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Review

An Investigation on Hybrid Particle Swarm Optimization Algorithms for Parameter Optimization of PV Cells

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Abstract: The demands for renewable energy generation are progressively expanding because of environmental safety concerns. Renewable energy is power generated from sources that are constantly replenished. Solar energy is an important renewable energy source and clean energy initiative. Photovoltaic (PV) cells or modules are employed to harvest solar energy, but the accurate modeling of PV cells is confounded by nonlinearity, the presence of huge obscure model parameters, and the nonattendance of a novel strategy. The efficient modeling of PV cells and accurate parameter estimation is becoming more significant for the scientific community. Metaheuristic algorithms are successfully applied for the parameter valuation of PV systems. Particle swarm optimization (PSO) is a metaheuristic algorithm inspired by animal behavior. PSO and derivative algorithms are efficient methods to tackle different optimization issues. Hybrid PSO algorithms were developed to improve the performance of basic ones. This review presents a comprehensive investigation of hybrid PSO algorithms for the parameter assessment of PV cells. This paper presents how much work is conducted in this field, and how much work can additionally be performed to improve this strategy and create more ideal arrangements of an issue. Algorithms are compared on the basis of the used objective function, type of diode model, irradiation conditions, and types of panels. More importantly, the qualitative analysis of algorithms is performed on the basis of computational time, computational complexity, convergence rate, search technique, merits, and demerits.

Keywords: energy harvesting; photovoltaic; metaheuristic; particle swarm optimization

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1. Introduction

In the 26th United Nations Climate Change Conference (COP26), countries decided to move towards clean energy to limit the increase in average global temperature. It is very important to reduce dependency on the usage of fossil fuels, as these fuels are the main drivers of global warming. These circumstances direct us towards clean and renewable energy [1]. Scientific and industrial communities put substantial efforts in harvesting energy from surrounding energy sources (e.g., solar, wind, and hydropower) [2–4].

Among numerous clean energy sources, solar energy harvesting is an appropriate candidate, and the market share of solar energy systems is speedily rising [5,6]. Solar energy generation plants are designed by connecting several photovoltaic (PV) cells in serial or parallel arrangements. Electricity distribution grids and solar energy plants are connected and simultaneously operated [7,8]. Power output from solar energy plants is influenced by operational and environmental conditions [9,10]. Instabilities in power generation affect the economic prospect of solar energy plants [11,12]. Therefore, the efficiency of solar energy generation systems should be enhanced by the effective modeling and parameter assessment of PV cells or modules. The assessment of unknown parameter PV cells and the appropriate modeling of PV systems are of the utmost importance. Parameter assessment is a nontrivial task because of nonlinear, multivariable, and multimodal characteristics [13]. Throughout the past few decades, there have been noteworthy advancements to understand the characteristics of PV systems by means of mathematical modeling. PV cells could be successfully analyzed through single-(SDM), double- (DDM), and triple-diode (TDM) models [13–15].

Metaheuristic algorithms are widely discussed and have successfully been applied for the parameter estimation of PV systems and various other applications [16–31]. Metaheuristic algorithms are computational intelligence paradigms that are especially used for sophisticated solutions of optimization problems. The advantages and disadvantages of these algorithms are classified on the basis of good trade-offs regarding exploitation and exploration abilities. One essential circumstance is that various algorithms should be benchmarked and equated on a job that is similar to the design optimization problem at hand. Metaheuristic algorithms can be classified in a variety of ways due to their various characteristics [24]. Figure 1 demonstrates the classification of metaheuristic algorithms into four groups: evolution-based, human-related, nature-inspired, and bio-inspired algorithms. Another probable classification of some particular methods is represented in Figure 2.

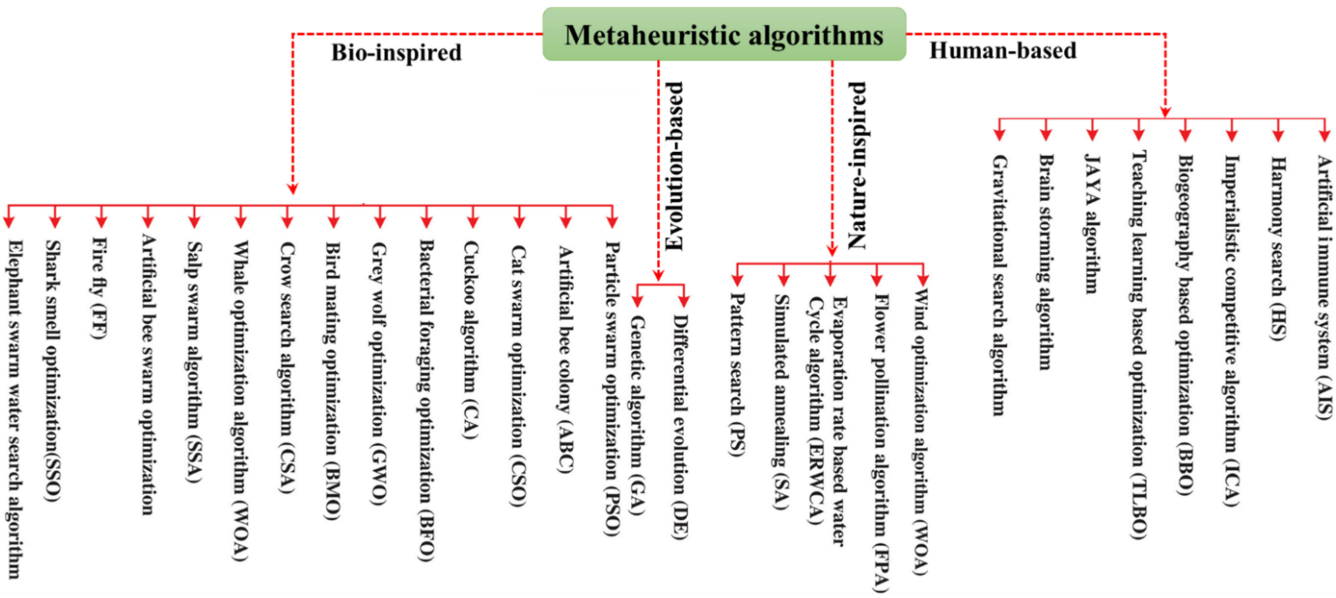

Figure 1. Different metaheuristic methods for assessment of unknown parameters of PV cells or modules (adapted with permission from Ref. [13]. Copyright 2022 John Wiley and Sons).

