COMPARATIVE ANALYSIS OF METAHEURISTIC MPPT ALGORITHMS IN PV SYSTEM UNDER NON-LINEAR LOADS

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ABSTRACT

This project focuses on the maximum power point tracking (MPPT) under partial shading conditions. Partial shading conditions significantly impact the performance of photovoltaic (PV) systems, leading to reduced energy output and efficiency. MPPT algorithms play a crucial role in optimizing PV system performance under partial shading conditions. Metaheuristic algorithms have gained popularity in recent years due to their ability to efficiently track the Global Maximum Power Point (GMPP) under partial shading conditions.

Among metaheuristic algorithms, three popular optimization MPPT techniques are compared in this work: Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and Dragonfly Optimization Algorithm (DFO). A novel hybrid PSO-DFO algorithm is proposed in this paper, which stands out for its higher stability and efficiency in converging to the MPP under partial shading conditions. Simulation results on a four-panel PV system with a DC-DC boost converter in MATLAB/Simulink demonstrate that the proposed hybrid PSODFO achieves a tracking factor of 97%, outperforming GWO (92%), PSO (90%), and standalone DFO (94%).

Keywords: *MPPT, Partial Shading, Metaheuristic Algorithms, PSO, GWO, DFO, Hybrid PSO-DFO, PV System, Boost Converter.*

1. INTRODUCTION

In the last few decades, it has become inevitable to focus on sustainable renewable energy production due to environmental problems such as the rapid growth of population, increasing energy consumption, decreasing fossil fuel reserves, and greenhouse gas emissions from fossil fuels. In terms of providing an unlimited supply, solar energy is one of the most preferred renewable electricity generation sources [1].

Solar panels consist of solar arrays formed by grouped solar cells. These arrays generate DC powerusing solar radiation from the sun [2]. Under constant temperature and constant solar radiation conditions, the power generatedby a PV system increases in direct proportion to the connected load. After the panel reaches the maximum power point (MPP), thepower starts to decrease even as the load increases. This MPP may shift due to changing atmospheric conditions (such as temperature and solar radiation), panel pollution, and shading. Therefore, power optimization is necessary to ensure maximum efficiencyfrom PV panels [3].

The power optimization made to extract maximum efficiency from solar panels is called Maximum Power Point Tracking (MPPT). The fundamental principle of MPPT is to adjust the duty cycle of the power electronics converter at the output of the PV panel so that the PV panel operates at the maximum power point continuously. Many MPPT applications have been proposed recently [4]. The most common of these is the traditional Perturb and Observe (P&O) method, where the power obtained with a reference current and voltage is

compared with the PV power obtained from the current and voltage. According to the difference, the power is maintained at the maximum through a voltage increase and decrease technique in constant step
[5].

Various other methodssuch as Incremental Conductance (IC/IncCon), constant voltage method, and variable-step P&O have also been examined in many studies. However, it has been determined that almost all these methods have delayed response problems [6]. More intelligent methodshave been needed, as classical algorithms did not provide sufficient efficiency in tracking the global maximum points (GMPP) and often lodge in local maximum points (LMPP) formed under partial shading conditions [7]. For this reason, fuzzy logic [8-13], artificial neural networks [1216], and metaheuristic methods [17-23] have been discussed by many researchers. The main purpose of intelligent algorithms is to guarantee tracking of the GMPP regardless of partial shading and variable temperature conditions [19].

Metaheuristic algorithms have been presented by many authors as a viable solution for tracking GMPP with much higher efficiency. Therefore, in this paper, an analysis has been made on the tracking performance of the most widely used metaheuristic algorithms. Furthermore, a hybrid PSO-DFO algorithm is proposed by combining the best position of the particle in the PSO algorithm with the best position of the swarm from the dragonfly algorithm.

