and (8), are transformed into fuzzy variables by the first component.

$$\Delta V = V_{pv}(k) - V_{pv}(k-1) \quad (7)$$

$$\Delta P = P_{pv}(k) - P_{pv}(k-1) \quad (8)$$



**Figure 3: FLC control structure**

The membership rules, which interpret the user's main logic, make up the second functional block. Table 5 lists 25 fuzzy language rules for 25 distinct situations. This table shows negative large, medium, small, zero, positive small, medium, and significant as NB, NM, NS, Z, PS, PM, and PB. The two examples that follow show how if-then statements were used to create these rules:

- If( $\Delta V$  is NS)and( $\Delta P$  is Z)then( $\Delta D$  is NS);
- If( $\Delta V$  is PB)and( $\Delta P$  is PS)then( $\Delta D$  is PM).

"Defuzzification" is the third functional block is responsible for converting the inference block's verbal rules into precise numerical values. The Matlab software's fuzzy toolbox was used to setup and create the input and output membership functions.

**PI controller:**

PI controllers are commonly utilized in a variety of industrial domains due to their reliable performance, simplicity, and ease of implementation<sup>37</sup>. A well calibrated PI controller ensures that the two gains are at their best. The proportional gain (KP) is the first component, while the integral gain (KI) is the second. The whale

optimization technique, genetic, cuckoo search, and artificial bee colony are some of the optimization methods that researchers use to change PI controllers to reduce the error associated with PV MPPT approaches. The optimization cost function maximizes MPPT performance utilizing the four standard indicators IAE, ISE, ITAE, and ITSE by reducing IC's error signal  $e(t)$  using equation Eq. (8). The recommended control method's improved findings are more properly shown.

$$\begin{cases} IAE = \int_0^{t_{ss}} |e(t)|.dt \\ ISE = \int_0^{t_{ss}} e^2(t).dt \end{cases} \quad (9)$$

$$\begin{cases} ITAE = \int_0^{t_{ss}} t.|e(t)|.dt \\ ITSE = \int_0^{t_{ss}} t.e^2(t).dt \end{cases} \quad (10)$$

where  $t_{ss}$  is the temporal response in steady state and  $e(t) = dI(t)/dV(t) + I(t)/V(t)$

### Arithmetic optimization algorithm:

In 2021, Abualigah proposes "AOA," a unique meta-heuristic optimization technique. The AOA was inspired by how mathematical operators are used to solve mathematical problems. Addition (A), multiplication (M), subtraction (S), and division (D) are examples of these fundamental arithmetic operations. As seen in Fig. 4a, such an AOA consists of two stages: exploration and exploitation.

According to Equation (11) the AOA optimization approach starts with a matrix of randomly selected solutions (X). The optimal solution so far is considered to be the best one at each iteration.

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,n} \end{bmatrix} \quad (11)$$

Selecting search phases like intensification and diversification is necessary when the AOA algorithm begins. Therefore, Eq. (12) is used to determine the Math Optimizer Accelerated function (MOA) in the succeeding search phases.

$$MOA(C\_Iter) = Min + C\_Iter \frac{Max - Min}{M\_Iter} \quad (12)$$

The terms *Min* and *Max* stand for the accelerated function's lowest and highest values, respectively.  $MOA(C\_Iter)$  shows how much the function is valued at its latest recent repetition.  $C\_Iter$  indicates that there are now one to the maximum number of iterations in the repetition range ( $M\_Iter$ ).

**Exploration phase.** (M) or (D) arithmetic operators carry out the exploration phase because their values are widely scattered (relating to various fields). However, unlike other operators like S and A, these operators have a lot of dispersion, which makes it difficult for them to close the target. Four arithmetic procedures construct a function to show the impact of the different operators' distribution values. The determination of a practically ideal solution, which may be recognized after several repetitions, is therefore aided by the exploration stage. In addition, this technique facilitates better communication, assisting with the exploitation phase of the search process. This phase is executed if  $r1 > MOA$ , where  $r1$  is a selected at random number between 0 and 1. The second M operator is inconsequential until this operator completes its task, and the D operator applies the revised position if  $r2 < 0.5$  ( $r2$  is another randomly selected value from the range [0,1]). The M operator is used to update the position otherwise. Equation (13), when applied to this search phase, provides the arithmetic representation.

