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Performance Enhancement of Photovoltaic System Using Nature Inspired Optimization Algorithms

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A B S T R A C T

In recent times, consumption of non-renewable energy sources has been growing, because of the rise in population. The persistent exploitation of the conventional energy sources like fossil fuels, etc. led to insufficiency in the energy sources.Thus, the researchers detected an extra energy sourcenamed Renewable Energy Source, which serve as a best alternative for the conventional energy sources. Solar is considered to be the efficient one, because of its easy availability and pollution free nature among the Renewable Energy Sourceslike. The usage of power electronic converters is required due to it is hard to obtain constant voltage from Photovoltaic system because of its sporadic nature.Thus, the paper develops a comprehensive analysis of distinct nature inspired optimization algorithm utilized to improve the performance of Photovoltaic system. Detecting the difficulties faced by the sporadic nature of solar energy and limitations of conventional maximum power point tracking approaches under dynamic and partial shading conditions, the research evaluates many optimization algorithms. Moreover, the integration of advanced algorithms, serves as a development of more effective and adaptive optimization approaches.Additionally, the paper deliberates the benefits, limits and potential areas for future research of each optimization algorithm in the circumstance of Photovoltaic system performance improvement.

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1. Introduction

The demand for electrical energy has been continually increasing since the industrial period, which is due to the vast usage of conventional fuel technologies and its impacts. This leads to research moving towards renewable energy technologies that offer pollution-free energy, which are also free of cost [1-3]. Many different Renewable Energy Source (RES) exists and among them Solar is considered to be the optimal one, due to its availability and cleanliness [4-6]. Normally, the solar power attained from the irradiation of sun is converted into electrical power with the aid of Photovoltaic (PV) system and is fed to the grid or load [7-9]. With the goal of achieving, the optimal energy from PV system, many different PV models, which relies on voltage and current are modelled [10]. Moreover, in real time applications, the PV with single and double diode models are mostly employed, which are depicted in Figure 1. Besides, the appropriate modelling of PV module relies on the parameter models that are normally changing with respect to the climatic conditions and the unstable running conditions namely faults and the aging [11-13].

In case of large scale energy generation, if local conditions are taken into consideration when arranging the PV modules, then it is possible to achieve clean and efficient energy, which is further used for meeting the utility grid demands or for the Electric vehicles [14-16]. The great reduction in the material cost of PV, as well as the sustainability of PV, led to the widespread of PV system in real life conditions. Nevertheless, the major concerns related with the practical implementation of photovoltaic system are its short life cycle and the reduced energy efficiency, which are formed due to the hot spots and power losses generated because of the partial conditions [17-19]. Moreover, based on classical techniques, better MPPT performance is attained by PV system beneath uniform irradiation levels. Additionally, when the PV system operates in partial shadow conditions, different local maximum points occur because bypass diodes that are primarily employed to reduce the impact of hot spots are present [20-22].

One of the main problems with power quality while using photovoltaic (PV) technology is voltage violation, which is particularly noticeable in LV distribution networks during the peak PV generating time [23-24]. The PV output's probability distributions, varies according to the type of day and time [25].

Grid connected solar systems frequently use central inverters with dc-dc converters to obtain electricity from the entire PV array. However, due to PV array's partial shadow generation and topology's sensitivity to mismatches, where significant power losses may occur and these conditions may exist. Utilizing distributed dc-dc converters and the multistring topologies are another method of configuring a PV array. This technique reduces power losses and allows for maintenance costs of a complete PV array [26-29]. An efficient extraction of a full power is possible by the connection of each PV string to different DC-DC converter with a modified MPPT. DC-DC converters can be formed with either a series output configuration or a parallel output configuration in a multistring PV system [30-31]. Nevertheless, it may experience a cross coupling issue in the system with a series configuration, where the malfunction of one converter prevents the operation of the others [32-33]. Figure 2 illustrates the electrical energy flow in PV system.

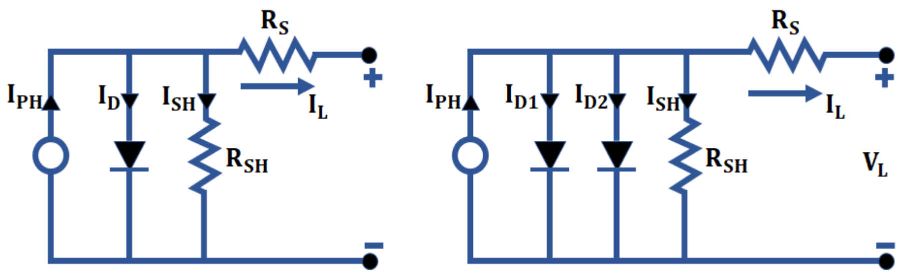

Figure 1. Structural modelling of PV Module

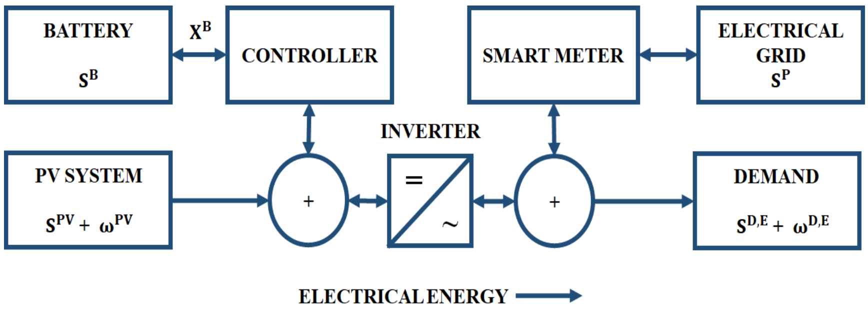

Figure 2. Illustration of Electrical energy flow in photovoltaic grid system

The extraction of parameters and precise modelling that accurately capture the non-linear features of solar cell current and voltage are the most crucial difficulties faced in development of PV technology. These factors were heavily considered when simulating, assessing and maximising the quantity of energy obtained from PV systems [34-36]. The solar PV model's parameters are influenced by temperature and irradiation. Consequently, accurate parameter estimation is required to model solar PV [37-38]. Various approaches have been presented to figure out the variables of different designs, whether they involve experimental samples or data from data sheets. The three categories of approaches include heuristic methods, analytical methods and numerical methods [39-41].

To overcome specific drawbacks of the previous methods, such as convexity, high sensitivity and differentiability to its beginning parameter values, the heuristic procedures to approximation model parameters are typically inspired by biological processes [42-44]. Because of its accuracy, dependability and independence from initial values, heuristic approaches often yield superior outcomes than other approaches [45-46]. Many scholars have been working very hard currently to employ algorithm based metaheuristic to solve these kinds of challenges. Natural occurrences like swarming activity, systems that take into account on nature and physics have an impact on these structures [47-50]. It is evident that every strategy has benefits and limitations of its own, and thus insufficient learning algorithm solve every complicated problem. Therefore, it is possible to extract utmost power from a PV system by implementing specific optimization techniques. It improves the performance of PV system by maintaining a constant DC link voltage. A numerous PV system optimization methods are compared to classify the most effective approach. Henceforth, the primary contribution of this article is presented below,

- The paper offers a comprehensive comparative study of various nature-inspired optimization algorithms utilized for increasing performance of PV systems. This analysis delivers valued insights into relative benefits and drawbacks of each algorithm in optimizing different aspects of PV system performance.
- Through emphasizing the advantages, limitations and potential areas for future research of each optimization algorithm, the paper provides valuable insights to researchers. By optimizing energy generation, system efficiency, and economic viability, the paper contributes to advancing the feasibility and scalability of solar energy solutions.

2. Review on Recent Optimization Algorithms used in PV Fed Systems

Numerous methods have been implemented to enhance the efficacy of PV system to obtain the most possible electricity from PV system and a constant DC link voltage. The methods subsequently employed to enhance PV performance are explained in the following paragraphs.

2.1 Autonomous Groups PSO (PSOAG)

The PSOAG algorithm has better convergence speed and improved capability to escape local optima that is critical for accurately modeling the nonlinear characteristics of PV systems. It explores the application of the one-diode PV model, assessing it over experimental characteristic curves data. This estimation is attained utilizing a novel variant of the PSO algorithm known as PSOAG. This approach improves PSO's performance by enabling quicker convergence rates and improved avoidance of local minima/maxima. The study presents six variations of the PSOAG algorithm, thereby extending the pool to nine versions, including the previously reported three iterations of PSOAG. This diversity allows for a comprehensive exploration of social behaviors within the optimization process. Analysis of the outcomes validates important improvements attained by the proposed method. Moreover, there is a notable enhancement of up to 20% in the convergence rate. These findings underscore the efficacy of the developed PSOAG algorithms in optimizing the one-diode model of PV solar cells, showcasing their potential for advancing optimization techniques in this domain. Autonomous groups may struggle to adapt to dynamic environments or problem landscapes. Changes in the problem structure or resource availability may render predefined group configurations ineffective, necessitating frequent reconfiguration and potentially disrupting optimization performance [51-55].

2.2 Linear Programming (LP) Optimization

LP has the capability to deliver fast, globally optimal solutions under linear constraints, making it perfect for real-time energy controlling in PV-fed systems. For all cost function and the restrictions, the LP model of the optimization issue reduces to linear connections. This simplicity results from presuming a linear battery behavior and continuous efficacy of converter connected to ESS. As a result, the suggested optimization issue stays linear. There are five variables that need to be considered when making a decision: the energy produced via PV plant *is* $\mathrm{E_{pv}}$ the energy obtained or inserted into the grid is $\mathrm{E_{grid}}$ the energy discharge of the batteries is $\mathrm{E_{ess}^{dis}}$, and State of Charge of the ESS is SOC. Equation (1) states objective of maximizing revenue from energy exported from grid. Maximizing the proceeds from the energy delivered to grid is the goal, which is stated as follows:

$$\mathrm{R}\left(\mathrm{E_{pv}},\mathrm{E_{ess}^{dis}},\mathrm{E_{ess}^{cha}},\mathrm{E_{grid}},\mathrm{SOC}\right)=\sum_{t=1}^{T}\mathrm{C_{grid}}\left(t\right)\mathrm{E_{grid}}\left(t\right) \quad (1)$$

