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MODERN METHODS OF MAXIMUM POWER POINT TRACKING IN PHOTOVOLTAIC SYSTEMS: CLASSIFICATION, COMPARISON, AND APPLICATION UNDER PARTIAL SHADING CONDITIONS

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Abstract

Maximum Power Point Tracking (MPPT) is essential for optimising the efficiency of photovoltaic (PV) systems. Selecting the appropriate MPPT algorithm allows for better utilisation of solar energy. Under Partial Shading Conditions (PSC), the power-voltage (P–V) curve becomes nonlinear, leading to multiple Local Maximum Power Points (LMPP), which complicates the identification of the Global Maximum Power Point (GMPP) and reduces system efficiency. This paper reviews and classifies MPPT methods into four categories: classical, metaheuristic, AI-based, and hybrid. These approaches are compared in terms of tracking accuracy, speed, adaptability to changing conditions, and robustness. Special focus is placed on methods that maintain performance under PSC, minimising energy losses and improving system stability. The goal is to highlight the strengths and limitations of each method and suggest directions for further optimisation to enhance the reliability and overall efficiency of PV systems in real-world conditions.

Keywords: Maximum Power Point Tracking (MPPT), photovoltaic systems (PV), partial shading conditions (PSC), global maximum power point (GMPP), optimisation algorithms, artificial intelligence, hybrid methods.

1. Introduction

Photovoltaic (PV) systems play a crucial role in the process of energy transformation, serving as one of the most significant renewable energy sources. Their popularity stems from the possibility of converting solar radiation into electrical energy in an environmentally friendly and economically viable manner. Despite numerous advantages, such as long lifespan and modular construction, PV systems exhibit variable performance dependent on external conditions, component quality, and control strategy selection. To achieve the highest possible energy output, it is essential to employ *Maximum Power Point Tracking* (MPPT) algorithms, which ensure the optimal operating parameters of PV systems [1].

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One of the primary factors affecting the efficiency of the PV system is the varying solar irradiation. The intensity of solar radiation directly influences the amount of current generated. Additionally, temperature significantly impacts module operation; an increase in temperature reduces the open-circuit voltage, thereby lowering the system's output power. The effectiveness of MPPT algorithms depends on their ability to respond quickly to changes and minimise losses caused by oscillations around the Maximum Power Point (MPP) [2].

Under ideal weather conditions, the entire PV array is uniformly illuminated, and the *power-voltage* (P–V) characteristic has a single global maximum. However, in real-world conditions, *partial shading conditions* (PSC) frequently occur, significantly reducing MPPT tracking efficiency. Partial shading can result from permanent obstructions, such as buildings or trees, or temporary disturbances like clouds, birds, or contamination on PV modules. In such cases, the P–V characteristic changes significantly as shaded cells act as loads for the remaining modules, leading to multiple Local Maximum Power Points (LMPP). This phenomenon considerably reduces energy efficiency and contributes to the formation of the so-called hot spots [3].

In partial shading conditions, conventional MPPT algorithms, such as Perturb and Observe (P&O) or Incremental Conductance (INC), may become trapped at a local maximum instead of identifying the Global Maximum Power Point (GMPP) [4, 5]. Consequently, to effectively address varying external conditions, several types of MPPT algorithms have been developed. The first category includes metaheuristic algorithms, such as Particle Swarm Optimisation (PSO), Genetic Algorithms (GA), the *Grasshopper Optimization Algorithm* (GOA) and the Firefly Algorithm (FA). These methods exhibit greater precision in the tracking of GMPP but require longer convergence times and greater computational resources [6]. Another category comprises *artificial intelligence* (AI)-based MPPT algorithms, including *Artificial Neural Networks* (ANN), *Fuzzy Logic* (FL), and adaptive control systems such as *Adaptive Neuro-Fuzzy Inference Systems* (ANFIS). These methods adapt well to changing conditions, although their effectiveness depends on the quality of training data and the computational capacity of the system [7]. The final group consists of hybrid algorithms that combine the characteristics of different methods, thereby improving the accuracy of the GMPP tracking while reducing oscillations around the optimal operating point [8].

Alongside algorithm development, advances have also been made in measurement systems and data analysis methods. Research into economic solar simulators and testing systems for PV panels has improved access to precise laboratory measurements [7, 9]. Comparing MPPT techniques in terms of GMPP tracking precision and response time facilitates better selection of methods for various applications [10]. The solutions utilised in thermoelectric cell measurements may also provide a foundation for developing more precise data acquisition systems [11]. In signal analysis contexts, reduction of dimensionality and feature selection methods have gained popularity [12, 13].

The purpose of this article is to review and analyse MPPT methods, with particular emphasis on their effectiveness under PS conditions. A classification of algorithms is presented covering conventional, metaheuristic, artificial intelligence-based and hybrid methods. In addition, their ability to track GMPP, operational speed, and resilience to dynamic atmospheric conditions is discussed. The paper also highlights potential directions for future research aimed at improving the reliability and efficiency of PV systems in practical applications.

1.1. Key Evaluation Parameters

Tracking efficiency – the ratio of the extracted energy to the theoretically maximum achievable energy.

Tracking accuracy – how precisely GMPP is found and maintained.

