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RESEARCH PAPER

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MPPT Algorithm Based on Zebra Optimization Algorithm for Solar Panels System with Partial Shading Conditions

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ABSTRACT

The use of solar panels is being pursued as a solution to reduce dependence on fossil fuels. However, solar panels face challenges such as power fluctuations due to environmental conditions and partial shading. To address these issues, an MPPT technique using Zebra Optimization Algorithm (ZOA) has been developed, which integrates foraging behaviour and defensive strategies to achieve GMPP. Simulation testing results show the superiority of ZOA over PSO in achieving GMPP. ZOA's contribution in addressing this problem is to efficiently perform a global search to find the optimal MPP, even under varying partial shading conditions. The algorithm mimics the behaviour of zebras in foraging and defending against predator attacks, enabling a fast solution search process and higher precision. ZOA can overcome the local maxima trap by expanding the search space, allowing solar panels to function close to optimal efficiency even if there is shading on a portion of the module. This improves system stability and performance and reduces energy loss due to partial shading. ZOA achieved a tracking accuracy of 99.99% with an average tracking time of 0.779 seconds and with a power gain of 28.5%, surpassing PSO with an accuracy of 95.18%, an average trcking time of 0.850 seconds with a power gain of 24.68%. In hardware testing, ZOA is also superior to PSO with an average tracking accuracy of 98.96% while PSO is 97.22%. These results underline the outstanding performance of the ZOA algorithm in optimising the power output of solar panels.

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1. INTRODUCTION

The increasing need for electrical energy encourages the use of fossil fuels, which ultimately causes progressive depletion of fossil fuel reserves over time [1]. Environmental damage is a direct consequence of the operation of fossil fuel power plants, as they emit greenhouse gases and contribute to pollution. To address this pressing problem, alternative energy sources such as solar power plants (PV) have been developed. The use of PV modules offers many benefits, such as utilizing energy from sunlight at no cost, low operational and maintenance costs, quiet operation, and easy installation, has low maintenance costs and can last for 10 to 15 years with minor servicing [2]. However, the energy conversion efficiency in PV systems is relatively low. Variations in environmental conditions such as solar radiation and temperature cause differences in the unique patterns observed in PV curves. Therefore, the main challenge in PV modules is to continuously track MPP. This requires additional techniques such as MPPT. The use of MPPT is implemented with a power electronics interface such as a DC-DC Buck Converter.

Conventional MPPT algorithms such as Perturb & Observe (P&O), Incremental Conductance (IC), and Fuzzy Logic Control (FLC) are commonly used to solve these challenges, but they struggle in handling non-uniform conditions like partial shading [1] . Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), have been introduced as alternatives but still face difficulties in avoiding Local Maximum Power Point (LMPP) traps in partial shading conditions. This indicates the need for more advanced algorithms to improve tracking speed and accuracy in locating the Global Maximum Power Point (GMPP).

Several MPPT methods, including P&O, Hill Climbing (HC), and IC algorithms, have been proposed [3]. These methods track the maximum power output of a solar panel by comparing the current and previous power levels. However, traditional methods often suffer from slow tracking speeds due to the power comparison process. Variations in sunlight and other environmental factors can lead to local MPPs and GMPP in PV systems, complicating the power generation process [4]. [2] Studies have shown that partial shading caused by trees, clouds,

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or buildings can reduce energy output by as much as 80% in large-scale PV installations. Other research indicates that even with conventional MPPT, energy losses due to shading can reach up to 30%, highlighting the importance of addressing this issue. Factors like dust, cloud cover, or buildings causing uneven sunlight can reduce energy production in solar power plants. Traditional algorithms often struggle to find GMPP in partial shading conditions and tend to get stuck at LMPP.

This research introduces a new MPPT approach using metaheuristic techniques inspired by natural processes like evolution and animal behavior. Metaheuristic algorithms aim to find optimal solutions to complex problems and are classified into different types, including swarm-based, evolution-based, and physics-based methods. Swarm-based algorithms, such as Ant Colony Optimization (ACO) [5], Particle Swarm Optimization (PSO) [6], and Artificial Bee Colony (ABC) [7], are known for mimicking the collective behavior of animals. These methods are effective in optimizing complex systems, with ACO inspired by the foraging behavior of ants, PSO mimicking birds' flocking behavior, and ABC based on bees' food search strategies.

[3] The Zebra Optimization Algorithm (ZOA) was chosen in this study because it offers certain advantages over other algorithms. ZOA balances exploration and exploitation more effectively, which helps it avoid getting trapped in LMPP. Additionally, ZOA has a higher convergence speed compared to algorithms like PSO and is more adaptable in real-time to changing environmental conditions, making it particularly suitable for handling partial shading problems. Metaheuristic algorithms like the Gray Wolf Optimizer (GWO) [8], Spotted Hyena Optimizer (SHO) [9], Whale Optimization Algorithm (WOA) [10], Chameleon Swarm Algorithm (CSA) [11], and the Marine Predator Algorithm (MPA) [12] and others have been developed by studying survival tactics of animals. These techniques take inspiration from how animals hunt and survive in nature. The development of such algorithms has yielded positive results, as seen in new methods like the Tunicate Swarm Algorithm (TSA) [13], Raccoon Optimization Algorithm (ROA) [14], Salp Swarm Algorithm (SSA) [15], Cheetah Optimization (CO) [16], Manta Ray Foraging Optimization (MRFO) [17], Harris Hawks Optimization (HHO) [18], Aquila Optimizer (AO) [19], Coyote Optimization Algorithm (COA) [20], and Slime Mould Algorithm (SMA) [21] which incorporate foraging behaviors into their design.

The ZOA algorithm has proven to be highly effective in solving optimization problems. Benchmark functions like unimodal and multimodal, along with CEC2015 and CEC2017 test functions, have been used to assess its performance [24]. By mimicking zebra behavior, ZOA has shown promise for solving complex optimization tasks. However, to date, no research has been done specifically on using ZOA for MPPT in PV systems under partial shading conditions. This research aims to explore the potential of using ZOA in solar panel systems to improve energy generation under such conditions. ZOA is a metaheuristic method introduced for MPPT applications. It works by treating zebras as individuals within a population, using strategies like exploration and exploitation to solve optimization problems. ZOA is implemented in the Buck Converter for MPP tracking, modifying population members through phases of foraging and predator avoidance. During each iteration, the best candidate solution (or duty cycle) is updated and saved. The ZOA algorithm has demonstrated its ability to adapt to changes in solar irradiance and accurately find the maximum power point in solar panels. The algorithm was tested in both normal and partial shading conditions, and its performance was compared to the PSO algorithm. [4] The primary goal of this research is to develop and apply the ZOA-based MPPT method in PV systems under partial shading conditions. Specifically, the research aims to: (1) improve maximum power tracking efficiency by utilizing ZOA's ability to avoid LMPP and find GMPP, (2) compare ZOA's performance with conventional MPPT algorithms like PSO in terms of convergence speed and tracking accuracy, and (3) test the ZOA algorithm in both simulation and hardware setups to demonstrate its effectiveness in real-world PV systems. [5] The methodology of this study involves two main stages. First, simulations are conducted using PSIM to evaluate ZOA's performance under various conditions, including normal and partial shading. Second, hardware testing is conducted on real PV systems using a Buck Converter to assess ZOA's ability to improve energy production under varying sunlight conditions, and its performance is compared to the PSO algorithm.

