

Design of MPPT Controller for Photovoltaic Systems under Partial Shading Conditions Using SMA and GWO Algorithms

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Abstract - The power-voltage (P-V) characteristic of photovoltaic (PV) systems operating under partial shading conditions (PSC) becomes highly nonlinear, resulting in several local maximum power points (LMPPs) that make many traditional maximum power point tracking (MPPT) techniques unable to locate the global maximum power point (GMPP) consistently. In this study, two advanced MPPT controllers based on the Grey Wolf Optimiser (GWO) and the Slime Mould Algorithm (SMA) are developed and evaluated for extracting maximum power from PV systems during both uniform irradiance (UI) and nonuniform irradiance (NUI) conditions. The performance of each controller is examined through MATLAB/Simulink simulations by analysing GMPP tracking accuracy, convergence time, and dynamic response. Experimental validation is performed using a real-time digital control hardware setup to assess the controllers under diverse irradiance conditions. Results show that while the SMA-based controller demonstrates good adaptability and effective exploration capability, the GWO-based controller offers superior tracking speed, improved stability, and more reliable identification of the GMPP. Overall, the comparative analysis confirms that GWO delivers the best performance among the evaluated algorithms for MPPT under partial shading.

Keywords: PV system, DC-DC Boost converter, MPPT, SMA algorithm, GWO algorithm, partial shading condition.

I. INTRODUCTION

The growing global demand for clean and sustainable energy has significantly accelerated the adoption of photovoltaic (PV) technology as an alternative to fossil-fuel-based power generation. However, the practical efficiency of PV systems is strongly influenced by factors such as mismatch losses, module ageing, dirt accumulation, dynamic irradiance, and shading effects, all of which reduce power output and system reliability [1]–[4]. To address these challenges, Maximum Power Point Tracking (MPPT) controllers are essential components of PV power-conditioning units,

ensuring optimal extraction of energy by continuously adjusting the operating voltage and current of the PV array under varying environmental conditions [5]–[7].

Traditional MPPT techniques such as Perturb and Observe (P&O) and Incremental Conductance (IC) have been widely adopted due to their simplicity, low implementation cost, and ease of integration. However, these methods suffer from steady-state oscillations, slow tracking dynamics, and poor performance under rapidly changing irradiance or partial shading conditions (PSC) [8], [9], [21]. To overcome these limitations, modern optimization-based and intelligent MPPT methods have been extensively explored, including Particle Swarm Optimization (PSO), Cuckoo Search, Ant Colony Optimization, Artificial Bee Colony, Salp Swarm Optimization, Grey Wolf Optimization (GWO), and hybrid evolutionary algorithms [10]–[17]. These techniques demonstrate superior global search ability, enhanced tracking accuracy, and improved convergence speed, especially in the presence of multiple peaks in the PV power curve caused by PSC.

Among these advanced approaches, GWO has received notable attention for its simple structure, fast convergence, and strong ability to locate the global maximum power point (GMPP) under non-uniform irradiance [11], [15], [22]. Conversely, the recently introduced Slime Mould Algorithm (SMA) exhibits excellent adaptive weighting, strong balance between exploration–exploitation, and robust performance on complex multimodal optimization landscapes, making it a promising candidate for MPPT applications in PSC environments [17], [18]. Comparative studies and optimization-based PV control frameworks further emphasize the need for intelligent MPPT methods that effectively manage the nonlinear and time-varying characteristics of PV systems [19].

The performance of MPPT algorithms is also highly dependent on the choice of DC–DC converter topology, which influences dynamic response, voltage regulation capability, input–output gain, and efficiency under different climatic

conditions [20], [23]–[25]. Numerous studies highlight the significance of converter design in improving overall system stability and MPPT effectiveness, especially for applications involving partial shading and distributed PV configurations [23]–[26].

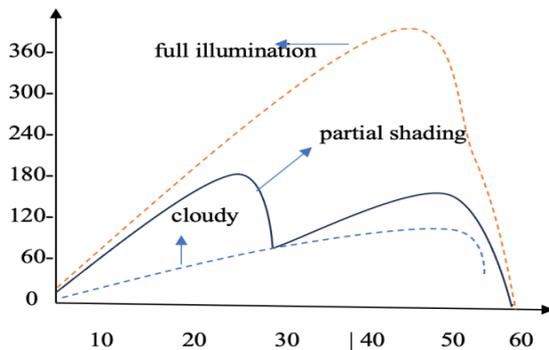


Figure 1: Partial shading conditions of a PV panel

Overall, the literature establishes a clear transition from classical MPPT methods toward advanced metaheuristic algorithms to achieve faster, more accurate, and globally optimal tracking performance. In particular, GWO and SMA have emerged as powerful optimization tools capable of handling nonlinear, multimodal power characteristics under partial shading. Motivated by these advancements, this work investigates and compares the performance of GWO- and SMA-based MPPT controllers to determine which algorithm offers superior tracking efficiency, convergence response, and reliability under challenging PSC scenarios.