$$x_{i,j}(C\_Iter + 1) = \begin{cases} best(x_j) \div (MOP + \epsilon) \times ((UB_j - LB_j) \times \mu + LB_j), r2 < 0.5 \\ best(x_j) \times (MOP + \epsilon) \times ((UB_j - LB_j) \times \mu + LB_j), otherwise \end{cases} \quad (13)$$

where  $x_{i,j}(C\_Iter + 1)$  is the answer to the following iteration,  $best(x_j)$  shows the precise position of the most effective solution found to date,  $\epsilon$  is a tiny number,  $UB_j$  and  $LB_j$  are the  $j$ th location's upper and lower limits, respectively.  $\mu$  is a regulating element intended to alter the search procedure, and it is set at 0.499 according to the evaluation,  $MOP$  represents the probability coefficient for the math optimizer, which is determined using Equation (14).

$$MOP(C\_Iter) = 1 - (C\_Iter)^{1/\alpha} / (M\_Iter)^{1/\alpha} \quad (14)$$

where  $\alpha$  is a delicate component that, after several efforts, is developed at number 5. It influences the efficacy of the exploitation throughout the iterations.

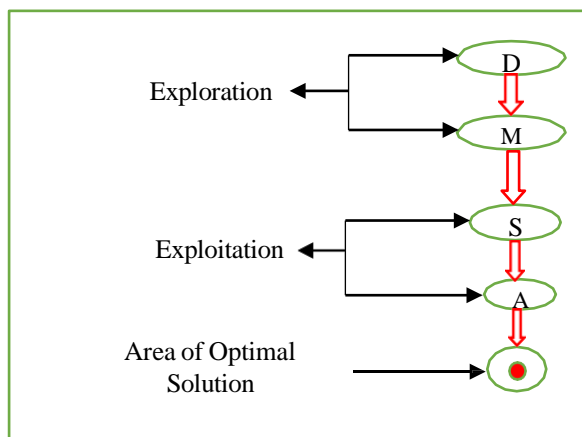


Figure 4(a): Arithmetic operator hierarchy

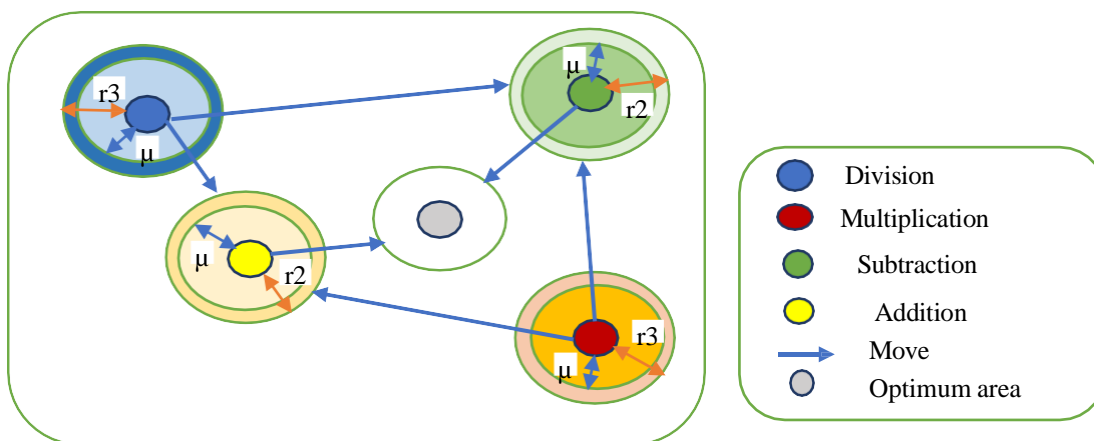


Figure 4(b): Model for changing the placements of arithmetic operators in AOA in the direction of the ideal region

