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Grey Wolf Optimization-Based Global Mppt For Solar-Assisted Hybrid Energy Systems in Oil and Gas Production Facilities

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ABSTRACT - Partial shading in photovoltaic (PV) modules produces multiple power peaks that reduce system efficiency if the global maximum power point is not properly tracked. This condition commonly occurs in oil and gas production facilities due to shadows from industrial structures, requiring MPPT methods with reliable global tracking capability. This study evaluates the Grey Wolf Optimization (GWO) algorithm for global MPPT under eight partial shading scenarios (12.5%–100%) using MATLAB/Simulink simulation. The results show that GWO successfully tracks the global maximum power point under single-, double-, and triple-peak conditions. Under 12.5% shading, the system produces 277.0 W with an efficiency of 99.78%; under 25% shading, it produces 266.7 W with an efficiency of 99.85%; and under 37.5% shading, it produces 204.2 W with an efficiency of 99.90%. Across all scenarios, the algorithm achieves efficiencies above 99% with an average efficiency of 99.61%, which is higher than the 97.20% reported in previous studies. This efficiency improvement of approximately 2–4% increases the contribution of solar energy in PV–diesel hybrid systems and potentially reduces fuel consumption while improving power supply reliability for critical loads in oil and gas production facilities. Unlike conventional metaheuristic approaches such as PSO-MPPT, Flower Pollination Algorithm (FPA), and Differential Evolution (DE), which are sensitive to parameter tuning or prone to premature convergence, the proposed GWO implementation employs a hierarchical three-agent update mechanism (α, β, δ) that enhances global exploration capability across complex multi-peak P–V characteristics. This distinguishes the present study from prior GWO-based MPPT work that relied solely on the alpha agent for position update.

Keywords: solar module, grey wolf optimization, partial shading, hybrid energy system.

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INTRODUCTION

The increasing awareness of climate change has accelerated the integration of renewable energy technologies in various industrial sectors, including oil and gas production facilities. Photovoltaic (PV) systems are increasingly applied in remote and offshore locations to support operational loads such as well monitoring systems, SCADA, and instrumentation equipment (Orosz et al., 2024; Teh et al., 2021). In many facilities, PV is integrated with diesel generators or energy storage to form hybrid energy systems that improve reliability and reduce fuel consumption (Ali et al., 2024; Saleem et al., 2024). However, maintaining optimal PV power output in industrial environments remains challenging due to dynamic environmental conditions such as solar irradiance variation, temperature changes, and partial shading (Hussin et al., 2025; Zulfadli et al., 2022).

Partial shading conditions in oil and gas production facilities are often more complex than those in conventional PV installations. Industrial structures such as flare stacks, drilling towers, pipe racks, cranes, and storage tanks frequently create irregular shadow patterns on PV arrays (Islam et al., 2013; Lian et al., 2013. Environmental factors including clouds, dust, and industrial particles can further intensify shading effects (Khaing et al., 2014; Nguyen, 2015). As a result, PV arrays under partial shading produce nonlinear current–voltage (I–V) and power–voltage (P–V) characteristics with multiple power peaks due to bypass diode operation (Silvestre et al., 2009). In such conditions, conventional MPPT algorithms may become trapped at local maxima instead of identifying the global maximum power point, reducing the efficiency of PV energy harvesting (Femia et al., 2004). Various MPPT techniques have been proposed to address this problem. Conventional methods such as perturb and observe (P&O) and incremental conductance (IC) are simple and widely implemented but are less effective under partial shading conditions (Ananda-rao et al., 2025; Asyadi & Muliadi, 2023). Intelligent and soft-computing approaches such as fuzzy logic controllers also require complex rule bases and parameter tuning (Chiu, 2010). Metaheuristic algorithms including Ant Colony Optimization, Firefly Algorithm, Artificial Bee Colony, and Particle Swarm Optimization have been introduced to improve global search capability, although their tracking stability and computational complexity may vary (Ishaque & Salam, 2012; Sundareswaran et al., 2015). Grey wolf optimization (GWO), proposed by Mirjalili et al., is a metaheuristic algorithm inspired by the social hierarchy and hunting mechanism of grey wolves (Mirjalili et al., 2014). The algorithm has advantages such as a small number of control parameters and stable exploration capability in complex optimization problems (Nimma et al., 2018). Previous studies have demonstrated the potential of GWO in MPPT applications under changing irradiation conditions (Mohanty et al., 2017) and partial shading scenarios (Faulianur et al., 2018; Nimma et al., 2018).

However, most existing studies focus primarily on algorithmic performance and limited shading scenarios, while the application of global MPPT algorithms in industrial environments such as oil and gas production facilities has not been extensively investigated. Therefore, the novelty of this study lies in the application of Grey Wolf Optimization for global MPPT under realistic partial shading scenarios in oil and gas production facilities, combined with the evaluation of its impact on PV–diesel hybrid energy systems.

MATLAB/Simulink simulations are used to analyze PV array behavior under multiple shading patterns and to evaluate the capability of GWO in tracking the global maximum power point. The results aim to support reliable renewable energy integration in hybrid power systems used in oil and gas operations.

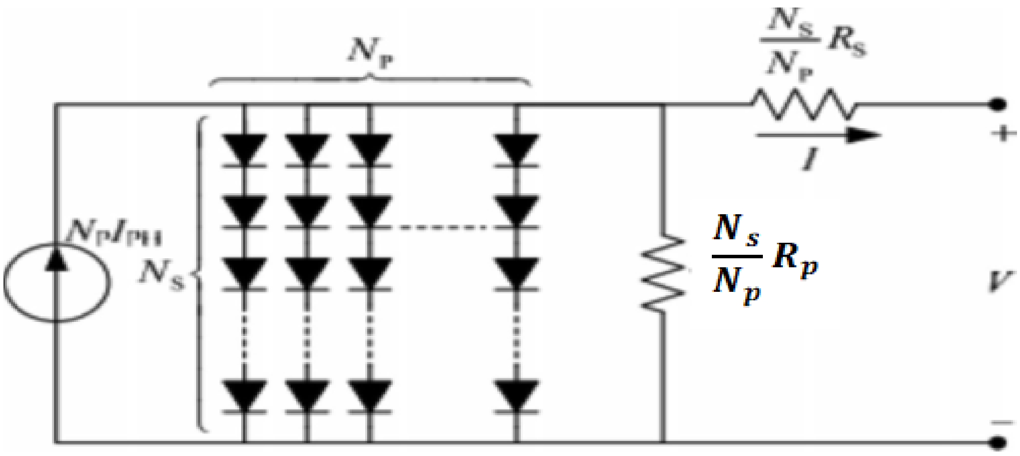

Figure 1. Equivalent diagram of a solar module (Ghosh & Mandal, 2023; Nguyen, 2015).

MODELLING OF SOLAR MODULE

Photovoltaic (PV) systems function to convert solar radiation energy into electrical energy (Govindarajan et al., 2025). In hybrid energy systems at oil and gas production facilities, accurate modeling of solar module characteristics, which generally uses one or two important diode models, is essential to ensure the reliability of power supply in remote locations (Villalva et al., 2009). The single diode model is more commonly used because it is simple yet representative in describing the electrical characteristics of solar cells through the parameters Iph, Id, Ip, as well as series resistance (Rs) and parallel resistance (Rp) (Jazayeri et al., 2013):

$$I = I_{ph} - I_0\left[e^{\frac{q(V+IR_s)}{nkT}} - 1\right] - \frac{(V+IR_s)}{R_p} \quad (1)$$

An arrangement of several solar cells in a single unit is called a solar module. These modules can then be connected in series or in parallel to form an array. The equivalent diagram of a solar module is shown in Figure 1.

The solar module modeling equation is expressed as follows (Ghosh & Mandal, 2023; Nguyen, 2015):

$$I = N_p\left\{I_{ph} - I_0\left[exp\left(\frac{V/N_s + IR_s/N_p}{nVt}\right) - 1\right]\right\} - I_{sh} \quad (2)$$

With

$$V_T = \frac{kT}{q} \quad (3)$$

$$I_{sh} = \frac{V\left(\frac{N_p}{N_s}\right) + IR_s}{R_p} \quad (4)$$

where I is the output current, V is the output voltage, n is the diode ideality factor, T is the cell temperature, k is the Boltzmann constant, q is the electron charge, and Rs and Rp represent series and parallel resistances.

Partial shading conditions and bypass diodes

Partial shading frequently occurs in oil and gas facilities due to shadows from structures such as flare stacks, pipes, and processing equipment. Uneven irradiation across PV modules produces nonlinear I–V and P–V characteristics. In series configurations without protection, shaded cells may behave as open circuits (Jung et al., 2014). Therefore, bypass diodes are installed to allow current to bypass shaded modules and reduce power loss (Muliadi et al., 2021; Silvestre et al., 2009), as illustrated in Figure 2. However, before activation, shaded cells may experience reverse bias that can cause overheating and degradation (Jung et al., 2014; Muliadi et al., 2021).