The goal of this study is to apply the Zebra Optimization Algorithm (ZOA) in MPPT systems for solar panels under partial shading conditions. The main objective is to enhance maximum power tracking by minimizing the effects of partial shading, which often causes significant power loss by trapping the system in LMPP. The contribution of this research lies in applying ZOA to MPPT systems under partial shading conditions, introducing an effective global search mechanism that expands the solution search space, avoids LMPP traps, and provides faster convergence than the PSO MPPT method. Simulation and hardware tests show that ZOA outperforms PSO in partial shading scenarios, leading to better power tracking and overall energy efficiency.

2. MATERIALS AND METHOD

This system was developed with the main objective of maximising the power output of three solar panels connected in series. Although these panels can be

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affected by partial shadows, which can often lower the efficiency in energy collection, this system is designed to overcome such challenges. The ZOA algorithm consists of three main phases, namely initialisation, food search phase, and defence strategy. The data obtained from the input voltage and current sensors are sent to the STM32F4-Discovery microcontroller, which is in charge of calculating the MPPT and generating duty cycles for the Buck converter. The output voltage and current sensors serve to monitor the output of the Buck converter. The MOSFET driver serves to ensure that the voltage reaches the specified limit before controlling the MOSFET, while information regarding the system parameters is displayed on the LCD screen. Figure 1 shows the system block diagram and Figure 2 shows the system hardware.

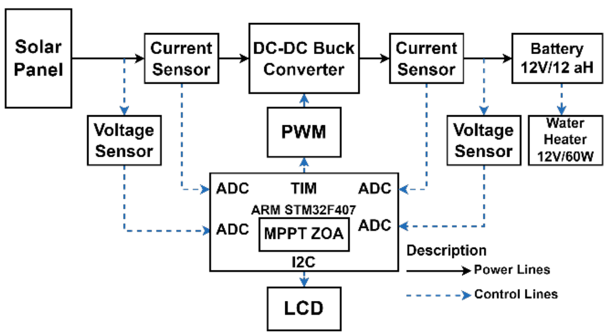

Fig. 1. Block Diagram System

The ZOA steps for MPPT start with initialization of initial parameters, followed by evaluation of the output power of the solar panel to be used as target power, selection of the best individual based on the duty cycle that has been initialized, the algorithm will work using phase 1 and phase 2, until the iteration is fulfilled then the algorithm will stop, then from the duty cycle in both phases obtained the algorithm will determine the best power to be stored and sent to the converter.

Simulation testing is carried out by setting the temperature parameter of the solar panel at 25°C, the light intensity according to the predetermined shading pattern. PSIM software was chosen for its ability to simulate power systems in real-time and provide comprehensive analysis tools. Features such as harmonic analysis and extensive component models as well as lighter weight applications make PSIM superior to other software such as MATLAB/Simulink. For hardware testing of partial shading pattern is done by covering the solar panel partially using tinted film with 80% density in accordance with the partial shading pattern. Hardware testing is carried out when the intensity of sunlight is in maximum conditions with the average irradiation obtained above 1000 W/m^2 and weather conditions are very bright without clouds.

Potential sources of error in this experiment include uncontrolled fluctuations in temperature and light intensity. Measurement errors in the current and voltage sensors can also cause bias in the results obtained. To minimise this bias, sensor measurements were taken repeatedly with a consistent time span and to make the sensors in the system take accurate readings.

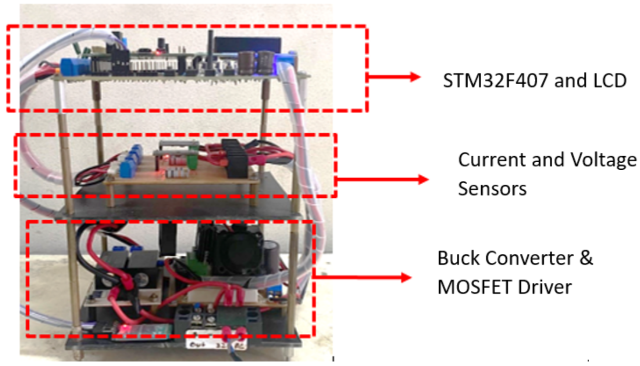

Fig. 2. Hardware

A. Solar Panel

Currently, a widely developed renewable power source is Photovoltaic (PV) power generation [27]. Solar panels harness sunlight by using photovoltaic cells, which then convert this solar energy into electricity. The number of solar cells in a panel is directly correlated to the amount of energy produced. The equivalent circuit of a solar panel includes a current source, a diode that represents the cell connection, and two resistors that provide results according to the lighting level [28]. One is a parallel resistor known as RSH, and the other is a series resistor known as RS. These resistors function to represent the internal resistance in the solar cell. Figure 3 provides a visual representation of this circuit configuration [22].

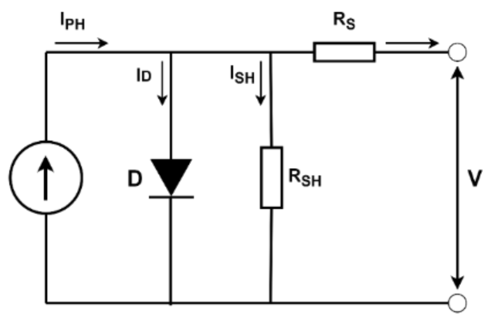

Fig. 3. solar panel equivalent circuit

From Figure 3, the equivalent equation for solar panels refer to (1).

$$I = I_{PH} - I_D = I_{PH} - I_S \left[exp\left(\frac{q(V+IR_S)}{A\,kT_C}\right) - 1\right] - \frac{(V+IR_S)}{R_{sh}} \quad (1)$$

where I indicate something, q shows something the photocurrent produced by solar radiation is denoted as I_{PH}. The reverse saturation current of the diode, denoted as I_D, is the current that flows through the diode when it is not exposed to light. The electron charge is represented by q. The term R_S denotes the resistance in the series

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configuration of PV cells. By analyzing the volt-ampere characteristics of solar cells, the coefficient A can be determined through a comparison between theoretical predictions and experimental data. This coefficient is used to assess the quality of the cell and can take values ranging from 1 to 5. Boltzmann's constant is denoted as k. T_C represents the current operating temperature of the device. Lastly, R_{SH} represents the shunt resistance of the cell. Table 1 is the specifications of the solar panels used.