Where T is the amount of time steps that are taken into consideration, and C_{grid} is the spot price of energy. We optimize at a temporal granularity (Δt) of 30 minutes for the next three days in our case study. Notably, one of the choice variables is the energy produced via PV plant. In situations where it would be more cost-effective to reduce PV production—such as when the spot price is negative this strategy gives the operator that option. As a result, the PV plant's ability to produce electricity is limited by its maximum output. The boundaries of the decision variables are,

$$0\le \mathrm{E_{pv}}\le E_{pv}^{max} \quad (2)$$

$$0\le \mathrm{E_{ess}^{dis}}\le P_{max}^{dis}\times\Delta t \quad (3)$$

$$0\le \mathrm{E_{ess}^{cha}}\le P_{max}^{cha}\times\Delta t \quad (4)$$

$$-\infty\le \mathrm{E_{grid}}\le +\infty \quad (5)$$

$$SOC_{min}\le \mathrm{SOC}\le SOC_{max} \quad (6)$$

Conservation equations (2) to (6) deliver operational constraints for the PV generation, the battery charging/discharging, SOC limits, and grid exports. The framework's equilibrium of energy, as determined by:

$$E_{pv}+E_{ess}^{dis}-E_{ess}^{cha}+E_{grid}=0 \quad (7)$$

The difference in SOC between two time phases, which is correspond to the energy entering and leaving the ESS is,

$$\left(SOC\left(t\right)-SOC\left(t-1\right)\times ESS_{capa}=\eta_{ess}\eta_{dis}^{cha}\mathrm{E_{ess}^{cha}}-\frac{\mathrm{E_{ess}^{dis}}}{\eta_{dis}^{dis}} \quad (8)$$

Here, $SOC(0)$ stands initial SOC. LP model aims to minimalize the COE by optimally scheduling the energy flow while assuring energy balance that aids to diminish operational cost and enhance economic viability. Equations (7) and (8) are used to reflect energy balance and the battery SOC flux through time. LP is primarily suited for linear objective functions and may not adequately represent complex optimization goals, such as maximizing energy yield while minimizing costs or considering multiple conflicting objectives simultaneously. This limitation restricts the ability to capture diverse optimization criteria effectively [56-59].

2.3 Chaotic Flower Pollination Algorithm (CFPA)

The CFPA has improved global search capability and earlier convergence, attained via the incorporation of chaos theory into the traditional FPA approach. The presented CFPA is a hybrid technique that modifies the FPA variable by substituting chaotic variables for random values. Furthermore, the local pollination and switch probability p are manipulated through the application of chaos. In a typical FPA, this parameter is regarded as only one variable. However, p signifies inversely reduced via growing number of iterations; the result is a modified version that looks like this,

$$\rho=\rho_{max}+\frac{\rho_{max}-\rho_{min}}{T} \quad (9)$$

Here t denotes actual iteration number and T represents maximum value of iterations. Equation (9) defines switch probability p in the CFPA. The lowest and greatest values of p are shown by ρ_{min} = 0.6 and ρ_{max} = 0.8, correspondingly. CFPA involves several parameters, including the chaotic maps' parameters and algorithm-specific parameters. The performance of CFPA can be sensitive to these parameters, and selecting appropriate values may require extensive tuning, which can be time-consuming and computationally expensive [60-64].

2.4 Incremental Conductance (INC) MPPT Algorithm

INC method utilized P-V curve’s slope to trace MPP via locating peak of the curve. By looking at the connection among conductance values, which can be described as follows, one can ascertain where PV module's operation is in the P-V curve:

$$\frac{dI}{dV} = -\frac{I}{V} \tag{10}$$

$$\frac{dI}{dV} > -\frac{I}{V} \tag{11}$$

$$\frac{dI}{dV} < -\frac{I}{V} \tag{12}$$

These equations (10)–(12) are based on P-V curve's slope at MPP equals zero, which suggests:

$$\frac{dP}{dV} = 0 \tag{13}$$

Since P = V I,

$$I + V\frac{dI}{dV} = 0 \tag{14}$$

The DC-DC converter's duty cycle decreases if equation (10) is satisfied; on the other hand, if equation (11) is accurate, the duty cycle increases. In the meantime, when equation (12) meets the criteria, the duty cycle stays unaltered. At MPP, the slope defined in the power voltage relation (13) leads to current and duty cycle of the converter express on equation (14). Figure 3 shows how the INC algorithm functions in its entirety.

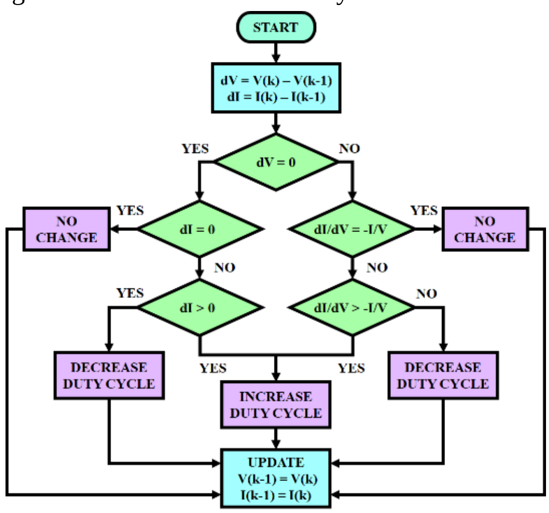

Figure 3. Flowchart of INC algorithm

Partial shading conditions where some PV cells/modules are shaded while others are illuminated, the IncCond algorithm may struggle to accurately track the global MPP. This results in suboptimal power output and reduced efficiency, as the algorithm may mistakenly settle at a local MPP as a replacement of the global MPP. In partial shading and dynamic conditions, the INC-MPPT algorithm face difficulties to precisely locating global MPP because of occurrence of many peaks in P-V curve. The algorithm relies on expression to find the MPP that function well in unchanging irradiance but mislead the controller in to settling at local MPP in partial conditions. Dynamic variations in irradiance and temperature also produce oscillations in the operating point, necessitating quick adjustments in the duty cycle. While INC adaptively responds to these changes, its performance declines in complex shading situations, often leading to suboptimal energy harvesting. [65-69]

2.5 Ant Colony Optimization (ACO) Algorithm

The ACO algorithm has robust ability to track global MPP in complex, multi-modal P-V curves, particularly under varying circumstance. In PV power generation systems using Power Conditioning Systems (PSCs), this study offering an improved ACO method for MPPT. With this new algorithm, the more successful ants those who can find significant food sources continue to search, and the less successful ones are progressively eliminated from the ant colony. Comprehensive simulations and actual results show that this technique reduces computing costs and improves convergence characteristics. Initially, ants are scattered randomly across the solution space, with the total ant population denoted as N. Following with calculates the PV power corresponding to each ant's position. Moving forward, the algorithm identifies ant location, which produces highest PV power, marking it as the Elite ant location. This distinguished ant is visually distinguished, often by being depicted in a larger size, while the proportions of other ants are adjusted relative to the PV power they've uncovered. Then the ant positioned optimally remains stationary, while all other ants converge towards this location. This pruning process sets the stage for the optimization of the ant colony. The optimization loop continues reiterated until the population size decreases to a predetermined value, M. Finally, from the remaining M ant positions, the one yielding the highest PV power is selected, signaling the termination of the program. This method efficiently directs solution space, leveraging the collective intelligence of ant colony to optimize the MPPT process effectively. This method optimizes the MPPT process efficiently, leveraging the collective intelligence of the ant colony to navigate the solution space effectively. ACO may encounter challenges in handling complex constraints, especially in PV system optimization problems with nonlinear constraints or discrete decision variables. Ensuring feasibility while exploring the solution space can be non-trivial and may require additional problem-specific modifications or constraint handling techniques. The ACO algorithm effectively explores the multi-modal P-V and complex characteristics to detect the global MPP. By allowing only the most successful ants to continue searching and pruning the less effective ones, the algorithm evades premature convergence to local peaks produced by shading. The elite ant approach assures that the global best solution is preserved, whereas others adaptively converge toward it. This collective search behavior enables ACO to respond efficiently to rapidly varying irradiance and temperature conditions, though managing nonlinear constraints still need modifications. [70-74]

2.6 Sequential Minimal Optimization (SMO) Algorithm

SMO has fast and effective parameter tuning by diminishing RMSE, making it appropriate for controller gain optimization in PV systems. The goal of applying SMO to the PV cell designs' variable selection is to reduce the RMSE value. The cost function is modified in each iteration in accordance with the experimental results derived from the inductor-voltage characteristic; hence, obtaining the parameters requires minimization. The fitness parameter of the algorithm determines how quickly and efficiently the PV system parameters are optimized. As a result, we recommend using the stochastic SMO approach to determine the PV system's controller gains. The discrepancy between each measured and approximated pair is evaluated using the RMSE, expressed as follows,

$$RMSE = \sqrt{\frac{1}{q}\sum_{i=1}^{q} f(parameter)^2} \qquad (15)$$

The suggested method looks for the smallest RMSE, as shown by equation (15), where q stands number of experimental data points or sample size. The SMO method is utilized for approximating the model's parameters according to a rule that is indicative of the solution vector throughout the process. However, it needs extra adaptations to manage non-linearities, increasing complexity. While SMO is effective for solving linearly separable problems, its performance can degrade for non-linearly separable problems commonly encountered in PV system optimization. Adapting SMO to handle non-linearities may require additional techniques, such as kernel methods, which can increase computational complexity and memory requirements [75-78].

2.7 Self-Adaptive Multi-Population RAO Algorithm

SAP-RAO algorithm has advantages of simplicity, parameter-free nature and capability to dynamically adjust population size, making it highly adaptive for PV system optimization. RAO is a straightforward approach for optimization that requires no parameters. The RAO method's primary concept is that each iteration's updated solutions are determined by the best and worse solutions According to the determined goal function, the population size is adjusted in for each iteration of SAP-RAO algorithm.

$$X_{new} = X_{old} + r_1\left(X_{best} - X_{worst}\right) \qquad (16)$$

Equation (16) relates the update of each solution to the difference between the best and worst solutions to finding a better solution. SAMRA's self-adaptive mechanisms for managing multiple populations may not always led to effective exploration and exploitation of solution space. If subpopulations are not efficiently handled, the algorithm converge prematurely or get stuck in suboptimal regions, especially when tackling multi-modal or highly nonlinear PV system behaviors. In some cases, suboptimal population management strategies may hinder the algorithm's capability to converge high-quality solutions, especially in complex or dynamic optimization landscapes [79-82].