This paper is organized as follows: Section 2 presents a literature survey. Section 3 formulates the problem. Section 4 describes the PV system modeling. Section 5 discusses MPPT algorithms including PSO, GWO, DFO, and the proposed hybrid PSO-DFO. Section 6 presents the MATLAB/Simulink modeling and simulation results. Section 7 draws the conclusion, followed by references.

2. LITERATURE SURVEY

N. Khanam, B. H. Khan and T. Imtiaz [1] presented a comparative study on maximum power extraction from solar PV systems using meta-heuristic MPPT techniques. Their work highlighted that the environmental challenges of rapid population growth and fossil fuel dependence have made solar energy one of the most preferred renewable sources. The study established a foundation for applying intelligent optimization techniques to PV systems.

M. A. Elgendy, B. Zahawi, and D. J. Atkinson [5] assessed the implementation of the perturb and observe MPPT algorithm for PV pumping applications. They demonstrated that while P&O is widely used, its fixed-step nature leads to suboptimal tracking under rapidly changing irradiation conditions. This analysis motivated the development of more adaptive, intelligent MPPT techniques.

H. Elaissaoui, M. Zerouali, A. E. Ougli and B. Tidhaf [13] proposed an MPPT algorithm based on fuzzy logic and artificial neural network (ANN) for a hybrid solar/wind power generation system. Their results showed that combining intelligent control methods significantly improves the tracking accuracy under non-uniform irradiation conditions, though the computational requirements are higher compared to classical methods.

N. Bilgin and I. Yazici [23] provided a detailed comparison of maximum power point tracking methods using metaheuristic optimization algorithms for photovoltaic systems. Their study compared the PSO, GWO, and other algorithms, noting that swarm-based methods provide significantly better performance for multi-peak P-V curves under partial shading. This work forms a major reference for the present paper.

H. Li, D. Yang, W. Su, J. Lu and X. Yu [40] proposed an overall distribution particle swarm optimization MPPT algorithm for photovoltaic systems under partial shading. Their method addressed the premature convergence problem common in standard PSO by distributing the initial particle positions across the search space, achieving a more reliable global search.

The Dragonfly Optimization Algorithm was first introduced by Seyedali Mirjalili [56] as a new metaheuristic optimization technique modeled on the swarming behaviors of dragonflies. The algorithm demonstrated excellent convergence properties due to its dual search modes (exploitation via neighborhood and exploration via Lévy flight), making it particularly suitable for complex, multipeaked optimization landscapes such as those encountered in partial shading MPPT.

3. PROBLEM FORMULATION

The power efficiency of photovoltaic energy systems primarily depends on climatic conditions such as solar irradiation and temperature. Traditional MPPT algorithms perform insufficiently when reaching Global Maximum Power Points (GMPPs)under partial shading conditions. This is because partial shading creates multiple local MPPs on the P-V characteristic curve, and conventional methods such as P&O and Incremental Conductance tend to converge to local maxima rather than the true global maximum.The specific problems addressed in this work are:

1. Partial shading leads to a multimodal P-V characteristic, causing traditional MPPT algorithms to fail in identifying the GMPP.
2. Standalone metaheuristic algorithms (PSO, GWO, DFO) each have limitations: PSO is prone to premature convergence; GWO has high power oscillations; DFO does not track previously obtained potential solutions.
3. A hybrid approach combining the strengths of PSO's memory-guided search with DFO's neighborhood-based dynamics is needed to achieve superior tracking factor, lower power oscillation, and faster convergence.

To address these problems, this paper proposes a hybrid PSO-DFO algorithm that integrates the Pbest and Gbest memory mechanisms from PSO into the DFO framework, while constraining the Lévy flight to prevent excessive divergence.

4. PV SYSTEM DESCRIPTION AND MODELING

4.1 PV Modeling

The fundamental element of PV systems are cells formed with diodes whichcan be made from various semiconductor materials [23]. The photovoltaic cell is modelled using a single diode connected in anti-parallel to a current source, along with series resistance Rs and shunt resistance Rsh to represent real cell behavior.