Oscillation reduction – how well voltage/power fluctuations are minimised.

Convergence time – the time to reach GMPP after a change.
Voltage stability – ability to hold steady output voltage.
Robustness to PSC – effectiveness under partial shading and multiple local maxima.

2. Classification of MPPT Methods

To maximise energy use in PV systems, effective MPPT algorithms are essential. They differ in complexity, speed, efficiency, PSC resistance, and hardware requirements. Based on the analysis of literature sources, MPPT methods can be classified according to the following categories:

– Conventional methods include techniques such as P&O, INC, and *Hill Climbing* (HC). They are characterised by simplicity of implementation, low computational complexity, and effective operation under uniform irradiation conditions. In partial shading, these algorithms often stall at a local power maximum, reducing energy efficiency [1, 3, 4, 14].
– Intelligent methods include approaches based on Artificial Neural Networks, Fuzzy Logic Controllers, Adaptive Neuro-Fuzzy Inference System, and *Reinforcement Learning* (RL). These algorithms are distinguished by high adaptability and good efficiency in changing environmental conditions but require suitable training datasets and substantial computational resources [2, 15–17].
– Metaheuristic methods employ algorithms inspired by natural and social phenomena, such as Particle Swarm Optimisation, Genetic Algorithm, *Whale Optimization Algorithm* (WOA), *Grey Wolf Optimizer* (GWO), and *Salp Swarm Algorithm* (SSA). These methods effectively bypass local maxima and reach the GMPP even under challenging PS conditions. Particularly, *Variable Step Particle Swarm Optimization* (VS-PSO) [18], *Enhanced Whale Optimization Algorithm* (EWOA) [19], and *War Strategy Optimization* (WSO) [20] demonstrate significant advantages over classical methods.
– Hybrid methods combine features of two or more methods, such as P&O with PSO or INC with ANN. They offer a better compromise between operational speed and effectiveness, although their implementation may be more complex and require precise parameter tuning [17, 20, 21].

2.1. Conventional vs. Intelligent Methods

Conventional methods are employed for simple applications, particularly under uniform illumination conditions. For instance, the INC algorithm performs well with low dynamics of changing conditions but fails under PS conditions, as it cannot distinguish between local and global maxima [3, 8, 18].

Intelligent methods, on the other hand, are more flexible, adaptive, and perform better under disturbances (*e.g.*, shading, temperature changes), although their effectiveness depends on input data quality, parameter selection, and the training process [2, 16].

2.2. Classification of MPPT Based on Operating Conditions

Under *uniform irradiation conditions* (UIC), there is one clear maximum power point, making classical MPPT methods (such as P&O, INC) and simplified metaheuristic algorithms, like the basic version of PSO, effective [1, 3].

Under partial shading conditions, the power curve contains multiple local maxima, complicating the identification of GMPP. Therefore, advanced metaheuristic methods (EWOA, VS-PSO) and artificial intelligence systems (ANN, ANFIS) are the most effective in such scenarios [20].

2.3. Application of MPPT in Different PV System Configurations

Autonomous (off-grid) PV systems require simple, reliable methods with low computational complexity. Classical algorithms are commonly used for these applications [1, 6]. Grid-tied PV systems demand accuracy and rapid response to changing irradiance conditions; therefore, algorithms that reduce oscillations and feature rapid reaction times, such as WSO, which stabilises power within 0.22 s, are preferred [20]. However, hybrid PV systems require flexibility and integration capabilities with other energy conversion systems. Hybrid or intelligent systems capable of dynamically adjusting operating parameters are preferred here [19–21].

3. Classical MPPT Methods

Classical MPPT methods are popular because of their simplicity, but their effectiveness decreases under partial shading conditions. To compare the effectiveness, complexity, and suitability of various classical MPPT methods for different applications, a summary is presented in Table 1 [1–3, 6, 22].

Table 1. Advantages and disadvantages of classical maximum power point tracking methods.

MPPT Method	Advantages	Disadvantages	Efficiency under Partial Shading Conditions
Perturb and Observe (P&O)	Simple implementation, low computational complexity	Oscillations around MPP, risk of getting stuck at a local MPP under PSC	Low
***Hill Climbing* (HC)**	Fast response under stable conditions	High sensitivity to fluctuations, similar issues as in P&O	Low
***Incremental Conductance* (INC)**	More accurate MPP identification, good adaptation to changing conditions	Higher computational complexity, potential errors in the presence of multiple LMPPs	Medium

Classical MPPT algorithms work well under uniform irradiation but fail under partial shading. This has increased interest in intelligent and metaheuristic methods.

3.1. Perturb and Observe

The P&O method involves periodically introducing small changes in voltage or current (perturbations) and then observing their effect on the output power. If the power increases, the perturbation continues in the same direction; if not, the direction of change is reversed. This is the most commonly used MPPT method; however, its drawbacks include oscillations around the MPP and difficulty distinguishing between local and global power maxima under PS conditions [1, 3, 6].

3.2. Hill Climbing (HC)

The Hill Climbing method is based on searching for the maximum power point by modifying the operating parameters of the inverter (e.g., voltage), similar to the P&O method. However, HC differs in how it determines the direction of change, which is based on the sign of the derivative of power with respect to voltage. Its drawbacks also include oscillations and low efficiency under PS conditions [6, 22].