This paper compares the performance of the SMA and GWO Maximum Power Point Tracking (MPPT) algorithms under both uniform irradiance and partial shading conditions. The photovoltaic system was modelled and simulated in MATLAB/Simulink, and voltage regulation was achieved using a boost DC–DC converter.

Under partial shading conditions, the nonlinear and multi-peak nature of the P–V characteristic significantly challenges the ability of MPPT algorithms to locate the true global maximum power point. Among the advanced optimization techniques, the Grey Wolf Optimizer (GWO) and the Slime Mould Algorithm (SMA) have demonstrated strong capability in addressing these issues. The GWO algorithm, inspired by the social hierarchy and coordinated hunting behaviour of grey wolves, achieves a strong balance between exploration and exploitation. This results in faster convergence, improved accuracy in identifying the GMPP, and stable operation even when irradiance changes rapidly. In comparison, the SMA-based MPPT controller exhibits strong adaptability and effective search behaviour, allowing it to handle multi-peak power curves with good precision and reduced oscillations.

Both algorithms were implemented in MATLAB/Simulink with a boost DC–DC converter for performance evaluation. Simulation and experimental results show that SMA achieves high tracking efficiency and maintains smooth power extraction, while GWO consistently provides superior tracking speed, greater stability, and more reliable GMPP detection under severe partial shading. Overall, the comparative analysis confirms that although both algorithms enhance MPPT performance under dynamic conditions, GWO delivers the most robust and efficient tracking capability, making it highly suitable for PV systems operating under nonuniform irradiance.

II. METHODOLOGY AND SYSTEM DESIGN

The methodology adopted in this work focuses on modelling, controlling, and comparing four MPPT techniques integrated with a photovoltaic (PV) system. The study emphasises how these MPPT algorithms respond to different levels of solar irradiance. A detailed simulation model was created in MATLAB/Simulink to assess the performance and effectiveness of these MPPT techniques. With particular attention to their efficiency under partial shading conditions.

A. System Overview

The main components of the solar PV system are as follows:

- **PV array:** Transforms sunlight into electrical energy for use in the system.
- **MPPT controller:** Continuously adjusts the operating point of the PV system to extract the maximum possible power.
- **Boost DC–DC converter:** Increases the PV array’s output voltage to match the load requirements.
- **Load:** Represents the connected power demand or the grid interface.

Figure 2 illustrates the system’s schematic layout. The control approach works by modifying the duty cycle of the DC–DC converter, ensuring the PV system operates at or close to the Maximum Power Point (MPP). This regulation relies on real-time measurements of voltage and current from the sensors.

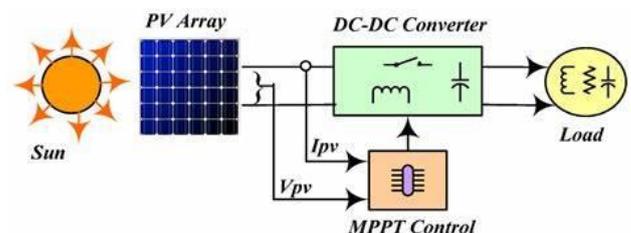


Figure 2: Schematic configuration of the system

B. PV Array Modelling

In this study, the photovoltaic (PV) array is represented using the The PV module is commonly represented using the single diode model. Its equivalent circuit includes:

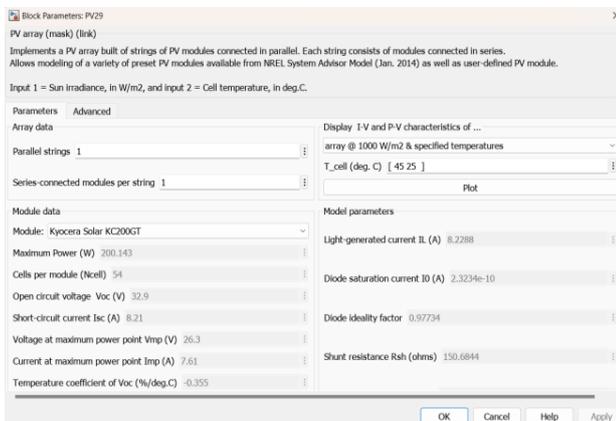
- A **current source** (I_L) representing the photocurrent generated by sunlight.
- A **diode** representing the p–n junction of the cell.
- A **series resistance** (R_s) accounting for internal resistive losses.
- A **shunt resistance** (R_{sh}) representing leakage current paths.