2.8 Manta Ray Foraging Optimization (MRFO)

MRFO has global search capability, mainly suitable for extracting the Global MPP in complex, multi-peaked P-V curves of shaded PV arrays. This work presents a new Global MPPT that makes use of the recently developed MRFO. The GMPP of a Triple-Junction solar array that operates under shadow is extracted using the suggested MRFO-based MPPT. MRFO, a metaheuristic method of optimization based by manta rays' foraging behavior for collecting prey. Three forage operators are used in this method: chain, cyclone, and somersault foraging. Manta rays view locations with a high concentration of plankton as attractive during the chain foraging phase, since they represent the best solution. As a result, they arrange themselves into a chain for foraging. Every individual advances in the direction of the food supply, adjusting its position in response to the position of person in front of it and ideal solution found in each iteration. Mathematically, this chain foraging method stated as:

$$x_i^{(t+1)} = \begin{cases} x_i^{(t)} + r.\left(x_{best}^{(t)} - x_i^{(t)}\right) + \alpha\left(x_{best}^{(t)} - x_i^{(t)}\right) & i = 1 \\ x_i^{(t)} + r.\left(x_{i-1}^{(t)} - x_i^{(t)}\right) + \alpha\left(x_{best}^{(t)} - x_i^{(t)}\right) & i = 2,\ldots,N \end{cases} \tag{17}$$

$$\alpha = 2 \times r \times \sqrt{\left|log\left(r\right)\right|} \tag{18}$$

The MRFO is described in Equations (17) and (18), where each individual follows the one in front of it before moving toward the best-found solution. MRFO's adaptability to dynamic environments or changing problem conditions may be limited. Since MRFO relies on fixed population size and predefined strategies for exploration and exploitation, it may struggle to dynamically adjust its search strategy and adapt to evolving optimization requirements or environmental changes [83-87].

2.9 Genetic Algorithm Based On Non-Uniform Mutation (GAMNU)

GAMNU has enhanced precision in parameter estimation and its capability to transition from broad exploration to focused local search via non-uniform mutation. In order to precisely determine unknown variables of single and double diode simulations across a range of PV cell and module methods, this work presents a novel optimization genetic technique. The GAMNU method is an improved version of the traditional GA. This strategy involves an initial exploration of the entire solution space, transitioning to a more focused search as the population converges in specific regions. Particularly, statistical findings indicate that GAMNU works more accurately than other optimization techniques, indicating its potential application to actual energy-related optimization issues. GA-based non-uniform mutation approaches may encounter scalability issues when applied to large-scale PV system optimization problems with a high constraint. As the problem size increases, the computational complexity of maintaining the mutation rate schedule and updating the population may become prohibitive, leading to longer optimization times [88-92].

2.10 The New Musical Chairs Algorithm

The NMCA has dynamic balance among exploration and exploitation, permitting effective tracking of Global Peak (GP) in MPPT applications. To attain effective MPPT, it is essential to balance exploration and exploitation in the course of optimization iterations, as was mentioned in the introduction. Initially, a maximum number of search agents are deployed to improve exploration and prevent premature convergence, akin to players circulating chairs while music plays. As iterations progress, the number of agents are gradually diminished to prioritize exploitation, mirroring the gradual removal of chairs in the game's progression. In MCA's initialization phase, players (representing search agents) are randomly assigned positions, akin to the initial placement of players in the musical chairs game. Subsequently, fitness values are determined based on the PV system performance. During each iteration, the loser exits, and chairs with the lowest fitness are removed. Optimization iterations commence by adjusting player positions using Eqn. (19), with fitness values reassessed based on the PV system's objective function. Winners occupy chairs with higher fitness values, simulating players aiming for the nearest or ahead chairs in the musical chairs game.

As iterations progress, the number of chairs and players decreases until a single chair remains, representing the GP. The performance of MCA as corroborated by the simulation and experimental results sections,

$$d_{pk}^{i} = d_{pk}^{i-1} + M.\frac{|u|}{v^{1/\beta}}.\left(d_{best} - d_{pk}^{i}\right) \tag{19}$$

$$\sigma_\alpha = \left(\frac{\gamma\left(1+\beta\right).\sin\left(\pi.\frac{\beta}{2}\right)}{\gamma\left(\frac{1+\beta}{2}\right).\beta.2^{\left(\frac{\beta-1}{2}\right)}}\right) \tag{20}$$

Equation (20) measure the fitness of each player to find out which player stays based on the performance of PV system. Upon convergence, players may cluster around the GP, impeding detection of any shifts in peak position amidst shading pattern changes. Therefore, to identify shading pattern changes, it's crucial to detect acute changes in generated power. The severe variation in PV produced power can be detected using Eqn. (21), as follows:

$$\left|\frac{P_i - P_{i-1}}{P_{i-1}}\right| > \varepsilon \tag{21}$$

NMCA may be prone to premature convergence, where the search process stagnates prematurely, resulting in suboptimal solutions. This can occur if the players converge too quickly to local optima, preventing the algorithm from exploring other potentially better solutions [93-97].

2.11 Improved Grey Wolf Optimizer (I-GWO)

I-GWO has improved global search ability and reduced risk of premature convergence via randomized initialization and neighbor-based learning. In an effort to reduce the possibility of entering local optima, Improved GWO was developed to improve GWO. This improvement comprises a unique search approach including phases for choosing and updating, as seen by the dashed line in the flowchart. The following is a thorough explanation of the enhancement: - Extending initialization by dispersing wolves at random around the search area, as provided by Equation (22).

$$X_{ij} = LB_j + rand_j\left(0,1\right)\left(UB_j - LB_j\right) \quad (22)$$

The Dimension Learning-based Hunting (DLH) process is used to improve tracking behavior. Every wolf in DLH gains knowledge from its neighbors.

$$R_i\left(t\right) = X_i\left(t\right) - X_{i-GWO}\left(t+1\right) \qquad (23)$$

Equation (23) support each wolf to learn from its neighbors. The optimizer aims to find better solutions and avoid being trapped in local optima. GWO's exploration strategy may not always effectively explore the solution space, especially in complex or multimodal optimization landscapes. In some cases, the algorithm may converge to suboptimal solutions due to inadequate exploration, limiting its capability to discovery globally ideal solutions in challenging optimization difficulties [98-102].

2.12 Bat Algorithm (BA) in PV MPPT Application

The BA has fast convergence, simplicity and better performance in low-dimensional optimization problems. In nature, bats emit pulses with varying frequencies and loudness, using the echoes to glean information about prey. They also share this knowledge within their swarm to aid others in finding food. The BA mirrors this behavior, leveraging it to search for optimal solutions across diverse real-life problems. Recognized for its rapid convergence, BA often outperforms other techniques such as PSO. BA involves bats navigating a three-dimensional space by emitting high-frequency pulses (typically between 10 and 100 Hz) and analyzing the resulting echoes to discern differences in sound intensity and delay times. Based on this echo recognition, bats adjust their speed and orientation and share this information with their peers. While BA excels in low-dimensional optimization difficulties, it fail to effective in high-dimensional scenarios due to its tendency to converge rapidly during initialization. However, BA remains an excellent choice for applications such as MPPT in PV systems, where the system typically involves only one variable.

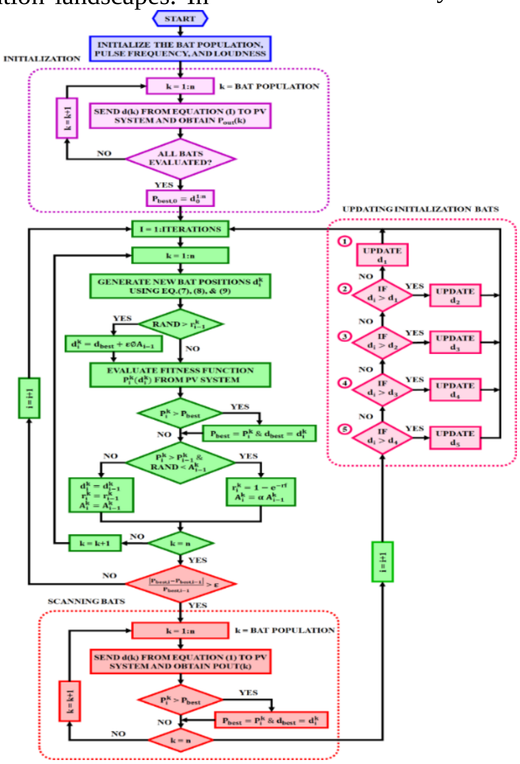

Figure 4. Flowchart of BA

BA's scalability to large-scale PV MPPT applications may be limited because of its population-based nature and the computational complexity of maintaining multiple bats. As the problem size increases, BA's performance may deteriorate, and it may struggle to efficiently discover the solution space and converge to high-quality solutions within a reasonable time frame [103-107].

2.13 Improved Moth-Flame Whale Optimization Algorithm (IMWOA)

IMWOA has greater convergence speed and predictive accuracy in optimizing complex, nonlinear models for predicting the PV power. This work created a model for predicting for short-term PV power forecast utilizing the IMWOA and Support Vector Machine (SVM). The approach outperformed other models for forecasting PV power under both cloudy and bright situations. Significant achievements include the effective creation of IMWOA and the improvement of its efficiency through the optimized use of mutation and adaptive variables in the WOA. Across a broad range of operations, the IMWOA models fared better than other models both in terms of error in prediction and convergence speed. With IMWOA, the optimal C and σ ratio was successfully identified in SVM, further increasing the forecast precision for PV output power. Future research directions include exploring various weather conditions in real environments for more comprehensive analysis and advancing long-term PV forecasting to enhance the operational safety and stability of power grid networks [108-112].

2.14 Improved Social Spider Algorithm (SSA)

The Improved SSA has improved capability to avoid local minima over its elimination strategy, which confirms broader exploration of the solution space. The SSA, although having a fast convergence rate, frequently becomes stuck in local minimums and is unable to reach the global minimum in numerous cases. We provide a revised plan to improve the algorithm's performance in order to overcome this constraint. In this method, an elimination phase is introduced to modify the movement of spiders toward desirable solutions. A predetermined number of the poorest solutions are removed at the beginning of each session, and new solutions are added to an updated search space. Spiders can now take other routes in search of the optimal solution. We can reduce possibility of flattering stuck in local minimums and find optimal solutions faster by putting these improvements into practice. Additionally, to support the memory requirements of each spider, memory allocation is provided after generating new spiders. The execution of this Improved ISSA is showed in Figure 4.

The changes made to the original algorithm, graphically indicated by blue blocks. In the meantime, Figure 5 provides a summary of the solar cell system's properties. The difference between the forecast and restrained currents is calculated for every algorithm iteration. ISSA algorithm's main goal is to reduce this RMSE number. The algorithm searches the search space to find and estimate the PV cell model's unknown parameters in order to accomplish this. Despite its empirical success in various applications, SSA lacks a strong theoretical foundation compared to some traditional optimization techniques. This can make it challenging to analyze its convergence properties and guarantees of finding the optimal solution [113-116].