In a very recent work, Karambasti et al. employed a genetic (GE) algorithm for small-scale power-water production based on the integration of a Stirling engine and a multieffect evaporation desalination system [32]. For partially shaded conditions, an ant colony optimization (ACO)-based hybrid MPPT controller for photovoltaic systems was studied by Chao et al. [33]. Recently, we implemented arithmetic algorithm for the parameter extraction of fuel cells [34]. The grey wolf optimization (GWO) algorithm was employed to enhance the performance of a dual-energy gamma-ray-based three-phase flow meter [35]. Artificial neural network (ANN)-based methods were also used to solve optimization problems [36,37]. Orosz et al. summarized different nature-inspired multiobjective optimization techniques [24]. Different types of population-based optimization methods, e.g., genetic algorithm (GA), differential evolution (DE), cuckoo search (CS), firefly algorithm (FA), tunicate swarm algorithm (TSA), whale optimization algorithm (WOA), opposition-based TSA (OTSA), and particle swarm optimization (PSO), were successfully used for parameter optimization of solar cells [23–31].

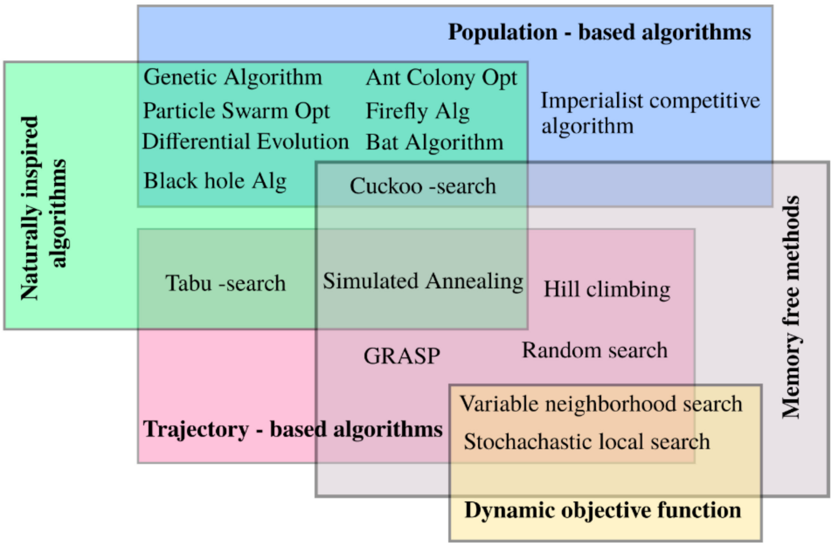

Figure 2. Metaheuristic methods and their categorization (reprinted from Ref. [24]).

Swarm-intelligence-based algorithms are stimulated by the social behavior of animals, insects, birds, and fish. A widespread method is particle swarm optimization (PSO), which is inspired by the actions of bird flocks. These birds fly to find their best location (position) through the search space. Though several PSO and other metaheuristic algorithms were developed, none provides an optimal explanation to all sets of problems, as per the 'no such thing as a free lunch' theorem' [38,39]. This directs researchers and scientists to further develop new algorithms or modify previous algorithms to resolve optimization problems. PSO and modified PSO algorithms are studied for various engineering applications e.g., speech emotion recognition, railway controls, job shop scheduling problems, geotechnical engineering, load flow control, source seeking problems, elevator door systems, quad assignment problems, equipment possession quantity, optimal designs of PID controllers, parameter estimation of photovoltaic cells or modules, and the beam-slab layout design of rectangular floors [40–49]. Hajihassani et al. studied PSO algorithms for applications in geotechnical engineering [43]. In a very recent work, Huang et al. proposed a multilayer hybrid fuzzy classification-based PSO for speech emotion recognition [40].

This review article summarizes recent developments in hybrid PSO algorithms for the parameter assessment of PV cells or modules. This article is useful for researchers who are working on the parameter optimization of different issues. Although PSO algorithms are applicable for different types of applications, we limited this analysis to only the parameter optimization of PV cells or modules.

2. Estimating PV Cell/Module Parameters

Figure 3 illustrates the different processes involved in the parameter assessment of PV cells or modules. Generally, any PV cell or module is modeled using an electrical equivalent circuit, which preferably includes a current source, diode, and resistors. Equivalent circuits can be articulated employing three types of models, namely, SDM, DDM, and TDM, and each model has advantages and disadvantages. The number of diodes in the model decides the accuracy of I–V curve estimation. SDMs are usually employed for modeling PV cells or modules because of their reliability, accuracy, and simplicity [49]. Other models are also used for more accurate curve reproduction and the inclusion of recombination losses [13–15]. However, the complexity of the simulation process is significantly increased.

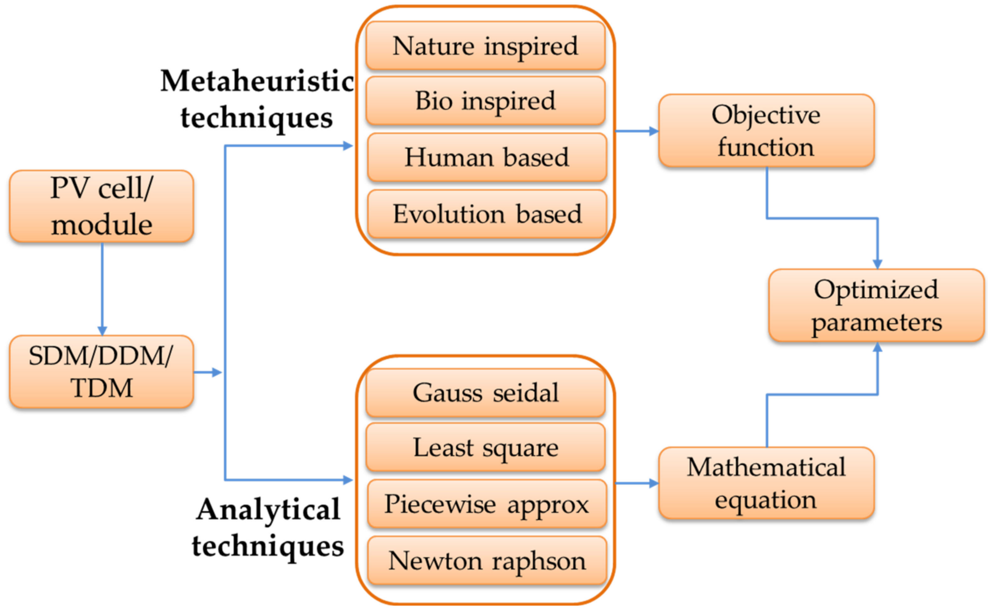

Figure 3. Different processes for modeling and parameter estimation of PV cells. PV: photovoltaic, SDM: single-diode model, DDM: double-diode model, and TDM: triple-diode model (adapted with permission from Ref. [13]. Copyright 2022 John Wiley and Sons).