The output current I of the PV module is described by the nonlinear current–voltage (I – V) relationship

$$I = I_L - I_0 \left[\exp\left(\frac{V + IR_s}{nVT} - 1\right) - \frac{V + IR_s}{R_{sh}} \right] \quad (1)$$

Where:

- I_0 is the diode saturation current,
- V_T denotes the thermal voltage, and
- n diode ideality factor.



III. MPPT CONTROL STRATEGY

In the Literature, many MPPT techniques are proposed using evolutionary algorithm (EA) techniques or other methods under partial shading conditions, such as follows.

A. Slime Mould Optimization Algorithm (SMA)

The Slime Mould Algorithm (SMA) is a new optimization method developed by Li and his team in 2020. It is inspired by slime mould, a simple organism that searches for food in nature. Slime moulds change their movement depending on food availability.

Scientists studied this behaviour and converted it into mathematical rules.

These rules form the SMA algorithm, which helps find the best solution to a problem.

SMA copies this behaviour:

- It starts with many possible solutions (agents), like many slime mould strands searching for food.
- Each solution evaluates how “good” it is using a fitness value.
- Based on this value, the algorithm decides whether to explore new regions or focus on the best region found so far.
- With very few control parameters, SMA automatically balances between wide search and fine-tuning.

1) Updating Position – Main Equation

The general position update rule is:

$$X(t + 1) = \begin{cases} X_b(t) + v_b \cdot W \cdot (X_A(t) - X_B(t)), & r < p, \\ v_c \cdot X(t), & r \geq p, \dots(2) \end{cases}$$

This equation decides where the slime mould moves next.

- If the random number r is smaller than p , the agent moves toward the best solution found so far (food source).
- If r is larger than p , the agent just keeps moving in its current direction.
- $X(t)$ → current position
- $X(t+1)$ → new position
- X_b → best agent (highest food smell)
- X_A, X_B → random agents used to create variation
- v_b, v_c → vibration factors controlling movement
- W → weight representing the slime mould’s strength
- This equation helps balance exploration vs exploitation.

2) Control Parameter p

$$p = \tanh\left(\frac{S(i) - DF}{l}\right) \dots\dots\dots(3)$$

- p controls whether the slime mould explores or goes toward food.
- It depends on the fitness rank of each solution.
- When a solution is close to the best one, p increases, causing more exploitation.
- When it is far, p decreases, causing more exploration

3) Vibration Parameter

$$v_b = [-a, a]$$

$$a = \text{actanh}\left(-\frac{t}{t_{max}}\right) \dots\dots\dots(4)$$

This adjusts how strongly the slime mould moves.

- At the beginning (small t), movement is large → more exploration
- Later (large t), movement becomes small → more fine search

This helps the algorithm converge smoothly.

4) Weight Function W

$$W_i = \begin{cases} 1 + r \cdot \log\left(\frac{bf - S(i)}{bf - wf + 1}\right), & \text{if condition,} \\ 1 - r \cdot \log\left(\frac{bf - S(i)}{bf - wf + 1}\right), & \text{otherwise.} \end{cases} \dots\dots\dots (5)$$

The weight W represents the slime mould’s “power” or “energy.”

- If an agent has good fitness, its W is higher → it becomes stronger and moves more confidently.
- If an agent has poor fitness, its W decreases → weaker movement.

Flow chart of the SMA

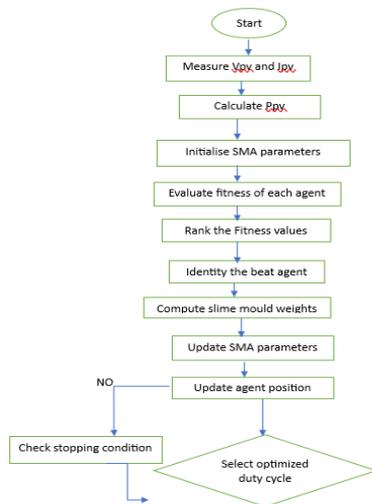


Figure 3: Slime Mould Optimization

B. Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) is based on the social structure and cooperative hunting strategies of grey wolves. In this algorithm, the wolves are organised into four hierarchical levels.

- **Alpha (α):** Represents the leader of the pack, corresponding to the best solution.
- **Beta (β) and Delta (δ):** Represent the second- and third-best solutions, helping the alpha wolf direct and refine the search for the optimal solution.

- **Omega (ω):** The rest of the wolves, which follow the decisions of the leading members.

