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Comparative Evaluation of Metaheuristic MPPT Algorithms for PV Systems Under Partial Shading Conditions

Nima Shafagatian[1] | Mohammadreza Rahimi[1]| Reza Noroozian[1]| Hamid Karimi[2]
[1] Department of Electrical Engineering, University of Zanjan, University Blvd., Zanjan 45371-38791, Iran
[2] Department of Electrical and Computer Engineering. Qom University of Technology. Qom, Iran
Corresponding author's email: noroozian@znu.ac.ir

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ABSTRACT

Enhancing the energy output of photovoltaic (PV) systems is essential due to their inherently limited efficiency. Consequently, maximum power point tracking (MPPT) techniques have become a crucial component in photovoltaic systems for improving energy harvesting efficiency. However, conventional MPPT methods often require accurate mathematical modeling of PV systems, which remains a significant challenge due to their highly nonlinear behavior. To address this issue, researchers have proposed various MPPT strategies. The complex nonlinear behavior of PV systems makes pattern extraction difficult, often leading to simplified assumptions that may reduce tracking accuracy and overall system performance. This study investigates the performance of five metaheuristic optimization algorithms for MPPT under partial shading conditions (PSC) to improve PV system efficiency. The considered algorithms include Particle Swarm Optimization Algorithm (PSOA), Grey Wolf Optimization Algorithm (GWOA), Cuckoo Search Optimization Algorithm (CSOA), Genetic Algorithm (GA), and Quantum-Inspired Evolutionary Algorithm (QIEA). Although several studies have investigated metaheuristic MPPT techniques under partial shading conditions, relatively limited research has provided a comprehensive comparative evaluation of swarm-based, evolutionary-based, and physics-inspired optimization approaches considering tracking efficiency and dynamic response characteristics. The results demonstrate that the physics-inspired QIEA achieves a superior balance between exploration and exploitation, thereby enhancing its ability to accurately identify the global maximum power point.

I. Introduction

Despite the limited availability of conventional energy resources, global electricity demand continues to increase steadily. Consequently, the demand for renewable and environmentally friendly energy sources has grown significantly, with photovoltaic systems emerging as one of the most attractive solutions due to the clean, inexhaustible, and non-polluting nature of solar energy. In addition, PV systems are considered cost-effective and sustainable alternatives for future energy generation. However, the efficient utilization of PV systems remains challenging because their output characteristics are highly nonlinear and strongly affected by environmental conditions such as solar irradiance and temperature variations. These fluctuations often result in multiple power peaks, particularly under PSC.

Therefore, maximizing the performance of photovoltaic modules requires continuous tracking of the maximum power point (MPP) under varying operating conditions. Maximum power point tracking techniques are specifically designed to ensure PV systems operate consistently at their optimal power point. Several MPPT techniques have been proposed in the literature, including the Hill Climbing Technique (HCT), the Incremental Conductance method, the Fractional Open-Circuit Voltage method, and the Fractional Short-Circuit Current method. Generally, MPPT systems consist of a switch-mode power converter and a control algorithm that tracks the MPP. Developing robust energy conversion techniques with effective MPPT capability is essential for maintaining voltage stability and improving energy extraction under rapid environmental changes and varying load conditions. Several modifications have been introduced to improve the performance of conventional MPPT techniques, particularly under rapidly changing irradiance conditions. For instance, the method proposed in [1] employs a simple mathematical relationship between the load line and the I–V characteristic curve to achieve fast MPP tracking. Similarly, the approach presented in [2] introduces a dynamic MPPT controller capable of handling rapid irradiance variations and PSC by utilizing a scanning-based technique to identify the global maximum power point. Nevertheless, conventional MPPT techniques face considerable challenges when dealing with nonlinear objective functions and multiple decision variables. As a result, researchers have increasingly focused on heuristic and metaheuristic optimization approaches to address these limitations [3]. Metaheuristic algorithms employ iterative and intelligent search strategies inspired by natural or physical phenomena. Their effectiveness relies on achieving a suitable balance between exploration and exploitation processes [4]. Exploration refers to the global search capability for identifying promising regions within the search space, whereas exploitation focuses on refining solutions around the best candidate points. A proper balance between these two mechanisms is essential for obtaining an optimal solution. Traditional gradient-based MPPT methods, such as Perturb and Observe (P&O), HCT, and InC, often exhibit poor performance under PSC because they are unable to distinguish between local maximum power points (LMPPs) and the global maximum power point [5]. Therefore, numerous studies have investigated the application of heuristic optimization algorithms for improving MPPT performance. Effective MPPT methods play a critical role in regulating PV system output power and reducing power fluctuations caused by changes in solar irradiance, temperature, and shading [6,7]. By continuously tracking the MPP, these algorithms enhance the stability, reliability, and overall efficiency of PV power generation systems [8,9]. Among the proposed methods, several studies have demonstrated the effectiveness of Particle Swarm Optimization Algorithm (PSOA)-based approaches. In [10], a hybrid MPPT method combining PSOA and the Incremental Conductance technique was proposed to improve GMPP detection performance. In [11], PSOA was integrated with the Genetic Algorithm to reduce computational complexity. Furthermore, [12] presented an improved PSOA approach that reduces steady-state oscillations. Additional investigations into PSOA under PSC were conducted in [13], where a nonlinear inertia weight strategy was employed to enhance tracking performance. In [14], the authors evaluated the performance of the Cuckoo Search Optimization Algorithm and compared it with the conventional P&O method. The results showed that the CSOA achieved faster tracking performance, requiring only 22 ms compared to 45 ms for the P&O method. Moreover, the CSOA required only voltage and current sensors, thereby reducing implementation cost. In [15], a hybrid CSOA-Golden Section Search (GSS) method was proposed to improve convergence speed and tracking accuracy. In this approach, CSOA first identifies the region around the MPP, and the GSS algorithm then precisely determines the GMPP. Recent studies have focused on improving MPPT performance under partial shading conditions using intelligent and hybrid optimization techniques. Wang et al. [16] proposed a hybrid POA&PO approach with high tracking efficiency and rapid convergence; however, the hybrid structure increased the computational complexity. [17] Comprehensively reviewed recent intelligent MPPT techniques and highlighted the effectiveness of machine-learning-driven metaheuristic strategies, although limited comparative dynamic analyses were provided. In [18], comparative evaluations of PSO-, GA-, and ACO-based MPPT methods demonstrated improved tracking performance under PSC, but only a limited number of shading scenarios were investigated. Moreover, [19] introduced a heap-based optimization method with high tracking accuracy and reduced settling time, although implementation complexity remained a challenge. These limitations motivate further comparative investigations of different metaheuristic optimization approaches for MPPT applications under PSC. Motivated by these advancements, this study investigates the performance of five MPPT optimization algorithms under PSC, namely QIEA, GWOA, PSOA, CSOA, and GA. These algorithms are comparatively evaluated from the perspectives of swarm-based, evolutionary-based, and physics-inspired optimization approaches to improve PV system efficiency and enhance dynamic response performance under partial shading conditions.As a result, the main contributions of this study can be summarized as follows:

- ✓ A comprehensive comparative evaluation of different metaheuristic optimization categories, including swarm-based, evolutionary-based, and physics-inspired algorithms, for MPPT applications under partial shading conditions.

- ✓ Investigation of the tracking performance of PSOA, GWOA, CSOA, GA, and QIEA in terms of convergence behavior, oscillation characteristics, and global maximum power point tracking capability under identical operating conditions.

- ✓ Comparative assessment of the dynamic response performance of the investigated MPPT techniques, including tracking stability, overshoot, undershoot, and settling time characteristics under partial shading conditions.

The remainder of this paper is organized as follows. Section 2 presents the system description. Section 3 describes the proposed cost function. Section 4 explains the methodologies of the investigated optimization algorithms. Section 5 discusses the simulation results and comparative analysis, while Section 6 concludes the paper.

II. PV description

A photovoltaic (PV) system consists of multiple solar cells connected in series and parallel configurations to achieve the desired voltage and current levels. Series connections increase the output voltage, whereas parallel connections increase the output current. Under partial shading conditions, the presence of bypass diodes results in multiple peaks in the power–voltage (P–V) characteristics, including several local maximum power points (LMPPs) and a single global maximum power point. To mitigate hot-spot formation during PSC, bypass diodes are connected in parallel with each PV module. Hot spots occur when shaded modules consume power rather than generate it, potentially leading to overheating and damage to the PV system. The incorporation of bypass diodes improves system reliability and protects the PV modules under non-uniform irradiance conditions. Figure 1 illustrates the overall structure of the proposed heuristic-based MPPT system. In addition, Figure 2 presents the PSC scenario along with the corresponding P–V characteristic curve. The following equation represents the single-diode model of a PV cell.

$$I = I_{pv} - I_0\left[exp(\frac{V+IR_s}{V_t} - 1)\right] - \frac{V+IR_s}{R_p} \quad (1)$$

I_{pv} denotes the current generated by incoming light;

$\left[exp(\frac{V+IR_s}{nV_t} - 1)\right]$ represents the Schottky diode current;

I_0 signifies the leakage current;

V_t indicates the thermal voltage of the diode;

R_s refers to the series resistance in the analogous model of the photovoltaic cell;

I is the corresponding current;

R_p Denotes the model's parallel resistance

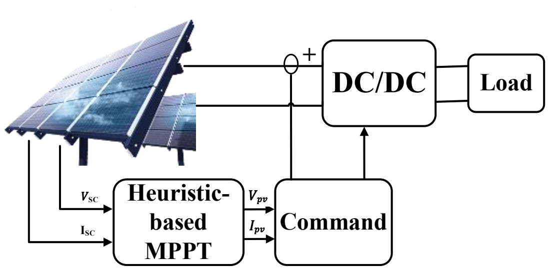

Fig. 1. Schematic of heuristic-based MPPT system.

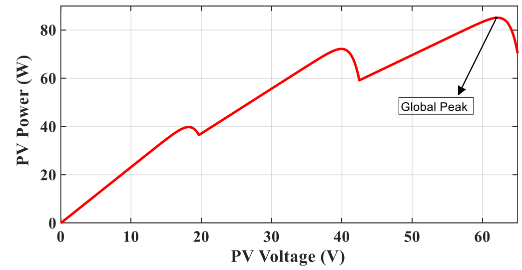

Fig. 2. P–V curves under PSC.

III. Cost Function

The cost function for the suggested issue may be described as Eq. (2). The cost function presented in Eq. (2) was formulated to achieve a balanced trade-off between maximum power extraction and dynamic response performance under partial shading conditions. The first term maximizes the extracted output power relative to the PV system's rated power, while the remaining terms penalize undesirable transient characteristics, including overshoot, undershoot, and settling time. The weighting coefficients w_1, w_2, and w_3 were selected empirically through repeated simulation trials to provide an appropriate trade-off between tracking accuracy and dynamic response stability. Larger values of w_1 prioritize maximizing output power, whereas increasing w_2 and w_3 place greater emphasis on reducing transient oscillations and improving settling characteristics. Although the selected weighting coefficients provided satisfactory performance under the investigated PSC scenario, a more comprehensive sensitivity analysis considering different weighting combinations and operating conditions is recommended for future investigation.

$$v_i^{k+1} = \omega \times v_i^k + c_1 r_1 (p_{local\ best,i}^k - p_i^k) + c_2 r_2 (p_{\text{global}\ best}^k - p_i^k) \quad (2)$$

Minimization

$$J = \omega_1\left(1 - \frac{P_{max}}{P_{rated}}\right) + \omega_2(O_v + U_s) + \omega_3 T_s \quad (3)$$

where,

J is the aggregate cost function designated for minimization;

P_{rated} is the nominal power output of the PV cell under conventional test circumstances;

P_{max} signifies the maximum power output under PSC;

The weighting variables $(\omega_1, \omega_2, \omega_3)$ serve to equilibrate the relative significance of the different terms.