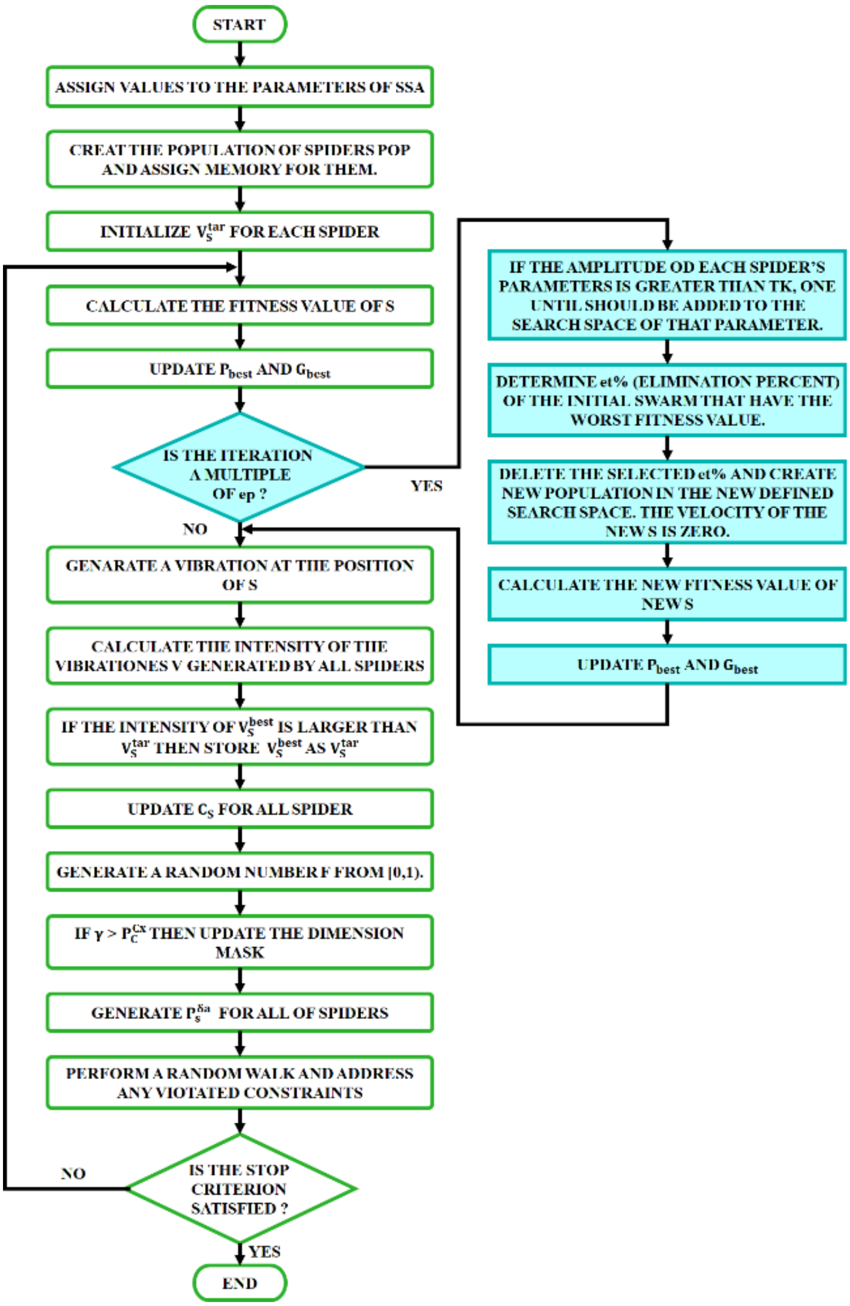

Figure 5. Flowchart of SSA

2.15Hunter-Prey Optimization (HPO)

HPO has efficient balance among exploration and exploitation, permitting it to direct complex and multimodal PV optimization landscapes. This algorithm draws inspiration from the hunting and protective behaviors, observed across various species of flora and fauna to achieve efficient optimization. The algorithm operates through three distinct steps: Step 1 involves the arbitrary initialization of the population, Step 2 computes the fitness function to constrain the search area for exploration, and Step 3 focuses on exploitation, wherein critical operations are performed among the entire population to develop prominent individuals. The search process unfolds in two stages: "exploration" and "exploitation." Exploration refers to algorithm's tendency for unpredictable behaviors and significant solution deviations, aiding in the discovery of unexplored regions with potential. Once promising areas are identified, random behaviors are minimized to explore the vicinity of these advantageous spots, a process known as exploitation. Within this algorithm, the hunter discerningly selects prey distanced from the group, observing their return before initiating an attack.

$$C = 1 - iter\left(\frac{0.98}{max_{iter}}\right) \tag{24}$$

$$Z = \left(R_1 * INX\right) + R_2 * INX) \tag{25}$$

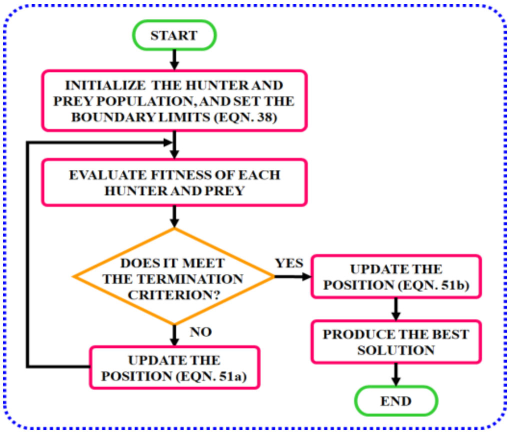

Figure 6. Flowchart of HPO

Equations (24) and (25) are used in HPO to steer the search of Equation (24) to support exploration by allowing the hunters to move randomly and Equation (25) enables exploitation by guiding the movement toward the best solutions. Despite its empirical success in certain applications, HPO lacks a strong theoretical foundation compared to some traditional optimization techniques. This can make it challenging to analyze its convergence properties and provide guarantees of finding the optimal solution in all cases [117-120].

3. Comparative Analysis

Table 1 illustrates the comparative analysis carried out among the different optimization techniques employed in PV system.

Table 1. Comparative Analysis between distinct algorithms

Sl. No	Author /Year/ Reference	Types of Algorithm	Methodology	Advantages	Drawbacks
1.	Loubna Bousselamti et al [2020] [121]	Partial Swarm Optimization method	To reduce Levelized Cost of Electricity (LCOE) that all things are considered as restricting the system efficacy, the Particle Swarm Optimization method is employed.	It is simpler to implement, robust to control parameters and computational efficiency. The PSO algorithm optimizes the parameters of system to diminish the LCOE, assuring maximum energy yield at lower cost.	The major drawback is that confronting the PSO algorithm is that they often converge to some local optimization.
2.	Imran Pervez et al [2021] [122]	ANN (Artificial Neural network)	To allow sufficient outcome and to reject computational load, an ANN based MPPT is employed.	It ensures that the loads receive maximum current to be used.	It offers shorter lifespan due to more electronic components and more thermal stress.
3.	Liu et al [2021] [123]	Adaptive Wind Driven Optimization Algorithm(AWDO)	To derive unspecified criterion of a single diode solar PV cell model, a new version of algorithm named AWDO algorithm is established.	Optimisation tool with the greatest effectiveness and superiority.	Specifically, they are incompetent when it comes to specifying global MPPs under P&O situations.
4.	Ahmed A. Zaki Diab et al [2020] [124]	Coyote Optimization Algorithm (COA)	Coyote optimization algorithm is executed for drawing out the unspecified parameters presented in PV modules and solar cell	It has very simple application with only two control parameters and have better tracking	They will easily get trapped in poor local optimum and low convergence speed.

			various models.	Properties.	
5.	Neeraj Priyadarshi et al [2019] [125]	PSO	To attain speedy and highest PV power along with a zero oscillation tracking, an ANFIS-PSO is launched.	It doesn't require extra sensor for measuring of irradiance and temperature variable.	Sensitive to a small number of fuzzy rules at first The more fuzzy rules there are, the harder it is to compute.
6.	Ali M. Eltamal Y et al [2021] [126]	Demand Response Strategy (DRS)	A new DRS is executed that finds the tariff of electricity based on charging/discharging state of the battery.	Obtain lower energy cost by curtailing energy usage at peak times when energy is more expensive.	Peak demand exceeds maximum supply levels that the electric power industry can generate, resulting in power outages and long shedding.
7.	Ehsan Moshksar et al [2018] [127]	Extremum Seeking Control Algorithm(ESCA)	The non-linear and uncertain problems like strong concavity feature of PV power output, considered measurable signal which need to be maximal in optimization are sorted out by using an estimation based ESCA.	The gradient of the unknown function is estimated using a perturbation signal.	It introduces very slow perturbation signal, which make optimization process very slow.
8.	Ke Guo et al [2020] [128]	Improved Gray Wolf Optimizer Algorithm (IGWO)	An IGWO method, which is a GMPPT control approach, is implemented according to the topology of the converter and external environment sudden changes considerations.	Its tracking time is only 0.24s and attains 98.54 % efficiency under severe PSCs.	Slow convergence speed, imprecise solution, and susceptibility to local optimum.
9.	Senapati et al [2025] [129]	JAYA Algorithm	For sorting out MPPT problem in solar PV system under partial shading conditions competently the subtle cubic spline guided JAYA Algorithm is developed.	It enhances tracking efficiency and addresses better PV MPPT problems and converges faster.	Its implementation is not easy as it have maximum number of iteration.
10.	M. S. AL-SAUD et al [2020] [130]	Bat Algorithm	The most conventional MPPT technique don't use GP under partial shading conditions. Hence bat algorithm, the metaheuristic technique is used to overcome this.	It uses simple concept and structure which have good exploitation ability.	It requires parameter tuning to achieve better search output and improvised method to accelerate the convergence for performance enhancement.

Additionally, a comparison of the various optimization algorithms is performed in relation to various parameters in Table 2 that has been presented below.

Table 2. Comparative analysis in terms of different parameters

Qualities	MVPA	COA	ANFIS-PSO	ESCA
GMPPT Capability	Yes	Yes	Yes	Yes
Efficacy	High	High	High	High
Reliability	High	High	High	High
Tracking Speed	High	Medium	High	High
Steady State Oscillations	No	No	No	Low
Performance complexity	Low	Low	Low	Medium

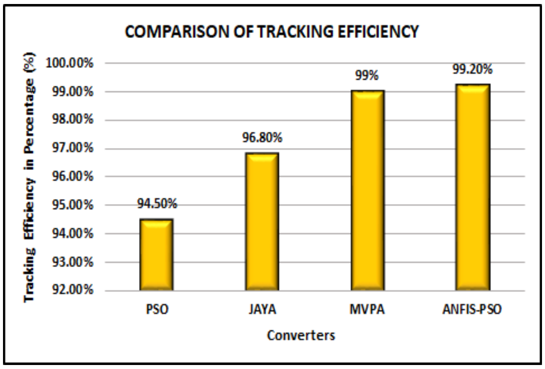

Figure 7. Tracking Efficiency comparison

According to the evaluation, it is shown that ANFIS-PSO algorithm outperforms other methods including MVPA, COA, and ECSA in terms of reliability, steady state oscillations, and effectiveness, tracking speed, performance complexity and GMPPT capability.