Encircling Prey

The wolves update their positions with respect to the prey (i.e., the optimal solution) using the equations:

$$D^{\vec{}} = |C^{\vec{}} \cdot X^{\vec{}}p(t) - X^{\vec{}}(t)| \quad (6)$$

$$X^{\vec{}}(t+1) = X^{\vec{}}p(t) - A^{\vec{}} \cdot D^{\vec{}} \quad (7)$$

Where:

- $X^{\vec{}}p(t)$ is the prey’s position (the best solution so far),
- $X^{\vec{}}(t)$ is the position of a wolf,
- $A^{\vec{}} = 2a \cdot r_1 - a_1$ $C^{\vec{}} = 2r_2$,
- a decrease linearly from 2 to 0 over the course of iterations,
- r_1 and r_2 are random numbers in the range [0,1].

Hunting Strategy

The hunting process is modelled by updating wolf positions relative to the three leading wolves (α, β, δ) as:

$$X^{\vec{}}(t+1) = \frac{\vec{X}1 + \vec{X}2 + \vec{X}3}{3} \dots\dots\dots(8)$$

Here, $X^{\vec{}}_1$, $X^{\vec{}}_2$, and $X^{\vec{}}_3$ represent the calculated positions with respect to α, β, and δ.

Flow chart of the GWO algorithm

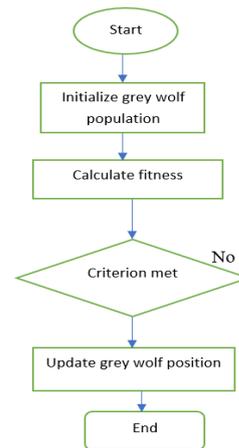


Figure 4: Grey Wolf Optimization

IV. DC-DC BOOST CONVERTER DESIGN

To make the PV array voltage output change and equal the load value or grid value, a boost converter is inserted. The duty cycle D created by the MPPT command controls it and the voltage output of the converter is calculated as a product of

D and the maximum output voltage. The key specifications are presented in Table 1.

$$V_{out} = \frac{V_{in}}{1-D} \quad (9)$$

Table 1: Key specifications

Parameter	Value
Inductor (L)	1.145 mH
Capacitor (C1 & C2)	10 μF, 0.4567 μF
Load Resistance	50 Ω
Switching Frequency	50 kHz
Switch	MOSFET
Diode	Ideal

V. SIMULATION ENVIRONMENT AND SETUP

The complete system was simulated in MATLAB/Simulink, where the PV array, MPPT controller, and converter were captured as shown in Figure.

- Solar irradiance profiles: 1000 W/m² (uniform), 800,600,400 ,200W/m² (partial shading)
- Temperature: Fixed at 25°C
- Metrics analysed: Power output, voltage, convergence speed, tracking efficiency.

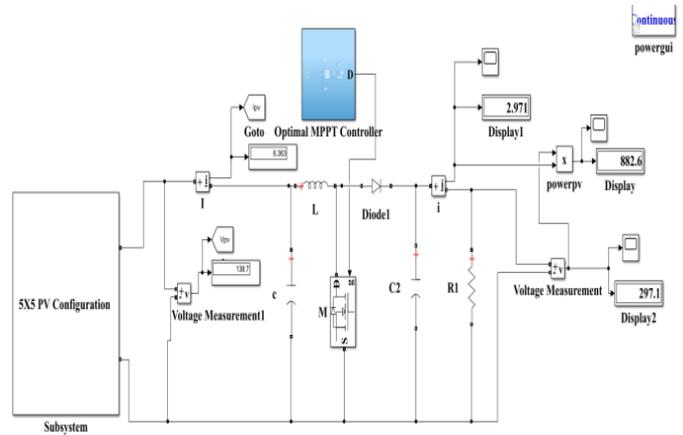


Figure 5: Simulink model for GWO Algorithm MPPT under Partial Shaded Conditions

VI. RESULT AND DISCUSSION

In this study, the performance of advanced Maximum Power Point Tracking (MPPT) techniques, namely the Grey Wolf Optimizer (GWO) and the Slime Mould Algorithm (SMA), was analysed through comprehensive MATLAB/Simulink simulations. Among these, GWO demonstrated superior performance, showing faster convergence, stronger global search ability, and more reliable tracking of the Maximum Power Point (MPP), particularly under partial shading conditions. The objective is to evaluate how effectively these algorithms identify and track the MPP of a photovoltaic (PV) system under both uniform irradiance and partial shading scenarios.