Table 1. Specification solar panel

Parameter	Value
Pmax	50 W
Vmp	13.93 V
Imp	2.45 A
Voc	18.7 V
Isc	3.33 A

Partial shade reduces the efficiency of solar panels by blocking some sunlight from reaching the cells, limiting their ability to convert solar energy into usable power. As a result, the overall efficiency of the solar panel is reduced, resulting in a reduction in the amount of electricity produced when compared to its performance under ideal circumstances.

B. Partial Shading Condition

To meet voltage and current requirements, solar cells are usually arranged in parallel, series, or a combination of both to form a PV array. Under partial conditions such as clouds, buildings, or trees, solar radiation can vary across PV array modules, and this can cause multiple LMPPs to appear on the power-voltage curve. As a result, the power-voltage curve that is formed becomes more complex, having many peaks in a long sequence. In general, the shadow may be fully or partially according to the percentage of area that shades the PV module [29].

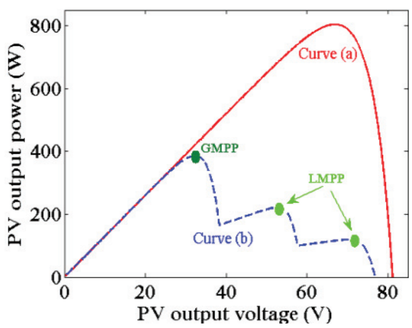

Fig. 4. Solar panel curve when partial shading occurs [25]

Figure 4 illustrates the impact of partial shading on the P-V curves. Curve (a) shows the normal power-voltage and current-voltage curves, while curve (b) is the condition when the solar panel is in partial shadow resulting in multiple peaks, including GMPP and LMPP. MPPT systems with simple algorithms such as P&O often face difficulties in detecting multiple peaks that appear due to the partial shadowing phenomenon. Partial shadowing occurs when solar panels do not receive light evenly due to shadows from objects such as trees, buildings, or clouds. When one or more PV modules are shaded, it affects the power generated by other PV modules, which get proper radiation [30]. This condition leads to the creation of more than one maximum power point, which is difficult to identify with simple algorithms. In addition, the time of occurrence of partial shadows varies, depending on external factors, such as changes in the direction of the sun or shifts in the clouds in the sky. These dynamic weather conditions further complicate the power detection and optimization process, often resulting in a decrease in the maximum power output that the solar panels can produce. PV systems depend on solar radiation levels to generate power, and tests will be conducted under various partial shade conditions as shown in Figure 5.

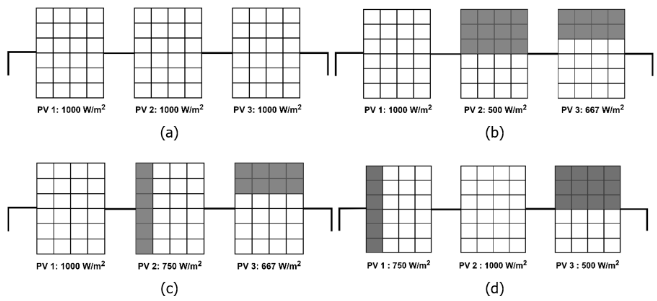

Fig. 5. Solar Panel Irradiation Pattern, (a) Normal Condition, (b) Shading Pattern 1, (c) Shading Pattern 2, (d) Shading Pattern 3

In this research, the three imagery patterns used are assumed to have different causes. The first shading pattern is caused by taller buildings blocking some of the solar panels, causing uneven sunlight to be received. In the second and third shading patterns, it is assumed that shading is caused by dirt such as trash, dust and bird droppings covering part of the solar panel.

C. Buck Converter

The Buck Converter functions as a DC-DC converter that regulates the MPP of the PV module. Recognizing the importance of understanding that converters experience continuous changes in input current, voltage, and power as a result of radiation and temperature fluctuations is critical. In addition, the converter's duty cycle is continuously modified so that it can precisely follow the MPP of the PV module. For more complete information

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about the Buck Converter parameters used to track MPP, it is shown in Table 2 [26].

Table 2. Specification converter

Parameter	Value
Inductor	180 uH
capasitor	304 µF
Resistor	2.05 Ω
Freq *Switching*	40 kHz

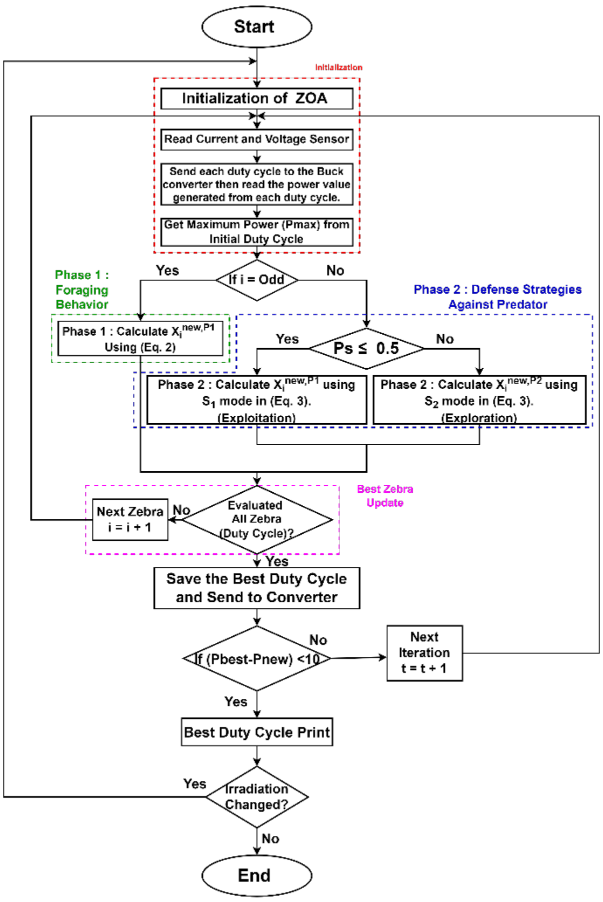

Fig. 6 Flowchart of ZOA on MPPT

D. *Zebra Optimization Algorithm* (ZOA)

Zebras are known for their black-and-white markings, long legs for running, single toe on each foot, long neck, and grazing head. Zebras can determine how often they forage and defend against predators according to environmental conditions. They focus on finding food and staying safe from predators. Pioneer zebras create pathways for other zebras to graze. To avoid predators, they use zigzagging and swarming movements. ZOA's design is inspired by this intelligent behavior [23]. Figure 6 is the ZOA flowchart when applied to the MPPT system.

Initialization ZOA, a population-based optimizer, uses zebras as individual potential solutions in the search area. The algorithm incorporates the natural behaviour of wild zebras to guide its members, with two different phases in each iteration. Phase 1 is used in odd iterations and phase 2 in even iterations to improve optimization.