Table 3. Evaluation of tracking effectiveness

MPPT controller	Efficiency (%)	Tracking time (s)
PSO	94.5%	5.3s
JAYA	96.8%	4.9s
MVPA	99%	3.2s
ANFIS-PSO	99.2%	2.1s

Table 3 denotes the different MPPT controller approaches regarding tracking efficiency (%) and tracking response(s). According to the Table 3, the PSO tuned ANFIS BASED MPPT controller achieves maximum tracking efficiency 99.2% with fast tracking time 2.1s. Figure 7 illustrates the comparative analysis amid the different optimization techniques, with respect to tracking efficiency. According to the analysis, ANFIS-PSO outperforms other techniques including PSO, JAYA, MVPA and ANFIS PSO with a tracking efficiency of 99.2%.

4. Conclusion

In the present period, the PV system's wide availability and pollution-free nature have reached a huge height. The PV module typically connects solar cells in parallel and series to transform solar energy into electricity. Although it is not viable to connect a load directly to a PV panel. It is essential to enhance systems output because of the intermittent nature of PV systems. As a result, DC-AC and DC-DC converters are exploited for controlling and supplying PV output to grid or load. Furthermore, a variety of optimization-based techniques are operated to extract most power from PV system and to maintain a consistent DC link voltage. A comparative analysis has been performed between various optimization methods employed in the PV system, so as to identify the significant one. The comparison of findings indicates that the ANFIS-PSO method operates better than other methods. Therefore, it is probable to significantly improve PV system's performance in future by employing unique hybrid optimization algorithms and by data mining techniques. However, some algorithms have complexities under difficult situations such as nonlinear and partial shading, diminishing tracking efficacy and convergence reliability. Furthermore, computational overheads and scalability for high-dimensional optimization issues are not extremely analyzed. The hybrid optimization approach incorporating AI based forecasting or adaptive control approaches are explored in the future research. Furthermore, the multi-objective optimization considering economic and environmental metrics maybe integrated for performance enhancement.

List of Abbreviations

Abbreviations	Explanation	Abbreviations	Explanation
RES	Renewable Energy Source	REF	Renewable Energy Fraction
PV	Photovoltaic	COE	Cost of Energy
RESCA	Reformed Electric System Cascade Analysis	EGR	Energy Generation Ratio

MPPT	Maximum Power Point Technique	DRO	Distributionally Robust Optimization
HRES	Hybrid Renewable Energy System	VVPO	Volt-VAR Pressure Optimization
BESS	Battery Energy Storage System	P&O	Perturb and Observe
NIS	Non-intermittent Source	MPP	Maximum Power Point
WECS	Wind Energy Conversion System	RCPSO	Real Coded Particle Swarm Optimization
FEE	Final Excess Energy	RECKF	Robust Extended Complex Kalman Filter
NPC	Net Present Cost	SPVA	Solar Photovoltaic Array
CFPA	Chaotic Flower Pollination Optimization Algorithm	GMPP	Global Maximum Power Point
FRA	Flow Regime Algorithm	PSCs	Partially Shaded Circumstances
STF	Search Type Factor	LIPO	Lipschitz Optimization
SARAP	Search Algorithm Referencing Adjacent Point Optimization Algorithm	MPSO	Modified PSO
MRFO	Manta Rays Foraging Optimization Algorithm	SMO	Social Mimic Optimization Algorithm
DPVS	Distributed Photovoltaic Stations	EVCS	Electric Vehicle Charging Stations
SBMPO	Sampling Based Model Predictive Optimization	EM	Energy Management
MFOGI	Multilayer Fifth Order Generalized Integrator	TGOA	Team Game Optimization Algorithm
LSTM	Long Short Term Memory	HPO	Human Psychology Optimization
THD	Total Harmonic Distortion	DDM	Double Diode Model
SDM	Single Diode Model	LCOE	Levelized Cost of Electricity
ANN	Artificial Neural network	AWDO	Adaptive Wind Driven Optimization
COA	Coyote Optimization Algorithm	DRS	Demand Response Strategy
BFBIC	Boost Full Bridge Isolated Converter	SOC	State of Charge

References

[1] Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, *35*(7), 3833-3879. https://doi.org/10.1177/0958305X241256293

[2] Sakouvogui, A., Diarra, A., Oulare, F., Camara, E. O., Barry, S., & Keita, M. (2021). *Multidisciplinary Technovation*. *Nature*, *3*(4). https://doi.org/10.34256/irjmt2142

[3] Dharmarajan, R., & Ramachandran, R. (2019). PV module parameters estimation using Newton Raphson. *International Research Journal of Multidisciplinary Technovation*, *1*(4), 28-40. https://doi.org/10.34256/irjmt19219

[4] Priyadarshi, N., Padmanaban, S., Hiran, K. K., Holm-Nielson, J. B., & Bansal, R. C. (Eds.). (2021). *Artificial intelligence and internet of things for renewable energy systems* (Vol. 12). Walter de Gruyter GmbH & Co KG. https://doi.org/10.1515/9783110714043-202

[5] Gunapriya, B., Abinaya, I., Karthik, M., & Vidhya, H. (2020). Anti-wind up PI controller with tracking for motor drive system: Modelling, simulation and implementation in lab view based FPGA. *International Journal of Recent technology and Engineering*, 8(5). DOI:10.35940/ijrte.D9510.018520

[6] Munir, S. (2022). Estimator Torsi Beban Sistem Servo Modular MS150 DC Berbasis Jaringan Syaraf Tiruan. *CYCLOTRON*, *5*(2). https://doi.org/10.30651/cl.v5i2.12936

[7] Vijayan, V., Mohapatra, A., Singh, S. N., & Dewangan, C. L. (2023). An efficient modular optimization scheme for unbalanced active distribution networks with uncertain EV and PV penetrations. *IEEE Transactions on Smart Grid*, *14*(5), 3876-3888. https://doi.org/10.1109/TSG.2023.3234551

[8] Wang, H., Binti Mansor, N. N., & Mokhlis, H. B. (2024). Novel hybrid optimization technique for solar photovoltaic output prediction using

Improved Hippopotamus Algorithm. *Applied Sciences*, 14(17), 7803. https://doi.org/10.3390/app14177803.

[9] Kavin, K. S., & Subha Karuvelam, P. (2023). PV-based grid interactive PMBLDC electric vehicle with high gain interleaved DC-DC SEPIC Converter. *IETE Journal of Research*, *69*(7), 4791-4805. https://doi.org/10.1080/03772063.2021.1958070

[10] Nafeh, A. E. S. A., Omran, A. E. F. A., Elkholy, A., & Yousef, H. M. (2024). Optimal economical sizing of a PV-battery grid-connected system for fast charging station of electric vehicles using modified snake optimization algorithm. *Results in Engineering*, *21*, 101965. https://doi.org/10.1016/j.rineng.2024.101965

[11] Kavin, K. S., (2020). Energy Management of AC Grid by the Solar PV System Using Landsman Converter. https://dx.doi.org/10.2139/ssrn.3668766

[12] Abdulla, H., Sleptchenko, A., & Nayfeh, A. (2024). Photovoltaic systems operation and maintenance: A review and future directions. *Renewable and Sustainable Energy Reviews*, *195*, 114342. https://doi.org/10.1016/j.rser.2024.114342

[13] Saxena, A., Kumar, R., Sagade, A. A., Singh, D. B., Tyagi, V. V., Cuce, E., & Goel, V. (2024). A state-of-art review on photovoltaic systems: Design, performance, and progress. *Process Safety and Environmental Protection*, *190*, 1324-1354. https://doi.org/10.1016/j.psep.2024.07.111

[14] Nezhad, M. A., & Bevrani, H. (2023). μ and H∞ optimization control based on optimal oxygen excess ratio for the Proton Exchange Membrane Fuel Cell (PEMFC). *Journal of Industrial &Management Optimization*, *19*(6). DOI: 10.3934/jimo.2022116

[15] Antarasee, P., Premrudeepreechacharn, S., Siritaratiwat, A., & Khunkitti, S. (2022). Optimal design of electric vehicle fast-charging station's structure using metaheuristic algorithms. *Sustainability*, *15*(1), 771. https://doi.org/10.3390/su15010771

[16] Kraiem, H., Flah, A., Mohamed, N., Alowaidi, M., Bajaj, M., Mishra, S., & Sharma, S. K. (2021). Increasing electric vehicle autonomy using a photovoltaic system controlled by particle swarm optimization. *IEEE Access*, *9*, 72040-72054. https://doi.org/10.1109/ACCESS.2021.3077531

[17] Singh, B., Verma, A., Chandra, A., & Al-Haddad, K. (2020). Implementation of solar PV-battery and diesel generator based electric vehicle charging station. *IEEE Transactions on Industry Applications*, *56*(4), 4007-4016. https://doi.org/10.1109/TIA.2020.2989680

[18] Elshara, R., Hançerlioğullari, A., Rahebi, J., & Lopez-Guede, J. M. (2024). PV cells and modules parameter estimation using coati optimization algorithm. *Energies*, *17*(7), 1716. https://doi.org/10.3390/en17071716

[19] Habib, H. U. R., Waqar, A., Junejo, A. K., Elmorshedy, M. F., Wang, S., Büker, M. S., & Kim, Y. S. (2021). Optimal planning and EMS design of PV based standalone rural microgrids. *IEEE Access*, *9*, 32908-32930. https://doi.org/10.1109/ACCESS.2021.3060031

[20] Irshad, A. S., Ludin, G. A., Masrur, H., Ahmadi, M., Yona, A., Mikhaylov, A., & Senjyu, T. (2023). Optimization of grid-photovoltaic and battery hybrid system with most technically efficient PV technology after the performance analysis. *Renewable Energy*, *207*, 714-730. https://doi.org/10.1016/j.renene.2023.03.062

[21] Golroodbari, S. Z., & Van Sark, W. (2020). Simulation of performance differences between offshore and land- based photovoltaic systems. *Progress in Photovoltaics: Research and Applications*, *28*(9), 873-886. https://doi.org/10.1002/pip.3276

[22] Arandian, B., Eslami, M., Khalid, S. A., Khan, B., Sheikh, U. U., Akbari, E., & Mohammed, A. H. (2022). An effective optimization algorithm for parameters identification of photovoltaic models. *IEEE Access*, *10*, 34069-34084. https://doi.org/10.1109/ACCESS.2022.3161467

[23] Long, W., Wu, T., Xu, M., Tang, M., & Cai, S. (2021). Parameters identification of photovoltaic models by using an enhanced adaptive butterfly optimization algorithm. *Energy*, *229*, 120750. https://doi.org/10.1016/j.energy.2021.120750