3.3. Incremental Conductance (INC)

The INC method compares incremental changes in current and voltage to directly determine the MPP. The MPP condition is met when the ratio of the changes in current and voltage is equal to the negative conductance. Unlike P&O and HC, this method offers greater accuracy and better performance under varying conditions, however, it is more computationally complex and does not guarantee avoidance of all local MPPs [3, 6, 22].

4. Intelligent MPPT Algorithms

Intelligent MPPT algorithms utilise techniques that enable more precise tracking of the maximum power point and provide better adaptation of the PV system to changing conditions, such as partial shading.

4.1. Artificial Intelligence (AI) Algorithms

Compared to classical methods, artificial intelligence algorithms offer greater operational precision, flexibility, and resilience to rapidly changing environmental conditions [2, 6]. The four most commonly used AI algorithms: fuzzy logic, artificial neural networks, reinforcement learning, and Bayesian networks are discussed below.

4.1.1. Fuzzy Logic Control (FLC)

Fuzzy logic is one of the most commonly used intelligent methods in MPPT optimisation for PV systems. The advantage of the FLC algorithm is its ability to operate effectively despite incomplete and imprecise input data, as well as its simple implementation based on intuitive decision rules [17]. FLC consists of three main stages:

1. **Fuzzification**, which involves converting input variables (such as voltage, voltage change ΔV, current, and current change ΔI) into fuzzy values using membership functions, as shown in (1):

$$\mu_A(x) : X \rightarrow [0, 1], \tag{1}$$

   where $\mu_A(x)$ is the degree of membership of element x to fuzzy set A, and X is the input space.
2. **Rule base**, which includes a set of "*if–then*" rules, such as the one presented in (2):

$$\text{If } \Delta P > 0 \text{ and } \Delta V > 0, \text{then } \Delta D = \text{positive}, \tag{2}$$

   where ΔP is the power change, ΔV is the voltage change, and ΔD is the change in the duty cycle.
3. **Defuzzification**, which converts the fuzzy output into a crisp control value, such as the duty cycle (D), using the centroid method, as defined in (3):

$$D = \frac{\sum \mu(D_i) \cdot D_i}{\sum \mu(D_i)}, \tag{3}$$

   where D_i is a particular duty cycle value and $\mu(D_i)$ is its membership degree according to the inference rules.

FLC is characterised by good noise immunity and effective performance under changing environmental conditions [17, 26].

4.1.2. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) are used to predict the optimal operating parameters of a PV system, especially under partial shading conditions. A typical ANN architecture consists of an input layer, hidden layers, and an output layer [16, 23]. The most commonly used activation function is the sigmoid function, as given in (4):

$$f(z) = \frac{1}{1+e^{-z}}, \tag{4}$$

where z is the weighted sum of the inputs of the neuron.

Training an ANN involves minimising the MSE function (Mean Squared Error), as shown in (5):

$$E = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{5}$$

where y_i is the actual value, $\hat{y}_i$ is the value predicted by the network and N denotes the number of samples (or observations) in the training dataset. ANN are highly effective, but they require a large training dataset and considerable computational power [16, 23].

4.1.3. Reinforcement Learning Algorithms (RL)

Reinforcement learning algorithms optimise their performance through interaction with the environment and by maximising the received reward. In photovoltaic systems, the control action involves modifying the duty cycle of the DC–DC converter to optimise system performance, and the reward is defined as the improvement in output power, calculated by the given (6):

$$R_t = P_{t+1} - P_t, \tag{6}$$

where P_t is the power at time t and R_t is the reward obtained for taking the action.

The RL algorithm uses the concept of $\pi(a|s)$, defined as the probability of taking action a in state s, with the goal of maximising the expected cumulative reward, expressed in (7):

$$V^{\pi}(s) = E[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \ldots |s], \tag{7}$$

where γ is the discount factor.

Moreover, RL algorithms have proven to be effective in adapting to dynamic changes in irradiance [15].

4.1.4. Bayesian Networks (BN)

Bayesian Networks are graphical probabilistic models that allow for the representation and analysis of cause-and-effect relationships. A BN defines the joint distribution of random variables as shown in (8):

$$Z = Z_1, \ldots, Z_n : P(Z) = \prod_{i=1}^{n} P(Z_i|Pa(Z_i)), \tag{8}$$

where $Pa(Z_i)$ denotes the parent nodes of the random variable Z_i and n denotes the number of random variables.

In the context of MPPT, Bayesian Networks can be used to predict the optimal operating point based on measurements of voltage, current, temperature, and irradiance, while accounting for measurement uncertainties [20, 25]. Their main advantage lies in their ability to integrate available information and operate effectively under incomplete data conditions.

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4.2. Metaheuristic MPPT Methods

Metaheuristic methods for MPPT are essential due to their ability to effectively search for GMPP, especially under partial shading conditions, where classical methods often fail due to the presence of multiple local maxima [24].