Ov is the highest overshoot in output power during disturbances;

Us is the maximum undershoot;

Ts is the settling time of the output power during disturbances.

IV. Evaluation of the presented method

As stated above, this study examines the use of five algorithms—PSOA, GWOA, CSOA, GA, and QIEA—for efficient MPPT in solar cells under partial shading conditions, while accounting for PQ.

B. PSOA-based MPPT Technique (Swarm-based Technique)

The behavior of bird flocking is analogous to PSOA, which is also inspired by biological phenomena. To achieve optimal results, it operates with minimal assumptions. The fundamental concept of this bio-inspired technique is to view each PV array or module as a molecule, with the MPP functioning as the target to be monitored. Each photovoltaic module functions as a subordinate to a master module within this structure, interacting with its master controller to monitor the requisite MPP [24]. Initially, PSOA produces a population of individual swarms, which signify probable solutions, and these "particles" traverse the search space. They observe the paths of adjacent particles alongside their own. The position of a particle is dictated by the most advantageous solution recognized by the whole population $P^i_{Local\ best}$ and the optimum particle in its proximity $P^k_{Local\ best}$. The particle's position is modified based on the best particle nearby and the ideal solution identified by the whole population of particles. Eq.(3) is executed to alter the location of a particle. The GMPP can be easily monitored because the PSOA strategy is based on the search method. When the MPP point is followed, the enhanced PSOA technique can reduce steady-state oscillations, as explained in specific literature. To prevent superfluous and excessive searching, particles can be effectively initialized around the MPP, ensuring that the swarm efficiently explores the area and rapidly converges to the true MPP. Parameter control is a critical attribute of this methodology. Figure 3 depicts the flowchart of the proposed PSOA-based MPPT algorithm.

where,

w	is the inertia weight;
c_1, c_2	are the rising speed coefficients;
r_1, r_2	is the particle index;
k	is the iteration index;
v_i^k	is the velocity of the ith particle at the kth iteration;
$P^k_{Localbest,i}$	is the local best;
P_i^k	represents the position of the ith particle at the kth iteration;
$P^k_{global\ best}$	represents the best position experienced by all particles up to the kth iteration;

C. GWOA-based MPPT Technique as a swarm-based technique

The GWOA emulates the leadership structure and hunting strategies of grey wolves in the wild, as presented in [22]. Grey wolves are apex predators that live communally in packs. The program models the social order via four classifications of grey wolves: alpha (α), beta (β), delta (δ), and omega (w). In the GWOA design, the optimal solution is designated as alpha (α), while the second and third best options are referred to as beta (β) and delta (δ), respectively. The residual candidate solutions are designated as omega (w). Figure 4 delineates the three primary phases of the GWOA, including searching for, pursuing, and monitoring prey, surrounding prey, and assaulting prey. These stages are essential for executing optimization. In the course of a hunt, grey wolves surround their quarry, a behavior represented by the following equations:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}_p(t)\right| \tag{4}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{5}$$

In this context, t signifies the current iteration, D, A, and C imply coefficient vectors, $\vec{X}_p(t)$ represents the position vector of the prey, and X indicates the position vector of the grey wolf. The vectors A and C are computed in the following manner:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{6}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{7}$$

The components decline linearly from 2 to 0 during the repetitions, while $\vec{r}_1, \vec{r}_2$ are random vectors within the interval [0, 1]. Alpha wolves often lead the hunt, with beta and delta wolves following closely behind. Delta and omega wolves attend to the injured members of the pack. The alpha wolf, with superior knowledge of the prey's position, directs the hunt, culminating in an assault when the prey ceases to move. The controller monitors V_{pv} and I_{pv} via sensors for various duty ratios of grey wolves, and calculates the output power. Under PSC, the P–V curve shows many peaks, including several local peaks (LPs) and a single global peak (GP). When wolves identify the MPP, their respective coefficient vectors move toward zero. The proposed method combines GWOA with direct duty-cycle control. At the MPP, the duty cycle remains unchanged, reducing the steady fluctuations common in traditional MPPT systems and decreasing power losses caused by these fluctuations, thereby enhancing system efficiency. In the GWOA-based MPPT implementation, the duty cycle D is described as a Gray wolf. Therefore, Eq. (5) can be revised as follows:

$$D_i(k+1) = D_i(k) - A \cdot D \tag{8}$$

Consequently, the fitness function of the GWOA is articulated as:

$$P(d_i^k) > P(d_i^{k-1}) \tag{9}$$

where;

p denotes power

d signifies the duty cycle

i indicates the quantity of current gray wolves

k represents the number of repeats

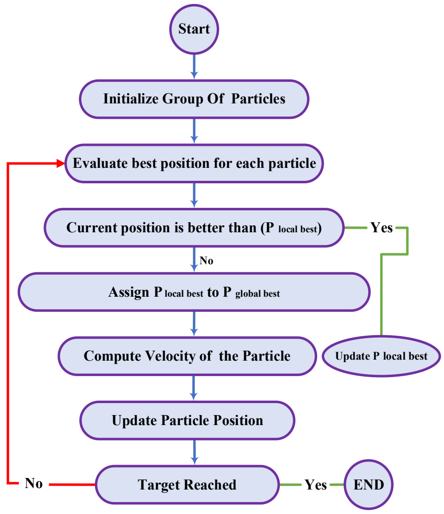

Fig. 3. Flowchart of the PSOA algorithm.