[24] Mubaarak, S., Zhang, D., Chen, Y., Liu, J., Wang, L., Yuan, R., & Li, M. (2020). Techno-economic analysis of grid-connected PV and fuel cell hybrid system using different PV tracking techniques. *Applied Sciences*, *10*(23), 8515. https://doi.org/10.3390/app10238515

[25] Abdolrasol, M. G., Ayob, A., Mutlag, A. H., & Ustun, T. S. (2023). Optimal fuzzy logic controller based PSO for photovoltaic system. *Energy Reports*, *9*, 427-434. https://doi.org/10.1016/j.egyr.2022.11.039

[26] Diab, A. A. Z., Sultan, H. M., Aljendy, R., Al-Sumaiti, A. S., Shoyama, M., & Ali, Z. M. (2020). Tree growth based optimization algorithm for parameter extraction of different models of photovoltaic cells and modules. *IEEE*

Access, *8*, 119668-119687. https://doi.org/10.1109/ACCESS.2020.3005236

[27] Ernst, M., Liu, X., Asselineau, C. A., Chen, D., Huang, C., & Lennon, A. (2024). Accurate modelling of the bifacial gain potential of rooftop solar photovoltaic systems. *Energy Conversion and Management*, *300*, 117947. https://doi.org/10.1016/j.enconman.2023.117947

[28] Liu, H., Zhang, Y., Ge, S., Gu, C., & Li, F. (2019). Day-ahead scheduling for an electric vehicle PV-based battery swapping station considering the dual uncertainties. *IEEE Access*, *7*, 115625-115636. https://doi.org/10.1109/ACCESS.2019.2935774

[29] Naser, A. T., Mohammed, K. K., Ab Aziz, N. F., binti Kamil, K., & Mekhilef, S. (2024). Improved coot optimizer algorithm-based MPPT for PV systems under complex partial shading conditions and load variation. *Energy Conversion and Management: X*, *22*, 100565. https://doi.org/10.1016/j.ecmx.2024.100565

[30] Ibrahim, A. W., Shafik, M. B., Ding, M., Sarhan, M. A., Fang, Z., Alareqi, A. G., & Al-Rassas, A. M. (2020). PV maximum power-point tracking using modified particle swarm optimization under partial shading conditions. *Chinese Journal of Electrical Engineering*, *6*(4), 106-121. https://doi.org/10.23919/CJEE.2020.000035

[31] Wu, A., Gong, R., Mao, J., Yu, X., He, J., & Li, E. X. (2024). Voltage Feed-Forward Control of Photovoltaic-Battery DC Microgrid Based on Improved Seeker Optimization Algorithm. *IEEE Access*, *12*, 46067-46080. https://doi.org/10.1109/ACCESS.2024.3382134

[32] Bollipo, R. B., Mikkili, S., & Bonthagorla, P. K. (2020). Critical review on PV MPPT techniques: classical, intelligent and optimisation. *IET Renewable Power Generation*, *14*(9), 1433-1452. https://doi.org/10.1049/iet-rpg.2019.1163

[33] Hanzaei, S. H., Gorji, S. A., & Ektesabi, M. (2020). A scheme-based review of MPPT techniques with respect to input variables including solar irradiance and PV arrays' temperature. *IEEE Access*, *8*, 182229-182239. https://doi.org/10.1109/ACCESS.2020.3028580

[34] Hussaian Basha, C. H., & Rani, C. (2020). Performance analysis of MPPT techniques for dynamic irradiation condition of solar PV. *International Journal of Fuzzy Systems*, *22*(8), 2577-2598. https://doi.org/10.1007/s40815-020-00974-y

[35] Lopez, L., Lopez, I., Gomez-Cornejo, J., Aranzabal, I., & Eguia, P. (2025). Analysis of impact for PV-BES strategies in low-voltage distribution system. *Electrical Engineering*, *107*(2), 2147-2162. https://doi.org/10.1007/s00202-024-02620-4

[36] Motahhir, S., Chouder, A., El Hammoumi, A., Benyoucef, A. S., El Ghzizal, A., Kichou, S., & Silvestre, S. (2020). Optimal energy harvesting from a multistrings PV generator based on artificial bee colony algorithm. *IEEE Systems Journal*, *15*(3), 4137-4144. https://doi.org/10.1109/JSYST.2020.2997744

[37] Zaghba, L., Borni, A., Benbitour, M. K., Fezzani, A., Alwabli, A., Bajaj, M., & Ghoneim, S. S. (2024). Enhancing grid-connected photovoltaic system performance with novel hybrid MPPT technique in variable atmospheric conditions. *Scientific Reports*, *14*(1), 8205. https://doi.org/10.1038/s41598-024-59024-4

[38] Shaheen, A. M., Ginidi, A. R., El-Sehiemy, R. A., & Ghoneim, S. S. (2020). A forensic-based investigation algorithm for parameter extraction of solar cell models. *IEEE Access*, *9*, 1-20. https://doi.org/10.1109/ACCESS.2020.3046536

[39] Liu, H., Wang, S., Liu, G., Zhang, J., & Wen, S. (2020). SARAP algorithm of multi-objective optimal capacity configuration for WT-PV-DE-BES stand-alone microgrid. *IEEE access*, *8*, 126825-126838. https://doi.org/10.1109/ACCESS.2020.3008553

[40] Premkumar, M., Jangir, P., Ramakrishnan, C., Nalinipriya, G., Alhelou, H. H., & Kumar, B. S. (2021). Identification of solar photovoltaic model parameters using an improved gradient-based optimization algorithm with chaotic drifts. *IEEE Access*, *9*, 62347-62379. https://doi.org/10.1109/ACCESS.2021.3073821

[41] Pradhan, C., Senapati, M. K., Malla, S. G., Nayak, P. K., & Gjengedal, T. (2020). Coordinated power management and control of standalone PV-hybrid system with modified IWO-based MPPT. *IEEE Systems Journal*, *15*(3), 3585-3596. https://doi.org/10.1109/JSYST.2020.3020275

[42] Angadi, S., Yaragatti, U. R., Suresh, Y., & Raju, A. B. (2021). System parameter based performance optimization of solar PV systems with perturbation based MPPT algorithms. *Energies*, *14*(7), 2007. https://doi.org/10.3390/en14072007

[43] Revathy, S. R., Kirubakaran, V., Rajeshwaran, M., Balasundaram, T., Sekar, V. C., Alghamdi, S., & Anbese, E. M. (2022). Design and analysis of ANFIS–based MPPT method for solar photovoltaic applications. *International*

Journal of Photoenergy, *2022*(1), 9625564. https://doi.org/10.1155/2022/9625564

[44] Babu, D. V. S., Jayavani, L., Bhuvaneswari, T. R., Mageswaran, R., Kavin, K. S., & Kaliappan, K. (2024). IoT interfaced improved smart P&O MPPT assisted PV-wind based smart grid monitoring system. *In 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT),* 1, 1078-1084. https://doi.org/10.1109/ICCPCT61902.2024.10673150

[45] Saberi, A., Niroomand, M., & Dehkordi, B. M. (2023). An improved P&O based MPPT for PV systems with reduced steady- state oscillation. *International Journal of Energy Research*, *2023*(1), 4694583. https://doi.org/10.1155/2023/4694583

[46] Moyo, R. T., Tabakov, P. Y., & Moyo, S. (2021). Design and modeling of the ANFIS-based MPPT controller for a solar photovoltaic system. *Journal of Solar Energy Engineering*, *143*(4), 041002. https://doi.org/10.1115/1.4048882

[47] Ahmed, M., Abdelrahem, M., Harbi, I., & Kennel, R. (2020). An adaptive model-based MPPT technique with drift-avoidance for grid-connected PV systems. *Energies*, *13*(24), 6656. https://doi.org/10.3390/en13246656

[48] Abdel-Rahim, O., & Wang, H. (2020). A new high gain DC-DC converter with model-predictive-control based MPPT technique for photovoltaic systems. *CPSS Transactions on Power Electronics and Applications*, *5*(2), 191-200. https://doi.org/10.24295/CPSSTPEA.2020.00016

[49] Kavin, K. S., Subha Karuvelam, P., Devesh Raj, M., & Sivasubramanian, M. (2024). A novel KSK converter with machine learning MPPT for PV applications. *Electric power components and systems*, 1-19. https://doi.org/10.1080/15325008.2024.2346806

[50] Kavin, K. S., Karuvelam, P. S., Kumar, R. T., Sivasubramanian, M., Kavitha, P., & Priyadharsini, S. (2023, July). GWO Optimized PI Controller Fed PV Based Interleaved Luo Converter for EV Applications. In *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICCCNT56998.2023.10307340

[51] Alshabi, M., Ghenai, C., Bettayeb, M., & Ahmad, F. F. (2021). Estimating one-diode-PV model using autonomous groups particle swarm optimization. *IAES International Journal of Artificial Intelligence*, *10*(1), 166. DOI: 10.11591/ijai.v10.i1.pp166-174

[52] Singh, A., Sharma, A., Rajput, S., Bose, A., & Hu, X. (2022). An investigation on hybrid particle swarm optimization algorithms for parameter optimization of PV cells. *Electronics*, *11*(6), 909. https://doi.org/10.3390/electronics11060909

[53] El Hariz, Z., Hicham, A., & Mohammed, D. (2022). A novel optimiser of MPPT by using PSO-AG and PID controller. *International Journal of Ambient Energy*, *43*(1), 5199-5206. https://doi.org/10.1080/01430750.2021.1934116

[54] Han, F., Abdelaziz, I. I. M., Ghazali, K. H., Zhao, Y., & Li, N. (2023). Optimized range-free localization scheme using autonomous groups particles swarm optimization for anisotropic wireless sensor networks. *IEEE Access*, *11*, 26906-26920. https://doi.org/10.1109/ACCESS.2023.3257567

[55] Shehata, A. A., Refaat, A., Ahmed, M. K., & Korovkin, N. V. (2021). Optimal placement and sizing of FACTS devices based on Autonomous Groups Particle Swarm Optimization technique. *Archives of Electrical Engineering*, *70*(1), 161-172. DOI 10.24425/aee.2021.136059

[56] David, M., Boland, J., Cirocco, L., Lauret, P., & Voyant, C. (2021). Value of deterministic day-ahead forecasts of PV generation in PV+ Storage operation for the Australian electricity market. *Solar Energy*, *224*, 672-684. https://doi.org/10.1016/j.solener.2021.06.011

[57] Georgiou, G. S., Christodoulides, P., & Kalogirou, S. A. (2020). Optimizing the energy storage schedule of a battery in a PV grid-connected nZEB using linear programming. *Energy*, *208*, 118177. https://doi.org/10.1016/j.energy.2020.118177