4.2.1. Particle Swarm Optimization Algorithm (PSO)

The Particle Swarm Optimization algorithm is inspired by the social behaviour of birds and fish moving in flocks or schools [24]. Each particle in the solution space represents a possible operating point of the PV system. The particle's position and velocity are updated according to (9) and (10) [18, 24]:

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \left(p_i^{\text{best}} - q_i(t)\right) + c_2 \cdot r_2 \left(g_i^{\text{best}} - q_i(t)\right), \tag{9}$$

$$q_i(t+1) = q_i(t) + v_i(t+1), \tag{10}$$

where $v_i(t+1)$ is the new velocity of the particle, $q_i(t+1)$ is the new position of the particle, w is the inertia weight balancing exploration and exploitation, c_1 and c_2 are acceleration coefficients regulating the influence of the personal and global best solutions, r_1 and r_2 are random numbers in the range (0,1), p_i^{best} is the best local solution found by the particle, and g_i^{best} is the best global solution found by the entire swarm.

PSO effectively selects PV operating points through dynamic velocity adjustment. It reduces the time to reach the GMPP and improves the tracking accuracy by approximately 9.8% compared to classical methods [18].

4.2.2. Genetic Algorithm (GA)

The Genetic Algorithm mimics the process of biological evolution: selection, crossover, and mutation. In this algorithm, the chromosomes represent the power points of the PV panels. The fundamental operational step is the selection of the best candidates based on the fitness function (output power of the PV system), defined in (11):

$$f(u) = P\left(V_u, I_u\right), \tag{11}$$

where P denotes the power generated at voltage V_u and current I_u for chromosome u [15].

The Crossover and mutation processes enable a more effective exploration of the solution space, preventing the algorithm from getting stuck in local power maxima. GA improves the classification accuracy of the GMPP due to better diversity within the population of candidate points, resulting in improved MPPT stability under shading conditions by up to 5-7% [15, 21].

4.2.3. Ant Colony Optimization (ACO)

The Ant Colony Optimization algorithm is inspired by the behaviour of ants discovering paths to food by leaving pheromone trails. Each path represents a potential PV operating point. The probability of an ant selecting a given path is calculated using (12) [26]:

$$P_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum\limits_{k \in N_i} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}}, \tag{12}$$

where τ_{ij} is the pheromone intensity on the path from point i to j, η_{ij} is a heuristic related to the distance from the optimal point, α and β are algorithm parameters controlling the influence of pheromones and heuristics, and N_i is the set of available neighbouring points.

ACO effectively selects the best paths (PV operating points), increasing the accuracy of the search around the global maximum and improving the classification of its tracking by up to 10% compared to classical MPPT methods [25, 26].

4.2.4. Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer algorithm reflects the social hierarchy of a wolf pack, consisting of leaders (alpha, beta, and delta). The position of the wolf (solution) is updated using (13) and (14) [20, 25]:

$$\vec{D} = |\vec{C} \cdot \vec{Q}_p(t) - \vec{Q}(t)|, \tag{13}$$

$$\vec{Q}(t+1) = \vec{Q}_p(t) - \vec{A} \cdot \vec{D}, \tag{14}$$

where $\vec{Q}_p$ represents the position of the alpha, beta, or delta leader, and $\vec{A}$ and $\vec{C}$ are coefficients that regulate the movement of wolves around the leaders. The vector $\vec{D}$ describes the difference between the position of the wolf and that of the leader (alpha, beta or delta) scaled by the coefficient $\vec{C}$. It determines how far and in which direction the wolf should move to approach the leader during the optimisation process.

The GWO algorithm demonstrates high accuracy in classifying the Global Maximum Power Point, while also reducing tracking time and minimising the risk of premature convergence. Thanks to hierarchical leader selection, it improves MPPT stability by approximately 30% compared to standard techniques [20].

4.2.5. Firefly Algorithm (FA)

The Firefly Algorithm is inspired by the behaviour of fireflies which attract one another based on the intensity of emitted light. In the MPPT context, the intensity of the light represents the power output of the PV system. The attractiveness between two fireflies is calculated using (15) [17, 24]:

$$\beta(r) = \beta_0 e^{-\gamma r^2}, \tag{15}$$

where β_0 is the initial attractiveness, γ is the light absorption coefficient, and r is the distance between two fireflies.

FA enables a more effective exploration of the solution space, particularly in scenarios involving multiple local power maxima. Studies indicate that applying FA increases the classification accuracy of the global power maximum from around 83% to as much as 96.5%, especially under dynamic lighting conditions [17].

4.3. Algorithms Inspired by Physical Phenomena

Algorithms inspired by physical phenomena represent a group of methods that mimic natural processes such as metal annealing, gravity, or airflows. Their application in MPPT systems allows for more effective identification of GMPP, especially under variable operating conditions.

4.3.1. Simulated Annealing (SA)

The Simulated Annealing (SA) algorithm is inspired by the physical process of annealing in metals, where the operating points of the PV system are treated as energy states that are gradually explored to identify the GMPP. SA enables the algorithm to escape local extrema by randomly selecting new operating points, even if they momentarily yield lower performance, increasing thus the chances of reaching the global optimum [8].

The probability of accepting a new solution is defined in (16):

$$P\left(\Delta P, T\right) = \begin{cases} 1, & \text{if} \quad \Delta P \geq 0 \\ e^{\frac{\Delta P}{T}}, & \text{if} \quad \Delta P < 0 \end{cases}, \tag{16}$$

where ΔP is the change in power (the difference between the new and the previous solution), and T represents the system temperature, which decreases progressively with each iteration.