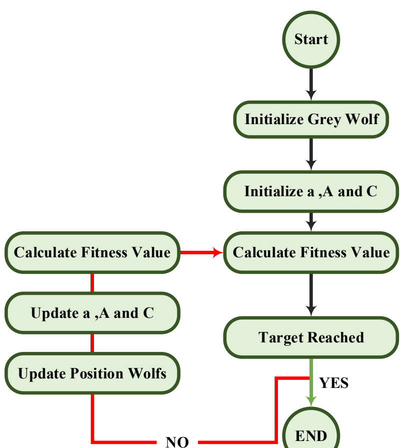

Fig. 4. Flowchart of the GWOA.

D. CSOA-based MPPT technique as a swarm-based method

This method uses the characteristics of the cuckoo bird as a metaphor for finding the best solution in MPPT. This concept, explained in [23], shows the tracking technique. The cuckoo's egg represents the best new solution, while the eggs already in the nest stand for the existing solutions. By applying an appropriate fitness function, suboptimal solutions (old eggs) are gradually replaced by the optimal solution (cuckoo's egg). Figure 5 illustrates the planned CSOA-based MPPT methodology. The cuckoo search method is based on three principles.

- ❖ Each cuckoo successively deposits eggs in randomly selected nests.
- ❖ The nests preserve the highest quality eggs for subsequent generations.
- ❖ The quantity of accessible host nests is constant, while the likelihood of a host bird detecting a cuckoo's egg ranges from 0 to 1. In this situation, the host bird may either eliminate the egg or forsake the nest to build a new one.

To simplify, this last assumption is represented by substituting nests with new ones (exhibiting random configurations) if a bird identifies an egg that does not belong to it, resulting in its destruction via rapid flight. [24] offers a comprehensive elucidation of this technique. The fitness function (F) has two parameters, namely the operating voltage of the PV array (V) and the step size α for optimizing the GMPP, which is illustrated in Eq.(10):

$$F = f(v) \text{ and } V_i^{t+1} = V_i + \alpha \oplus levy(\lambda) \qquad (10)$$

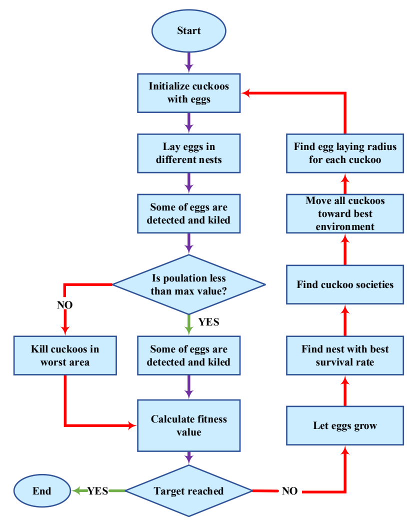

Fig. 5. Flowchart of the CSOA algorithm

E. GA based MPPT Technique as an Evolutionary Method

The GA remains the most effective method among evolutionary approaches; therefore, it has been selected for comparison. Following previous methodologies, the GA begins with an initial population (initial solution). The controller measures V_{pv} and I_{pv} calculates the output power. The GA then applies a series of genetic operators, including selection, crossover, and mutation, on the population to generate a new set of individuals. The selection operator chooses parents based on their fitness, while the crossover operator combines the genetic material of the selected parents to create new offspring. The mutation operator introduces random variations in the offspring to explore different areas of the search space. This iterative process continues until the convergence criterion is met. The final solution, representing the optimal values of the control variables V_{pv} and I_{pv} , aligns with the maximum power point (MPP) of the solar cell. The genetic algorithm effectively solves the maximum power point tracking problem by exploring the search space and converging on the optimal solution. This method is especially useful when the power output function is complex or nonlinear, as the evolutionary algorithm can handle such situations effectively. Figure 6 shows the flowchart of the proposed genetic algorithm-based maximum power point tracking method.

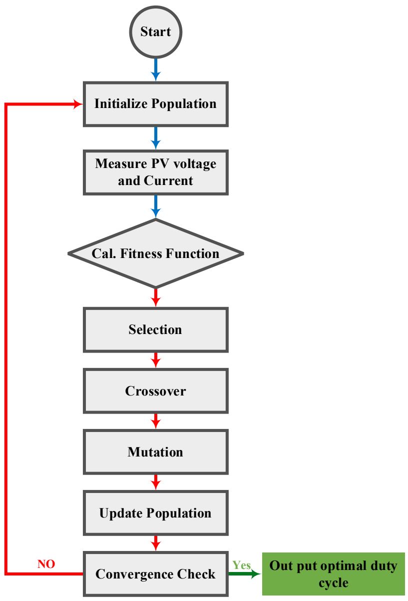

Fig. 6. Flowchart of the GA algorithm

F. QIEA-based MPPT Technique as Physics-based Method

The Quantum-Inspired Evolutionary Algorithm is an innovative evolutionary algorithm inspired by concepts from quantum computing [25], [26]. Quantum Evolutionary Algorithms (QIEA) use a probabilistic representation based on the quantum bit, or qubit, unlike conventional evolutionary algorithms that use binary, arithmetic, or symbolic representations. The qubit serves as the essential unit of information in quantum computing, capable of being in a superposition of states. The qubit-based system enables QIEA to present a wide range of possible solutions within its group, thereby enhancing its ability to explore options. QIEA utilizes an innovative Q-bit format, characterized as a kind of probabilistic encoding. A qubit is the fundamental unit of information in quantum error analysis (QIEA) and is represented by a pair of integers (α, β), satisfying the condition $|\alpha|^2 + |\beta|^2 = 1$. Here, $|\alpha|^2$ denotes the likelihood of the qubit being in the '0' state, while $|\beta|^2$ signifies the probability of it being in the '1' state. A qubit may occupy the '0' state, the '1' state, or a linear superposition of both states. A single Q-bit encoded as a sequence of m Q-bits is denoted as:

$$\begin{gathered}[\alpha_1 \quad \beta_1 \quad \alpha_2 \quad \beta_2 \quad . \quad . \quad . \quad \alpha_m \quad \beta_m]^T \\ |\alpha|^2 + |\beta|^2 = 1, i = 1,2,\ldots,m\end{gathered} \tag{11}$$