A. Case studies:

1) Full Irradiance Condition (Unshaded)

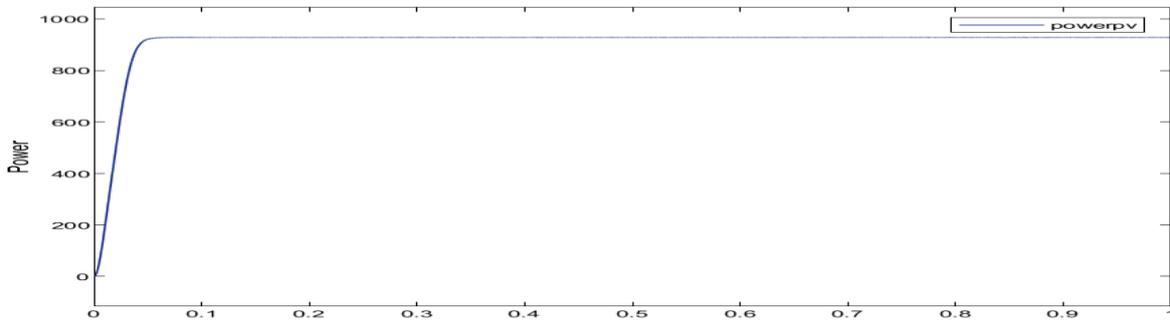
The Maximum Power Point Tracking (MPPT) techniques Slime Mould Algorithm (SMA) and Grey Wolf Optimizer (GWO) are evaluated under partial shading conditions. The SMA algorithm demonstrated effective global search capability and stable tracking performance under varying irradiance. The GWO technique, however, delivered the best overall results, achieving higher output power, superior efficiency, and more stable voltage–current characteristics. Among the tested algorithms, GWO demonstrated the highest tracking accuracy, the fastest convergence, and the most reliable power extraction capability under partial shading conditions.

Table 2: Full Irradiance Conditions

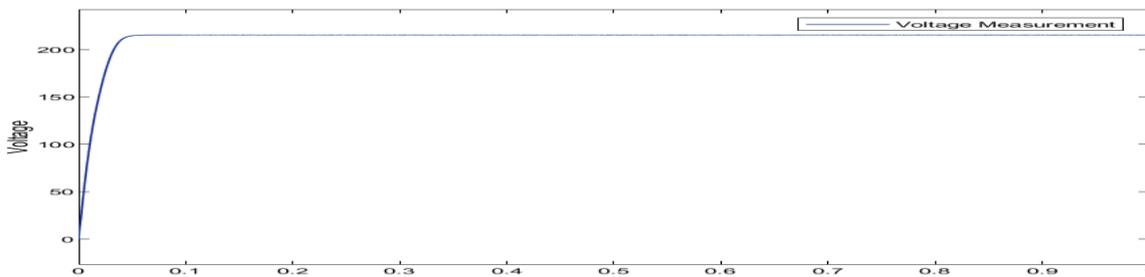
Module1	Module2	Module3	Module4	Module5	SMA algorithm Max. power	GWO Algorithm Max. Power
1000	1000	1000	1000	1000	928.8	1000

Un-shading Condition of the SMA Algorithm Wave forms:

Power:



Voltage:



Current:

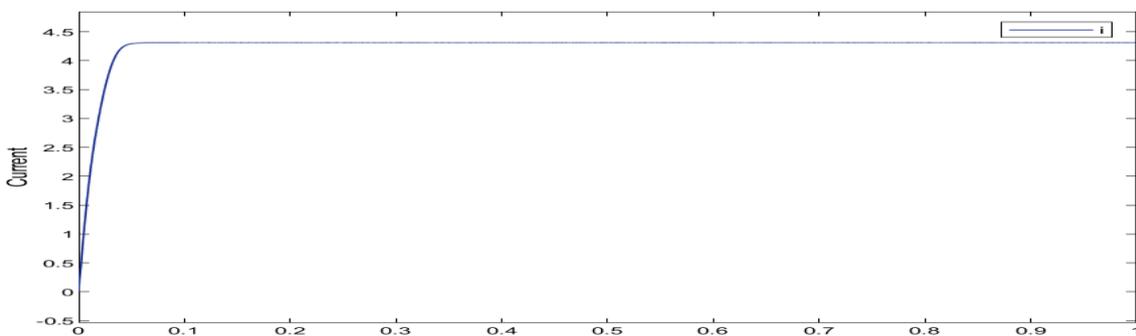
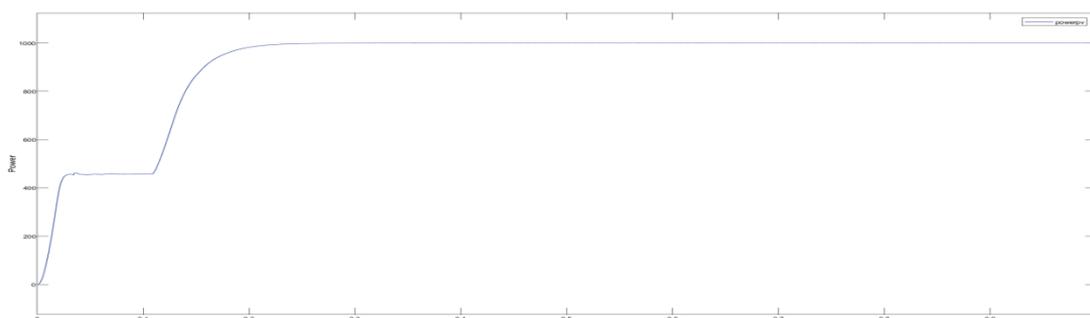