### Exploitation phase:

(S) or (A) mathematical operators perform in the exploitation phase because of their highly focused results. For this phase,  $r1 < MOA$  is the prerequisite. If  $r3 < 0.5$  ( $r3$  is a random number between  $[0,1]$ ), operator S is in charge of updating the position; otherwise, operator A is ignored until this operator reaches its objective. Otherwise, the (A) operator updates the positioned. (15) represents the mathematical model of this search phase. The parameter  $\mu$  is well thought out to provide a randomized outcome at each repeat, which keeps the investigation flowing throughout the initial and last trials. The process of updating a search solution's position based on the D, M, S, and A operator is shown in Figure 4b.

$$x_{i,j}(C\_Iter + 1) = \begin{cases} best(x_j) - (MOP + \epsilon) \times ((UB_j - LB_j) \times \mu + LB_j), & r3 < 0.5 \\ best(x_j) - (MOP + \epsilon) \times ((UB_j - LB_j) \times \mu + LB_j), & otherwise \end{cases} \quad (15)$$

The following is a summary of the AOA steps:

**Step 1:** Select a suitable population and the most iterations that are permitted, and set the AOA design parameters ( $\alpha=5$ ,  $\mu = 0.499$ ).

**Step 2:** The solution positions should be initial set at random.

**Step 3:** For such solutions, compute the objective function as in Eqs. (9 and 10). Select which is the best answer so far and mark it as such.

**Step 4:** As in Eqs. (11, 12), update MOA and MOP, accordingly.

**Step 5:** Produce three randomized numbers ( $r1, r2$ , and  $r3$ ).

**Step 6:** Update D operator solution positions if  $r1 > MOA$  and  $r2 > MOA$  and  $r2 > 0.5$  using Eq. (13) or modify S operator solution positions if  $r1 < MOA$  and  $r3 < MOA$  and  $r3 > 0.5$  using Eq. (15).

**Step 7:** If the new answers are better suited than the previous ones, after the solutions have been relocated, calculate the new objective function and switch them appropriately.

**Step 8:** If the limit restriction is the same as the most recent version, then display the optimum solution (KP, KI).

The following succinctly describes the primary benefits of the relevant AOA over existing optimization methods: (i) There are just two control elements required for this novel optimization method, which has a simple structure consisting of a few mathematical operations. (ii) In the exploration stage, it has a large search space. However, for AOA to function effectively during the exploitation phase, various upgrades and changes are required. Furthermore, any optimization method that has a special solution for every optimization issue is preferred by AOA. As there is no one optimization technique that can solve every optimization issue, the no free lunch hypothesis states that optimization outcomes vary depending on the situation.

#### 4. Result and Discussion

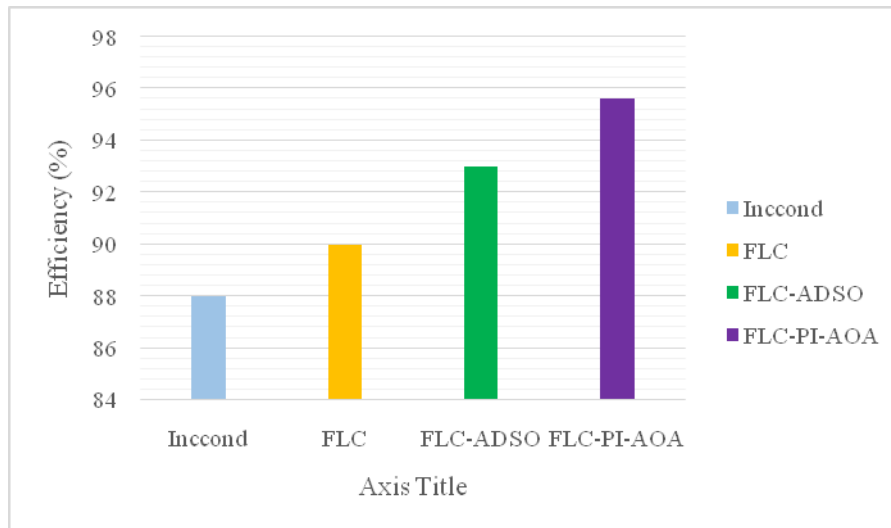
To assess the suggested fuzzy-AOA MPPT controller's efficacy, a comprehensive experimental setup was established using a commercial photovoltaic (PV) panel, a DC-DC boost converter, and a dSPACE DS1104 real-time control platform. The test conditions were designed to replicate real-world operating environments under variable solar irradiance and temperature.