The output current according to this electrical circuit is obtained by Kirchhoff's Current Law as:

$$Is = Iph - Id - Ish \quad \ldots \ (1)$$

Where: Iph is the current generated by the solar cell, Id is the diode saturation current, and Ish is the parallel resistor current.

Equation (1) is rearranged using the Shockley equation for an ideal diode:

$$Is = Iph - I0\,[\exp(q(V + Rs\cdot Is) / nKTk) - 1] - (V + Rs\cdot Is) / Rsh \quad \ldots \ (2)$$

Where: Is is the current of the PV cell, V is the voltage of the PV cell, I0 is the diode saturation current, n is the diode ideality factor, Rs and Rsh are series and parallel resistors, Tk is the cell temperature, K is the Boltzmann constant (1.38×10^{-23} J/K), and q is the electron charge (1.602×10^{-19} C).

Solar cells are connected in series to form modules that increase the output voltage, and modules are connected in parallel to increase output current, forming PV arrays for higher power generation [23].

4.2 V-I Characteristic of PV Arrays

In PV arrays, the output power varies with temperature and solar radiation. As solar radiation increases, the generated current increases; as temperature increases, the generated voltage decreases [23]. Some solar cells may generate lower power due to partial shading caused by external factors such as clouds, pollution, andbuildings [24]. This reduces the output power and the overall system performance.When each cell of the solar panel absorbs solar irradiation equally, only one MPP occurs on the PV curve. However, if modules are exposed to different solar irradiation dueto partial shading, multiple MPPs are formed — the largest being the Global MPP (GMPP) and the others being Local MPPs (LMPPs) [25].

In PV systems under partial shading, the shaded panel emits heat while consuming power from nonshaded panels, limiting the current of seriesconnected panels. Bypass diodes are connected in parallel to each panel to overcome this issue. Under partial shading, bypass diodes become forward biased, carrying the shaded panel's current and complicating the PV module's characteristic curve. As a result, traditional MPPT algorithms fail to determine the GMPP and may settle at an LMPP [26,27,28].

4.3 Photovoltaic Technology

Photovoltaic technology is the field of research and engineering related to devices that directly convert sunlight into electricity using semiconductor materials exhibiting the photovoltaic effect. The photovoltaic effect involves the creation of voltage in a material upon exposure to electromagnetic radiation.

A PV system consists of multiple interconnected components including solar panels, a solar inverter, mounting structures, cabling, and optionally a battery storage system. PV systems range from small rooftop installations to large utility-scale power stations.

The solar cell is the elementary building block of photovoltaic technology. Solar cells are made of semiconductor materials, most commonly silicon. A p-n junction established within the silicon creates an electric field that separates photo-generated electron-hole pairs, driving current through an external circuit when light is absorbed.

5. MPPT ALGORITHMS

A general block diagram of the MPPT control in PV systems involves the PV source, a DC-DC converter (typically a boost converter), and the MPPT controller, which continuously monitors PV voltage and current and adjusts the duty cycle to maintain operation at the MPP. DC-DC converters are used in applications where a linear average output voltage is required, which can be higher or lower than the input voltage [29].The maximum power point is defined as the point where the slope of the P-V characteristic curve is zero (dP/dV = 0). As atmospheric conditions change, the voltage and current values at the MPP shift, requiring continuous monitoring and comparison with the previous state [30].

5.1 Particle Swarm Optimization Algorithm (PSO)

The Particle Swarm Optimization algorithm (PSO) was developed by Kennedy and Eberhart in 1995 [23]. This algorithm is based on a swarm that moves stochastically in the search space. Each element in the swarm is called a particle, and the velocities and positions of these particles are recorded. Particles move at a certain speed to reach the best position of the swarm.