[58] Sangaiah, A. K., Tirkolaee, E. B., Goli, A., & Dehnavi-Arani, S. (2020). Robust optimization and mixed-integer linear programming model for LNG supply chain planning problem. *Soft computing*, *24*(11), 7885-7905. https://doi.org/10.1007/s00500-019-04010-6

[59] Ramli, S. P., Mokhlis, H., Wong, W. R., Muhammad, M. A., Mansor, N. N., & Hussain, M. H. (2021). Optimal coordination of directional overcurrent relay based on combination of improved particle swarm optimization and linear programming considering multiple characteristics curve. *Turkish Journal of Electrical Engineering and Computer Sciences*, *29*(3), 1765-1780. Doi: 10.3906/elk-2008-23

[60] Daqaq, F., Ouassaid, M., Kamel, S., Ellaia, R., & El-Naggar, M. F. (2022). A novel chaotic flower pollination algorithm for function optimization and constrained optimal power flow considering renewable energy sources. *Frontiers in Energy Research*, *10*, 941705. https://doi.org/10.3389/fenrg.2022.941705

[61] Daqaq, F., Ellaia, R., & Ouassaid, M. (2020, November). A constrained chaotic flower pollination algorithm for solving ORPD problem. In *2020 international symposium on advanced electrical and communication technologies (ISAECT)* (pp. 1-6). IEEE. https://doi.org/10.1109/ISAECT50560.2020.9523712

[62] Mergos, P. E., & Yang, X. S. (2021). Flower pollination algorithm parameters tuning. *Soft computing*, *25*(22), 14429-14447. https://doi.org/10.1007/s00500-021-06230-1

[63] Khluabwannarat, P., & Puangdownreong, D. (2021). Optimal fractional-order PID controller design for BLDC motor speed control system by using parallel flower pollination algorithm. *An International Journal of Research and Surveys*, *15*(2). Doi: 10.24507/icicel.15.02.165

[64] Dhivya, S., & Arul, R. (2021, April). Improved flower pollination algorithm-based optimal placement and sizing of DG for practical indian 52 bus system. In *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, 1-5. https://doi.org/10.1109/IEMTRONICS52119.2021.9422562

[65] Cortes-Vega, D., Alazki, H., & Rullan-Lara, J. L. (2022). Current sensorless MPPT control for PV systems based on robust observer. *Applied Sciences*, *12*(9), 4360. https://doi.org/10.3390/app12094360

[66] Endiz, M. S. (2024). Design and implementation of microcontroller-based solar charge controller using modified incremental conductance MPPT algorithm. *Journal of Radiation Research and Applied Sciences*, *17*(2), 100938. https://doi.org/10.1016/j.jrras.2024.100938

[67] Harrison, A., Alombah, N. H., & de Dieu Nguimfack Ndongmo, J. (2023). A new hybrid MPPT based on incremental conductance- integral back stepping controller applied to a PV system under fast- changing operating conditions. *International Journal of Photo energy*, *2023*(1), 9931481. https://doi.org/10.1155/2023/9931481

[68] Shang, L., Guo, H., & Zhu, W. (2020). An improved MPPT control strategy based on incremental conductance algorithm. *Protection and Control of Modern Power Systems*, *5*(2), 1-8. https://doi.org/10.1186/s41601-020-00161-z

[69] Feroz Mirza, A., Mansoor, M., Ling, Q., Khan, M. I., & Aldossary, O. M. (2020). Advanced variable step size incremental conductance MPPT for a standalone PV system utilizing a GA-tuned PID controller. *Energies*, *13*(16), 4153. https://doi.org/10.3390/en13164153

[70] Krishnan G, S., Kinattingal, S., Simon, S. P., & Nayak, P. S. R. (2020). MPPT in PV systems using ant colony optimisation with dwindling population. *IET Renewable Power Generation*, *14*(7), 1105-1112. https://doi.org/10.1049/iet-rpg.2019.0875

[71] González-Castaño, C., Restrepo, C., Kouro, S., & Rodriguez, J. (2021). MPPT algorithm based on artificial bee colony for PV system. *IEEE Access*, *9*, 43121-43133. https://doi.org/10.1109/ACCESS.2021.3066281

[72] Chao, K. H., & Rizal, M. N. (2021). A hybrid MPPT controller based on the genetic algorithm and ant colony optimization for photovoltaic systems under partially shaded conditions. *Energies*, *14*(10), 2902. https://doi.org/10.3390/en14102902

[73] Xia, K., Li, Y., & Zhu, B. (2024). Improved photovoltaic MPPT algorithm based on ant colony optimization and fuzzy logic under conditions of partial shading. *IEEE Access*, *12*, 44817-44825. https://doi.org/10.1109/ACCESS.2024.3381345

[74] Huang, K. H., Chao, K. H., & Lee, T. W. (2023). An improved photovoltaic module array global maximum power tracker combining a genetic algorithm and ant colony optimization. *Technologies*, *11*(2), 61. https://doi.org/10.3390/technologies11020061

[75] Charfeddine, S., Alharbi, H., Jerbi, H., Kchaou, M., Abbassi, R., & Leiva, V. (2022). A stochastic optimization algorithm to enhance controllers of photovoltaic systems. *Mathematics*, *10*(12), 2128. https://doi.org/10.3390/math10122128

[76] Rezk, H., & Fathy, A. (2020). Stochastic fractal search optimization algorithm based global MPPT for triple-junction photovoltaic solar system. *Energies*, *13*(18), 4971. https://doi.org/10.3390/en13184971

[77] Fu, C., Zhang, L., & Dong, W. (2022). Research and application of Mppt control strategy based on improved slime mold algorithm in shaded conditions. *Electronics*, *11*(14), 2122. https://doi.org/10.3390/electronics11142122

[78] Srinivasan, R., & Ramalingam Balamurugan, C. (2022). Deep neural network based MPPT algorithm and PR controller based SMO for grid connected PV system. *International Journal of Electronics*, *109*(4), 576-595. https://doi.org/10.1080/00207217.2021.1914192

[79] Ramadan, A., Kamel, S., & Ibrahim, A. (2021). Parameters estimation of photovoltaic cells using self-adaptive multi-population Rao optimization algorithm. *Aswan University Journal of Sciences and Technology, 1*(1), 26-40.

[80] Rao, R. V., & Pawar, R. B. (2020). Self-adaptive multi-population Rao algorithms for engineering design optimization. *Applied Artificial Intelligence*, *34*(3), 187-250. https://doi.org/10.1080/08839514.2020.1712789

[81] Federici, L., Benedikter, B., & Zavoli, A. (2020, July). EOS: a parallel, self-adaptive, multi-population evolutionary algorithm for constrained global optimization. In *2020 IEEE congress on evolutionary computation (CEC)* (pp. 1-10). IEEE. https://doi.org/10.1109/CEC48606.2020.9185800

[82] Kumar, V., & Yadav, S. M. (2020). Self-adaptive multi-population-based Jaya algorithm to optimize the cropping pattern under a constraint environment. *Journal of Hydro informatics*, *22*(2), 368-384. https://doi.org/10.2166/hydro.2019.087

[83] Fathy, A., Rezk, H., & Yousri, D. (2020). A robust global MPPT to mitigate partial shading of triple-junction solar cell-based system using manta ray foraging optimization algorithm. *Solar Energy*, *207*, 305-316. https://doi.org/10.1016/j.solener.2020.06.108

[84] Aly, M., & Rezk, H. (2021). A MPPT based on optimized FLC using manta ray foraging optimization algorithm for thermo‐ electric generation systems. *International Journal of Energy Research*, *45*(9), 13897-13910. https://doi.org/10.1002/er.6728

[85] Mahmoud, M. M., Atia, B. S., Abdelaziz, A. Y., & Aldin, N. A. N. (2022). Dynamic performance assessment of PMSG and DFIG-based WECS with the support of manta ray foraging optimizer considering MPPT, pitch control, and FRT capability issues. *Processes*, *10*(12), 2723. https://doi.org/10.3390/pr10122723

[86] Xie, R., Wu, S., & Yang, B. (2023, July). MPPT design for hybrid PV-TEG system under partial shading condition via Manta Ray Foraging Optimization. In *2023 5th International Conference on Power and Energy Technology (ICPET)* (pp. 765-770). IEEE. https://doi.org/10.1109/ICPET59380.2023.10367668

[87] Alturki, F. A., Omotoso, H. O., Al-Shamma'a, A. A., Farh, H. M., & Alsharabi, K. (2020). Novel manta rays foraging optimization algorithm based optimal control for grid-connected PV energy system. *IEEE Access*, *8*, 187276-187290. https://doi.org/10.1109/ACCESS.2020.3030874

[88] Saadaoui, D., Elyaqouti, M., Assalaou, K., & Lidaighbi, S. (2021). Parameters optimization of solar PV cell/module using genetic algorithm based on non-uniform mutation. *Energy Conversion and Management: X*, *12*, 100129. https://doi.org/10.1016/j.ecmx.2021.100129

[89] Zhao, J., He, K., Kang, L., & Wang, X. (2025). Genetic algorithm with enhanced non-uniform mutation strategy for high-order polynomial optimization in temperature drift compensation of quartz flexible accelerometers. *Sensors and Actuators A: Physical*, *387*, 116371. https://doi.org/10.1016/j.sna.2025.116371

[90] Hassan, A., Bass, O., & Masoum, M. A. (2023). An improved genetic algorithm based fractional open circuit voltage MPPT for solar PV systems. *Energy Reports*, *9*, 1535-1548. https://doi.org/10.1016/j.egyr.2022.12.088

[91] de Oliveira, F. M., Brandt, M. H. M., Salvadori, F., Izquierdo, J. E. E., Cavallari, M. R., & Ando Junior, O. H. (2024). Development of an MPPT-based genetic algorithm for photovoltaic systems versus classical MPPT techniques in scenarios with partial shading. *Inventions*, *9*(3), 64. https://doi.org/10.3390/inventions9030064

[92] Hilali, A., Mardoude, Y., Essahlaoui, A., Rahali, A., & El Ouanjli, N. (2022). Migration to solar water pump system: Environmental and economic benefits and their optimization using genetic algorithm Based MPPT. *Energy Reports, 8*, 10144-10153. https://doi.org/10.1016/j.egyr.2022.08.017

[93] Eltamaly, A. M. (2021). A novel musical chairs algorithm applied for MPPT of PV systems. *Renewable and Sustainable Energy Reviews*, *146*, 111135. https://doi.org/10.1016/j.rser.2021.111135

[94] Eltamaly, A. M., & Rabie, A. H. (2023). A novel musical chairs optimization algorithm. *Arabian Journal for Science and Engineering*, *48*(8), 10371-10403. https://doi.org/10.1007/s13369-023-07610-5

[95] Alshareef, M. J. (2025). An enhanced fractional open circuit voltage MPPT method for rapid and precise MPP tracking in standalone

photovoltaic systems. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3543327

[96] Eltamaly, A. M., & Almutairi, Z. A. (2025). A novel star-nosed mole optimization algorithm applied for MPPT of PV systems. *Scientific Reports*, *15*(1), 17807. https://doi.org/10.1038/s41598-025-02938-4

[97] Eltamaly, A. M., & Almutairi, Z. A. (2025). Synergistic Coordination Between PWM Inverters and DC-DC Converters for Power Quality Improvement of Three-Phase Grid-Connected PV Systems. *Sustainability*, *17*(8), 3748. https://doi.org/10.3390/su17083748

[98] Ramadan, A. E., Kamel, S., Khurshaid, T., Oh, S. R., & Rhee, S. B. (2021). Parameter extraction of three diode solar photovoltaic model using improved grey wolf optimizer. *Sustainability*, *13*(12), 6963. https://doi.org/10.3390/su13126963

[99] Hou, Y., Gao, H., Wang, Z., & Du, C. (2022). Improved grey wolf optimization algorithm and application. *Sensors*, *22*(10), 3810. https://doi.org/10.3390/s22103810

[100] Liu, J., Wei, X., & Huang, H. (2021). An improved grey wolf optimization algorithm and its application in path planning. *IEEE Access*, *9*, 121944-121956. https://doi.org/10.1109/ACCESS.2021.310897.