Figure 4 illustrates the SDM equivalent circuit of a standard PV cell. The diode (D) is connected to the current source in parallel. Moreover, the shunt resistor (R_{sh}) and series resistance (R_s) are connected for the consideration of losses due to carrier recombination and metallic junction. According to Figure 4, the electrical behavior of PV cell is expressed as:

$$I = I_p - I_0\left[exp\left(\frac{q_e V}{ak_B T}\right) - 1\right] \quad (1)$$

where I, I_p, I_0, V, a, and T are output current, photocurrent, reverse saturation current, output voltage, quality factor, and cell temperature, respectively. The Boltzmann constant (k_B) is 1.3806 $\times$ 10^{-23} m^2·kg/s^{2}K, and elementary charge (q_e) is 1.602 $\times$ 10^{-19} C.

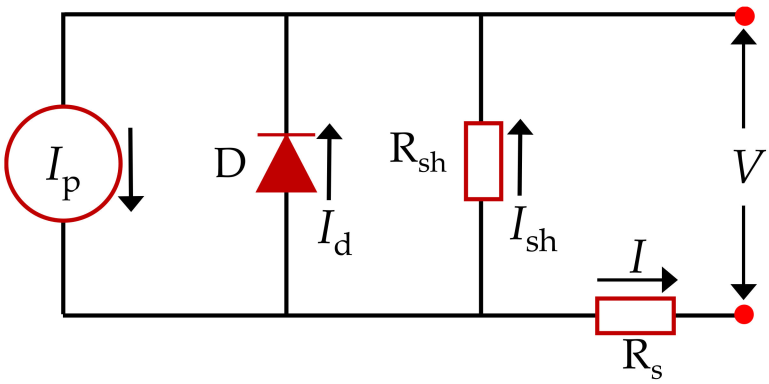

Figure 4. SDM equivalent circuit of standard PV cell.

The assessment of each unknown parameter and the process of PV modeling are of utmost importance. Besides model selection, another key step is to select a method for the estimation of unknown parameters. Generally, the two technique types that are employed for unknown-parameter determination are analytical and metaheuristic methods [50]. Analytical methods apply different operating conditions and available manufacturer datasheets to attain PV characteristics [50,51]. Metaheuristic methods employ the curve fitting technique to assess PV characteristics (I–V curve). Thus, the datasheet of a predicted I–V curve is matched with the manufacturer and/or measured datasheets [52]. Metaheuristic methods are more useful for enhanced performance and reduced computational load than analytical ones are. A combination of the two methods can also provide superior performance.

Table 1 displays the different error functions applicable for the evaluation of metaheuristic and other optimization algorithms. These functions are absolute error (AE), individual absolute error (IAE), relative error (RE), mean square error (MSE), mean bias error (MBE), root mean square error (RMSE), and the sum of squared error (SSE) [53–55]. Among them, the commonly used objective function to analyze efficiency is the RMSE metric. In the case of SDM, five parameters (I_p, I_{sd}, a, R_s and R_{sh}) should be assessed to obtain the minimal value of the RMSE.

Table 1. Various performance parameters.

Error Metrics	Function
Individual absolute error	$\text{IAE} = \lvert I_\text{m} - I_\text{s} \rvert$
Relative error	$\text{RE} = \frac{(I_\text{m} - I_\text{s})}{I_\text{s}}$
Absolute error	$AE = \left\lvert \sum_{i=0}^{N} I_\text{m} - I_\text{s} \right\rvert$
Mean absolute error	$\text{MAE} = \sum_{i=0}^{N} \frac{(I_\text{m} - I_\text{s})}{N}$
Normalized mean absolute error	$\text{NMAE} = \sum_{i=0}^{N} \frac{(I_\text{m} - I_\text{s})/I_\text{s}}{N}$
Mean bias error	$\text{MBE} = \frac{(I_\text{m} - I_\text{s})}{N}$
Root mean square error	$\text{RMSE} = \sqrt{\frac{\left(\sum_{i=0}^{N} I_\text{m} - I_\text{s}\right)^2}{N}}$

Note: I_m, actual (measured) current; I_s, calculated/estimated current; number of data points in I–V characteristics, N.

Different algorithms are mainly employed to optimize the unknown parameters of equivalent models (SDM, DDM, and TDM) of PV cells. Another objective is to diminish the error among measured and assessed datasets. The RMSE objective function is expressed as

$$\text{RMSE} = \sqrt{\frac{1}{k} \sum_{N=1}^{k} f(V_l, I_l, X)} \tag{2}$$

where, I_l and V_l are the measured current and voltage parameters of the PV cell/module. The number of the experimental dataset is represented by parameter k. Vector X denotes the best solution. In the case of SDM [13,15]:

$$\begin{cases} f_\text{single}(V_l,\ I_l,\ X) = I_p - I_{sd}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_1 k_B T}\right) - 1\right] - \frac{V_l + I_l R_s}{R_{sh}} - I_l \\ (X = I_p,\ I_{sd},\ a\ ,\ R_s,\ R_{sh}\ ) \end{cases} \tag{3}$$

For the DDM [14,15]:

$$\begin{cases} f_\text{double}(V_l,\ I_l,\ X) = I_p - I_{sd_1}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_1 k_B T}\right) - 1\right] \\ -I_{sd_2}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_2 k_B T}\right) - 1\right] - \frac{V_l + I_l R_s}{R_{sh}} - I_l \\ (X = I_p,\ I_{sd_1},\ I_{sd_2},\ a_1,\ a_2, R_s,\ R_{sh}\ ) \end{cases} \tag{4}$$

For the TDM [14,15]:

$$\begin{cases} f_\text{double}(V_l,\ I_l,\ X) = I_p - I_{sd_1}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_1 k_B T}\right) - 1\right] \\ -I_{sd_2}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_2 k_B T}\right) - 1\right] - I_{sd_3}\left[exp\left(\frac{q(V_l + I_l R_s)}{a_3 k_B T}\right) - 1\right] - \frac{V_l + I_l R_s}{R_{sh}} - I_l \\ (X = I_p,\ I_{sd_1},\ I_{sd_2},\ I_{sd_3},\ a_1,\ a_2,\ a_3, R_s,\ R_{sh}\ ) \end{cases} \tag{5}$$

As stated previously, equivalent circuit models can be differentiated on the basis of number of diodes in the circuit. Therefore, the number of unknown parameters is different for different models. Thus five, seven, and nine parameters need to be estimated for SDM, DDM, and TDM, respectively. The characteristics (V–I and P–I) of PV cells are described on the basis of the best-optimized parameters. Distinctive V–I and P–I curves of PV cells in standard conditions are shown in Figure 5.