According to the best position of the particles (Pbest) and the best position of the swarm (Gbest), values are updated at each iteration to reach the optimum solution. The velocity and position update equations are:

$$Vi(k+1) = \omega\cdot Vi(k) + c1\cdot r1\cdot(Pbest(i) - xi(k)) + c2\cdot r2\cdot(Gbest - xi(k)) \quad \dots \ (3)$$

$$xi(k+1) = xi(k) + Vi(k+1) \quad \dots \ (4)$$

Where: Vi(k) is the velocity of the i-th particle at iteration k; xi(k) is the position; Pbest(i) is the best value for the i-th particle; Gbest is the best global value of the swarm; ω is the weight function constant; c1 and c2 are positive constants in the range [0, 2]; r1 and r2 areuniformly random constants in the range [0, 1].

5.2 Grey Wolf Optimization Algorithm (GWO)

Gray Wolf Optimization (GWO) was developed inspired by the hunting behavior and social hierarchy of gray wolves [53]. In the social hierarchy, the alpha (α) wolf isthe leader and decision maker; beta (β) and delta (δ) wolves assist α in decision making; and omega (ω) wolves obey all other wolves.

During hunting, the positions of prey and wolves are expressed as vectors. The distance between a wolf and the prey, and the encircling behavior, are given by:

$$D = |C\cdot Xp(t) - Xi(t)| \quad \dots \ (5) Xi(t+1) = Xp(t) - A\cdot D \quad \dots \ (6)$$

The vectors A and C are calculated as: A = 2a·r1 − a and C = 2·r2, where a linearly decreases from 2 to 0 during iterations and r1, r2 are uniformly random constants in the range [0, 1].

5.3 Dragonfly Optimization Algorithm (DFO)

The Dragonfly Algorithm was first proposed by Seyedali Mirjalili in 2015, based on the behavior of dragonflies seeking food sources and escaping from enemies [54]. In the first step, a uniformly random swarm is generated and a step vector expressing the displacement request is created. The fitness function is calculated for each dragonfly; the best solution is the food source position and the worst is the enemy position.

The mathematical models of food attraction and enemy evasion are:

$F = X^{+} - X$ ... *(9)* $E = X^{-} + X$ ... *(10)*Where X^{+} is the position of the food source and X^{-} is the position of the enemy. If the current dragonfly has neighbors, three behavioralfactors govern its motion: Separation (S) prevents collisions, Alignment (A) synchronizes velocity, and Cohesion (C) maintains group proximity. The step and position vectors are updated as:$\Delta Xt+1 = (sS + aA + cC + fF + eE) + \omega \cdot \Delta Xt$ ... *(14)*$Xt+1 = Xt + \Delta Xt+1$ ... *(15)*

If the current dragonfly has no neighbors, Lévy flight is used for stochastic exploration of the search space, helping to escape local optima.

5.4 Proposed Hybrid PSO-DFO Algorithm

In the standard DFO algorithm, the position update action is calculated with two different equations depending on whether a neighborhood exists or not. However, in DFO, dragonflies are not programmed to follow previously obtained potential solutions [64]. This may lead to early or late convergence problems.

If the best-ever position Gbest reached by all dragonflies in the neighborhood, and the best position Pbest previously reached by the current dragonfly, are recorded and updated, potential global optimum points can be reliably tracked [64]. For this purpose, a hybrid PSO-DFO algorithm has been developed in this study, inspired by the PSO algorithm's particle and swarm memory mechanisms.

In addition, to prevent the Lévy flight from causing excessive divergence, the displacement request from the previous iteration is added to the random Lévy motion in the absence of a neighborhood. This modification significantly improves convergence stability.

The hybrid PSO-DFO algorithm works as follows: when a neighborhood relationship exists between dragonflies, the Pbest for each dragonfly is computed and the Gbest of the swarm is selected. The velocity vector is updated using the S, A, C, F, E factors along with the Pbest and Gbest information. When no neighborhood exists, the velocity of the previous iteration is applied and Gbest is tracked using Lévy flight.