In the early stages, high temperature allows the algorithm to explore a broad solution space, while in the later stages, as the temperature lowers, the search becomes more refined and focused on locating the global maximum [8, 15]. Implementing SA in MPPT applications can increase the accuracy of MPP classification by approximately 15–20% compared to conventional methods [8].

4.3.2. Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm is based on Newton's law of gravity. In this approach, each solution (an operating point of the PV system) is treated as a mass that attracts other masses in proportion to its objective function value, which in this case represents the generated power. The mass of a solution $m_i(t)$ is calculated according to (17):

$$m_i(t) = \frac{fit_i(t) - fit_{\text{worst}}(t)}{fit_{\text{best}}(t) - fit_{\text{worst}}(t)}, \tag{17}$$

where $fit_i(t)$ denotes the current objective function value of solution i, and $fit_{\text{best}}(t)$ and $fit_{\text{worst}}(t)$ are the best and worst objective function values in the current iteration, respectively [14].

Each solution updates its position (operating point) under the influence of the gravitational force exerted by better solutions in the population, enabling effective exploration of the search space to locate the global maximum. The application of GSA in MPPT can improve the GMPP identification accuracy from approximately 85–90% to around 95–98%, particularly under variable irradiance conditions [14, 23].

4.3.3. Wind-Driven Optimization (WDO)

The Wind-Driven Optimization algorithm mimics the dynamic behaviour of air in the atmosphere, where solutions are treated as air particles moving under the influence of wind pressure and turbulence. The position of a solution is updated using (18):

$$s_i^{(t+1)} = s_i^{(t)} + v_i^{(t+1)} \cdot \Delta t, \tag{18}$$

where $s_i^{(t)}$ represents the position (operating point) of the solution in iteration t, and $v_i^{(t+1)}$ is the velocity of the solution, updated based on local pressure differences, turbulence effects, and gravitational coefficients [27].

In partial shading conditions, WDO demonstrates excellent performance in locating the GMPP, achieving an accuracy of approximately 97%, which contributes significantly to the overall increase in generated power [25, 27].

4.4. Social Behaviour-Inspired Algorithms

Social behaviour-inspired algorithms leverage models of human interaction, learning, or culture to solve optimisation problems.

4.4.1. Teaching-Learning-Based Optimization (TLBO)

The TLBO algorithm is modelled on the classroom learning process, where a teacher imparts knowledge to students. It operates in two phases: the *teaching phase* and the *learning through interaction phase*. During the teaching phase, the student's position is updated using (19):

$$H_i^{\text{new}} = H_i + r(H_{\text{teacher}} - T_F \cdot \overline{H}), \tag{19}$$

where H_i is the current position of student i, H_{teacher} is the position of the best individual (teacher), $\overline{H}$ is the average position of the population, T_F is the teaching factor (typically 1 or 2), and r is a random number $r \in [0, 1]$.

In the second phase, students learn from each other by adjusting their positions based on randomly selected peers [16]. According to results from the literature, the application of TLBO in MPPT has improved the GMPP tracking efficiency from 91.4% to 96.2% under PSC [16].

4.4.2. Human Psychology Optimization Algorithm (HPO)

The Human Psychology Optimization algorithm is based on modelling psychological behaviours of individuals who aim to improve their position through imitation and avoidance of negative emotions. In MPPT applications, agents learn from their own past experiences and the outcomes of other individuals. HPO considers factors such as inspiration, frustration, and ambition. The agent's position is updated using (20):

$$b_i(t+1) = b_i(t) + \alpha\,(b_{\text{best}} - b_i(t)) + \beta\,(b_{\text{rand}} - b_i(t))\,, \tag{20}$$

where $b_i(t)$ is the current position of the agent, b_{best} is the position of the best-performing agent, b_{rand} is the position of a randomly selected agent, and α and β are coefficients representing emotional intensity. HPO demonstrates strong robustness to changing PV operating conditions and exhibits faster convergence compared to PSO and ACO [17].

4.4.3. War Strategy Optimization Algorithm (WSO)

The War Strategy Optimization algorithm is inspired by battlefield tactics and incorporates roles such as king (best agent), commander (second-best), and soldiers (remaining agents). This algorithm employs two main strategies: offensive (attack) and defensive (defence), along with dynamic adjustment of agent weights and ranks to avoid local optima. The agent's movement during an attack is defined in (21) [20]:

$$m_i(t+1) = m_i(t) + 2\rho\,(C - K) + \text{rand} \cdot (W_i \cdot K - m_i(t)), \tag{21}$$

where C is the commander's position, K is the king's position, W_i is the soldier's weight, and ρ and rand are random coefficients.

In the defensive strategy, the movement is described in (22):

$$a_i(t+1) = a_i(t) + 2\rho\,(K - a_{\text{rand}}) + \text{rand} \cdot W_i(C - a_i(t)), \tag{22}$$

where $a_i(t)$ is a current position of the i-th agent in the defence mode, K is is the king's position, a_{rand} is position of an agent randomly selected from the population, C is the commander's position, W_i is the soldier's weight and ρ and rand are random coefficients.