The Q-bit format has the benefit of probabilistically depicting a linear superposition of states. A three-qubit system with three pairs of amplitudes may represent information from eight unique states. This depiction illustrates a greater variety of populations compared to other forms. QIEA is a probabilistic algorithm, similar to several others. Nonetheless, QIEA distinctly sustains a population of Q-bit individuals denoted as $Q(t) = \{q_1^t, q_2^t, \ldots, q_n^t\}$at generation t, where n signifies the population size. Each Q-bit entity q_j^t for $j = 1,2,\ldots,n$ is delineated in (10). Figure 7 illustrates the comprehensive structure of QIEA.

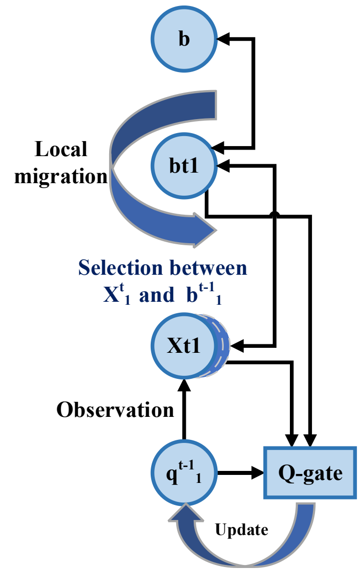

Fig. 7. Structure of QIEA algorithm.

- Initialization of $Q(t)$: In this phase, the values of α_i^0, β_i^0 for all q_j^0 j=1,2,...,n are set to $\sqrt{2}^{-1}$. This implies that each Q-bit individual, q_j^0, represents a variety of phases of the energy output of the photovoltaic cell.
- Binary Solution Generation: Binary solutions in $P(0)$ are produced by analyzing the states of $Q(0)$, where $P(0) = \{x_1^0, x_2^0, \ldots, x_n^0\}$ at generation $t = 0$. Each binary solution x_j^0 is a binary string of length m, created by choosing either 0 or 1 for each bit according to the probability $|\alpha_i^0|^2$ or $|\beta_i^0|^2$.
- Fitness Assessment: Each binary solution x_j^0 is assessed according to the power output of the solar cell.
- Choosing the First Best Solutions: The best solutions from $P(0)$ are found and written down in $B(0)$, where $B(0) = \{b_1^0, b_2^0, \ldots, b_n^0\}$ at the start of the generation.
- Picking of starting Optimal Values: The optimal solutions from $P(0)$ are chosen and recorded in $B(0)$, where $B(0) = \{b_1^0, b_2^0, \ldots, b_n^0\}$ and b_j^0matches x_j^0 at the beginning of the iteration.
- While Loop: In every repetition of the while loop, binary solutions in $P(t)$ are formed by watching the states of $Q(t-1)$ as in step 2, and each binary solution is assessed for fitness. Notice that x_j^t in $P(t)$ can come from many evaluations of q_j^{t-1} in $Q(t-1)$.

- Q-bit Update: The Q-bit entities in $Q(t)$ are modified utilizing Q-gates, which function as variation operators in QIEA. The revised Q-bits must adhere to the normalization requirement, $|\alpha'|^2 + |\beta'|^2 = 1$, where α' and β' represent the updated values. The subsequent rotation gate serves as a fundamental Q-gate in QIEA:

$$U(\Delta\theta_i) = \begin{bmatrix} cos(\Delta\theta_i) & -sin(\Delta\theta_i) \\ sin(\Delta\theta_i) & cos(\Delta\theta_i) \end{bmatrix} \tag{12}$$

In this context $\Delta\theta_i$ for $i = 1, 2, ..., m$, represents the rotation angle for each Q-bit, dictated by its sign and customized for the particular application.

- Best Solution Selection: The best solutions from $B(t-1)$ and $P(t)$ are selected and stored in $B(t)$. If the best solution in $B(t)$ outperforms the current best solution b, the stored solution b is updated.
- Global Migration: Upon meeting the global migration criterion, the optimal solution b is disseminated to $B(t)$on a worldwide scale.
- Local Migration: When the local migration criterion is met, the optimal resolution for a local group inside $B(t)$ is to relocate to other members of the same group.
- By adhering to these procedures, QIEA may proficiently monitor the maximum power point of a solar cell and enhance operational circumstances to get optimal power generation.