Phase 1 : Foraging Behaviour

Zebras primarily eat grasses and sedges, but can eat other plants if necessary. Plains zebras choose less nutritious tall grasses, which helps shorter grasses grow. In this research, we simulate zebra foraging to update our population members' strategies. The pioneer zebra leads the others to its whereabouts within the search territory. As a result, the application of Equations (2) allows for a mathematical model that accurately captures the zebra's movements in the foraging phase.

$$x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j}) \tag{2}$$

The duty cycle, denoted as $X_i^{new,P1}$, represents the updated duty cycle considering the initial phase. PZ, a pioneering zebra, is recognized as the optimal duty cycle. The variable r represents a random number within the range of 0 to 1. Furthermore, the value of I is calculated by rounding up the total of 1 and a random number, rand, that is also confined within the range of 0 to 1. Consequently, I can only take on the values of 1 or 2. If I equals 2, it implies that there will be a greater degree of changes in the movement of the population.

Phase 2 : Defence Strategies Against Predator

At this phase, the zebras employ their defence strategy to revise their positions within the search space. The approach varies depending on the predator they encounter. When confronted by lions, the zebras opt for an evasive manoeuvre, whereas with other predators, they adopt an offensive stance. These strategies and the corresponding update conditions can be mathematically represented through the following Equations (3).

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \; x_{i,j} + R \cdot (2_r - 1) \cdot \left(1 - \frac{t}{T}\right) \cdot x_{i,j}, \; P_s \leq 0.5; \\ S_2 : \; x_{i,j} + r \cdot \left(AZ_j - I \cdot x_{i,j}\right), else, \end{cases} \tag{3}$$

The updated duty cycle, denoted as $x_i^{new,P2}$, is determined based on the second phase of the process. Here, t represents the iteration count within the contour, while T signifies the maximum number of iterations allowed. Additionally, R is a fixed constant set at 0.01. PS refers to the probability of selecting one of the two randomly generated strategies from the range [0, 1]. AZ represents the state of the attacked zebra, and AZj denotes the value associated with the jth dimension [24].

The following is an illustration of manual calculations carried out starting from iteration i=1 to iteration i=3. These calculations were carried out under irradiation conditions of 1000 W/m^2, 500 W/m^2 and 667 W/m^2 with a

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duty cycle distribution of 18,24,32,46,72. Manual MPPT ZOA calculations are carried out according to the equations that have been created. This is used to find out whether the algorithm can work properly. The determination if the algorithm can work well is when the results of the duty cycle update on each duty cycle spread can approach the duty cycle with the best power where the best duty cycle value is 32 which is obtained from the simulation of PV characteristic testing found in the graph in Figure 7. Table 3 is a manual calculation on the first iteration. Manual calculation will be conducted as follows:

duty [0] = D_0^0=18
duty [1] = D_1^0=28
duty [2] = D_2^0=34
duty [3] = D_3^0=46
duty [4] = D_4^0=72

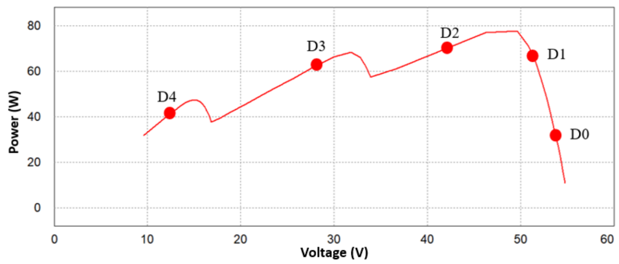

Fig. 7. Initial Duty Cycle Distribution

Table 3. Manual Calculation in 1st Iteration

Iteration 1	
***duty* [0]** = $D_0^1 = 18$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j})$ $x_{i,j}^{new,P1} = 18 + 0.9\,.\,(30 - 1 \cdot 18)$ $x_{i,j}^{new,P1} = 18 + 0.9\,.\,(30 - 18)$ $x_{i,j}^{new,P1} = 18 + 0.9\,.\,12$ $x_{i,j}^{new,P1} = 18 + 10.8$ $x_{i,j}^{new,P1} = \mathbf{28.8}$	***duty* [3]** = $D_3^1 = 46$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j})$ $x_{i,j}^{new,P1} = 46 + 0.9\,.\,(30 - 1 \cdot 46)$ $x_{i,j}^{new,P1} = 46 + 0.9\,.\,(30 - 46)$ $x_{i,j}^{new,P1} = 46 + 0.9\,.\,-16$ $x_{i,j}^{new,P1} = 46 + (-15.1)$ $x_{i,j}^{new,P1} = \mathbf{30.9}$
***duty* [1]** = $D_1^1 = 28$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j})$ $x_{i,j}^{new,P1} = 28 + 0.9\,.\,(30 - 1 \cdot 28)$ $x_{i,j}^{new,P1} = 28 + 0.9\,.\,(30 - 28)$ $x_{i,j}^{new,P1} = 28 + 0.9\,.\,2$ $x_{i,j}^{new,P1} = 28 + 1.8$ $x_{i,j}^{new,P1} = \mathbf{29.8}$	***duty* [4]** = $D_4^1 = 72$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j})$ $x_{i,j}^{new,P1} = 72 + 0.9\,.\,(30 - 1 \cdot 72)$ $x_{i,j}^{new,P1} = 72 + 0.9\,.\,(30 - 72)$ $x_{i,j}^{new,P1} = 72 + 0.9\,.\,-42$ $x_{i,j}^{new,P1} = 72 + (-41.1)$ $x_{i,j}^{new,P1} = \mathbf{30.9}$
***duty* [2]** = $D_2^1 = 34$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\,(PZ_j - I \cdot x_{i,j})$ $x_{i,j}^{new,P1} = 34 + 0.9\,.\,(30 - 1 \cdot 34)$ $x_{i,j}^{new,P1} = 34 + 0.9\,.\,(30 - 34)$ $x_{i,j}^{new,P1} = 34 + 0.9\,.\,-4$ $x_{i,j}^{new,P1} = 34 + (-3.1)$ $x_{i,j}^{new,P1} = \mathbf{30.9}$	

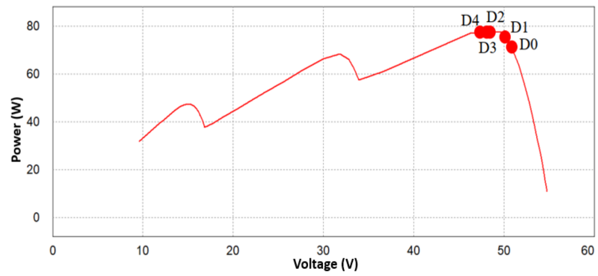

Fig. 8. ZOA MPPT Tracking Process in Iteration 1

It can be seen in Figure 8 that the updated duty cycle results using Phase 1 in 1st iteration are close to the GMPP peak. Furthermore, in the second iteration of the calculation, the algorithm will work in Phase 2 with Equation 2.Next, in the second iteration of the calculation, the algorithm will work in Phase 2 with Equation 2. Figure 9 is the tracking process in the 2nd iteration.