6. MODELLING AND SIMULATION

The metaheuristic MPPT algorithms focused on in this paper have been evaluated and compared to each other. The simulation was carried out on MATLAB R2018a using a computer with 16 GB RAM, 250 GB SSD, 1 TB HDD, and an Intel® Core™ i7-4700MQ CPU @ 2.40 GHz x64 processor.

6.1 PV System Parameters

Tables I and II show the characteristics of the PV panel and the parameters of the DC-DC boost converter used in the simulation, respectively.

TableI: PV Panel Parameters

Parameter	Value
Maximum PV Power	PMAX = 213 W
MPP Voltage	VMPP = 29 V
MPP Current	IMPP = 7.35 A
Open Circuit Voltage	VOC = 36.3 V
Short Circuit Current	ISC = 7.84 A
Cells Per Module	NCELL = 60
Parallel Strings	P = 2

Series Connected Modules per String	S = 2

Table II: DC-DC Boost Converter Parameters

Parameter	Value
Input Capacitor	CPV = 470 µF
Boost Inductor	LB = 2.5 mH
Output Capacitor	CO = 47 µF
Resistive Load	RL = 6 Ω
Switching Frequency	fs = 50 kHz

6.2 Simulation Setup

The modelled system consists of four PV panels, each with 213 W maximum power. To simulate partial shading conditions, while 1000 W/m² solar radiation was applied to two of the four panels, 800 W/m² and 600 W/m² solar radiations were applied to the other two panels respectively.

Ideally, the total system power is expected to reach up to 852 W if all panels receive 1000 W/m² solar radiation. Under partial shading conditions, the MPPT algorithm that keeps the total output power closest to 852W is considered the most performant. The tracking factor of each algorithm was examined by evaluating the difference between the required power and the actual steady-state power.

6.3 Simulink Circuit

Figure 1 shows the MATLAB/Simulink circuit model of thePSO-DFO MPPT-based PV system. The model includes the PV array block, current and voltage measurement subsystems (IPv and V0), the PSO_DFO MPPT control block, a PWM generator, a boost converter (with inductor L1, capacitors C1 and C0), a diode, and a resistive load (C3). The powergui block configures the discrete simulation with a time step of 1×10^{-5} s.

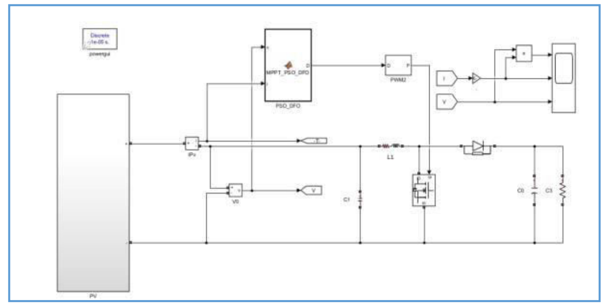

Figure 1: MATLAB/Simulink Circuit Model of the PSODFO MPPT-Based PV System R-load

6.4 Simulation Results

Figure 2 shows the output results for the R-Load configuration. The three plots display: (a) Output voltage (in volts) vs. time, (b) Output current (in amperes) vs. time, and (c) Output power (in watts) vs. time, all over a simulation period of 0 to 0.06 seconds.

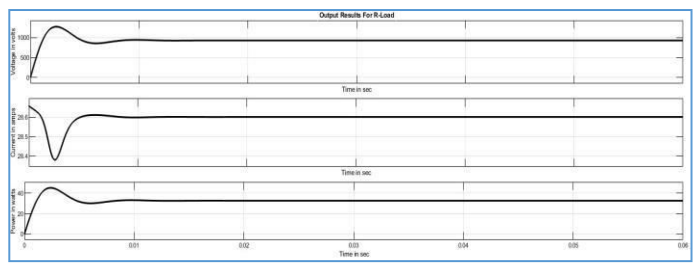

Figure 2: Simulation Output Results for R-Load — Voltage (top), Current (middle), Power (bottom)