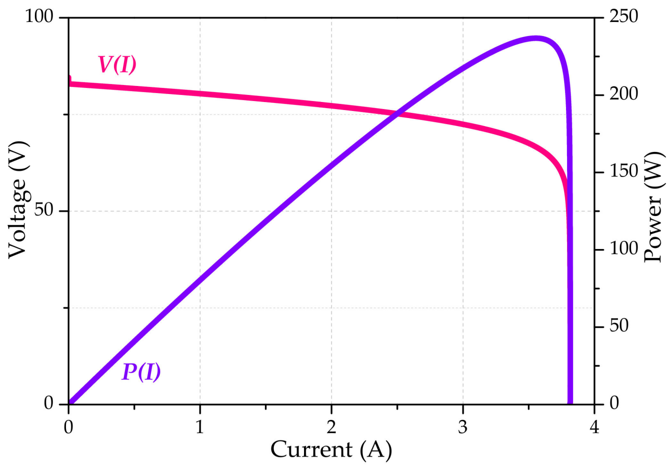

Figure 5. Characteristic curve of PV cells at standard conditions (reprinted from Ref. [10]).

3. Particle Swarm Optimization

The particle swarm optimization (PSO) method was introduced by J. Kennedy and R. C. Eberhard for solving nonlinear functions [56,57]. It is a population-based self-adaptive and nature-inspired stochastic optimization technique. The PSO algorithm works as follows. Initial particles are first created and assigned as initial velocities. The objective function is evaluated at every particle's location. The best function value and location are determined. In the next step, new velocities are selected on the basis of recent velocity, the best locations of individual particles, and the best locations of their adjacent particles. After that, the location, velocities, and neighbors of particles are iteratively updated. The new location is assessed by adding the velocity to the previous location. Locations are altered to retain particles within bounds. The process continues for several iterations till the algorithm arrives at a stopping criterion.

The PSO algorithm explores the space of an optimization problem by modifying the paths of individual members, called particles because these paths form partwise paths in a quasistochastic fashion. The motion of the swarming particle consists of two major parts, the stochastic and the deterministic parts. In this technique, each potential solution is considered to be a particle with its own random velocity and location in the search space. The search space is defined as the set of all probabilistic solutions for the problem to be optimized. Each particle achieves its best position and velocity according to the best solution (fitness) in the solution space. The i-th particle in the PSO algorithm updates its velocity and position at every t-th step according to the equations given below:

$$V_i^{t+1} = wV_i^t + r_1C_1\left(P_{best} - X_i^t\right) + r_2C_2\left(G_{best} - X_i^t\right) \tag{6}$$

In the above expression, the first, second, and third terms are previous velocity, cognitive learning, and social learning, respectively.

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{7}$$

where X_i^t and V_i^t designate the position and velocity vector of the i-th particle in the swarm, w represents the inertial weight to maintain the balance between local and global search ability, and C_1 and C_2 denote the acceleration constant and are predefined by the user.

r_1 and r_2 are random numbers generated in the range of (0, 1). P_{best} is the personal best position of the i-th particle at time t, and G_{best} is the global best position of the i-th particle within the swarm. The term inertial weight (w) was not initially included in the ordinary PSO; it was included by Shi and Eberhart in 1998 [56].

The representation of the PSO model is shown in Figure 6, where bold lines depict the velocity and position of the particle after each iteration, dotted lines depict the components of Equation (6), P_{best} denotes the personal best position of the particle, G_{best} represents global best position of particular particle in a search space, and X and Y represent the horizontal and vertical direction of search in a solution space, respectively.

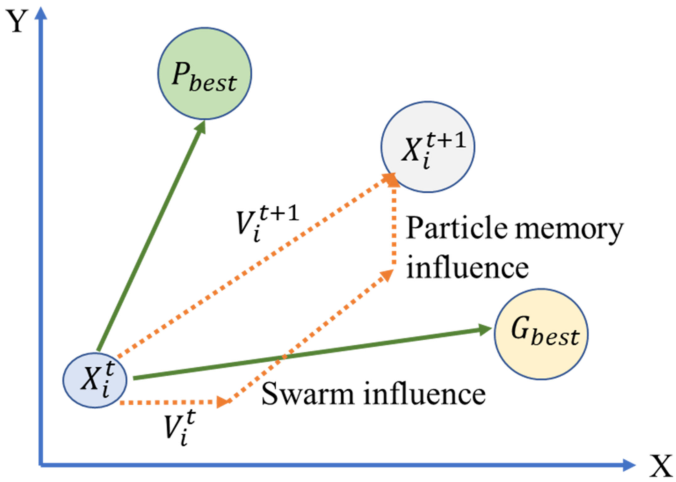

Figure 6. Representation of particle swarm optimization (PSO) model.

Pseudocode for implementation of PSO algorithm [Algorithm 1] is as follows:

Algorithm 1. Pseudocode of PSO

Objective function $f(x), x = (x_i, \ldots, x_p)^t$
Initialize locations X_i^t and velocity V_i^t of ith particles
Find G_{best} from min $[f(x_1), f(x_n)]$ (at $t = 0$)
while (max iteration)
 $t = t + 1$ (iteration counter)
for loop over all ith particles and all p dimensions
Generate new velocity V_i^{t+1} using Equation (6)
Calculate new locations $X_i^{t+1} = X_i^t + V_i^{t+1}$
Evaluate objective functions at new locations X_i^{t+1}
Find best current for each particle P_{best}
end for
Find the current global best G_{best}
end while
Output results P_{best} and G_{best}

The PSO algorithm also has certain advantages compared with numerous other continuous optimization techniques.

- ✔ It does not produce assertions about the consistency and the convexity of the optimization problem to be optimized.
- ✔ It is not necessary to measure the coefficient of the optimal solution.
- ✔ There is no need for good initial points of reference or extensive a priori knowledge of its most interesting regions of the search domain.

Now, we discuss modified and hybrid PSO algorithms, which are the derivative of basic PSO. Several investigators have endeavored to hybridize PSO through different methods and guaranteed upgrades according to the exhibition perspective.

4. Hybrid PSO Algorithms

PSO algorithms are efficient methods to tackle different optimization issues. Nevertheless, the fundamental PSO regularly experiences untimely convergence, and demonstrates poor performance for many intricate and multimodal optimization problems [42,49,57]. Several studies were conducted to improve the performance of basic PSO [58–73]. These improvements were largely focused on the population structure and the estimation process of the next velocity of every other particle. This helped to upsurge the effectiveness and consistency of the initial hunt process, and avert the amount of miscellany. Detailed analysis is devoted to monitoring the expansion of velocity, consistency, and convergence, and parameter changes. The hybridization of PSO through additional algorithms could significantly improve the performance of basic PSO [49,57–62]. The convergence rate of PSO could be exceptionally expanded by changing the speed increase proportion to the best design utilizing auxiliary boundaries [42]. Table 2 summarizes various hybrid PSO algorithms for the parameter assessment of PV cells.