Maximum power point tracking (MPPT)

MPPT ensures that PV systems operate at the maximum available power under varying environmental conditions (Lyden et al., 2013; Rana et al., 2018. An MPPT system typically consists of PV modules, a controller, and a DC–DC converter that adjusts the duty cycle based on voltage and current measurements to maintain optimal power output (Román et al., 2006), as shown in Figure 3.

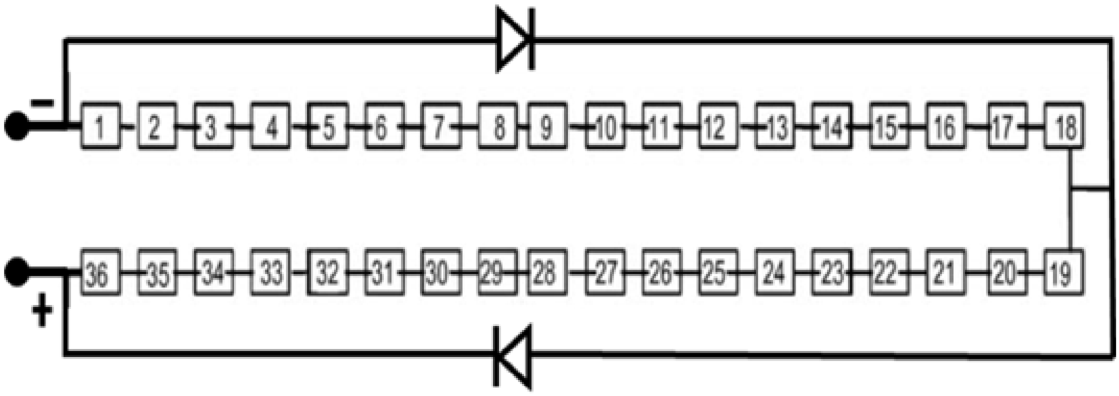

Figure 2. Modeling of a solar cell array with two bypass diodes (Muliadi et al., 2021; Silvestre et al., 2009

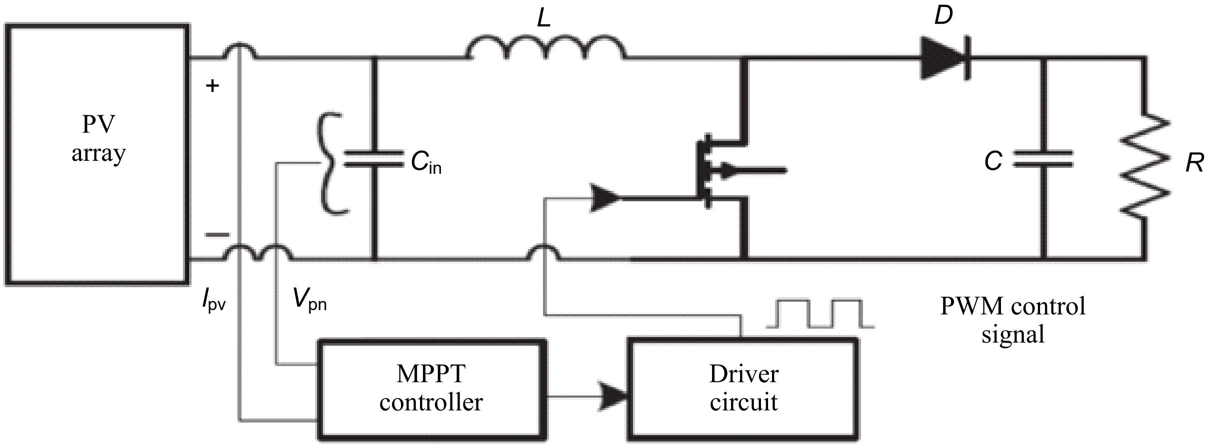

Figure 3. Block diagram of the tracking system

Grey wolf optimization (GWO) algorithm

Grey wolf optimization (GWO) is a metaheuristic algorithm inspired by the hierarchical hunting behavior of grey wolves (Mirjalili et al., 2014). The population is divided into alpha (α), beta (β), delta (δ), and omega (ω), where the alpha wolf represents the best solution. In this study, GWO is used to determine the optimal duty cycle of the converter to track the global maximum power point (GMPP) of the PV system under partial shading conditions.

METHODOLOGY

This study is conducted using MATLAB/ Simulink simulations to evaluate the performance of the grey wolf optimization (GWO) algorithm as a global maximum power point tracking (MPPT) method under partial shading conditions. The methodology includes solar module selection, PV array configuration, modeling and validation under standard test conditions (STC), development of partial shading scenarios, and implementation of the GWO algorithm to track the global maximum power point on the P–V curve. In addition, the study evaluates the contribution of PV energy in a PV–diesel hybrid system, including fuel consumption reduction, generator operating hours, reliability indicators, and economic implications. Compared to previous work where GWO used only the alpha parameter as the candidate solution (Mohanty et al., 2015), this study applies a hierarchical update mechanism using the three best solutions (alpha, beta, and delta) to improve global exploration capability and reduce the risk of convergence to local power peaks under complex partial shading conditions (Faulianur et al., 2018).

Selection of solar module type

The photovoltaic module used in this study is a polycrystalline SPN055P-N with a rated power of 55 Wp consisting of 36 cells. The module has a maximum voltage (Vmp) of 18.18 V, maximum current (Imp) of 3.1 A, open-circuit voltage (Voc) of 22.1 V, and short-circuit current (Isc) of 3.31 A. The module parameters are evaluated under standard test conditions (STC) with irradiation of 1000 W/m², temperature of 25°C, and Air Mass 1.5 (Pratama et al., 2019).

Determination of solar module configuration

The PV system consists of eight modules arranged in a 4S–2P configuration, where four modules are connected in series and two strings are connected in parallel. This configuration increases the output power and produces multiple peaks on the P–V curve under partial shading conditions. The total array dimension is approximately 260.8 cm × 127.8 cm.

Module configuration modeling and simulation

The PV array is modeled using MATLAB/ Simulink R2018b based on the electrical characteristics of the selected module. Model validation is performed under STC conditions (1000 W/m² irradiation and 25°C temperature) without shading to verify the accuracy of the PV electrical behavior.

Partial shading test scenario

Partial shading is simulated by installing bypass diodes on each module and applying different irradiation levels to represent shaded and unshaded modules. Unshaded modules receive 800 W/m², while shaded modules receive 400 W/m²at a constant temperature of 25°C. Eight shading patterns (A–H) ranging from 12.5% to 100% shading are evaluated to generate multiple peaks in the P–V curve and analyze the ability of the GWO algorithm to track the global maximum power point.

Application of the GWO method for MPPT

The Grey Wolf Optimization algorithm is implemented to determine the optimal duty cycle of the DC–DC boost converter for maximum power extraction. The overall procedure of the GWO-based MPPT algorithm used in this study is illustrated in Figure 6.

The algorithm is integrated with a boost converter with parameters L = 260 μH, Cin = 10 μF, Cout = 510 μF, and switching frequency fs = 100 kHz. The duty cycle is initialized within a range of 0–1 with a maximum of 90 iterations, while the control parameter a decreases linearly from 2 to 0. In each iteration, the PV power is calculated using:

$$P = V_{pv}\ x\ I_{pv} \quad (5)$$

$$MPPT - GWO\ Efficiency = \frac{P_{MPPT-GWO}}{P_{mpp}}\ x100\% \quad (6)$$

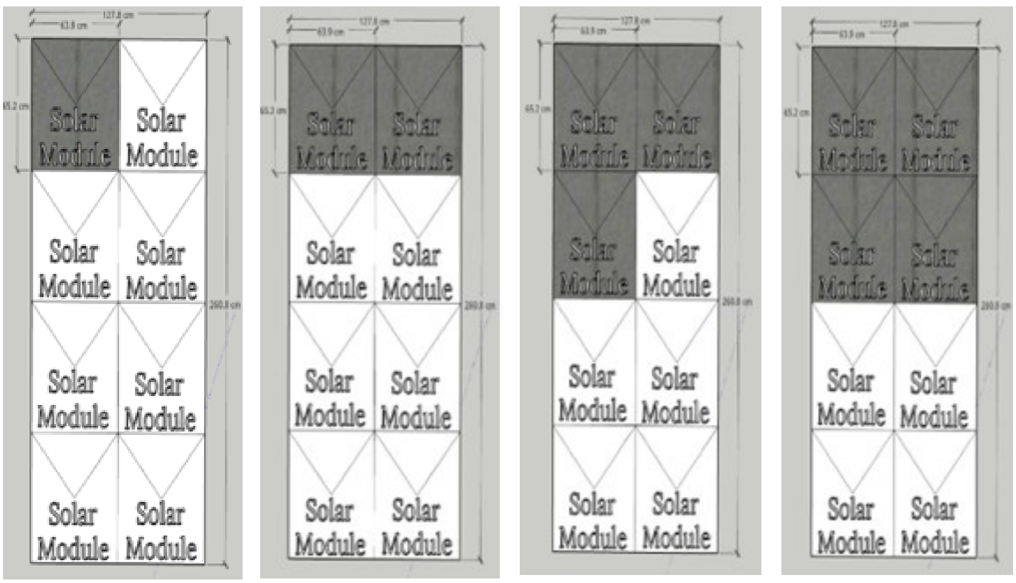

Figure 4. Shading conditions A-D for the module array: 12.5%, 25%, 37.5% to 50%

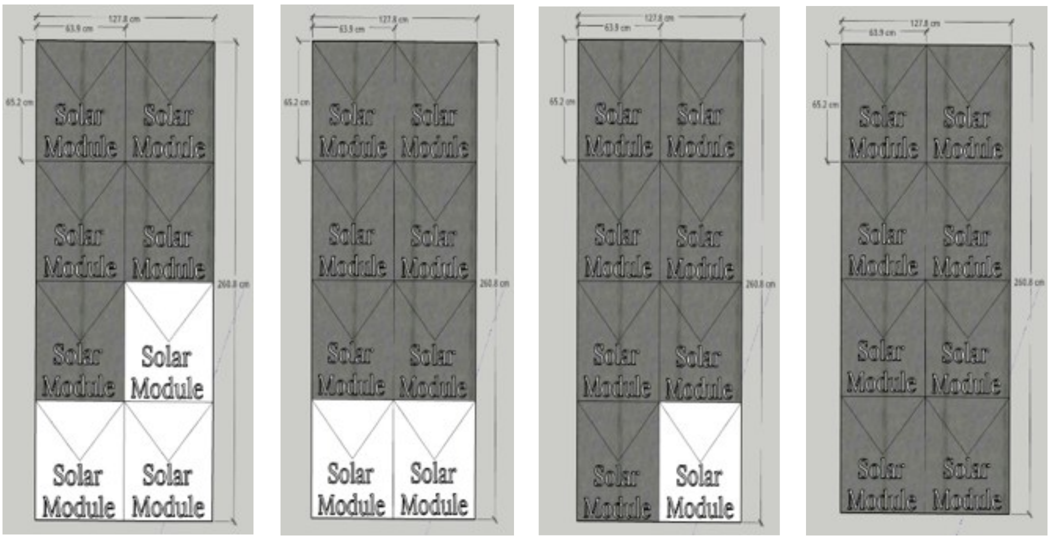

Figure 5. Module array shading conditions E-H: 62.5%, 75%, 87.5% to 100%

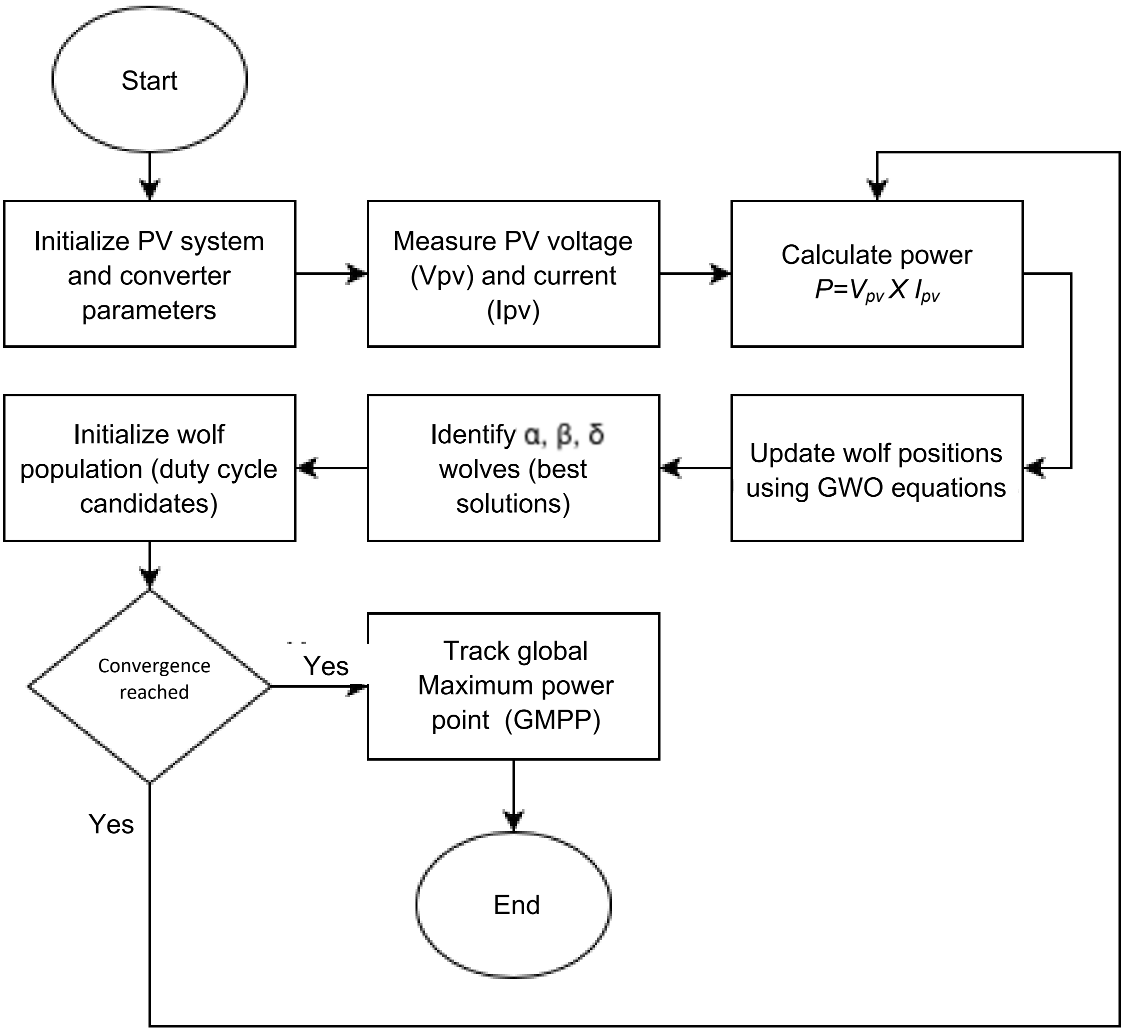

Figure 6. Flowchart of the GWO-based MPPT algorithm

The positions of the wolves are updated iteratively until convergence is achieved, allowing the algorithm to identify the global maximum power point.

$$Tracking\ Error\ = \frac{P_{mpp}\ -\ P_{MPPT}}{P_{mpp}}\ x\ 100\% \tag{7}$$

where PMPPT−GWOPMPPT−GWO represents the power obtained by the GWO algorithm and PmppPmpp is the theoretical maximum power obtained from the P–V curve. To evaluate tracking accuracy, the tracking error is calculated as:

RESULT AND DISCUSSION

One-point shading pattern (100%)

Under 100% shading conditions with uniform irradiation of 400 W/m² at 25°C, the P–V curve produces a single theoretical maximum power peak of 179.2 W based on MATLAB R2018b simulations shown in Figure 7.

The application of the GWO method produced a power of 178.7 W with an efficiency of 99.72% in Figure 13, only about 0.5 W different from the theoretical maximum value. This very small difference indicates a tracking error that can be almost ignored with a steady state time of about 1.25 seconds. These results show that under single-peak conditions, the GWO method works close to the theoretical maximum value without the risk of getting stuck at local peaks, in line with MPPT theory and compared to previous studies (Faulianur et al., 2018, which produced 173.3 W of power with 96.71% efficiency, this study shows an increase in efficiency of around 3%. This difference indicates that position updates based on alpha, beta, and delta provide higher accuracy in determining the optimal duty cycle.

Two-point shading pattern

At shading conditions of 12.5% and 25%, the P –V curve forms two power peaks due to differences in voltage characteristics between strings with bypass diodes under non-uniform irradiation.At 12.5% and 25% shading, even though the differences between power peaks were very small and there was a risk of getting stuck at local peaks, GWO still managed to track global peaks with efficiencies of 99.78% and 99.85%, respectively (Figure 9). Compared to the study (Faulianur et al., 2018, Efficiency at 12.5% and 25% conditions increased from 99.06% and 98.32% to 99.78% and 99.85%, demonstrating GWO's consistency in selecting the global peak when two peaks have very close values and supporting the goal of improving MPPT performance under multiple peak conditions. At 50%, 75%, and 87.5% shading, the P–V curve still forms two peaks but with a more significant difference in power between the local and global peaks in Figure 11.