Studies conducted under four different shading scenarios have shown that WSO achieved the highest dynamic accuracy, up to 98%, the shortest convergence time of approximately 0.21 seconds, and significantly reduced voltage fluctuations compared to PSO, *Grasshopper Opitimization Algorith* (GOA), and SSA algorithms [20].

5. Hybrid MPPT Methods

Modern PV systems require robust MPPT algorithms, which is why hybrid solutions combining classical methods, AI, metaheuristics, and *Field Programmable Gate Array* (FPGA)-based systems are gaining popularity.

5.1. Combination of Conventional Methods with AI

Combining classical approaches for MPPT detection, such as P&O and INC, with AI algorithms enables dynamic and precise adjustment of PV system operating parameters in response to changing environmental conditions. In his study, Hasan Gundogdu demonstrated the effectiveness of an ANN+GA model, in which a genetic algorithm optimised the structure and weights of an artificial neural network. As a result, the system was able to track the GMPP even in the presence of multiple local maxima, increasing the classification accuracy from 89.3% to 96.1% [16].

Makbul A.M. Ramli, on the other hand, employed an ANN to analyse P–V characteristics as well as the temperature and irradiance variability. The network was trained offline, and during the online testing, it achieved a GMPP detection accuracy of 96.7% [22].

In her work, Nikita Gupta presented a hybrid FLC+AI model, in which a fuzzy logic system was enhanced with a real-time mechanism for automatically modifying linguistic rules. This improved the tracking efficiency to 96.5%, compared to 90% for a standard FLC. The system responded dynamically to irradiance changes, smoothly adjusting the duty cycle value [23].

5.2. Hybrid Metaheuristic Algorithms

Combining metaheuristic methods with classical MPPT algorithms enhances the capabilities of solution space exploration and improves the response speed to changing external conditions. For example, Bo Yang applied a hybrid P&O+PSO algorithm, where the P&O method provided a fast response near the local operating point, while PSO was responsible for searching for global extrema. The tracking efficiency increased from 90.2% to 95.4%, and convergence time was reduced by 35% [14].

Silas Soo Tyokighir, in his work, described the VS-PSO algorithm, which adjusted the particle step amplitude depending on the optimisation stage. As a result, the algorithm reached the GMPP in just 10 iterations, whereas the standard PSO required 50 iterations. The average improvement in tracking accuracy increased by 9.8% compared to classical PSO [18].

Subhransu Sekhar Dash, on the other hand, described an Enhanced Whale Optimization Algorithm which distinguishes between local and global power maxima using dynamic "encircling target" strategies. EWOA improved the MPP tracking efficiency by approximately 4-5% in a 1000W system compared to classical PSO and WOA [19].

5.3. Integration of MPPT with Reconfigurable FPGA Systems

FPGA systems are becoming increasingly popular in MPPT applications due to their ability to perform parallel, fast, and reliable computations. In her study, Pallavee Bhatnagar presented a fuzzy logic controller implemented on an FPGA which achieved a response time of approximately 0.1 seconds and high output voltage stability. Under dynamic conditions such as passing clouds, the system automatically adjusted the operating point in real time [24].

Meanwhile, Nikita Gupta introduced the implementation of an ANFIS structure on FPGA. The use of parallel data processing enabled real-time updates of rules and weights in response to changes in irradiance. The system operated at a sampling frequency of 40 kHz, allowing a very rapid reaction to external environmental changes [23].

Hasan Gundogdu, on the other hand, described an integrated ANN+GA algorithm on an FPGA platform, which allowed real-time weight adjustments within the neural network. The adaptation time was reduced by more than 60% compared to a classical implementation. As a result, the system achieved a GMPP tracking efficiency exceeding 97% [16].

6. MPPT under Partial Shading Conditions (PSC)

Partial shading leads to uneven illumination across the surface of photovoltaic panels, resulting in the appearance of multiple LMPPs on the P–V characteristic. This effect is caused by the activation of bypass diodes in PV modules, which leads to a "stepped" I–V curve and the presence of multiple power peaks on the P–V curve [18, 20]. As demonstrated in the study, classical algorithms such as P&O and INC tend to get stuck at the local extrema, which can cause power losses of up to 20–25% under variable sunlight conditions [6, 18].

For example, Tummala Ayyarao showed that under shading conditions, a PV system consisting of three series-connected panels exhibited different local MPPs at voltages of 22.4 V, 33.3 V, and 38 V, of which only one corresponded to the actual GMPP, producing 94.16 W. Conventional algorithms typically selected the first local point, which was 6–10 W lower in power, thus reducing system efficiency [20].

Detecting PS conditions is essential for selecting an appropriate MPPT algorithm. Tummala Ayyarao also proposed a segmented analysis of the P–V curve, allowing the detection of voltage discontinuities as indicators of shading [20]. Alternatively, Muhammed Y. Worku and Makbul A.M. Ramli presented approaches based on neural networks that learn shading patterns from historical data and real-time measurements of irradiance and temperature [15, 22]. These methods achieved more than 95% accuracy and demonstrated significantly faster response times compared to classical algorithms [16].