Table 2. Comparison of different hybrid PSO algorithms for parameter approximation of PV systems.

Hybrid PSO	Objective Function Used	Type of Diode Model	Irradiation Conditions	Types of Panel
FODPSO (Fractional Order Darwinian PSO) [60]	IAE SIAE RMSE	SDM DDM	1000 W/m^2 at 33 °C	RTC silicon solar cell
			1000 W/m^2 at 45 °C	Photowatt PWP201PV Module
			675 W/m^2 at 48.3 °C	Monocrystalline cell (TSM185M-72M)
			616.4 W/m^2 at 47.4 °C	Polycrystalline cell (SW 250–260 poly)
NPSOPC (niche PSO in parallel computing) [61]	RMSE	SDM DDM PMM	1000 W/m^2 at 33 °C	RTC silicon solar cell
			1000 W/m^2 at 45 °C	Photowatt-PWP201PV module
EPSO (enhanced PSO) [63]	MSE	SDM DDM TDM	1000 W/m^2 at 33 °C	RTC silicon solar cell
			1000 W/m^2 at 45 °C	DPL Photowatt-PWP201PV module
PSOGWO (grey wolf optimization combined with PSO) [63]	RMSE	SDM	1000 W/m^2 at 25 °C	KC200GT PV module
			800 W/m^2 at 20 °C	SQ85 PV module
WOAPSO (whale optimization combined with PSO) [49]	RMSE	SDM DDM	1000 W/m^2 at 30 °C	RTC France solar cell
			1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2 at 25 °C	PV module (SS2018P)
CIWPSO (chaotic inertial weight PSO) [64]	RMSE IAE AE	SDM DDM	1000 W/m^2 at 33 °C	RTC France solar cell
			1000 W/m^2 at 45 °C	Photowatt PWP201PV module
			1000 W/m^2 at 47 °C, 800 W/m^2 at 44 °C, 600 W/m^2 at 42 °C, 400 W/m^2 at 36 °C, 200 W/m^2 at 27 °C	JKM330P-72 PV module

Table 2. *Cont.*

Hybrid PSO	Objective Function Used	Type of Diode Model	Irradiation Conditions	Types of Panel
CPMPSO (classified perturbation mutation-based PSO) [65]	RMSE IAE	SDM DDM	1000 W/m^2 at 45 °C	Photowatt-PWP201PV module
			1000 W/m^2 at 33 °C	RTC France solar cell
			51	STM6-40/36 PV module
			55	STP6-120/36 PV module
DEDIWPSO (double exponential function-based dynamic inertial weight PSO) [66]	RMSE IAE	SDM DDM	1000 W/m^2 at 33 °C	RTC France solar cell
			1000 W/m^2 at 45 °C	Photowatt PWP201PV module
SAIWPSO (simulated annealing inertia weight PSO) [67]	RMSE	SDM DDM	1000 W/m^2 at 33 °C	RTC France solar cell
PSOAG (autonomous groups PSO) [68,69]	CR RMSE MAE	SDM	1000 W/m^2 at 33 °C	RTC France solar cell
CPSO (chaos PSO) [70]	RMSE MAE RACF *	SDM DDM	1000 W/m^2 at 33 °C	RTC France solar cell
HPSOSA (hybrid PSO and simulated annealing) [70]	RMSE MAE RACF *	SDM DDM	1000 W/m^2 at 33 °C	RTC France solar cell

* RACF: residual autocorrelation function.

4.1. FODPSO

In a very recent work, Ahmed et al. proposed a fractional order Darwinian PSO (FODPSO) algorithm to find the parameters of PV cells [60]. In this research work, a modification was proposed for controlling the velocity of each particle by incorporating the concept of fractional order derivative.

The Grunwald–Letnikov definition is used to define the fractional derivatives as given below [60]:

$$D^{\alpha}[X(t)] = \frac{1}{T^{\alpha}} \sum_{k=0}^{r} \frac{(-1)^{k}\Gamma(\alpha+1)x(t-kh)}{\Gamma(\alpha+1)\Gamma(\alpha-k+1)} \tag{8}$$

where α is the derivative order, T is the period of sampling, and r is the truncation order. Other elements of Equation (8) were defined in [60]. The original velocity to implement fractional-order calculus on PSO (Equation (6)) is rewritten as:

$$V_{t+1} + V_t = C_1 \times rand(P - X_T) + C_2 \times rand(G - X_T) \tag{9}$$

The left-hand side of the above equation represents the discrete formula of the derivative of order number α = 1. Let us assume that $T = 1$; we arrive at

$$D^{\alpha}[V_{t+1}] = C_1 \times rand(P - X_T) + C_2 \times rand(G - X_T) \tag{10}$$

Equation (11) denotes the application of the fraction order number (Equation (8)) on the speed of particles with a range from α = 0 to α = 1 ($\Delta\alpha$ = 0.1) and r = 4:

$$\begin{gathered} V_{t+1} = \alpha V_t + \tfrac{1}{2}\alpha(1-\alpha)V_{t-1} + \tfrac{1}{6}\alpha(1-\alpha)(2-\alpha)V_{t-2} + \tfrac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha)V_{t-3} + \\ C_1 \times rand(P - X_T) + C_2 \times rand(G - X_T) \end{gathered} \tag{11}$$

The main benefit of the fractional calculus derivatives is the additional level of degree of freedom. Equation (11) shows the possibility to govern the speed of particles concerning the derivative order (α). This is the key benefit as compared to the basic PSO algorithm. The additional level of opportunity of fractional calculus derivation induction takes into consideration an exact depiction of the conduct of many cycles through the exact enhancement of framework display, planning, and control.

To show the effectiveness of FODPSO, eight metaheuristic algorithms (existing in the literature) are compared. Furthermore, two types of diode models (SDM and DDM) are exploited to show the efficiency of FODPSO. However, the authors considered only standard testing conditions for the measurement of current and voltage. Furthermore, there was no emphasis given on other objective functions such as MAE, NMAE, and MBE.

4.2. NPSOPC

The niche particle swarm optimization in parallel computing (NPSOPC)-based optimization algorithm was proposed by Lin and Wu in 2020 [61]. Niches in parallel architecture were set up with a PSO-based parameters extraction model to improve extraction performance. The process flow diagram of NPSOPC is provided in Figure 7.