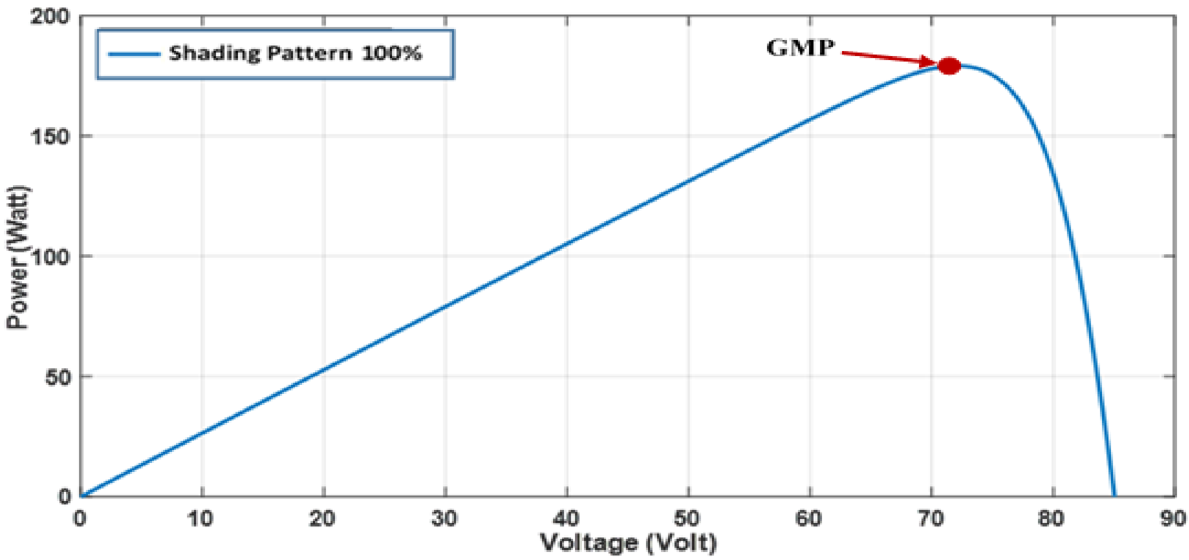

Figure 7. P-V characteristic curve of 100% shading patterns

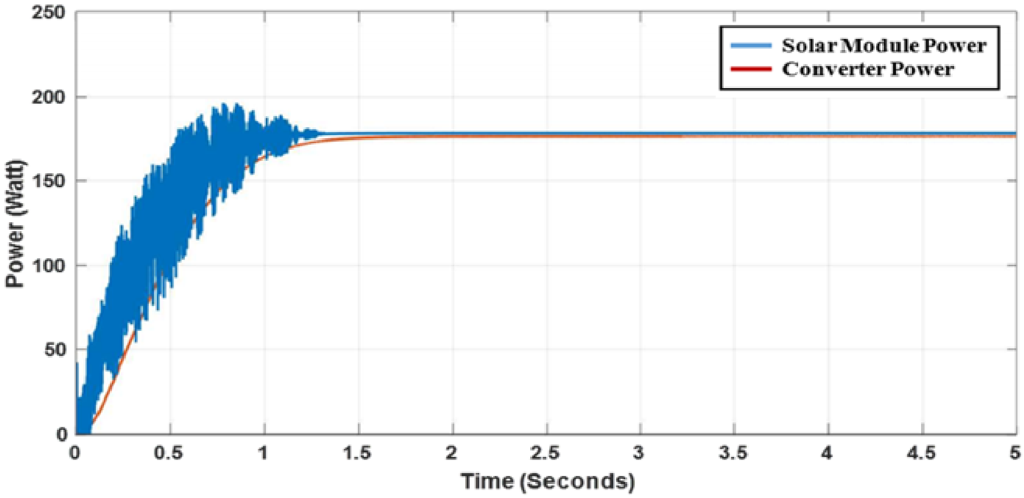

Figure 8. PMPPT-GWO tracking curve with 100% shading pattern

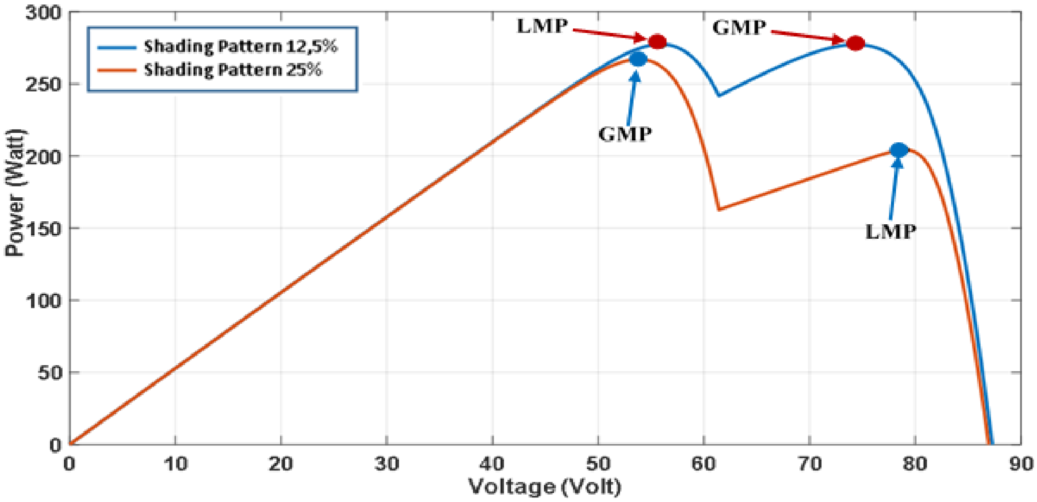

Figure 9. P-V characteristic curve of 12.5% and 25% shading patterns

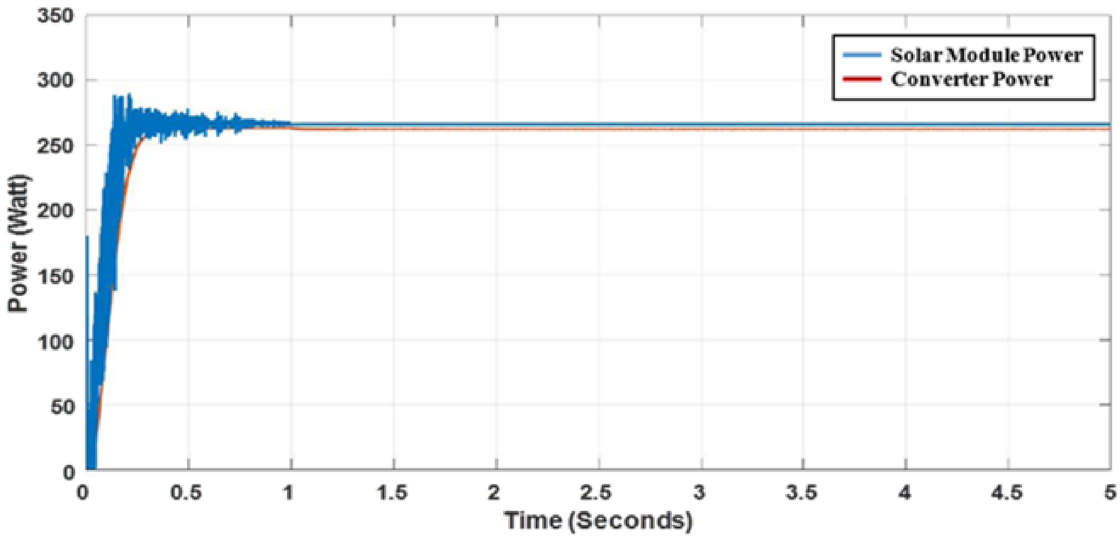

Figure 10. PMPPT-GWO tracking curve with 25% shading pattern

The global peak values are 194.7 W (50%), 186.5 W (75%), and 182.5 W (87.5%), respectively. GWO produces 193.7 W, 185.0 W, and 181.3 W with efficiencies of 99.49%, 99.20%, and 99.34%. Compared to the previous study (Faulianur et al., 2018), the most significant difference in efficiency occurred at 75% and 87.5% shading, where the previous study only achieved 93.62% and 95.34%, while this study remained above 99%.

A difference of more than 4% indicates that the previous method tended to get stuck at local peaks under highly non-uniform irradiation conditions. Therefore, these results demonstrate an improvement in the global exploration capability of the modified GWO in this study.

Three-point shading pattern (37.5% and 62.5%)

At 37.5% and 62.5% shading, the P–V curve forms three power peaks as shown in Figure 14. This condition represents a more complex optimization landscape than two peaks. At 37.5% shading, the global peak is at 204.4 W and GWO produces 204.2 W with an efficiency of 99.90%. At 62.5% shading, the global peak is 190.0 W and GWO produces 189.2 W with an efficiency of 99.56%.