V. Simulation Results

The simulation studies were conducted using a MATLAB/Simulink-based photovoltaic system model under predefined irradiance and partial-shading conditions. The investigated PSC scenarios were designed to provide a controlled, consistent environment for the comparative evaluation of MPPT algorithms under identical operating conditions. The simulations were conducted using synthetic irradiance profiles rather than experimentally measured datasets. In this study, a representative PSC scenario with rapid irradiance variation from 0.6 to 0.85 kW/m² was considered to provide a controlled comparative evaluation environment for the investigated MPPT algorithms. The selected scenario was intended to facilitate consistent analysis of convergence behavior, oscillation characteristics, and tracking performance under identical operating conditions. Although the adopted PSC scenario provided useful comparative insight, further investigations involving multiple stochastic shading patterns, noisy operating conditions, and experimentally measured irradiance profiles are recommended for future research. Figure 8 depicts the MPP tracking curve for the suggested system, showing a rapid rise in irradiance from 0.6 to 0.85 kW/m². This curve illustrates the irradiance pattern used to assess the proposed MPPT and the algorithms' effectiveness in pinpointing optimal locations. The red areas in Figure 8 indicate the optimal locations accurately identified by the PSOA, GWOA, and QIEA algorithms. The results for the initial irradiation situation of 0.6 kW/m² are further studied, and the effectiveness of all algorithms is evaluated. Figures 9 to 14 illustrate the outcomes of voltage, current, and output power derived from the five algorithms: PSOA, GWOA, CSOA, GA, and QIEA. Figures 9 and 10 illustrate the current scores achieved by the algorithms. The QIEA demonstrated superior tracking of current points with fewer oscillations relative to the other algorithms. This method reduces the mean overshoot and undershoot, as well as the settling time. Enhanced tracking speed, reduced oscillations, and increased precision will yield improved dynamic response performance. On the other hand, the control system produced the least satisfactory results and was unable to monitor the maximum power accurately. In the cases this study examined, the immediate and authentic implementation of shade modifications was the specific cause. Implementing the scenarios separately would have resulted in varied outcomes. Figure 10 also presents the outcomes of all algorithms for enhanced comparison in the steady-state mode. The QIEA attained more advantageous outcomes. A 17% undershoot is noted at the commencement of operation in the 0.4th second. During this interval, the GWOA improved by 10%. Nevertheless, the CSOA produced the most significant undershoot of around 26% at the 0.4-second mark. The settling time denotes the duration required to achieve 95% of the steady-state condition, characterized by variations of less than 3%.

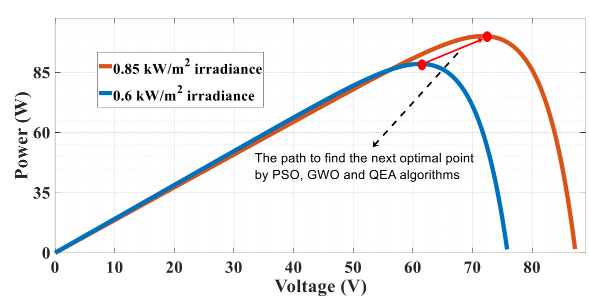

Fig. 8. Tracking curve for a sudden increase in irradiance.

It is important to note that although the GWOA seems to outperform the CSOA, and the CSOA appears inferior to the GWOA, there are occasions when this assessment is not totally correct. For instance, GWOA had a longer maximum settling time than CSOA at a specific point during operation. On average, the GWOA outperformed CSOA. Under typical conditions, average performance is generally the foremost consideration; nevertheless, in exceptional situations, such as with sensitive loads, the maximum and lowest values become critical. According to Figs. 10 and 12, the output current was comparatively lower while using the GA; however, the output voltage was greater with the GA in contrast to the other algorithms. The observed phenomena

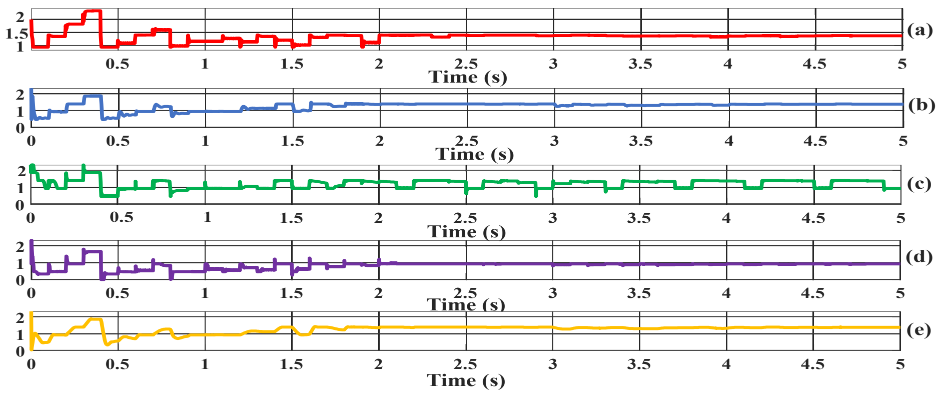

Fig. 9. Output current related to algorithms, (a) PSOA, (b) GWOA, (c) CSOA, (d) GA, (e) QIEA.

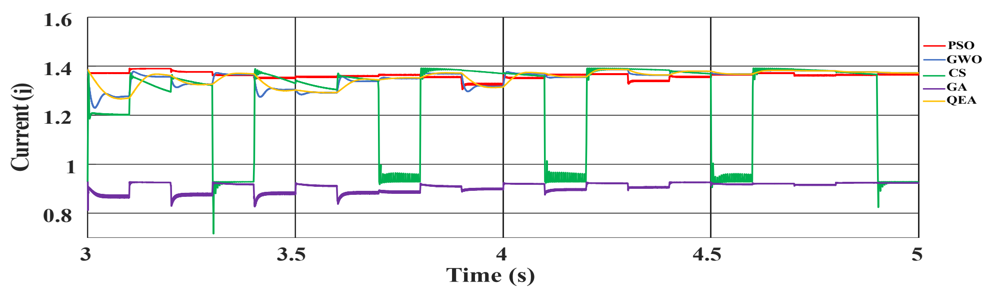

Fig. 10. Steady state of output current in all five algorithms.