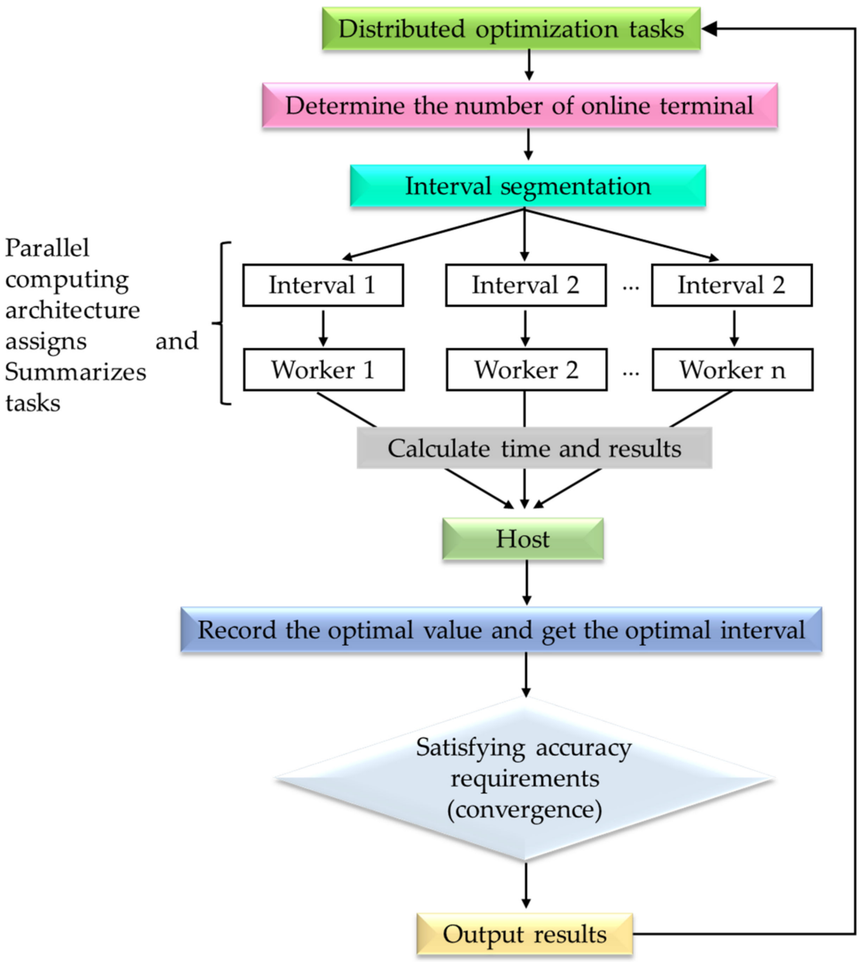

Figure 7. Process flow chart of parallel computing of NPSOPC (reprinted with permission from Ref. [61]. Copyright 2022 Elsevier).

Experimental validation was conducted by parameters identifying the cation of SDM and DDM for solar cells and monocrystalline PV modules. However, there is no experimental validation on other recent PV technologies such as thin-film and perovskite solar cells.

4.3. EPSO

In 2021, Wang R proposed an enhanced version of PSO termed as enhanced particle swarm optimization (EPSO). In this latest modification, the authors implemented an orthogonal opposition-based learning mechanism for initializing the position of the particles [62]. This method increased the PSO algorithm's convergence speed and improved global optimization quality. The swarm initiation employed in this investigation is shown in the following equation:

$$\begin{cases} \theta_{ld}(0) = \theta_{d,\min} + rand[\theta_{d,\max} - \theta_{d,\min}] \\ \quad l = 1, 2, L,\ N_p/2 \\ \theta_{ld}(0) = \theta_{d,\max} + \theta_{d,\min} - \theta_{l+N_p/2,\ d}(0) \\ \quad l = N_p/2 + 1,\ N_p/2 + 2,\ L,\ N_p \end{cases} \tag{12}$$

where $\theta_{ld}(0)$, $\theta_{d,\min}$, and $\theta_{d,\max}$ are the initial value, minimal, and maximal values of the candidate solution in the d-th dimension, respectively.

EPSO was tested for three diode models: SDM, DDM, and TDM. Experimental voltage and current were taken for the validation. The effectiveness of EPSO was verified on an RTC France solar cell and Photowatt PWP 201 PV module under standard temperature conditions. However, there was no validation for other types of PV modules such as monocrystalline and thin-film. Furthermore, there was no comparison provided by the authors for varying irradiance and temperature levels.

4.4. PSOGWO

In 2020, Premkumar et al. proposed a novel hybrid version of PSO known as particle swarm optimization and grey wolf optimization (PSOGWO) [63]. In this hybrid version, the GWO assists the PSO in decreasing the probability of escaping the local-optimum trap. To avoid the potential of a local-minimum trap, the GWO's exploration capabilities are employed to steer some particles towards partially improved positions rather than random locations. The mathematical model of PSOGWO is illustrated by the following equations.

$$V_{q+1}^{-i} = wV_q^{-i} + c_1 r_1 \left(X_1 - X_q^{-i} \right) + c_2 r_2 \left(X_2 - X_q^{-i} \right) + c_3 r_3 \left(X_3 - X_q^{-i} \right) \tag{13}$$

In addition to this, the efficacy of the hybrid PSOGWO was validated for the problem of parameter assessment, and its performance was compared with that of GWO and grey wolf optimizer–cuckoo search (GWOCS). However, PSOGWO and GWOCS algorithms have a great computing cost due to hybridization. Furthermore, the authors did not emphasize experimental validation under different climatic conditions.

4.5. WOAPSO

Recently, Sharma et al. proposed another hybrid version of whale optimization and PSO algorithms (WOAPSO) for the parameter optimization of PV cells [49]. The exploitation ability of PSO with adaptive weight function was used in pipeline mode with a WOA for its enhancement and to improve convergence speed of basic PSO. Figure 8 displays the process flowchart of WOAPSO algorithm implementation.