Compared to study (Faulianur et al., 2018, efficiency at 62.5% shading increased from 95.37% to 99.56%. The difference of more than 4% indicates that the simultaneous use of the three best solution agents significantly improves the ability to avoid local peak traps on curves with three peaks.

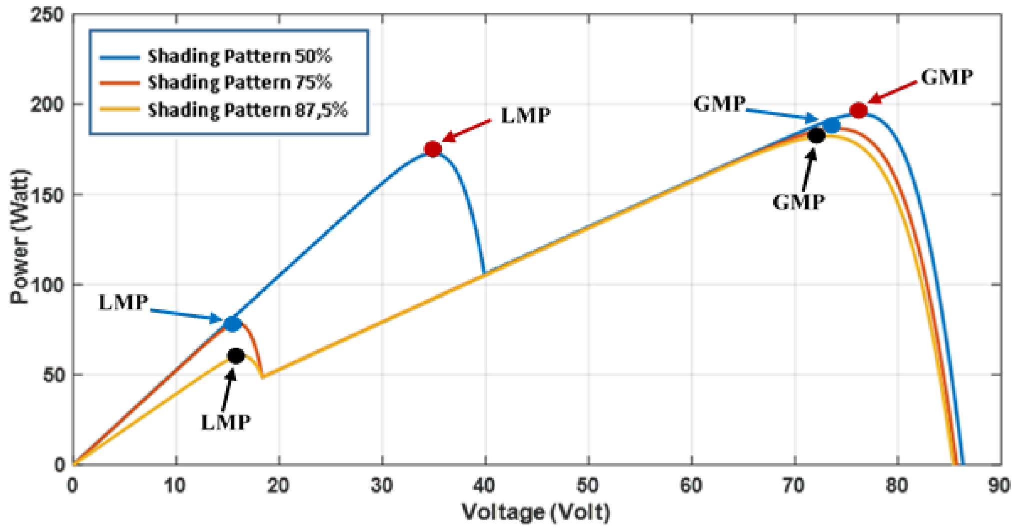

Figure 11. P-V characteristic curve of 50%, 75%, and 87.5% shading patterns

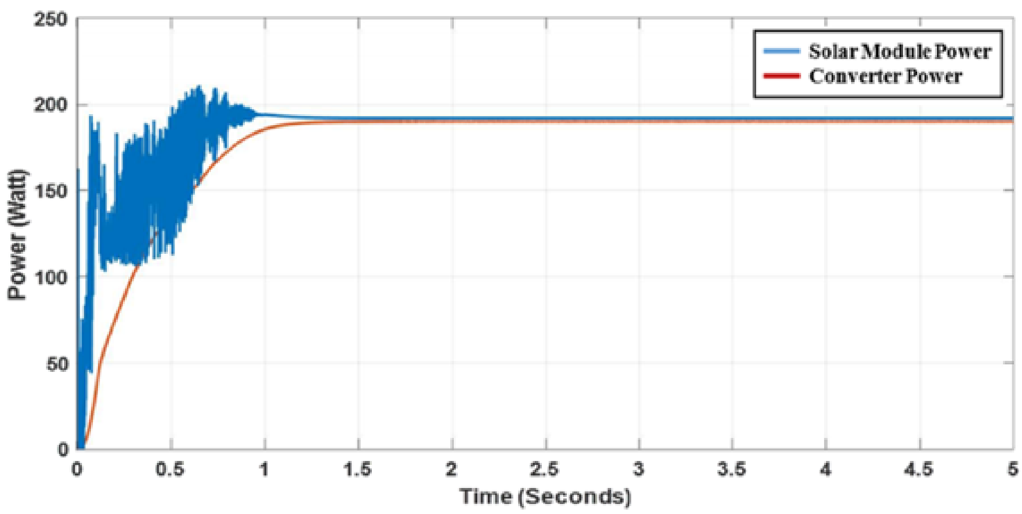

Figure 12. PMPPT-GWO tracking curve with 50% shading pattern

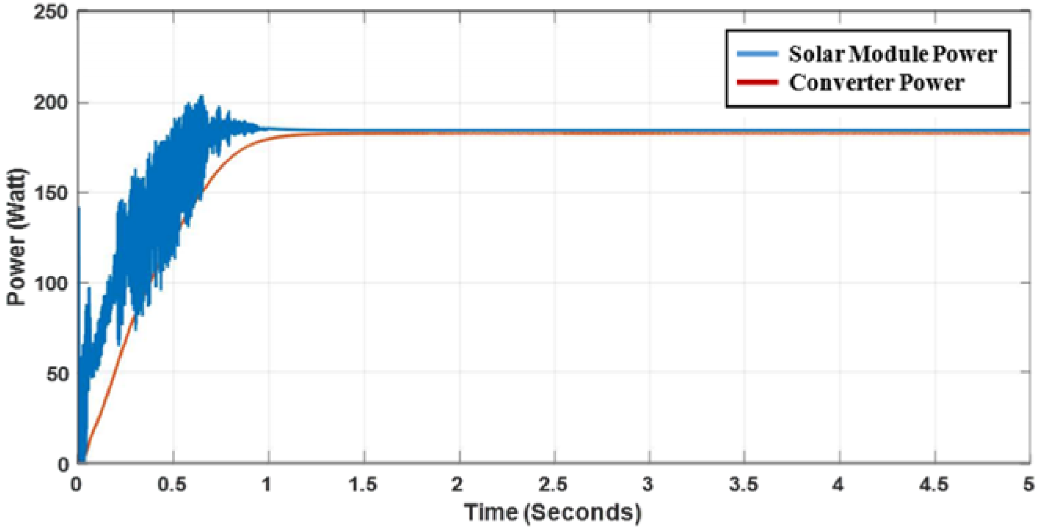

Figure 13. PMPPT-GWO tracking curve with 75% shading pattern

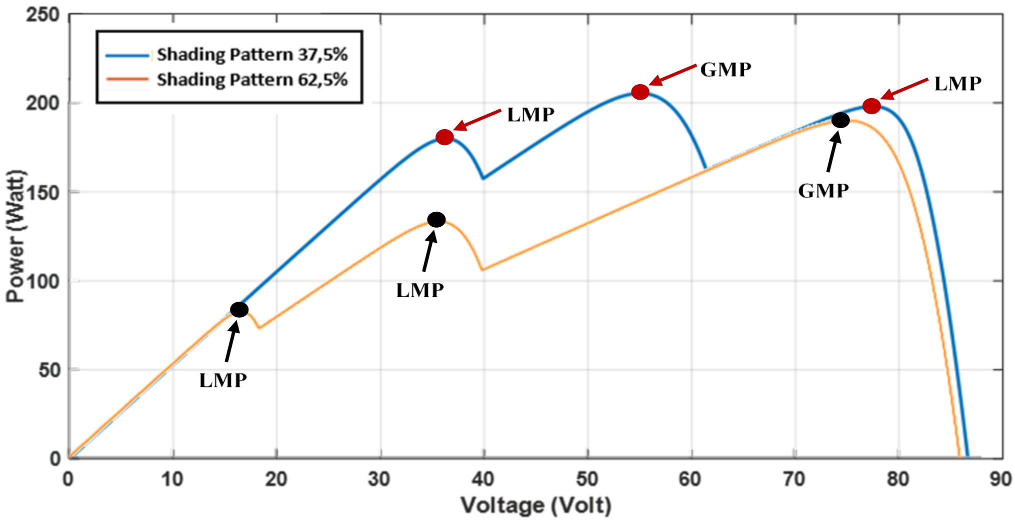

Figure 14. P-V characteristic curves of 37.5% and 62.5% shading patterns

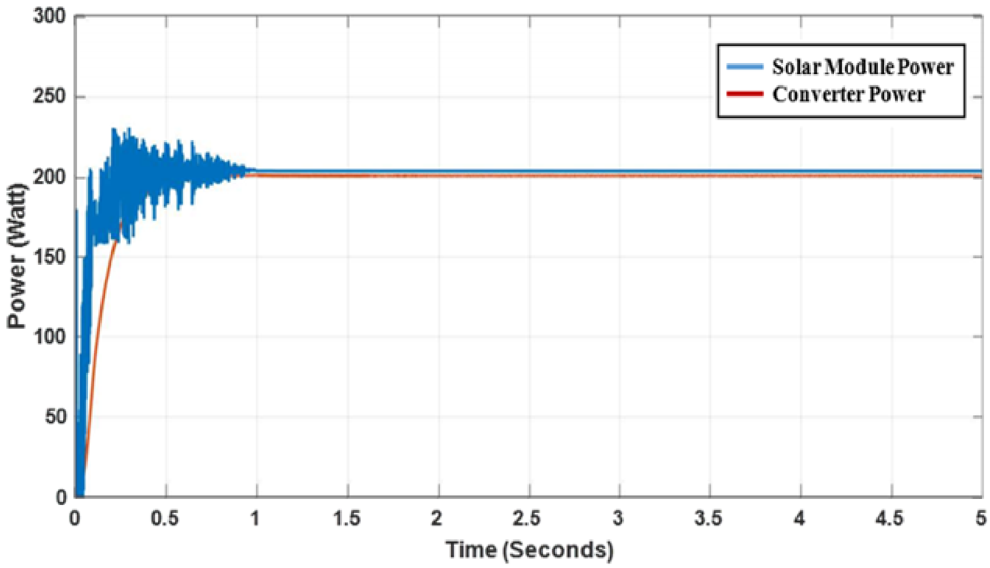

Figure 15. PMPPT-GWO tracking curve with 37.5% shading pattern

Energy harvested (kWh): comparison of baseline vs. GWO

Extracted energy is calculated from the output power of MPPT under constant irradiation conditions during the TT test duration:

$$E = \int_0^T P(t)\,dt \approx P_{MPPT} \times T \tag{8}$$

Since the results are in the form of constant power (W) per shading pattern, in order to compare energy transparently and replicatively, a 1-hour equivalent (T=1T=1 hour) is used:

$$E_{1h}(kWh) = \frac{P_{MPPT}(W)}{1000} \tag{9}$$

The baseline is taken from the Efficiency (%) column in Table 1, with baseline power estimates:

$$P_{baseline} = \eta_{ref} \times P_{mpp} \tag{10}$$

The average increase in equivalent energy (power weight) ≈ +2.30% compared to the baseline (calculated from all patterns). Compared to the baseline, GWO increases the average equivalent extracted energy by approximately 2.30%, especially in heavy shadow patterns (75%–87.5%) that tend to trap other methods at local peaks.

Load profile & energy demand (kWh)

As a real-world oil and gas field case study, data from the Aghar Oil Field – Western Desert, Egypt (Eni Solar Hybrid Technology) was used, which operates a 110 kWp PV integrated with a 200 kW diesel generator to supply three sucker-rod pumps totaling 113 kW, and previously used a 300 kW DG. The annual energy requirement of the facility (from field data) is:

$$E_{load,year} = \frac{450mwh}{tahun} \tag{11}$$

for the equivalent average load profile:

$$P_{avg} = \frac{E_{load,year}}{8760} \approx \frac{450}{8760} = 0.0514\,MW = 51.4kW \tag{12}$$

Context note on oil and gas loads: for other production facilities, process loads can be significantly larger (e.g., ESPs can range from 7.5 kW to >750 kW depending on well design), so this methodology remains relevant for large loads.

- Facility electricity consumption: 450 MWh/year
- Pump power (three sucker rods): 113 kW
- PV electricity generation: 50 MWh/year

Field case studies show that the production operation load (pumps) is continuous and significant (hundreds of MWh/year), so that even a small increase in PV energy (due to global MPPT) has a direct impact on reducing generator operation and diesel consumption.

Fuel saving & genset hours

From field data, diesel consumption without PV is 140,000 L/year for energy consumption of 450 MWh/year, resulting in equivalent specific fuel consumption:

$$SFC_{field} = \frac{140{,}000}{450{,}00} = \frac{0.311L}{kWh} \tag{13}$$

Table 1. Performance Comparison of PMPPT-GWO Under All Shading Patterns

Shading pattern	Peak type	Pmpp (W)	PMPPT-GWO this study (W)	Efficiency (%) this study	Efficiency (%) Ref. [27]
H (100%)	Single	179.2	178.7	99.72	96.71
A (12.5%)	Double	277.6	277.0	99.78	99.06
B (25%)	Double	267.1	266.7	99.85	98.32
D (50%)	Double	194.7	193.7	99.49	99.38
F (75%)	Double	186.5	185.0	99.20	93.62
G (87.5%)	Double	182.5	181.3	99.34	95.34
C (37.5%)	Triple	204.4	204.2	99.90	99.80
E (62.5%)	Triple	190.0	189.2	99.56	95.37
Average Efficiency	–	–	–	**99.61**	**97.20**

Table 2. Equivalent to 1 Hour Per Shadow Pattern

Pattern	Pmpp (W)	Pbaseline (W)	E1h baseline (kWh)	PGWO (W)	E1h, GWO (kWh)	GWO energy
H (100%)	179.2	173.30	0.173	178.7	0.179	+3.11%
A (12.5%)	277.6	274.99	0.275	277.0	0.277	+0.73%
B (25%)	267.1	262.61	0.263	266.7	0.267	+1.56%
D (50%)	194.7	193.49	0.193	193.7	0.194	+0.11%
F (75%)	186.5	174.60	0.175	185.0	0.185	+5.96%
G (87.5%)	182.5	174.00	0.174	181.3	0.181	+4.20%
C (37.5%)	204.4	203.99	0.204	204.2	0.204	+0.10%
E (62.5%)	190.0	181.20	0.181	189.2	0.189	+4.41%

The contribution of field PV is 50 MWh/year, and diesel savings are recorded at 15,000 L/year. Since the results show an average efficiency increase of 99.61% vs. an average baseline of 97.20% (Table 1), the annual PV energy increase "locked in" by global MPPT can be projected conservatively:

$$\Delta E_{PV} = E_{PV}\left(\frac{99.61}{97.20} - 1\right)$$
$$\Delta E_{PV} = 50 \times 0.02479 = \frac{1.24MWh}{tahun} \quad (14)$$

conversion to additional diesel savings:

$$\Delta Fuel = \Delta E_{PV}(kWh) \times SFC_{field}$$
$$\Rightarrow 1239.7 \times 0.311 = \frac{386L}{tahun} \quad (15)$$

Hybrid diesel consumption is calculated from diesel-only consumption minus savings. In the field case study, GWO is projected to increase PV energy production by approximately +1.24 MWh/year, equivalent to additional diesel fuel savings of approximately 386 liters per year, beyond the savings already proven in the field with hybrid systems.

Reliability indicator: operational

Since hybrid field systems generally maintain a 24-hour supply with generators as a firm supply, the most technical and measurable reliability indicator from the MPPT side is PV power loss due to incorrect tracking, which immediately becomes an additional burden on the generator:

$$P_{loss} = P_{mpp} - P_{MPPT} \Rightarrow \Delta P_{DG} \approx P_{loss} \quad (16)$$

Therefore, improved global MPPT reduces generator load variation/increase, especially when dynamic shadows (flare stack/pipe rack structures) change.

- F (75%): baseline P≈174.6P≈174.6 W → GWO 185.0185.0 W □ ΔP ≈ +10.4 W
- G (87.5%): baseline P≈174.0P≈174.0 W → GWO 181.3181.3 W □ ΔP ≈ +7.3 W
- E (62.5%): baseline P≈181.2P≈181.2 W → GWO 189.2189.2 W □ ΔP ≈ +8.0 W

GWO increases the operational reliability of hybrid systems by reducing PV power loss equivalent to the additional generator load, as generators do not need to cover deficits caused by MPPT getting stuck at local peaks, especially in heavy shading conditions.

Economic value

The economic value is calculated from the annual diesel savings multiplied by the industrial diesel price; for local consistency, the price of Industrial Diesel B40 from February 1 to 14, 2026, is used, which is around Rp 20,950/ L (regions 1–2).

$$\text{SavingRp} = \text{FuelSaved} \times \text{Pricediesel} \quad (17)$$

Simple payback (without NPV) uses CAPEX PV. For CAPEX PV in Indonesia, the commercial reference for 2024 is in the range of IDR 13–15 million/kWp; the median value of IDR 14 million/ kWp is used. The estimated investment (CAPEX) requirement for a ±110 kWp PV system, assuming a cost of IDR 14,000,000/kWp, is approximately IDR 1.54 billion. Based on field data, the hybrid

Table 3. Field Data-Based Scenario

Scenario	Energy PV (MWh/th)	Consumption diesel (L/th)	Diesel saving (L/th)
Diesel-only (without PV)	0	140,000	0
Hybrid + baseline MPPT	50.00	~125,000	15,000
Hybrid + GWO	51.24	~124,614	15,386

system generates diesel savings of ±15,000 liters per year, which is equivalent to cost savings of around Rp314,250,000 per year (15,000 × Rp20,950/liter). In addition, there are additional savings due to the increase in MPPT (GWO) performance of ±386 liters per year or around IDR 8,080,000 per year (386 × IDR 20,950/ liter). Thus, in terms of order of magnitude, the payback period based on field hybrid savings is approximately 4.9 years (Rp1.54 billion ÷ Rp314.25 million/year), not including additional savings from MPPT optimization, which further improves the system's economics.