AI algorithms such as ANN, FLC, and ANFIS allow for adaptive control of the duty cycle in response to changes in irradiance [16, 22, 23]. Makbul A.M. Ramli implemented an ANN trained on a dataset containing P–V characteristics, temperature, and irradiance levels, achieving a GMPP detection accuracy exceeding 96.7% [22]. The FLC algorithm used by Nikita Gupta improved tracking efficiency from 85–90% to 95–97% while reducing the average convergence time by approximately 0.5 seconds compared to classical approaches [23].

Evolutionary algorithms such as PSO, GA, WOA, and WSO effectively explore the solution space in the presence of multiple local extrema. Silas Soo Tyokighir applied VS-PSO, which reached the GMPP of 61 W in just 10 iterations (0.3 s), while standard PSO required 50 iterations and achieved only 55–58 W. This resulted in a 9.8% increase in tracking efficiency [18]. The WSO

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algorithm, inspired by military strategies, achieved an average efficiency of 96.8–98% under PS conditions, with a convergence time of just 0.21 s, much faster than GOA (0.76 s) and SSA (0.4 s) [20].

Bo Yang, in his study, presented a hybrid PSO+P&O algorithm, in which PSO explored the solution space after preliminary analysis by P&O, reducing the GMPP tracking time by 35% compared to standalone methods [14]. Hasan Gundogdu described an ANN model supported by GA, where the genetic algorithm optimised neural weights in real time, increasing tracking efficiency from 89.3% to 96.1% [16]. Meanwhile, the EWOA algorithm applies a "target encircling" strategy, where weaker solutions are discarded and the population converges around the best candidate, resulting in improved accuracy from 90.1% to 95.7% [19]. Hybrid approaches also allow for faster adaptation to changes in PSC without requiring full retraining of the model, making them more practical for real-time systems.

7. Comparison and Performance Analysis of MPPT Methods

This chapter compares the most important MPPT methods in terms of performance. The evaluation includes GMPP tracking efficiency, convergence time, voltage stability, implementation cost and complexity, and resistance to partial shading.

7.1. Energy Efficiency of Various Techniques

Table 2 presents a comparison of algorithms in terms of maximum power point tracking efficiency and average convergence time for MPPT methods, based on the analysis of literature sources [6, 7, 14, 16, 18–20, 23, 25], where MPPT algorithms were implemented on various hardware platforms. Classical methods (P&O, INC) were mainly tested on microcontrollers (*e.g.*, STM32, Arduino), while metaheuristic and AI algorithms (*e.g.*, PSO, ANN, RL) were evaluated in

Table 2. Comparison of MPPT algorithms in terms of maximum power point tracking efficiency and GMPP convergence time.

MPPT Algorithm	GMPP Efficiency [%]	Average Convergence Time [s]
Perturb and Observe (P&O)	85–90	~ 1.5
Incremental Conductance (INC)	88–91	~ 1.2
Particle Swarm Optimization (PSO)	91–93	~ 1.0
Variable Step Size Particle Swarm Optimization (VS-PSO)	98.3	~ 0.3
Genetic Algorithm (GA)	93–95	~ 0.6
War Strategy Optimization (WSO)	98–99.97	~ 0.23
Salp Swarm Algorithm (SSA)	94.3	~ 0.39
Grasshopper Optimization Algorithm (GOA)	93.9	~ 0.75
Artificial Neural Network (ANN)	96.7	~ 0.4
Fuzzy Logic Controller (FLC)	95.2	~ 0.5
Adaptive Neuro-Fuzzy Inference System (ANFIS)	96.1	~ 0.45
Enhanced Whale Optimization Algorithm (EWOA)	96.9	~ 0.37
Teaching-Learning-Based Optimization (TLBO)	94.4	~ 0.42
Human Psychology-Based Optimization (HPO)	93.5	~ 0.48

MATLAB/Python environments on computers with i7/i9 processors and GPUs. Some studies also used FPGA systems. The values presented are the average results of simulations and experiments.

Metaheuristic and AI-based algorithms such as VS-PSO and WSO offer the highest GMPP tracking efficiency and the fastest convergence.

7.2. Cost of Implementation and Complexity

Table 3 presents a comparison of algorithms in terms of implementation complexity, cost of deployment, and hardware requirements [6, 7, 16, 19, 20, 22, 23, 25].

Table 3. Comparison of MPPT algorithms in terms of implementation complexity, costs of deployment, and hardware requirements.

MPPT Algorithm	Implementation Complexity	Deployment Cost	Hardware Requirements
Perturb and Observe (P&O)	Low	Low	Microcontroller Unit (MCU)
Incremental Conductance (INC)	Low	Low	MCU
Particle Swarm Optimization (PSO)	Medium	Medium	DSP (Digital Signal Processor) or MCU
Genetic Algorithm (GA)	Medium	Medium	MCU or FPGA
War Strategy Optimization (WSO)	High	High	FPGA / DSP
Salp Swarm Algorithm (SSA)	Medium	Medium	MCU
Artificial Neural Network (ANN)	High	High	Memory + Processor
Fuzzy Logic Controller (FLC)	Medium	Medium	Fuzzy Controller Engine
Enhanced Whale Optimization Algorithm (EWOA)	High	High	DSP or FPGA
Teaching-Learning-Based Optimization (TLBO)	Medium	Medium	MCU
Human Psychology-Based Optimization (HPO)	Medium	Medium	MCU

As one can see, classical methods are low-cost and easy to implement, while advanced algorithms require more computing power and specialised hardware.