- *duty* [0] = $D_0^2 = 18$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 18 + 0.01 \cdot (2 \times 0.9 - 1) \cdot \left(1 - \frac{2}{3}\right) \cdot 18, P_s \leq 0.5; \\ S_2 : \ 18 + 0.9 \cdot (30 - 1 \cdot 18), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 18 + 0.01 \times (0.8) \times (0.3) \times 18, P_s \leq 0.5; \\ S_2 : \ 18 + 0.9 \times (12), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 18.0432, P_s \leq 0.5; \\ S_2 : \ 28.8\,, else, \end{cases}$$

- *duty* [1] = $D_1^2 = 28$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 28 + 0.01 \cdot (2 \times 0.9 - 1) \cdot \left(1 - \frac{2}{3}\right) \cdot 28, P_s \leq 0.5; \\ S_2 : \ 28 + 0.9 \cdot (30 - 1 \cdot 28), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 28 + 0.01 \times (0.8) \times (0.3) \times 28, P_s \leq 0.5; \\ S_2 : \ 28 + 0.9 \times (2), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 28.0672, P_s \leq 0.5; \\ S_2 : \ 29.8\,, else, \end{cases}$$

- *duty* [2] = $D_2^2 = 34$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 34 + 0.01 \cdot (2 \times 0.9 - 1) \cdot \left(1 - \frac{2}{3}\right) \cdot 34, P_s \leq 0.5; \\ S_2 : \ 34 + 0.9 \cdot (30 - 1 \cdot 34), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 34 + 0.01 \times (0.8) \times (0.3) \times 34, P_s \leq 0.5; \\ S_2 : \ 34 + 0.9 \times (-4), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 34.0816, P_s \leq 0.5; \\ S_2 : \ 30.4\,, else, \end{cases}$$

- *duty* [3] = $D_3^2 = 46$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 46 + 0.01 \cdot (2 \times 0.9 - 1) \cdot \left(1 - \frac{2}{3}\right) \cdot 46, P_s \leq 0.5; \\ S_2 : \ 46 + 0.9 \cdot (30 - 1 \cdot 46), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 46 + 0.01 \times (0.8) \times (0.3) \times 46, P_s \leq 0.5; \\ S_2 : \ 46 + 0.9 \times (-16), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 46.1104, P_s \leq 0.5; \\ S_2 : \ 31.6\,, else, \end{cases}$$

- *duty* [4] = $D_4^2 = 72$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 72 + 0.01 \cdot (2 \times 0.9 - 1) \cdot \left(1 - \frac{2}{3}\right) \cdot 72, P_s \leq 0.5; \\ S_2 : \ 72 + 0.9 \cdot (30 - 1 \cdot 72), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 72 + 0.01 \times (0.8) \times (0.3) \times 72, P_s \leq 0.5; \\ S_2 : \ 72 + 0.9 \times (-42), else, \end{cases}$$

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : \ 72.1728, P_s \leq 0.5; \\ S_2 : \ 34.2\,, else, \end{cases}$$

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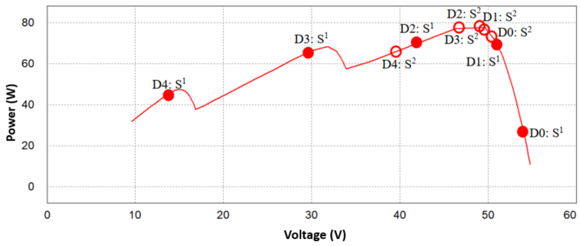

Fig. 9. ZOA MPPT Tracking Process in the 2nd Iteration

In the second iteration (even) the algorithm will spread the duty cycle from the calculations carried out. This aims to increase the duty distribution on the curve so that the algorithm can prevent getting stuck in LMPP. In Phase 2, if the algorithm works using Phase 2 with S_1 (Exploitation) mode, the ZOA algorithm will carry out a global search, so that the algorithm can find areas that have higher peak power (GMPP) so that this exploration phase can avoid the algorithm getting stuck in (LMPP). Meanwhile, if the algorithm works using Phase 2 with S_2 (Exploration) mode, the ZOA algorithm will carry out a local search aimed at optimizing previously found solutions and focusing on the area around the solutions found during the exploration phase. In this phase the ZOA algorithm will try to reach the point (GMPP) more accurately. Then in the 3rd iteration the ZOA algorithm will continue the calculation in the 1st iteration using Phase 1 referring to Table 4. Figure 10 is the result of duty cycle update using Phase 1 in the 3rd iteration.

Table 4. Manual Calculation in 3rd Iteration

Iteration 3	
***duty* [0]** = $D_0^3 = 28.8$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\left(PZ_j - I \cdot x_{i,j}\right)$ $x_{i,j}^{new,P1} = 28.8 + 0.9\,.(30 - 1 \cdot 28.8)$ $x_{i,j}^{new,P1} = 28.8 + 0.9\,.(30 - 28.8)$ $x_{i,j}^{new,P1} = 28.8 + 0.9\,.1.2$ $x_{i,j}^{new,P1} = 28.8 + 216$ $x_{i,j}^{new,P1} = \mathbf{29.88}$	***duty* [3]** = $D_3^3 = 30.9$ $x_{i,j}^{new,P1} = 30.9 + r\,.\left(PZ_j - I \cdot x_{i,j}\right)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 1 \cdot 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(-0.9)\ )$ $x_{i,j}^{new,P1} = 30.9 + (-0.81)$ $x_{i,j}^{new,P1} = \mathbf{30.09}$
***duty* [1]** = $D_1^3 = 29.8$ $x_{i,j}^{new,P1} = x_{i,j} + r\,.\left(PZ_j - I \cdot x_{i,j}\right)$ $x_{i,j}^{new,P1} = 29.8 + 0.9\,.(30 - 1 \cdot 29.8)$ $x_{i,j}^{new,P1} = 29.8 + 0.9\,.(30 - 29.8)$ $x_{i,j}^{new,P1} = 29.8 + 0.9\,.0.2$ $x_{i,j}^{new,P1} = 29.8 + 0.18$ $x_{i,j}^{new,P1} = \mathbf{29.98}$	***duty* [4]** = $D_4^3 = 30.9$ $x_{i,j}^{new,P1} = 30.9 + r\,.\left(PZ_j - I \cdot x_{i,j}\right)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 1 \cdot 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(-0.9)\ )$ $x_{i,j}^{new,P1} = 30.9 + (-0.81)$ $x_{i,j}^{new,P1} = \mathbf{30.09}$
***duty* [2]** = $D_2^3 = 30.9$ $x_{i,j}^{new,P1} = 30.9 + r\,.\left(PZ_j - I \cdot x_{i,j}\right)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 1 \cdot 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(30 - 30.9)$ $x_{i,j}^{new,P1} = 30.9 + 0.9\,.(-0.9)$ $x_{i,j}^{new,P1} = 30.9 + (-0.81)$ $x_{i,j}^{new,P1} = \mathbf{30.09}$	

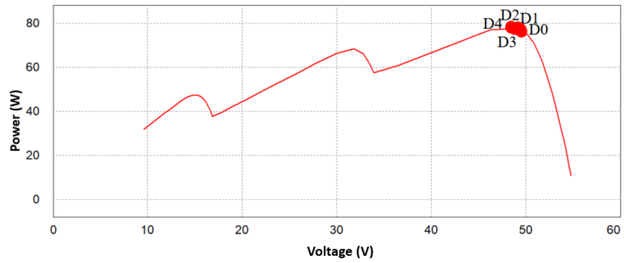

Fig. 10. ZOA MPPT Tracking Process in the 3rd Iteration

From the calculations that have been carried out, it can be concluded that the MPPT ZOA algorithm can maximize the power from PV without getting stuck at the LMPP peak. The results of duty cycle updates from all deployments obtained a duty cycle that is close to the duty cycle with the best power of 32 so that it can be said that the algorithm can track the maximum power of the solar panel.