Based on field data and industrial diesel prices for February 2026, the PV-diesel system shows a payback period of around 4.9 years, while the implementation of GWO provides additional incremental annual operational savings (IDR 8 million/year) through an increase in fully utilized PV energy.

Implications and fulfillment of objectives

In oil and gas production facilities, electrical energy is required not only for core production processes but also for supporting systems such as SCADA, RTU, communication networks, sensors, chemical injection pumps, and cathodic protection systems. These systems operate continuously in remote or offshore locations and are generally powered by diesel generators (DG). The integration of photovoltaic (PV) systems into hybrid energy configurations offers an effective solution to reduce fuel consumption and operational costs. However, the complex industrial structures present in oil and gas facilities, including flare stacks, drilling towers, and pipe racks, often cause partial shading on PV modules, resulting in nonlinear P–V characteristics with multiple power peaks.

Without an MPPT algorithm capable of global tracking, the system may become trapped at local maxima, leading to power losses and reduced solar energy contribution in hybrid systems. Several intelligent MPPT approaches have been proposed to address this problem. Fuzzy Logic Controller (FLC) methods demonstrate adaptive responses to irradiation and temperature changes (Ananda-rao et al., 2025; Asyadi & Muliadi, 2023), while T-S fuzzy methods improve control stability (Chiu, 2010). However, these methods rely heavily on rule bases and parameter tuning, and they are not specifically designed for global exploration in PV systems with multiple power peaks caused by severe partial shading. Metaheuristic algorithms have also been widely investigated to improve global search capability (Ghosh & Mandal, 2023). For example, the Firefly Algorithm and Ant Colony Optimization combined with the P&O method have demonstrated improved tracking under non-uniform irradiation conditions (Sundareswaran et al., 2014, 2015). Nevertheless, previous studies indicate that these algorithms may experience variations in convergence stability and sensitivity to parameter settings, which may reduce tracking reliability across different shading patterns.

The results of this study show that the grey wolf optimization (GWO) algorithm provides consistent global peak tracking across all tested shading scenarios (Villalva et al., 2009; Zulfadli et al., 2022). The algorithm maintains power output close to the theoretical maximum value under conditions with single, double, and triple power peaks. Compared with previous work by Pratama et al. 2019, which reported an average MPPT efficiency of approximately 97%, the average efficiency achieved in this study reaches 99.61%, representing an improvement of more than 2% in global tracking capability.

Although the convergence time of approximately one second is not always faster than some optimization methods such as PSO or FPA (Abou Houran et al., 2023; Jazayeri et al., 2013; Karatepe et al., 2008), the stability of global tracking across various shading scenarios indicates that GWO provides more consistent performance. In hybrid PV–diesel systems used in oil and gas production facilities, this improvement in MPPT efficiency can increase the contribution of solar energy by approximately 2–4%, which directly reduces diesel generator operating hours, fuel consumption, and greenhouse gas emissions.

From an energy system perspective, improving renewable energy utilization in industrial facilities contributes to reducing environmental impacts associated with fossil-fuel-based electricity generation (Nuraini & Lubis 2017). Renewable technologies such as solar energy systems have been increasingly investigated as alternatives for sustainable energy supply in oil and gas operations (Burhan A.S et al., 2020).

The reduction of diesel generator operation also has implications for fuel system durability and maintenance requirements (Mardono & Maymuchar 2022), while improved energy efficiency supports broader strategies for national energy resilience and environmental management in the petroleum sector (Sunarjanto & Kusumantoro 2015). In addition, the adoption of cleaner energy technologies contributes to mitigating environmental degradation associated with industrial energy use (Ulfiati 2022).

Therefore, the implementation of global optimization-based MPPT algorithms such as GWO not only improves the technical performance of PV modules but also enhances the reliability and sustainability of hybrid energy systems in oil and gas production facilities. The contribution of this research is reflected not only in improved numerical efficiency but also in its potential impact on operational efficiency, fuel savings, emission reduction, and long-term energy sustainability in industrial power systems.

CONCLUSION

This study demonstrates that the Grey Wolf Optimization (GWO) algorithm effectively tracks the global maximum power point in photovoltaic (PV) systems under partial shading conditions with multiple power peaks. Simulation results show that the proposed method achieves an average MPPT efficiency of 99.61%, which is higher than the 97.20% reported in previous studies. The algorithm consistently identifies the global power peak under single-, double-, and triple-peak conditions, indicating strong global exploration capability.

The improved tracking performance increases solar energy utilization in hybrid PV–diesel systems, which can reduce diesel generator operating hours, fuel consumption, and associated emissions while improving power supply reliability for critical loads in oil and gas production facilities. These results highlight the importance of global search-based MPPT algorithms in supporting renewable energy integration within industrial power systems. Future work will focus on real-time hardware implementation of the proposed GWO-based MPPT algorithm and its integration with advanced energy management systems for hybrid PV–diesel power plants in oil and gas operations.

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GLOSSARY OF TERMS AND SYMBOLS

Terms & Symbols	Description	Unit
PV (Photovoltaic)	A technology that converts solar radiation into electrical energy using semiconductor materials.	
MPPT (Maximum Power Point Tracking)	A control technique used in PV systems to ensure operation at the maximum power point under varying environmental conditions.	

GWO (Grey Wolf Optimization)	A metaheuristic optimization algorithm inspired by the social hierarchy and hunting behavior of grey wolves.
PSC (Partial Shading Condition)	A condition where PV modules receive uneven solar irradiation due to obstacles or environmental factors.
GMPP (Global Maximum Power Point)	The highest power point on the P–V curve under partial shading conditions where multiple local peaks exist.
LMPP (Local Maximum Power Point)	A local peak in the P–V curve that does not represent the maximum available power of the PV system.
DG (Diesel Generator)	A generator that converts diesel fuel into electrical energy, commonly used in remote oil and gas facilities.
STC (Standard Test Conditions)	Standard reference conditions for PV testing with irradiation of 1000 W/m², temperature of 25°C, and air mass of 1.5.
DC–DC Converter	A power electronic device used to regulate voltage levels in PV systems and implement MPPT control.
Duty Cycle	The ratio of the ON time to the total switching period in a DC–DC converter, used to control the operating point of the PV system.

REFERENCES

Abou Houran, M., Sabzevari, K., Hassan, A., Oubelaid, A., Tostado-Véliz, M., & Khosravi, N., (2023), Active power filter module function to improve power quality conditions using GWO and PSO techniques for solar photovoltaic arrays and battery energy storage systems. Journal of Energy Storage, 72(August). https://doi.org/10.1016/j.est.2023.108552

Ali, N. Ben, Basem, A., Jasim, D. J., Singh, P. K., Sultan, A. J., Rajab, H., Becheikh, N., Kolsi, L., & El-Shafay, A. S., (2024), Strategic integration of adiabatic compressed air energy storage in urban buildings: Enhancing energy efficiency through gray wolf optimizer-enhanced dynamic simulation framework. Journal of Energy Storage, 102(PB), 114103. https://doi.org/10.1016/j.est.2024.114103.

Ananda-rao, K., Rosmi, A. S., Taniselass, S., & Hanisah, N., (2025), MPPT Charge Controller using Fuzzy Logic for Battery Integrated with Solar Photovoltaic System. Journal of Advanced Research in Applied Sciences and Engineering Technology, 47(2), 171–182. https://doi.org/ https://doi.org/10.37934/araset.47.2.171182.

Asyadi, T. M., & Muliadi., (2023), The maximum power point tracking (MPPT) on changes in radiation and temperature of solar modules based on fuzzy logic controller (FLC). The 6th Engineering Science and Technology International Conference (ESTIC 2021), 2691, 060004–1–060004–060009. https://doi.org/https://doi.org/10.1063/5.0115030.

Burhan A.S, A. A., Aziz, D. F., & Hidayat, M. N., (2020), Parabolic Trough Collector Concentrating Solar Power As Steam Producer Using Solar Irradiation of Cepu, Blora, Central Java. Scientific Contributions Oil and Gas, 41(3), 155–168. https://doi.org/10.29017/scog.41.3.334.

Chiu, C.-S., (2010), T-S Fuzzy Maximum Power Point Tracking Control of Solar Power Generation Systems. IEEE Transactions on Energy Conversion, 25(4), 1123–1132. https://doi.org/10.1109/TEC.2010.2041551.

Faulianur, R., Sara, I. D., & Arnia, F., (2018), Simulasi Pelacakan Titik Daya Maksimum Modul Surya dengan Metode Grey Wolf Optimization. Jurnal Rekayasa Elektrika, 14(1), 26–34. https://doi.org/10.17529/jre.v14i1.8973.

Femia, N., Petrone, G., Spagnuolo, G., & Vitelli, M., (2004), Optimizing duty-cycle perturbation of P&O MPPT technique. PESC Record - IEEE Annual Power Electronics Specialists Conference, 3, 1939–1944. https://doi.org/10.1109/PESC.2004.1355414.