##### Hardware Setup:

- PV Panel: 200W monocrystalline module
- DC-DC Converter: Custom-designed boost converter rated at 250W
- dSPACE Controller: DS1104 board running in real-time with MATLAB/Simulink interface
- Irradiance Source: Variable-intensity halogen lamp for controlled testing
- Measurement Instruments: Tektronix digital oscilloscope, I-V tracer, NI DAQ modules

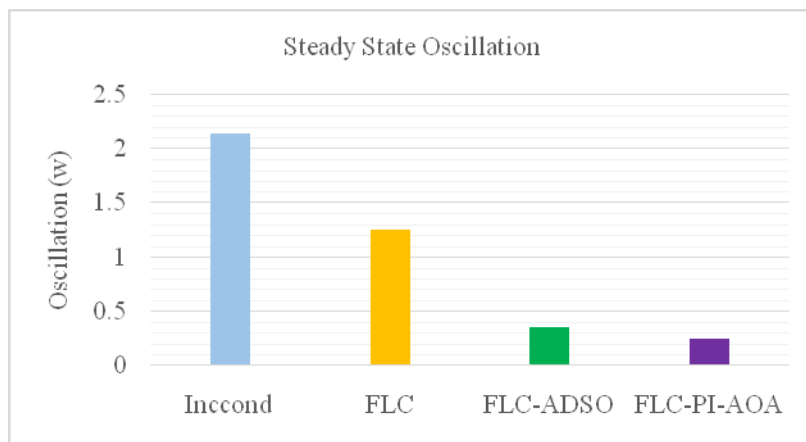
The Performance Metrics are the Tracking Efficiency (%), Steady-State Oscillation (Watts), Response Time (ms) and Overshoot (%).





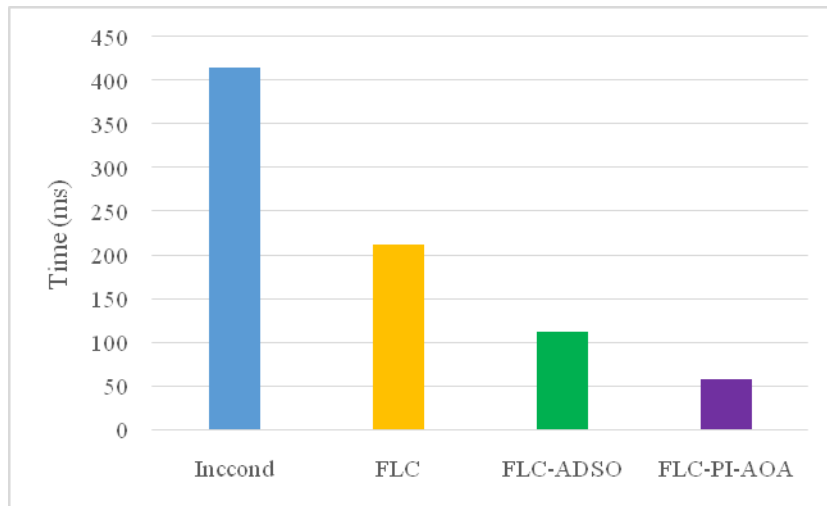
**Figure5:Tracking Efficiency Comparison**

Figure 5 represents the graph illustrates the tracking efficiency (%) of four different MPPT control methods: Incond, FLC, FLC-ADSO, and FLC-PI-AOA. Among these, the Incremental Conductance (Incond) method exhibited the lowest efficiency at around 88%, followed by the Fuzzy Logic Controller (FLC) with approximately 90% efficiency. The FLC enhanced with Adaptive Dove Swarm Optimization (FLC-ADSO) achieved a higher efficiency of about 93%, while the FLC-PI-AOA method demonstrated the best performance with the highest efficiency close to 96%. This comparison clearly indicates that incorporating optimization techniques like ADSO and AOA significantly improves MPPT tracking efficiency, with FLC-PI-AOA offering the most accurate and effective control among the evaluated methods.