[101] Taha, S. A., Al-Sagar, Z. S., Abdulsada, M. A., Alruwaili, M., & Ibrahim, M. A. (2025). Design of an efficient MPPT topology based on a grey wolf optimizer-particle swarm optimization (GWO-PSO) algorithm for a grid-tied solar inverter under variable rapid-change irradiance. *Energies*, *18*(8), 1997. https://doi.org/10.3390/en18081997

[102] Naserbegi, A., Aghaie, M., & Zolfaghari, A. (2020). Implementation of Grey Wolf Optimization (GWO) algorithm to multi-objective loading pattern optimization of a PWR reactor. *Annals of Nuclear Energy*, *148*, 107703. https://doi.org/10.1016/j.anucene.2020.107703

[103] Eltamaly, A. M., Al-Saud, M. S., & Abokhalil, A. G. (2020). A novel scanning bat algorithm strategy for maximum power point tracker of partially shaded photovoltaic energy systems. *Ain Shams Engineering Journal*, *11*(4), 1093-1103. https://doi.org/10.1016/j.asej.2020.02.015

[104] Ge, X., Ahmed, F. W., Rezvani, A., Aljojo, N., Samad, S., & Foong, L. K. (2020). Implementation of a novel hybrid BAT-Fuzzy controller based MPPT for grid-connected PV-battery system. *Control engineering practice*, *98*, 104380. https://doi.org/10.1016/j.conengprac.2020.104380

[105] de Jesús Rubio, J. (2023). Bat algorithm based control to decrease the control energy consumption and modified bat algorithm based control to increase the trajectory tracking accuracy in robots. *Neural Networks*, *161*, 437-448. https://doi.org/10.1016/j.neunet.2023.02.010

[106] Amalo, K. A., Birninkudu, S. I., Bukata, B. B., Salawudeen, A. T., & Ahmad, A. A. (2020, March). Cultured bat algorithm for optimized MPPT tracking under different shading conditions. In *2020 International Conference in mathematics, computer engineering and computer science (ICMCECS)* (pp. 1-8). IEEE. https://doi.org/10.1109/ICMCECS47690.2020.246985

[107] Kadhim, K. H. Solar PV System for Water Pumping Incorporating an MPPT based Bat Optimization Circuits and Systems. Doi: 10.5373/JARDCS/V12SP1/20201130

[108] Gao, B., Yang, H., Lin, H. C., Wang, Z., Zhang, W., & Li, H. (2022). A hybrid improved whale optimization algorithm with support vector machine for short-term photovoltaic power prediction. *Applied Artificial Intelligence*, *36*(1), 2014187. https://doi.org/10.1080/08839514.2021.2014187

[109] Percin, H. B., & Caliskan, A. (2023). Whale optimization algorithm based MPPT control of a fuel cell system. *International journal of hydrogen energy*, *48*(60), 23230-23241. https://doi.org/10.1016/j.ijhydene.2023.03.180

[110] Rana, N., Latiff, M. S. A., Abdulhamid, S. I. M., & Chiroma, H. (2020). Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments. *Neural Computing and Applications*, *32*(20), 16245-16277. https://doi.org/10.1007/s00521-020-04849-z

[111] Tiwari, A., & Agarwal, R. (2023). Optimal control for a photovoltaic integrated grid system using PSO and modified whale optimization to enhance power quality. *Engineering Research Express*, *5*(2), 025001. Doi: 10.1088/2631-8695/acc929

[112] Liu, Y. W., Feng, H., Li, H. Y., & Li, L. L. (2021). An improved whale algorithm for support vector machine prediction of photovoltaic power generation. *Symmetry*, *13*(2), 212. https://doi.org/10.3390/sym13020212

[113] Kashefi, H., Sadegheih, A., Mostafaeipour, A., & Mohammadpour Omran, M. (2021). Parameter identification of solar cells and fuel

cell using improved social spider algorithm. *COMPEL-The international journal for computation and mathematics in electrical and electronic engineering*, *40*(2), 142-172. https://doi.org/10.1108/COMPEL-12-2019-0495

[114] Koshkarbay, N., Mohammed, K. K., Mekhilef, S., Kuttybay, N., Almen, D., Saymbetov, A., & Nurgaliyev, M. (2025). Improved MPPT technology for PV systems using Social Spider optimization (SSO): Efficient handling of partial shading and load variations. *Electric Power Systems Research*, *247*, 111822. https://doi.org/10.1016/j.epsr.2025.111822

[115] Fathy, A., Kaaniche, K., & Alanazi, T. M. (2020). Recent approach based social spider optimizer for optimal sizing of hybrid PV/wind/battery/diesel integrated microgrid in aljouf region. *IEEE Access*, *8*, 57630-57645. https://doi.org/10.1109/ACCESS.2020.2982805

[116] Adhvaryyu, S., & Adhvaryyu, P. K. (2020). Application of bio-inspired social spider algorithm in multi-area economic emission dispatch of solar, wind and CHP-based power system. *Soft Computing*, *24*(13), 9611-9624. https://doi.org/10.1007/s00500-019-04468-4

[117] Pappu, S. L., & Janamala, V. (2023). A multi-objective hunter-prey optimization for optimal integration of capacitor banks and photovoltaic distribution generation units in radial distribution systems. *ITEGAM-JETIA*, *9*(43), 42-53. https://doi.org/10.5935/jetia.v9i43.907

[118] Li, Z., & Fu, C. (2024). Critical Analysis and Application of Enhanced Hunter-Prey Algorithm for MPPT in Photovoltaic Systems under Complex Partial Shading Conditions. http://dx.doi.org/10.21203/rs.3.rs-4460931/v1

[119] Ranga, M. R., RaoBathina, V., & Kotni, S. (2024, July). A review of solar cell parameters extraction using metaheuristic optimization methods based on various diode models. In *2024 International Conference on Computational Intelligence for Green and Sustainable Technologies (ICCIGST)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICCIGST60741.2024.10717470

[120] Li, Z., Fu, C., Zhang, L., & Zhao, J. (2024). Comprehensive Analysis of Improved Hunter–Prey Algorithms in MPPT for Photovoltaic Systems Under Complex Localized Shading Conditions. *Electronics*, *13*(21), 4148. https://doi.org/10.3390/electronics13214148

[121] Bousselamti, L., Ahouar, W., & Cherkaoui, M. (2020, September). Mono-objective optimization of PV-CSP system using PSO algorithm. In *2020 IEEE 4th International Conference on Intelligent Energy and Power Systems (IEPS)* (pp. 186-189). IEEE. https://doi.org/10.1109/IEPS51250.2020.9263232

[122] Pervez, I., Shams, I., Mekhilef, S., Sarwar, A., Tariq, M., & Alamri, B. (2021). Most valuable player algorithm based maximum power point tracking for a partially shaded PV generation system. *IEEE Transactions on Sustainable Energy*, *12*(4), 1876-1890. https://doi.org/10.1109/TSTE.2021.3069262

[123] Liu, H., Shi, Y., & Zhang, W. (2021, August). A MPPT Control Method Based on the Improved Wind-Driven Optimization. In *2021 IEEE 16th Conference on Industrial Electronics and Applications (ICIEA)*, 995-1000. https://doi.org/10.1109/ICIEA51954.2021.9516244

[124] Diab, A. A. Z., Sultan, H. M., Do, T. D., Kamel, O. M., & Mossa, M. A. (2020). Coyote optimization algorithm for parameters estimation of various models of solar cells and PV modules. *IEEE Access*, *8*, 111102-111140. https://doi.org/10.1109/ACCESS.2020.3000770

[125] Priyadarshi, N., Padmanaban, S., Holm-Nielsen, J. B., Blaabjerg, F., & Bhaskar, M. S. (2019). An experimental estimation of hybrid ANFIS–PSO-based MPPT for PV grid integration under fluctuating sun irradiance. *IEEE Systems Journal*, *14*(1), 1218-1229. https://doi.org/10.1109/JSYST.2019.2949083

[126] Eltamaly, A. M., & Alotaibi, M. A. (2021). Novel fuzzy-swarm optimization for sizing of hybrid energy systems applying smart grid concepts. *IEEE Access*, *9*, 93629-93650. https://doi.org/10.1109/ACCESS.2021.3093169

[127] Moshksar, E., Ghanbari, T., Samet, H., & Guay, M. (2018). Estimation-based extremum-seeking control: A real-time approach for improving energy efficiency in photovoltaic systems. *IEEE systems journal*, *13*(3), 3141-3152. https://doi.org/10.1109/JSYST.2018.2868125

[128] Guo, K., Cui, L., Mao, M., Zhou, L., & Zhang, Q. (2020). An improved gray wolf optimizer MPPT algorithm for PV system with BFBIC converter under partial shading. *IEEE Access*, 8, 103476-103490. https://doi.org/10.1109/ACCESS.2020.2999311

[129] Senapati, M. K., Pradhan, C., Padmanaban, S., & Al Zaab, O. (2025). Photovoltaic MPPT performance adaptability to partial shading resilience and load variations with modified adaptive jaya optimization. *IEEE Transactions on Consumer Electronics*. https://doi.org/10.1109/TCE.2025.3532660

[130] Eltamaly, A. M., Al-Saud, M. S., & Abokhalil, A. G. (2020). A novel bat algorithm strategy for maximum power point tracker of photovoltaic energy systems under dynamic partial shading. *IEEE Access*, 8, 10048-10060. https://doi.org/10.1109/ACCESS.2020.2964759