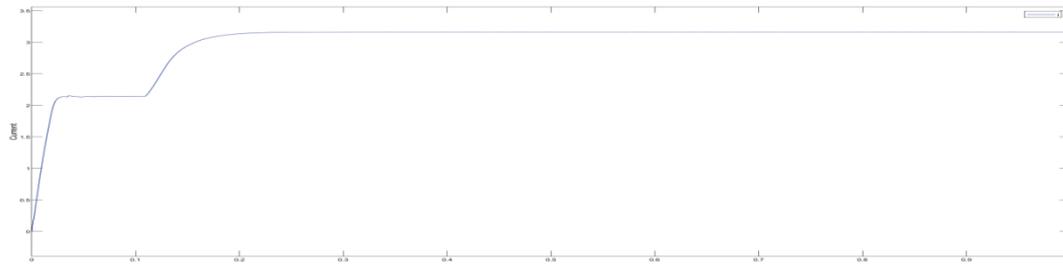
Figure 6: Maximum Power, Current, Voltage with SMA Algorithm

Un shading Condition of the GWO Algorithm wave form:

Power:



Current:



Voltage:

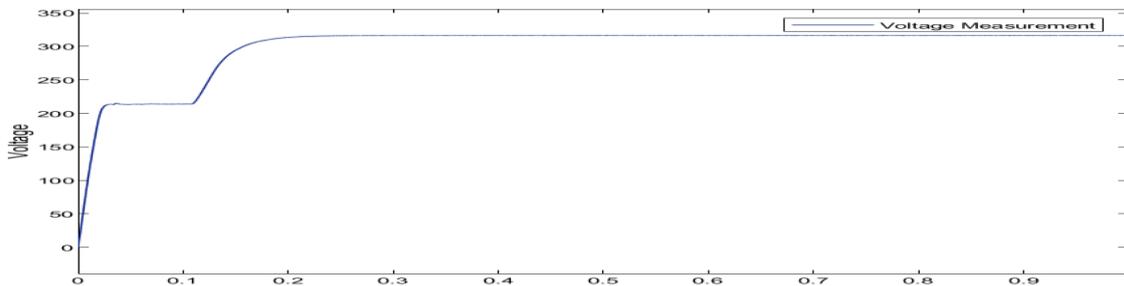


Figure 7: Maximum Power, Current, Voltage with GWO Algorithm wave form

2) Partial shading Conditions:

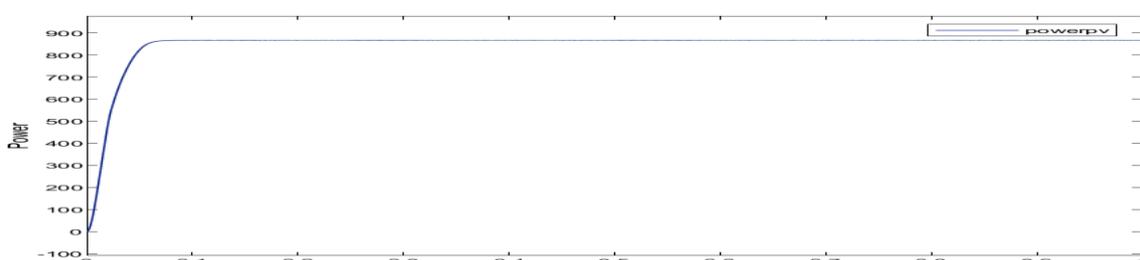
In partial shading scenarios, the evaluation was conducted using two MPPT techniques: the Slime Mould Algorithm (SMA) and the Grey Wolf Optimizer (GWO). Both algorithms were capable of handling the multiple peaks present in the P–V characteristics. However, SMA exhibited only moderate convergence with reasonably steady tracking. GWO, on the other hand, showed noticeably better performance by reaching the global maximum power point more quickly and with higher precision. Overall, GWO demonstrated the highest efficiency and most dependable tracking behaviour for PV systems subjected to partial shading.