3. RESULTS

This research conducted two different sets of experiments, specifically simulation and hardware integration. Simulation testing was carried out using PSIM software to determine the effectiveness of the ZOA algorithm, while hardware integration testing was carried out to determine the effectiveness of the ZOA algorithm when applied to hardware.

A. System Simulation Testing

The simulation was carried out using PSIM software. The performance test of the proposed algorithm was carried out by testing conditions without shading and with partial shading. The P-V characteristic curves of three partial shading patterns are shown in Figure 11, where each pattern has a global maximum power point (GMPP). The MPP value under normal conditions is 102.211 Watts, while the GMPP value in pattern 1 is 55.123 Watts, in pattern 2 it is 61.008 Watts and in pattern 3 it is 64.606 Watts. The simulation series can be seen in Figure 11. The comparison is carried out using the PSO algorithm.

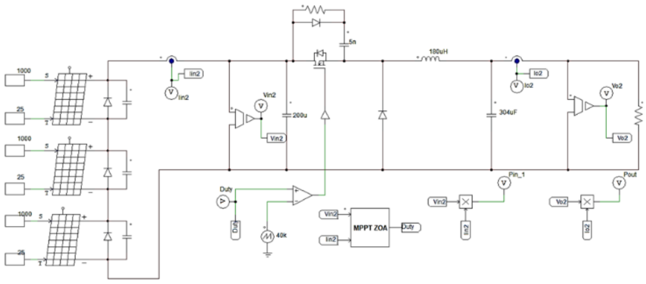

Fig. 11. Simulation *software Power Simulator* (*PSIM*)

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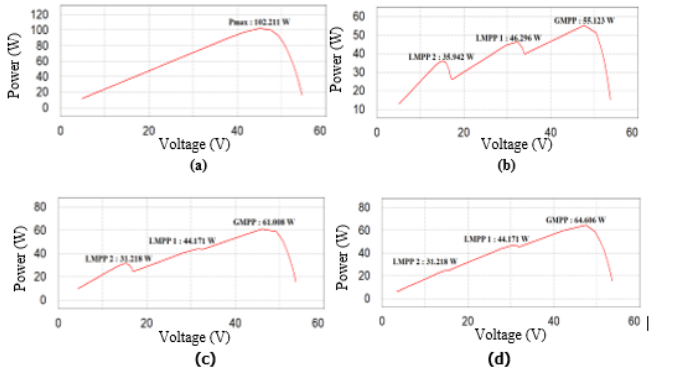

Fig. 12. P-V Characteristic Curve, a) Normal Condition, b) Shading Pattern 1, c) Shading Pattern 2, d) Shading Pattern 3

From Figure 12, namely testing the characteristics of solar panels, a P-V curve is obtained which will be used as a reference power value whether the algorithm can reach GMPP or is still stuck at LMPP. The simulation test results of MPPT ZOA and MPPT PSO are shown in Figure 13. A detailed description of Figure 13 is shown in Table 5.

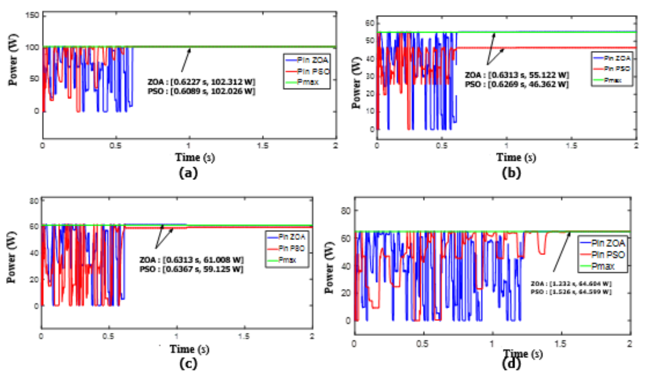

Fig. 13. Simulation Comparison Results of MPPT ZOA with MPPT PSO, a) Normal Condition, b) Shading Pattern 1, c) Shading Pattern 2, d) Shading Pattern 3

B. System Hardware Testing

Tests were carried out using various different solar irradiation conditions to test the reliability of the ZOA algorithm in achieving GMPP when applied to hardware. The purpose of this test is to ensure that the ZOA algorithm can work well under various solar irradiation conditions. During the test, data such as the power generated by the solar panel, the resulting current and voltage, and other parameters are measured and recorded. This data is then analyzed to evaluate the performance of the ZOA algorithm in achieving GMPP. In this test the ZOA algorithm will be compared with the PSO algorithm to determine the performance of MPPT ZOA in tracking solar panel power. The hardware integration testing process is shown in Figure 14.

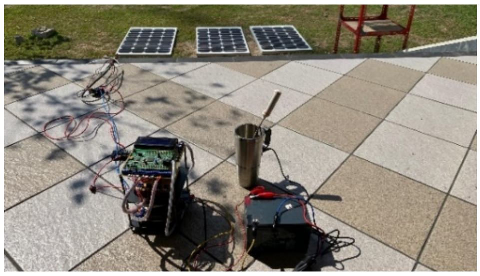
Fig. 14. Hardware testing

The first test carried out was the MPPT ZOA and MPPT PSO tests which aimed to find out how effective the two algorithms were in achieving GMPP. Determination of Pmax in this test is carried out by testing the P-V characteristics after carrying out the MPPT test which aims to find out the maximum power that can be produced by the solar panel and to find out how much accuracy can be produced from the two MPPT algorithms used. Figure 15 is the result of a comparison of MPPT ZOA with MPPT PSO. A detailed description of Figure 15 is shown in Table 6.