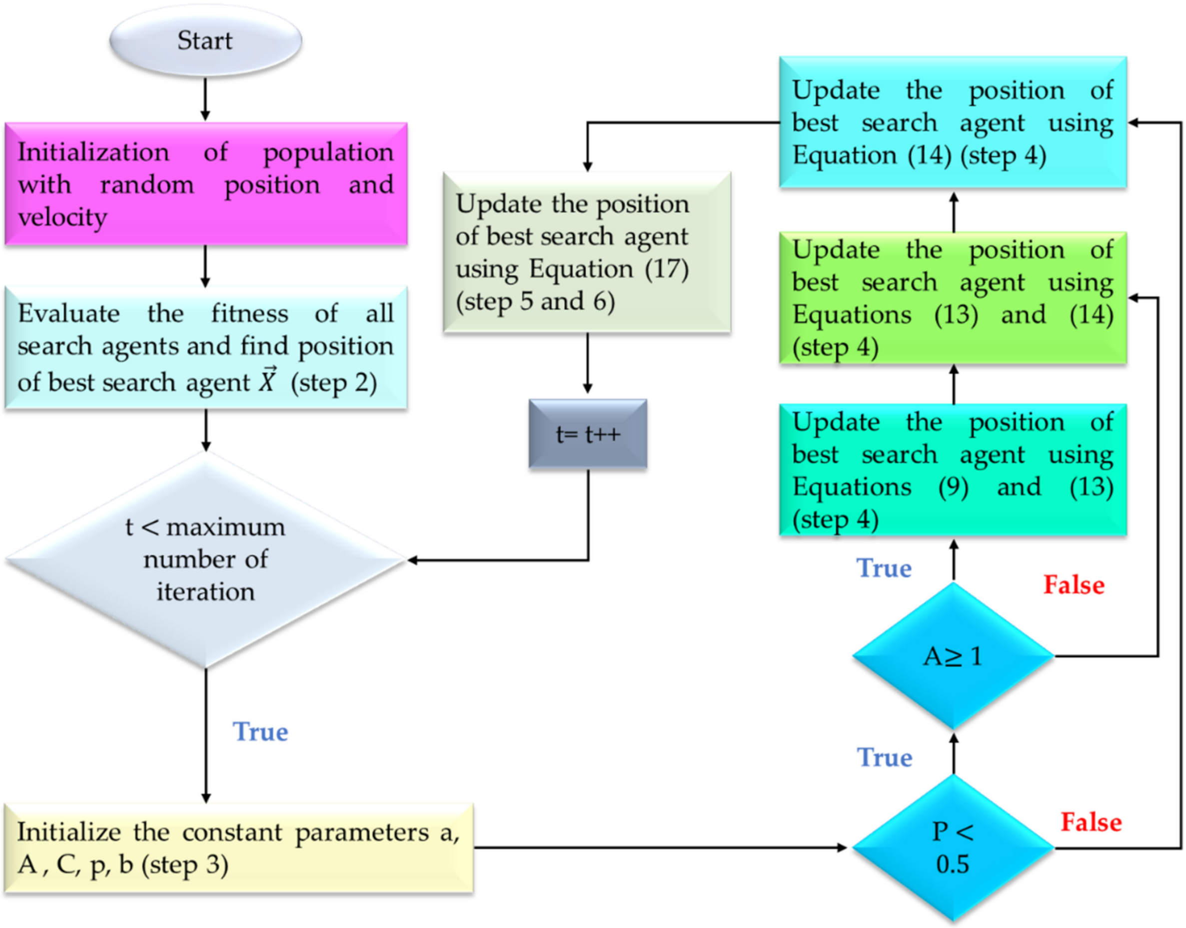

Figure 8. Flowchart of WOAPSO algorithm (reprinted from Ref. [49]).

4.6. CIWPSO

Recently, Kiani et al. developed an improved PSO employing chaotic inertial weight and acceleration coefficients [64]. In the CIWPSO algorithm, the performance of basic PSO is enhanced by employing two approaches: control inertial weight and acceleration coefficients. First, an appropriate balance between local and global search is accomplished by utilizing a sine chaotic inertial weight approach. Subsequently, an optimal solution is found by guiding acceleration coefficients with the tangent chaotic tactic (Figure 9).

The mathematical model of sine iterator based on chaotic search function is expressed as

$$X_{n+1} = \sin \pi x_n \tag{14}$$

Using Equation (14), the chaotic sequence (X_{n+1}) is engendered between 0 and 1. Factor w is exhibited as

$$w(it+1) = \varnothing \times \sin(\pi w_t) + \tau, \tag{15}$$

where $\varnothing$ and τ are constants [64]. The proposed CIWPSO method produced better outcomes to the DDM at the expense of greater computational weight than those of the SDM for the RTC France solar cell. For the Photowatt PWP201 PV module, SDM and DDM displayed similar outcomes as far as RMSE is concerned; however, DDM is computationally bulky in light of the number of included obscure parameters.

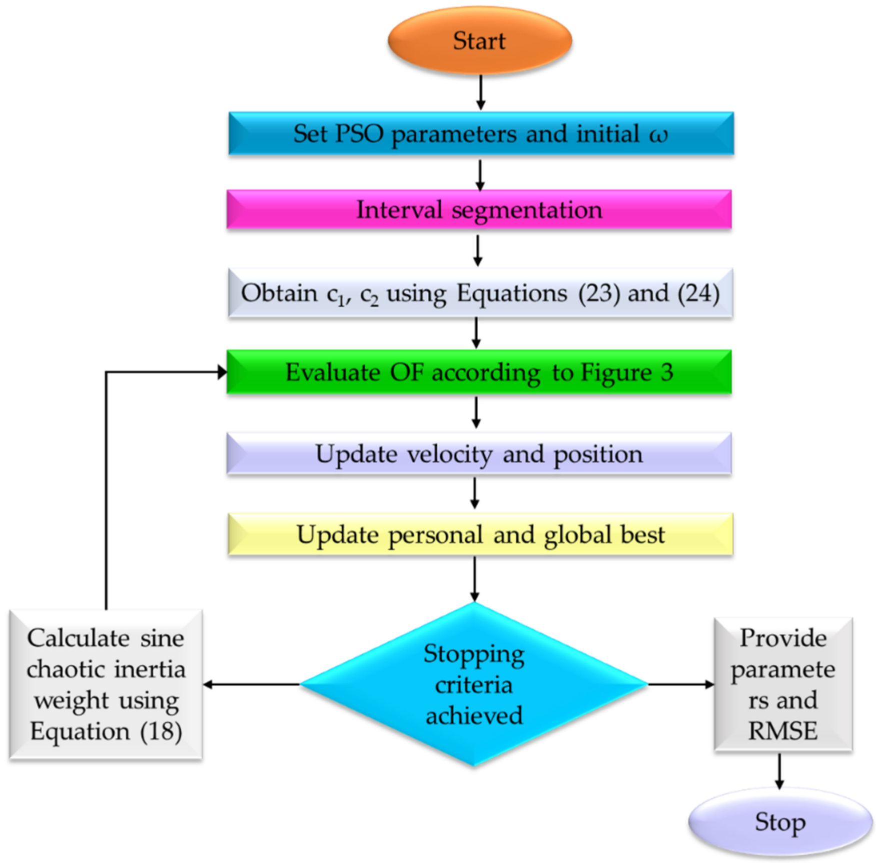

Figure 9. Flowchart of CIWPSO algorithm for parameter estimation of PV models (reprinted from Ref. [64]). Here, Figure 3 of Ref. [64] demonstrated the Newton Raphson method for the formulation of the objective function.