Table 3: Partial Shading Condition, Different Cases

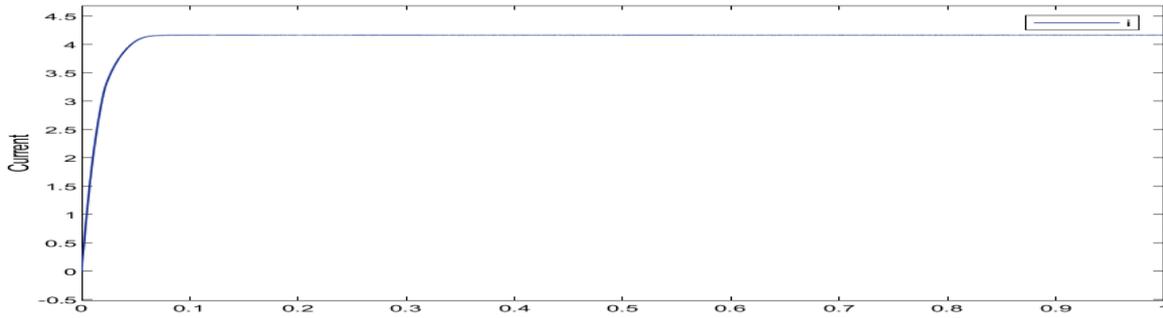
Different Cases	Module 1	Module 2	Module 3	Module 4	Module 5	SMA algorithm Max. power	GWO Algorithm Max. Power
Case 1	1000	1000	1000	1000	800	867.8	882.7
Case 2	1000	1000	1000	800	800	797.4	859
Case 3	1000	1000	800	800	800	724.9	839.5
Case 4	1000	800	800	800	800	755	822.7
Case 5	800	800	800	800	800	754.2	807.2
Case6	1000	800	600	400	200	338.3	366.5

Partial Shading Condition of the SMA Algorithm wave form:

Power:



Current:



Voltage:

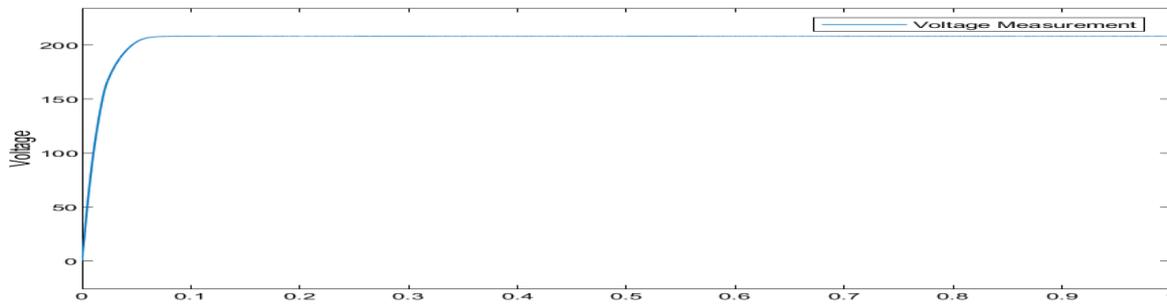
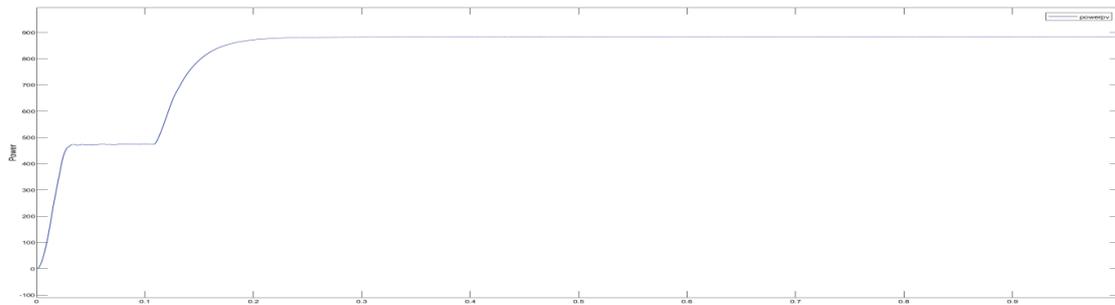


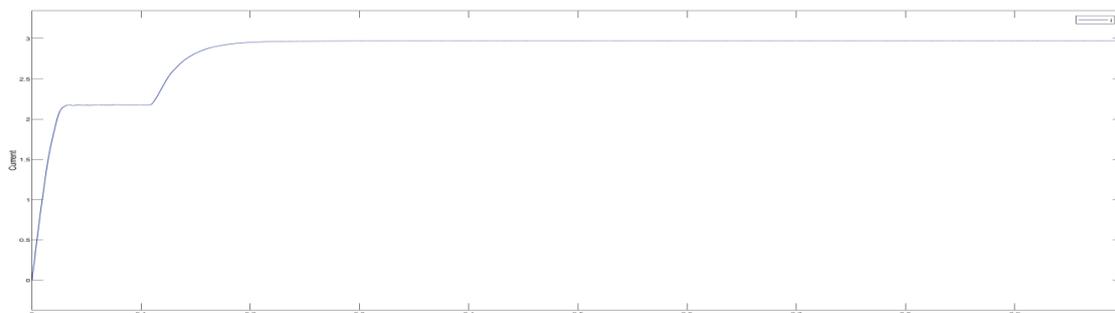
Figure 6: Maximum Power, Current, Voltage with GWO and SMA Algorithm