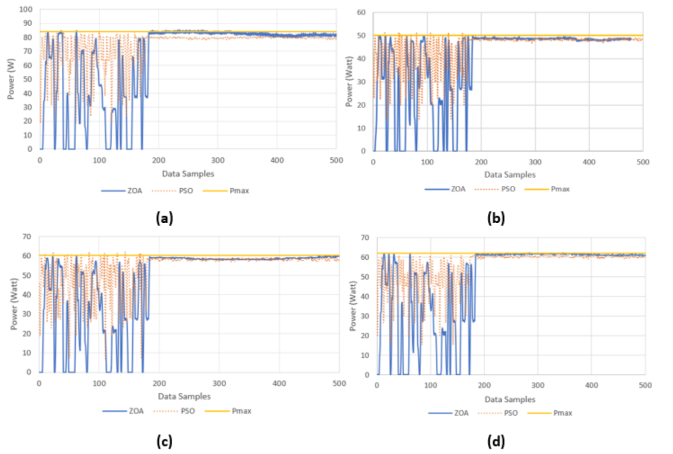

Fig. 15. Hardware Comparison Results of MPPT ZOA with MPPT PSO, a) Normal Condition, b) Shading Pattern 1, c) Shading Pattern 2, d) Shading Pattern 3

4. DISCUSSION

A. Simulation

From Figure 12, it is observed that the ZOA algorithm outperforms the PSO algorithm in every condition and shading pattern that has been tested. This is evident in the MPPT ZOA graph, which can achieve the Pmax value under all conditions, while the PSO algorithm fails to reach Pmax in several shading pattern scenarios. The results of the comparative simulation test between MPPT ZOA and MPPT PSO are shown in Table 5.

Table 5. Simulation Results of MPPT ZOA and MPPT PSO

Pattern of PV	Method	P_{max} (W)	P_{MPPT} (W)	Time (s)	Percentage (%)	Power (%)
Normal Conditions	ZOA	102.211	102.312	0.6227	100	7.40
	PSO		102.026	0.6089	99.81	7.14

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	NON MPPT		94.74	-	-	-
Pattern 1	ZOA	55.123	55.122	0.6313	99.99	30.32
	PSO		46.362	0.6269	84.10	17.15
	NON MPPT		38.41	-	-	-
Pattern 2	ZOA	61.008	61.008	0.6313	100	42.50
	PSO		59.125	0.6367	96.91	40.67
	NON MPPT		35.08	-	-	-
Pattern 3	ZOA	64.606	64.604	1.232	99.99	33.78
	PSO		64.599	1.526	99.92	33.78
	NON MPPT		42.78	-	-	-
Average tracking time, accuracy & power gain of MPPT ZOA				0.779	99.99	28.5
Average tracking time, accuracy & power gain of MPPT PSO				0.850	95.18	24.68

The simulation results comparing the ZOA and PSO algorithms reveal that the ZOA algorithm successfully produces maximum PV power, with results that are close to the target power. Meanwhile, the PSO algorithm yields power tracking results that are slightly below those of the ZOA algorithm, and in some cases, it cannot approach the target power. We acknowledge the importance of placing our findings in the context of previous research. Demonstrate various developed MPPT algorithms, each with its strengths and weaknesses. In this comparison, the ZOA algorithm shows better performance in more varied conditions, supporting our finding that ZOA is more responsive to environmental changes than PSO.

$$\%Power\ increase = \frac{Power\ MPPT - Power\ without\ MPPT}{Power\ MPPT} \times 100\% \quad (4)$$

In Table 5, the results show the percentage increase in power. The purpose of this calculation is to determine how much power the used algorithm increases compared to testing without MPPT. Non-MPPT power is obtained from the calculated duty cycle value, meaning it does not involve tracking time or accuracy. Non-MPPT power is used to determine the increase in power from the MPPT ZOA and PSO results. We agree that discussing the limitations and challenges of ZOA is essential. Although ZOA shows advantages, some potential challenges include high computational demands and implementation complexity in real-world scenarios, especially in real-time systems. This aligns with research by Sharma et al. (2021), which notes that more complex optimization algorithms can slow down system responses in dynamic environments. We recommend further research to develop solutions that enable ZOA to be applied more effectively in various practical scenarios.

On the other hand, the PSO algorithm can increase PV power by an average of 24.68%, with an average tracking accuracy of 95.18% and an average tracking time of 0.850 seconds. Figure 16 presents the graphical comparison of the power increase between MPPT ZOA and MPPT PSO.

We agree that the impact of environmental factors on ZOA's performance is crucial. That variables like temperature, humidity, and angle of light incidence can influence solar panel efficiency and MPPT algorithms. We suggest further research to understand how ZOA can be optimized in extreme environmental conditions and to test this algorithm in simulations that account for varying environmental factors.

Figure 16 illustrates the power increase curve for MPPT ZOA and PSO. This power increase test was conducted under four conditions: non-shading, pattern 1, pattern 2, and pattern 3. The power increase in MPPT ZOA is superior compared to MPPT PSO. We value the suggestion for a more structured approach to discussing the results. To improve clarity, we will categorize the results based on main themes, such as Power Accountability, Tracking Accuracy, and Response Speed. Which suggests that organizing research findings can help convey information more effectively and coherently.

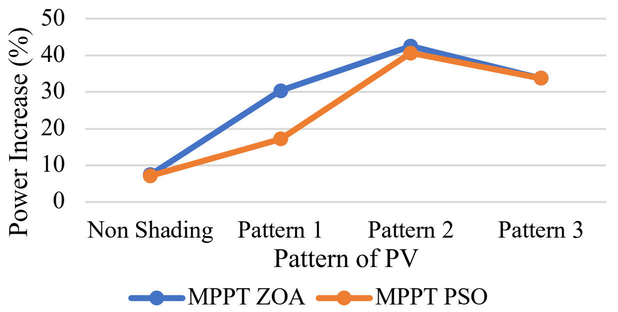

Fig. 16. Power Rise Curve of ZOA MPPT Simulation with PSO MPPT

B. Hardware

From Figure 15, the data shows that the ZOA algorithm is slightly superior when compared to the PSO algorithm in every condition and shading pattern that has been determined. This can be seen in the MPPT ZOA graph which can reach the Pmax value in each condition, while the PSO algorithm is still unable to reach Pmax in several conditions. The comparison test results of MPPT ZOA hardware with MPPT PSO are shown in Table 6.

Table 6. Comparison Results of MPPT ZOA and MPPT PSO Algorithms on Hardware

Pattern of PV	P_{max} (W)	PMPPT ZOA (W)	PMPPT PSO (W)	ZOA (%)	PSO (%)
Non Shading	83.94	83.82	79.35	99.86	94.67
Pattern 1	50.12	49.40	48.32	98.56	97.81
Pattern 2	60.15	59.23	58.12	98.47	98.13
Pattern 3	62.04	61.39	60.33	98.95	98.27
Average				98.69	97.22

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Table 6 shows the solar panel power when PV uses MPPT ZOA and PSO. In both non-shading and shading conditions, ZOA gets greater tracking accuracy than PSO. MPPT ZOA gets an average tracking accuracy of 98.96% while the PSO algorithm is 97.22%. Although simulation results show promising performance, ZOA MPPT has not been widely applied in the real world, especially in renewable energy applications such as solar panel systems. This gap in applications raises important questions about the practical feasibility of the algorithm and its ability to adapt to the complexity of real-world environments. To fully understand the potential of ZOA, it is imperative to conduct more extensive field testing under various conditions. These conditions should include dynamic weather patterns, which can significantly affect the efficiency and output of solar panel systems. For example, variations in sunlight intensity due to cloud cover, seasonal changes, and geographical differences can affect the performance of solar energy systems. The algorithm must demonstrate its ability to optimise energy production under these fluctuating conditions. Such comprehensive testing is essential not only to validate the performance of the algorithm but also to demonstrate its stability and effectiveness in the long run. By conducting rigorous field trials, researchers can gather valuable data on operational reliability, adaptability and overall efficiency in real-world applications. This will ultimately help build confidence in the potential of ZOA MPPT to improve the performance of renewable energy systems by using new optimisation methods to develop research in the field of MPPT on solar panels.