Ghosh, B., & Mandal, S., (2023), A New Approach for Solar Photovoltaic Parameter Extraction Using Metaheuristic Algorithms From Manufacturer Datasheet. IEEE Open Journal of Instrumentation and Measurement, 2(August), 1–12. https://doi.org/10.1109/ojim.2023.3318678

Govindarajan, L., Faizal, M., Batcha, M., Seri, S., & Kamil, M., (2025), Analysing the Performance of Large-Scale Rooftop Solar PV System Using Heliscope , PVsyst and PV * SOL Photovoltaic Simulation Software : As a Renewable Energy Strategy. 1(1), 192–207.

Hussin, M. Z., Jais, R. M., Omar, A. M., Sin, N. D. M., Rifin, R., & Setiawan, E. A., (2025), Health Performance Assessment of Grid-Connected PV Systems using Safe Operating Area Concept. Journal of Advanced Research in Applied Sciences and Engineering Technology, 48(1), 89–99. https://doi.org/10.37934/araset.48.1.8999.

Ishaque, K., & Salam, Z., (2012), A Deterministic Particle Swarm Optimization Maximum Power Point Tracker for Photovoltaic System under Partial Shading Condition. IEEE Transactions on Industrial Electronics, 60(8), 1–1. https://doi.org/10.1109/TIE.2012.2200223.

Islam, M. A., Merabet, A., Beguenane, R., & Ibrahim, H., (2013), Modeling solar photovoltaic cell and simulated performance analysis of a 250W PV module. 2013 IEEE Electrical Power and Energy Conference, EPEC 2013, 1–6. https://doi.org/10.1109/EPEC.2013.6802959.

Jazayeri, M., Uysal, S., & Jazayeri, K., (2013), A simple MATLAB/Simulink simulation for PV modules based on one-diode model. 2013 High Capacity Optical Networks and Emerging/Enabling Technologies, HONET-CNS 2013, 44–50. https://doi.org/10.1109/HONET.2013.6729755.

Jung, T. H., Kang, G. H., & Ahn, H. K., (2014), Optimal design of PV module with bypass diode to reduce degradation due to reverse excess current. Transactions on Electrical and Electronic Materials, 15(5), 279–283. https://doi.org/10.4313/TEEM.2014.15.5.279.

Karatepe, E., Hiyama, T., Boztepe, M., & Metin, C., (2008), Voltage based power compensation system for photovoltaic generation system under partially shaded insolation conditions. 49, 2307–2316. https://doi.org/10.1016/j.enconman.2008.01.012.

Khaing, H. H., Liang, Y. J., Nyein, N., Htay, M., & Fan, J., (2014), Characteristics of Different Solar PV Modules under Partial Shading. 8 (9), 1418–1422.

Lian, L., Maskell, D. L., & Patra, J. C., (2013), A novel ant colony optimization-based maximum power point tracking for photovoltaic systems under partially shaded conditions. Energy & Buildings, 58, 227–236. https://doi.org/10.1016/j.enbuild.2012.12.001.

Lyden, S., Haque, M. E., Gargoom, A., & Negnevitsky, M., (2013), Review of Maximum Power Point Tracking Approaches Suitable for PV Systems Under Partial Shading Conditions. October, 1–6.

Mardono, M., & Maymuchar, M., (2022), Study On The Impact Biodiesel Onto Fuel Pump And Nozzle Wear In 5 Kva Generator Diesel Engine. Scientific Contributions Oil and Gas, 33(2), 115–119. https://doi.org/10.29017/scog.33.2.814.

Mirjalili, S., Mirjalili, S. M., & Lewis, A., (2014), Grey Wolf Optimizer. Advances in Engineering Software, 69, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007.

Mohanty, S., Subudhi, B., Member, S., & Ray, P. K., (2015), A New MPPT Design Using Grey Wolf Optimization Technique for Photovoltaic System Under Partial Shading Conditions. 1–8.

Mohanty, S., Subudhi, B., & Ray, P. K., (2017), A grey wolf optimization based MPPT for PV system under changing insolation level. 2016 IEEE Students' Technology Symposium, TechSym 2016, 175–179. https://doi.org/10.1109/TechSym.2016.7872677.

Muliadi, M., Sara, I. D., & Suriadi, S., (2021), The effect of bypass diode installation on partially covered solar panel output power. IOP Conference Series: Materials Science and Engineering, 1087(1), 012077. https://

doi.org/10.1088/1757-899x/1087/1/012077.

Nguyen, X. H. (2015). Matlab/Simulink Based Modeling to Study Effect of Partial Shadow on Solar Photovoltaic Array. Environmental Systems Research, 4(1), 1–10. https://doi.org/10.1186/s40068-015-0042-1.

Nimma, K. S., Al-Falahi, M. D. A., Nguyen, H. D., Jayasinghe, S. D. G., Mahmoud, T. S., & Negnevitsky, M., (2018), Grey Wolf Optimization -Based Optimum Energy-Management and Battery-Sizing Method for Grid-Connected Microgrids. Energies, 11(4), 847. https://doi.org/10.3390/en11040847.

Nuraini, & Lubis E., (2017), Kontribusi Pembangkitan Energi Listrikterhadap Efek Rumah Kaca. Lembaran Publikasi Lemigas, VOL. 41.(NO. 1,), 41–46.

Orosz, T., Rassõlkin, A., Arsénio, P., Poór, P., Valme, D., & Sleisz, Á., (2024), Current Challenges in Operation, Performance, and Maintenance of Photovoltaic Panels. Energies, 17 (6), 1–22. https://doi.org/10.3390/en17061306.

Pratama, K. G. P., Hermawan, H., & Andromeda, T., (2019), Analysis Performance of Grid Tie Photovoltaic Type Polycrystalline Using Solar Irradiance Simulation. E3S Web of Conferences, 125(201 9). https://doi.org/10.1051/e3sconf/201912514013.

Rana, A. S., Nasir, M., & Khan, H. A., (2018), String level optimisation on grid-tied solar PV systems to reduce partial shading loss. IET Renewable Power Generation, 12(2), 143–148. https://doi.org/10.1049/iet-rpg.2017.0229.

Román, E., Alonso, R., Ibañez, P., Elorduizapatarietxe, S., & Goitia, D., (2006), Intelligent PV Module for Grid-Connected PV Systems. 53(4), 1066–1073.

Saleem, S., Ahmad, I., Ahmed, S. H., & Rehman, A., (2024), Artificial intelligence based robust nonlinear controllers optimized by improved gray wolf optimization algorithm for plug-in hybrid electric vehicles in grid to vehicle applications. Journal of Energy Storage, 75 (November 2023), 109332. https://doi.org/10.1016/j.est.2023.109332.

Silvestre, S., Boronat, A., & Chouder, A., (2009), Study of bypass diodes configuration on PV modules. Applied Energy, 86(9), 1632–1640. https://doi.org/10.1016/j.apenergy.2009.01.020.

Sunarjanto, D., & Kusumantoro, D., (2015), Optimasi Mewujudkan Ketahanan Energi Nasional: Penanganan Lingkungan Dan Migas Non Konvensional. Lemigas, 49(3), 4–7.

Sundareswaran, K., Peddapati, S., & Palani, S., (2014), MPPT of PV systems under partial shaded conditions through a colony of flashing fireflies. IEEE Transactions on Energy Conversion, 29(2), 463–472. https://doi.org/10.1109/TEC.2014.2298237.

Sundareswaran, K., Sankar, P., Simon, S. P., Nayak, S. R., & Palani, S., (2015), Development of an improved P&O algorithm assisted through a colony of foraging ants for MPPT in PV system. 3203(c). https://doi.org/10.1109/TII.2015.2502428

Teh, C. J. Q., Drieberg, M., Soeung, S., & Ahmad, R., (2021), Simple PV Modeling under Variable Operating Conditions. IEEE Access, 9, 96546–96558. https://doi.org/10.1109/ACCESS.2021.3094801.

Ulfiati, R., (2022), Contribution Ultra Violet Radiation On Degradation Of Biodegradable Base Oil. Scientific Contributions Oil and Gas, 32(1), 27–30. https://doi.org/10.29017/scog.32.1.830.

Villalva, M., Gazoli, J., & Filho, E., (2009), Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays. IEEE Transactions on Power Electronics, 24(5), 1198–1208. https://doi.org/10.1109/tpel.2009.2013862.

Zulfadli, T., Sary, R., & Nazar, M., (2022), Feasibility Study on the Use of On-Grid Rooftop Solar Power Plants to Reduce Electrical Energy Consumption at LPI. Dayah Ulee Titi Foundation. Desiminating Information on the Research of Mechanical Engineering-Jurnal Polimesin, 20(2).