Partial Shading Condition of the GWO Algorithm Wave forms:

Power:



Current:



Voltage:

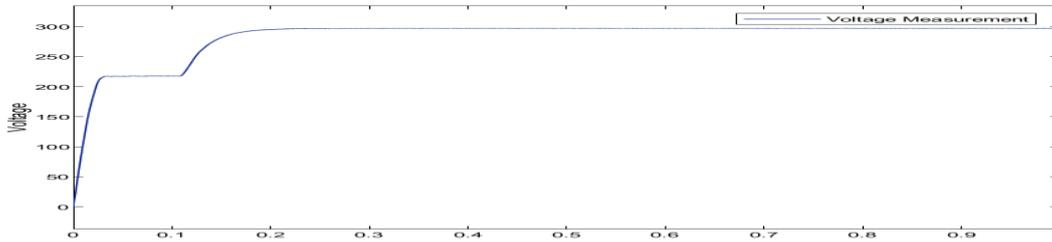


Figure 7: Maximum Power, Current, Voltage with GWO and SMA Algorithm

Comparison of the GWO and SMA algorithms in the partial shading condition

Different Combination of 1000 and (600 W/M²)

Table 3: Partial Shading Condition, Different Combination of 1000 and 600 (W/M²)

Different Cases	Module 1	Module 2	Module 3	Module 4	Module 5	SMA algorithm Max. power	GWO Algorithm Max. Power
Case 1	1000	1000	1000	1000	600	603.2	690.9
Case 2	1000	1000	1000	600	600	581.6	666.1
Case 3	1000	1000	600	600	600	591.1	644.9
Case 4	1000	600	600	600	600	614	626.1
Case 5	600	600	600	600	600	608.1	608.8

Table 5: Partial Shading Condition, Different Combination of 1000 and 400 (W/M²)

Different Cases	Module 1	Module 2	Module 3	Module 4	Module 5	SMA algorithm Max. power	GWO Algorithm Max. Power
Case 1	1000	1000	1000	1000	400	429.56	474.8
Case 2	1000	1000	1000	400	400	336.2	454.3
Case 3	1000	1000	400	400	400	338.4	436.5
Case 4	1000	400	400	400	400	344.2	419.6
Case 5	400	400	400	400	400	224.3	405.6

Table 6: Partial Shading Condition, Different Combination of 800 and 600 (W/M²)

Different Cases	Module 1	Module 2	Module 3	Module 4	Module 5	SMA algorithm Max. power	GWO Algorithm Max. Power
Case 1	800	800	800	800	600	582.5	673.2
Case 2	800	800	800	600	600	558.5	653.3
Case 3	800	800	600	600	600	601.4	636.6
Case 4	800	600	600	600	600	607.7	622
Case 5	600	600	600	600	600	608.1	608.8

Table 7: Partial Shading Condition, Different Combination of 600 and 400 (W/M²)

Different Cases	Module 1	Module 2	Module 3	Module 4	Module 5	SMA algorithm Max. power	GWO Algorithm Max. Power
Case 1	600	600	600	600	400	455.9	481.9
Case 2	600	600	600	400	400	323.9	440.5
Case 3	600	600	400	400	400	257.8	427.6
Case 4	600	400	400	400	400	300.2	416.1
Case 5	400	400	400	400	400	224.3	405.6

VII. CONCLUSION

This work presents a comparative evaluation of two advanced Maximum Power Point Tracking (MPPT) techniques, Grey Wolf Optimizer (GWO) and Slime Mould Algorithm (SMA) for a photovoltaic (PV) system operating under both uniform irradiance and partial shading conditions. The PV system was modelled in MATLAB/Simulink and integrated with a boost DC-DC converter to regulate the output voltage and enhance power extraction. Simulation results confirmed that both GWO and SMA were able to track the maximum power point under ideal irradiance levels; however, their performance differed significantly when shading was introduced. SMA provided stable tracking with moderate convergence behaviour, effectively handling the variations in the P-V characteristics. In comparison, GWO exhibited faster convergence, higher tracking precision, and superior capability to locate the global MPP even in complex shading patterns. Overall, GWO delivered the highest efficiency and most reliable dynamic response, establishing it as the best-performing MPPT method among the evaluated algorithms for real-time PV applications.

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