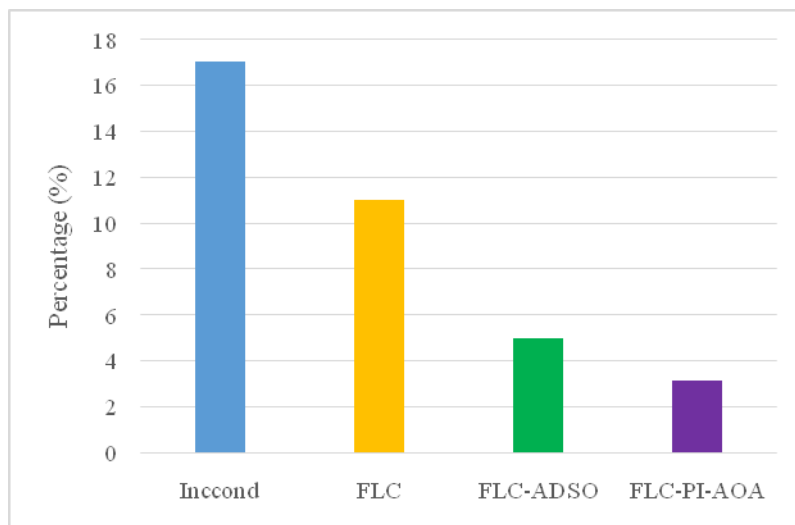
**Figure 6: Steady State Oscillation Comparison**

Figure 6 shows the steady-state oscillation on the graph (in watts) for different MPPT methods: Incond, FLC, FLC-ADSO, and FLC-PI-AOA. The Incremental Conductance (Incond) method exhibits the highest oscillation at around 2.1 W, followed by the Fuzzy Logic Controller (FLC) with approximately 1.3 W. The FLC-ADSO approach significantly reduces oscillation to about 0.3 W, while the FLC-PI-AOA method achieves the lowest oscillation, close to 0.2 W. This indicates that optimization techniques like ADSO and AOA help in minimizing steady-state oscillations, leading to more stable and efficient MPPT performance.



**Figure 7: Response Time (ms) Comparison**

Figure 7 shows the graph illustrates the response time (in milliseconds) for different MPPT methods: Incond, FLC, FLC-ADSO, and FLC-PI-AOA. At around 410 ms, the Incremental Conductance (Incond) approach has the longest reaction time; the Fuzzy Logic Controller (FLC) follows with about 210 ms. While the FLC-PI-AOA technique has the most rapidly reaction time, at 60 ms, the FLC-ADSO approach reduces the response time to about 115 ms. By attaining more rapidly convergence to the maximum power point, this comparison shows that optimization-based methods, particularly FLC-PI-AOA, significantly improve the dynamic performance of the MPPT system.



**Figure 8: Overshoot Comparison**

The graph in Figure 8 shows the percentage error for many MPPT control techniques: Incond, FLC, FLC-ADSO, and FLC-PI-AOA. With around 11% error, the Fuzzy Logic Controller (FLC) comes next after the Incremental Conductance (Incond) technique, which has the most inaccuracy at about 17%. While the FLC-PI-AOA technique has the least error at around 3%, the FLC-ADSO approach reduces the error to about 5%. This suggests that methods based on optimization, especially FLC-PI-AOA, greatly improve the tracking accuracy of the MPPT system by reducing control and forecast inaccuracies.