7.3. Stability and Adaptation Speed to Operating Conditions

In dynamic PV conditions, stability and quick adaptation are essential [6, 16, 18, 20, 22] (Tab. 4).

VS-PSO and WSO stand out for voltage stability, oscillation reduction, and strong robustness to partial shading conditions.

7.4. Best MPPT Methods for Different Applications

The selection of the optimal MPPT method depends, among other factors, on available computational resources, energy requirements, and operating conditions (including the presence of PSC). Table 5 presents recommendations based on specific applications [6, 7, 16, 18, 20, 24]:

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Table 4. Comparison of MPPT models in terms of voltage stabilisation time, oscillation reduction level, and resistance to variable external conditions (mainly PSC).

MPPT Algorithm	**Voltage Stabilisation Time [s]**	**Oscillation Reduction [%]**	**Robustness to PSC**
Particle Swarm Optimization (PSO)	~ 1.2	~ 25	Medium
Variable Step Size Particle Swarm Optimization (VS-PSO)	~ 0.3	~ 65	High
War Strategy Optimization (WSO)	~ 0.22	~ 70	Very High
Artificial Neural Network (ANN)	~ 0.4	~ 50	High
Adaptive Neuro-Fuzzy Inference System (ANFIS)	~ 0.45	~ 55	High
Salp Swarm Algorithm (SSA)	~ 0.39	~ 60	High

Table 5. Comparison of algorithms based on selection of the recommended MPPT method according to the application.

Application	**Recommended Algorithms**
Autonomous systems (off-grid)	*Perturb and Observe* (P&O), *Incremental Conductance* (INC)
Residential and commercial systems	*Particle Swarm Optimization* (PSO), VS-PSO, ANN
Industrial systems	*War Strategy Optimization* (WSO), EWOA, ANFIS
PSC / dynamic condition scenarios	WSO, VS-PSO, FLC+ANN, TLBO
FPGA / high-performance systems	WSO+FPGA, GA+ANN, ANFIS

It should also be noted here that algorithm selection depends on the application, from simple methods for off-grid systems to advanced hybrid techniques for industrial setups.

8. Conclusions

The dynamic development of PV systems and the growing demand for efficient, renewable energy sources have made Maximum Power Point Tracking a crucial area of focus. The aim of this article was to analyse contemporary MPPT methods, particularly in the context of PSC, which are one of the main causes of energy losses in PV systems. The study compares four main groups of methods: classical, metaheuristic, artificial intelligence-based, and hybrid, evaluating them in terms of efficiency, stability, implementation complexity, and adaptability to changing environmental conditions.

The collected results indicate that classical algorithms, such as P&O and INC, although still widely used due to their simplicity and low cost, exhibit low effectiveness under PSC. Their susceptibility to getting stuck at local maxima means that their energy efficiency rarely exceeds 90%, and the convergence time to the operating point often surpasses 1.2–1.5 seconds.

Significant progress has been observed with algorithms inspired by natural and social phenomena. Methods such as PSO, EWOA, and WSO successfully avoid local extrema and focus on searching the solution space toward the GMPP. For instance, WSO achieved a tracking efficiency of 98–99.97% and a convergence time of less than 0.25 seconds, and it is also characterised by high noise resistance and output voltage stability.

Artificial intelligence-based algorithms, such as ANN, FLC, and ANFIS, demonstrated excellent adaptability to varying environmental conditions. Studies have shown that ANN trained on P–V and irradiance data reached an efficiency of more than 96.7%, while FLC and ANFIS achieved 95.2% and 96.1%, respectively. However, their implementation requires considerable computational resources, adequate training data, and model validation tools. Nonetheless, they are well-suited for operation in dynamically changing conditions with numerous local MPPs.

Hybrid MPPT approaches proved to be effective by combining the strengths of different method categories. Integrating classical algorithms with AI (*e.g.* ANN+GA, FLC+ANN) or metaheuristics (*e.g.* PSO+P&O, VS-PSO) enabled high tracking efficiency while reducing convergence time and minimizing voltage oscillations. For example, applying VS-PSO reduced the number of iterations required to reach the GMPP from 50 to 10 and increased the system output by nearly 10%.

Based on the analysis, simple classical algorithms are effective for low-cost and autonomous systems under uniform irradiance. For commercial and industrial installations operating under PSC, intelligent or hybrid methods are more suitable. In embedded systems (*e.g.*, FPGA), advanced AI algorithms with real-time learning are recommended.

Despite the advantages of modern MPPT methods, challenges remain, such as algorithm complexity, the need for parameter adjustment, and integration with energy management systems. In commercial applications, compatibility and standardisation are also important. Future research should focus on the development of next-generation hybrid algorithms that integrate classical, metaheuristic, and AI elements into a self-learning, multi-stage decision-making model. Emphasis should also be placed on online learning algorithms that allow dynamic adaptation of MPPT strategies without the need for retraining.

In summary, the effectiveness of MPPT in modern PV systems depends on the selection of the right method for the operating conditions and the application. Only a comprehensive approach ensures maximum energy output, stability, and system reliability.

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