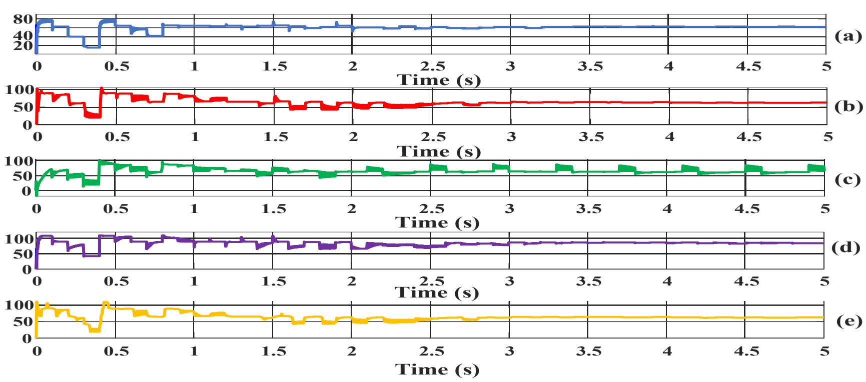

Fig. 11. Output voltage related to algorithms, a: PSOA, b: GWOA, c: CSOA, d: GA, e: QIEA

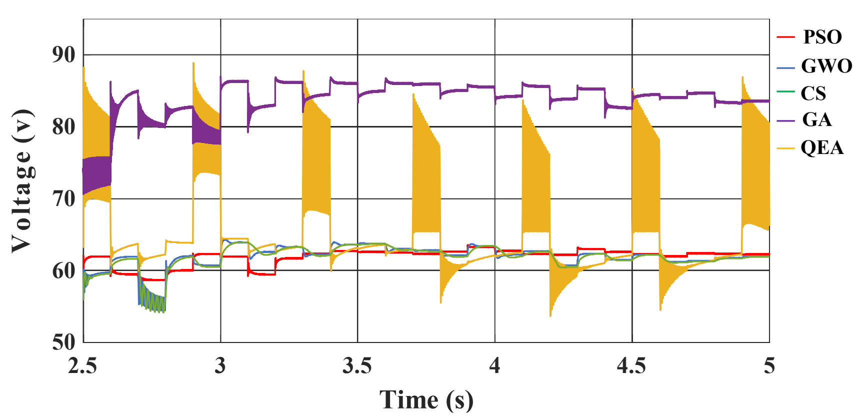

Fig. 12. Steady state of output voltage in all five algorithms.

may stem from the GA algorithm's inability to efficiently optimize the current control and maximize output current, as the optimization appears to have prioritized voltage regulation, resulting in elevated output voltage but diminished output current. Figures 11 and 12 illustrate the output voltage generated by the algorithms. These outputs are similar to the output current in terms of oscillations and transient response characteristics. The performance of QIEA surpasses that of the other algorithms, whereas CSOA exhibits the worst performance. The maximum overrun in the QIEA algorithm is 15%, but in the CSOA algorithm it is 26%. The QIEA algorithm demonstrates superior performance for average overshoots, undershoots, and settling time. The findings concerning the output power are illustrated in Figures 13 and 14. Consistent with prior findings regarding voltage and current, it is anticipated that the power output associated with the QIEA surpassed that of the other algorithms, while the results pertaining to the CSOA algorithm were the least favorable. The power output from the QIEA exhibits minimal oscillation. This is entirely undesirable in the CSOA algorithm. As shown in Figs. 13 and 14, starting at 2.5 seconds, while the other algorithms show little change, CSOA has caused large swings in the output power.

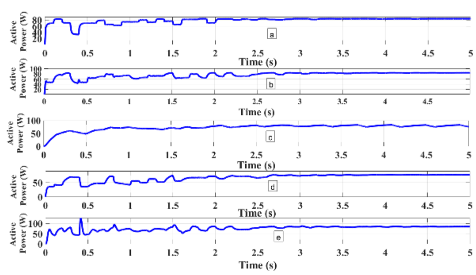

Fig. 13. Output power related to algorithms, a: PSOA, b: GWOA, c: CSOA, d: GA, e: QIEA

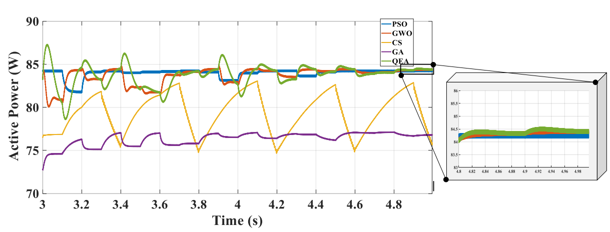

Fig. 14. Steady state of output power in all five algorithms.

Table 1 shows that when conditions are stable, the QIEA performs better than earlier methods in both following the current and producing power, reaching a maximum current of 1.37 A and the best output power of 84.8 W. The GWOA and PSOA exhibited commendable performance, with GWOA achieving 1.36 A and PSOA attaining 1.35 A, but yielding marginally lower power outputs. Conversely, the GA demonstrated the poorest performance in current tracking (0.95 A) and achieved an output power of 80.37 W. The CSOA did not converge, underscoring its ineffectiveness in this application. The QIEA and PSOA are endorsed for their exceptional efficacy in optimizing power production in shadowed environments. The physics-based Quantum-inspired Evolutionary Algorithm demonstrated superior performance in maximizing the power output of a solar cell, specifically by identifying the maximum power point under shadowed conditions and improving the stability and transient response of the output power. The Grey Wolf Optimizer algorithm, a technique based on swarm intelligence, succeeded the QIEA. The PSOA and GA ranked next, while the CSOA had the poorest performance. The intrinsic attributes and advantages of the various algorithmic methodologies elucidate the observed ranking. QIEA efficiently modeled the intricate non-linear behavior of the solar cell and precisely tracked the maximum power point, particularly under PSC. This arises from the algorithm's basis in quantum physics concepts, which enhanced comprehension of the system dynamics. Swarm-based algorithms, like GWOA and PSOA, are better at searching for solutions than the evolutionary GA method, which leads to better optimization results. The physics-based methodology of the QIEA finally achieved the optimal equilibrium between exploration and exploitation, leading to its enhanced performance in the maximum power point tracking test under shadowed conditions. Table 2 encapsulates the efficacy of the five methods. The presented comparative evaluation was performed under identical operating conditions to ensure a consistent performance assessment of the investigated MPPT algorithms. Although the obtained results demonstrate clear differences in convergence behavior and tracking performance, additional statistical investigations involving multiple independent simulation runs, mean performance values, standard deviation analysis, and detailed convergence curves would provide deeper insight into the robustness and repeatability of the investigated methods. These aspects are recommended for future investigation.