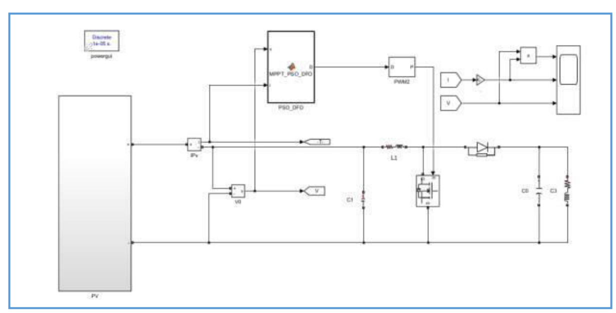

Figure 1: MATLAB/Simulink Circuit Model of the PSODFO MPPT-Based PV System RL-load

MPPT Algorithm	Maximum Power (W)	SteadyState Avg. Power (W)	Power Oscillation (%)	Tracking Factor (%)
GWO	828 W	818 W	1.79%	92%
PSO	825 W	820 W	2.07%	90%
DFO	833 W	813 W	1.492%	94%
PSO-DFO (Proposed)	835 W	825 W	1.231%	**97%**

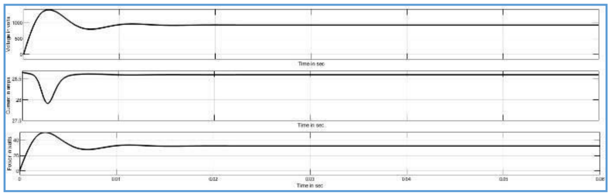

Figure 2: Simulation Output Results for RL-Load — Voltage (top), Current (middle), Power (bottom)

From the results, the voltage stabilizes at approximately 1000 V, the current settles at around 28.6 A, and the output power converges to approximately 28–30 W in the steady state after an initial transient peak. The system demonstrates fast convergence and stable operation under the hybrid PSO-DFO MPPT strategy.

6.5 Comparative Performance Analysis

Table III presents the detailed simulation results for all four algorithms, including the peak power, steady-state average power, power oscillation percentage, and tracking factor.

Table III: Simulation Results — Algorithm Comparison

It is observedthat the hybrid PSO-DFO algorithm gives better results than all other algorithms, achieving a tracking factor of 97% — the highest among all tested methods. The hybrid method also produces the highest steady-state average power (825 W) and the lowest power oscillation (1.231%). During simulations, it was noted that increasing the number of individuals in the swarm can cause convergence to a local maximum, while reducing individuals increases power fluctuations. Therefore, the number of individuals and iterations must be tuned individually for each algorithm.

7. CONCLUSION

In this study, PSO, GWO, and DFO metaheuristic MPPT algorithms were first compared to analyze their performance for MPPT tracking capability in PV systems under partial shading conditions.Then, a novel hybrid algorithm combining PSO and DFO was proposed for better performance.To make a comparative analysis, the behavior of the PV system under various irradiation levels and partial shading was considered. Each algorithm was tested on the same model consisting of four PV panels and a DC-DC boost converter in MATLAB/Simulink. Although all three analyzed algorithms yielded successful results for following the GMPP, output powers in steady-state conditions were found to be lower and high oscillations were observed.

The proposed hybrid PSO-DFO method has not only given the best result for tracking ability (97% tracking factor) but also provided higher steadystate output power (825 W) and the lowest power oscillations (1.231%) compared to standalone GWO, PSO, and DFO algorithms. The simulation results confirm that integrating the memory mechanisms of PSO into the DFO framework effectively addresses the convergence limitations of both individual algorithms.

Future work may explore the extension of this hybrid approach to three-phase grid-connected PV systems and evaluate performance under dynamic partial shading conditions with real-time hardware-the-loop testing.

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