In the field of solar energy, especially when dealing with solar panel systems subjected to partial shading, the ability to accurately track the MPP is critical. This need arises from the fact that partial shading can significantly alter the power output characteristics of solar panels, leading to multiple localised maximum points in the power-voltage curve. Therefore, the effectiveness of Maximum Power Point Tracking (MPPT) algorithms becomes crucial, as these algorithms must efficiently navigate these complexities to ensure optimal energy extraction. Among the various strategies used for MPPT, metaheuristic algorithms have become well-known for their adaptability and robustness in dynamic environments. Recent research has highlighted the Zebra Optimisation Algorithm (ZOA) as a standout algorithm in this domain. With an impressive average accuracy of 99.99%, ZOA has demonstrated its ability to consistently identify MPPs, even under challenging conditions such as partial shadows. This outstanding performance not only underscores the effectiveness of the algorithm, but also positions it as a leading choice among its peers in the MPPT field. When comparing ZOA with other widely used metaheuristic algorithms, the difference in tracking accuracy becomes apparent. Genetic Algorithm (GA), a traditional and well-established method, achieves an average accuracy of about 99.28% [31]. While this is commendable, it is still far from the accuracy demonstrated by ZOA. Similarly, the Salp Swarm Algorithm (SSA) recorded an accuracy of up to 97.62% [32], which, while useful, does not match the higher benchmarks set by ZOA and GA. Grey Wolf Optimizer (GWO) also showed strong performance, with an average accuracy of 99.77% [33], making it a competitive alternative for MPPT applications. Meanwhile, Firefly Algorithm (FA) lagged slightly behind, achieving an average accuracy of 96.80% [34]. Lastly, the Harris Hawk Optimisation (HHO) algorithm stands out with a tracking accuracy of 99.94% [18], further illustrating the diversity of effective strategies available for MPP tracking. In the realm of solar energy harvesting, particularly when dealing with solar panel systems that experience partial shading, the ability to accurately track the Maximum Power Point (MPP) is paramount. This necessity arises from the fact that partial shading can significantly alter the power output characteristics of solar panels, leading to multiple local maxima in the power-voltage curve. Consequently, the effectiveness of Maximum Power Point Tracking (MPPT) algorithms becomes crucial, as they must efficiently navigate these complexities to ensure optimal energy extraction. As advancements in the field of solar energy optimization continue to progress, the results obtained from these algorithms highlight the critical importance of selecting the appropriate method for maximizing energy production. The choice of algorithm can have profound implications for the efficiency of solar energy systems, particularly in environments where shading is a common occurrence. By optimizing the tracking of the maximum power point, these algorithms not only enhance the energy yield of solar panels but also contribute to the overall sustainability and viability of solar energy as a renewable resource. In conclusion, the ongoing research and development in MPPT techniques underscore the necessity of employing sophisticated metaheuristic algorithms tailored to the specific challenges posed by partial shading. As the technology evolves, the integration of advanced optimization strategies will play a pivotal role in improving the performance and reliability of solar energy systems, ultimately leading to greater adoption and utilization of solar power in the global energy landscape.

This research has significant implications for society, especially in improving the efficiency of renewable energy utilisation such as solar panels. With excellent MPPT accuracy through the application of ZOA, the system enables maximum power extraction from solar panels, even under complex partial shading conditions. This has a direct impact on reducing energy losses, which can economically reduce electricity costs for solar panel users, both individuals and communities. In addition, this increase in energy efficiency contributes to a reduction in the need for fossil-based energy sources, supporting the transition towards a cleaner and more sustainable environment. For rural communities or remote areas that rely on solar panels as their main source of energy, this technology offers a more stable and reliable solution.

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ZOA's ability to optimise power even under dynamic weather conditions makes it suitable for deployment in locations with uneven sunlight intensity throughout the day. Furthermore, this increased efficiency can encourage the accelerated adoption of solar panels in the household, industrial, and public infrastructure sectors, thereby expanding access to renewable energy and improving the overall quality of life. With this research, the public can obtain cost-effective and environmentally friendly solutions for energy needs, in line with the goal of sustainable renewable energy development.

This research reveals a new way to improve the efficiency of solar panel systems under partial shading with an animal behaviour-inspired optimisation approach. The application of ZOA enables solar panels to achieve higher efficiency under complex conditions, optimising renewable energy utilisation. These findings show the potential for large-scale application in distributed renewable energy systems, especially in areas with weather fluctuations. In addition, ZOA can be the basis for the development of more adaptive MPPT optimisation algorithms in the future.

5. CONCLUSION

The research focused on the use of the ZOA algorithm combined with MPPT (Maximum Power Point Tracking) on the Buck Converter under partial shading conditions. The test results show that the ZOA method is effective in maximizing power output in both shaded and non-shaded situations. A comparative analysis was conducted between the ZOA and PSO (Particle Swarm Optimization) methods to evaluate their performance in both conditions. The simulation results indicate that the ZOA method outperforms the PSO method, achieving an average accuracy of 99.99% and a faster tracking time of 0.779 seconds, with a power increase of 28.5%. In contrast, the PSO method achieved an average accuracy of 95.18% with a tracking time of 0.850 seconds and a power increase of 24.68%. Additionally, hardware testing showed that ZOA also outperformed PSO in power tracking, with ZOA achieving an accuracy of 98.96% compared to PSO's 97.22%. This highlights the importance of renewable energy sources in reducing reliance on fossil fuels, demonstrating significant implications for innovation in the renewable energy field. The conclusion also outlines future research directions, such as applying the ZOA algorithm to other types of converters, exploring the integration of ZOA with machine learning techniques, and developing a prototype monitoring system based on ZOA. The practical implications of these findings for industry stakeholders are crucial, as implementing the ZOA algorithm in MPPT systems can enhance the efficiency of power collection from solar panels and lower operational costs. A critical reflection on the limitations of this research reveals that, although the ZOA algorithm shows promising results, the study has constraints regarding scale and testing conditions that need further exploration. As the complexity of renewable energy systems increases, continuous innovation is necessary to address efficiency and reliability challenges, emphasizing the need for collaboration among researchers, industry, and government to foster an environment that supports research and the development of new technologies.

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