VI. Conclusion

This study examined the efficacy of five distinct algorithms—PSOA, GWOA, CSOA, GA, and QIEA—in optimizing the power output of a solar cell under partial shading conditions and enhancing the quality of the output power. The study's results indicated that among the five algorithms evaluated, the QIEA demonstrated superior performance. The QIEA demonstrated superior tracking of current points with reduced oscillations, less average overshoot and undershoot, and abbreviated settling periods relative to the other algorithms. These features led to the QIEA attaining the most advantageous output power results, accompanied by minimal oscillations. The GWOA algorithm outperformed the QIEA. PSOA and GA followed in the rankings. The CSOA algorithm had the poorest performance among the five algorithms evaluated. The QIEA's exceptional performance is due to its physics-based foundation, enabling it to predict the intricate non-linear behavior of the solar cell system and correctly monitor the highest power point, particularly under PSS conditions.

TABLE I Results under steady-state conditions.

Algorithm	Output Current (A)	Output Voltage (V)	Output Power (W)
PSOA	1.35	62.7	84.64
GWOA	1.36	62.0	84.32
CSOA	Not converged	Not converged	Not converged
GA	0.95	84.6	80.37
QIEA	1.37	61.9	84.8

TABLE II Comparative performance evaluation of the investigated MPPT algorithms under PSC

	Swarm-based methods			Evolutionary method	Physics-based method
	PSOA	GWOA	CSOA	GA	QIEA
Tracking speed	Moderate	Moderate	Low	Low	Fast
Tracking accuracy	Accurate	Accurate	Low	Low	Highly accurate
Convergence to global peak	Yes	Yes	No	No	Yes
Steady state oscillations	Low	Low	Very high	Moderate	Low
Implementation complexity	Low	Medium	Medium	Low	Medium

Swarm-based algorithms such as GWOA and PSOA show superior efficacy in exploring the solution space compared to GA; nevertheless, QIEA achieved the optimal equilibrium of exploration, exploitation, and comprehension of the solar cell system. Conversely, the CSOA algorithm failed to adequately represent the intricate non-linear attributes of the solar cell system when compared to alternative approaches, leading to its suboptimal performance. The obtained results were further compared with recently published MPPT techniques reported in the literature. Compared with conventional PSO- and GA-based methods, the QIEA demonstrated improved convergence characteristics and lower steady-state oscillations under partial shading conditions. The superior performance of the QIEA can be attributed to its effective balance between exploration and exploitation processes, which enables more accurate identification of the global maximum power point (GMPP). Moreover, the GWOA exhibited competitive tracking accuracy and relatively low oscillations compared with the CSOA and GA methods. Although the CSOA achieved acceptable convergence speed in some operating conditions, it suffered from significant oscillations and convergence instability under rapidly changing irradiance levels. In contrast, the GA showed relatively lower tracking accuracy due to premature convergence behavior and limited global search capability. Compared with recently published hybrid and intelligent MPPT approaches, the investigated algorithms demonstrated comparable tracking performance while maintaining relatively moderate implementation complexity. However, further investigation under stochastic shading conditions and noisy operating environments remains an important topic for future research.

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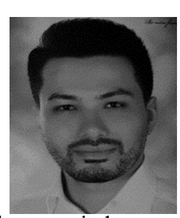

Nima Shafaghatian was born in Iran. He received his degree from Zanjan University and is currently studying Ph.D. there. He has authored several articles in well-known Journals published by IEEE, IET, and Springer. He has also published two books on renewable energy and the relationship between industry and academia. In addition to studying Ph.D., He is a lecturer at Al-Ghadir University in Zanjan and teaches electrical installations, smart home design, signals and systems, and the specialized language of electricity. His research interests include microgrids, power management, and the electricity market.

Mohammdreza Rahimi was born in Iran. He received his M.Sc. degree in Electrical Engineering from the University of Zanjan. He has published several scientific papers in electrical engineering and power systems. He is currently a lecturer at Iran National Skill University in Zanjan, where he teaches electrical engineering courses. In addition, he serves as a research assistant and is actively involved in academic and research activities. His research interests include power systems, microgrids, renewable energy resources, power management, and optimization.

Reza Noroozian received the B.Sc. degree from Tabriz University, Tabriz, Iran, in 2000 and the M.Sc. and Ph.D. degrees in electrical engineering from the Amirkabir University of Technology (AUT), Iran, in 2003 and 2008, respectively. He is a Full Professor at the Department of Electrical Engineering, University of Zanjan, Zanjan, Iran. His research interests include power electronics, power systems, power quality, integration and control of renewable generation units, custom power, micro-grid operation, distributed generation modeling, operation, and interface control.

Hamid Karimi received his B.Sc. and M.Sc. degrees in Electrical Engineering from Shahid Beheshti University (SBU) and Iran University of Science and Technology (IUST), Tehran, Iran, in 2015 and 2017, respectively. He obtained his Ph.D. in Electrical Engineering from Iran University of Science and Technology (IUST) in 2022. His research interests include power system operation optimization, multi-objective optimization, and game theory. He is currently an Assistant Professor at the Faculty of Electrical and Computer Engineering, Qom University of Technology (QUT), Iran.