### Conclusion

This study greatly improved the performance of photovoltaic (PV) system MPPT by utilizing a PI controller set using the Arithmetic Optimization Algorithm (AOA) and verified on the dSPACE real-time hardware platform. Compared to conventional techniques, the AOA-based tuning increased tracking efficiency, reduced steady-state oscillations, and shortened reaction time, hence ensuring more accurate and effective energy harvesting under

dynamic conditions. The evaluation confirmed the recommended approach's effectiveness and practical viability. The method can be expanded for future work by including adaptive or self-learning optimization algorithms that dynamically retune the PI parameters in real-time, including partial shading scenarios, and evaluating the system's robustness under very changing weather patterns and grid-connected micro grid applications.

## References

1. Al Nabulsi, A. and Dhaouadi, R., 2012. Efficiency optimization of a DSP-based standalone PV system using fuzzy logic and dual-MPPT control. *IEEE Transactions on Industrial informatics*, 8(3), pp.573-584.
2. Liu, C.L., Chen, J.H., Liu, Y.H. and Yang, Z.Z., 2014. An asymmetrical fuzzy-logic-control-based MPPT algorithm for photovoltaic systems. *Energies*, 7(4), pp.2177-2193.
3. Dounis, A.I., Kofinas, P., Alafodimos, C. and Tseles, D., 2013. Adaptive fuzzy gain scheduling PID controller for maximum power point tracking of photovoltaic system. *Renewable energy*, 60, pp.202-214.
4. Hamed, B.M. and El-Moghany, M.S., 2012. Fuzzy controller design using FPGA for photovoltaic maximum power point tracking. *International Journal of Advanced Research in Artificial Intelligence*, 1(3), pp.14-21.
5. Elkhateb, A., Abd Rahim, N., Selvaraj, J. and Uddin, M.N., 2014. Fuzzy-logic-controller-based SEPIC converter for maximum power point tracking. *IEEE Transactions on Industry Applications*, 50(4), pp.2349-2358.
6. Alabedin, A.Z., El-Saadany, E.F. and Salama, M.M.A., 2011, July. Maximum power point tracking for Photovoltaic systems using fuzzy logic and artificial neural networks. In *2011 IEEE Power and Energy Society General Meeting* (pp. 1-9). IEEE.
7. Kakosimos, P.E. and Kladas, A.G., 2011. Implementation of photovoltaic array MPPT through fixed step predictive control technique. *Renewable energy*, 36(9), pp.2508-2514.
8. Wang, Y., Ding, L. and Li, N., 2011, December. The application of fuzzy parameters self-tuning PID controller in MPPT of photovoltaic power system. In *Proceedings 2011 International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE)* (pp. 1129-1132). IEEE.
9. Tukiman, Z., 2012. *Fuzzy logic-genetic algorithm based maximum power point tracking in photovoltaic system* (Doctoral dissertation, Universiti Tun Hussein Onn Malaysia).
10. Berrazouane, S. and Mohammedi, K., 2014. Parameter optimization via cuckoo optimization algorithm of fuzzy controller for energy management of a hybrid power system. *Energy conversion and management*, 78, pp.652-660.
11. Hamed, B.M. and El-Moghany, M.S., 2013. Fuzzy controller design using FPGA for sun and maximum power point tracking in solar array system. *International journal of Modeling and Optimization*, 3(2), p.189.
12. Siano, P. and Citro, C., 2014. Designing fuzzy logic controllers for DC–DC converters using multi-objective particle swarm optimization. *Electric Power Systems Research*, 112, pp.74-83.
13. Roshan, R., Yadav, Y., Umashankar, S., Vijayakumar, D. and Kothari, D.P., 2013, April. Modeling and simulation of Incremental conductance MPPT algorithm based solar Photo Voltaic system using CUK converter. In *2013 International Conference on Energy Efficient Technologies for Sustainability* (pp. 584-589). IEEE.
14. Makhoulfi, M.T., Khireddine, M.S., Abdessemed, Y. and Boutarfa, A., 2014. Maximum power point tracking of a photovoltaic system using a fuzzy logic controller on DC/DC boost converter. *International Journal of Computer Science Issues (IJCSI)*, 11(3), p.1.
15. Kakosimos, P.E. and Kladas, A.G., 2011. Implementation of photovoltaic array MPPT through fixed step predictive control technique. *Renewable energy*, 36(9), pp.2508-2514.