4.7. CPMPSO

A characterized perturbation mutation-based PSO algorithm was proposed by Liang et al. for the accurate parameter extraction of PV modules [65]. The two strategies of perturbation mutation and damping bound handling were employed in a conventional PSO to provide a good trade-off between exploration and exploitation steps. For improving exploration, a larger perturbation mutation strategy was employed for the low-quality personal best location, and to avoid falling into the local optimum, a damping bound handling method was used.

$$z_{i,d} = \begin{cases} pbest_{i,d} + rand\left(pbest_{k_1,d} - pbest_{k_2,d}\right) \text{ If} \\ f(pbest) < mean(fitnesspbest) \\ pbest_{k_1,d} + rand\left(pbest_{k_2,d} - pbest_{k_3,d}\right) \text{ otherwise} \end{cases} \tag{16}$$

where $mean(fitnesspbest) = \left(\sum_{i=1}^{NP} f(pbest_i)\right)/NP$. NP represents the size of the population, and $z_{i,d}$ signifies the d-th dimension magnitude of the trail vector. The randomly generated integers within $[1, NP]$ were defined as k_1, k_2, and k_3, and they were mutually different. These integers were also dissimilar after i.

The variable value of trail vector that violates the boundary conditions is rearranged as follows:

$$z_{i,d} = \begin{cases} xmax_d, \text{ if } z_{i,d} > xmax_d \\ xmin_d, \text{ if } z_{i,d} < xmin_d \end{cases} \tag{17}$$

where $xmax_d$ and $xmin_d$ are the maximal and minimal boundary conditions of the d-th dimension of one inconstant.

$$z_{i,d} = \begin{cases} \text{If } x_{i,d} > xmax_d \\ x_{i,d} = xmax_d; v_{i,d} = -v_{i,d} \cdot rand \\ \text{elseif } x_{i,d} < xmin_d \\ x_{i,d} = xmin_d;\ v_{i,d} = -v_{i,d} \cdot rand \end{cases} \tag{18}$$

where $x_{i,d}$ is the d-th dimension of the position, and $v_{i,d}$ is d-th dimension of the velocity of the i-th particle. The range of the random numbers ($rand$) was from 0 to 1.

The authors validated the efficiency of CPMPSO on three types of solar panels: polycrystalline KC200GT, single-crystalline SM55, and thin-film ST40. However, there was no perfect match between experimental and simulated values.

4.8. DEDIWPSO

Kiani et al. proposed a double exponential function-based dynamic inertial weight (DEDIW) approach for the optimal parameter forecast of PV cells or modules. This method upholds a proper equilibrium between the exploitation and exploration processes to alleviate the early convergence issue of basic PSO [66].

The DEDIW method is propelled by the fast-developing nature of the exponential function, and consolidates the Gompertzian function, which is a vanishing double exponential function given below:

$$w(it+1) = y(exp - \exp(-R_i)) \tag{19}$$

$$R_i = \left(\frac{maxit - it}{maxit}\right) \tag{20}$$

where y = 1. The performance index (R_i) is assessed for individual particles at each iteration. The magnitude of w diminishes as the number of iterations increases.

Three case studies were performed for the assessment of the suggested technique: PV module (Photowatt PWP201), RTC France PV cell, and polycrystalline PV module JKM330P-72 (310 W) under actual climatic circumstances. However, computation time was longer than that of the conventional PSO because of the large number of tuning parameters in DEDIWPSO.

4.9. SAIWPSO

The SAIWPSO algorithm by Kiani et al. assessed the parameter of PV cells [67]. Inertial weight had a higher value at the initial stage (heating process) for global search. However, it progressively decreases (moderate cooling process) for local search. The mathematical formulation of the SAIWPSO search mechanism is given by the following equation:

$$w(iter) = w_{\min} + (w_{\max} - w_{\min}) \times temp^{(iter-1)} \tag{21}$$

SAIWPSO performed very well for the parameter extraction of RTC France solar cells. However, the computational complexity of SAIWPSO was greater than that of other metaheuristic algorithms. In addition to this, current and voltage are measured under standard temperature conditions.

4.10. PSOAG

In 2021, an improved version of PSO known as AGPSO was presented [68]. In AGPSO, all particles are first divided into different groups, and these groups then use the different types of functions for tuning social and cognitive parameters. This modification leads to fast convergence and avoids local minima.

Pseudocode for the implementation of the PSOAG algorithm [Algorithm 2] is as follows [68,69]:

Algorithm 2. Pseudocode of the PSOAG algorithm.

```
Create and initialize a D-dimensional PSO
Randomly divide particles into autonomous groups
Repeat
  Calculate particles fitness P_best and G_best
  For each particle:
    Extract the particle group
    Use its group strategy to update C_1 and C_2
    Use C_1 and C_2 to update velocities (6)
    Use new velocities to define new positions (7)
  End for
Until stopping condition is satisfied.
```

Experimental results in this study depict that there was 14% improvement in computation cost, and 20% improvement in terms of convergence rate compared to other metaheuristic algorithms. However, no comparison was provided with new metaheuristic techniques.

4.11. CPSO

The CPSO algorithm was proposed as a low-computational-complexity method for parameter estimation of PV cells/modules [70,71] where the chaotic search-based method is employed to overcome the tendency of PSO to become stuck in a local solution. Chaos is a well-known nonlinear event in physical systems. Randomicity, monotonicity, and nonrepeat ability are features of chaotic variables. The following equation illustrates the efficient search strategy of the chaos mechanism. Inertial weight in CPSO decreased linearly:

$$w = w_{\max} + itr_{\mathrm{curr}}(w_{\max} - w_{\min})G \tag{22}$$

where $w_{\max}$, $w_{\min}$, itr_{curr}, and G are the maximal inertial weight, minimal inertial weight, current number of iterations, and maximal number of iterations, respectively.

In that research study, the effectiveness of CPSO is shown by taking three indices: RMSE, MBE, and MAE. However, there was no proper validation provided by the authors for different environmental conditions.

4.12. Hybrid PSO and Simulated Annealing (HPSOSA)

Mughal et al. proposed another hybrid version of PSOSA for the parameter estimation of PV cells. In this hybrid version, premature convergence problem PSO was removed by including the simulated annealing (SA) algorithm in pipeline mode [70]. First, the best global solution is generated by PSO algorithm. Then, this best solution is taken as input by SA algorithm to further improve the solution (Figure 10).

Furthermore, the authors took RMSE and MAE as two objective functions for measuring the effectiveness of HPSOSA, and tested their algorithm on the RTC France solar cell. No experimental validation was provided by the authors for other solar panels under different climatic conditions.

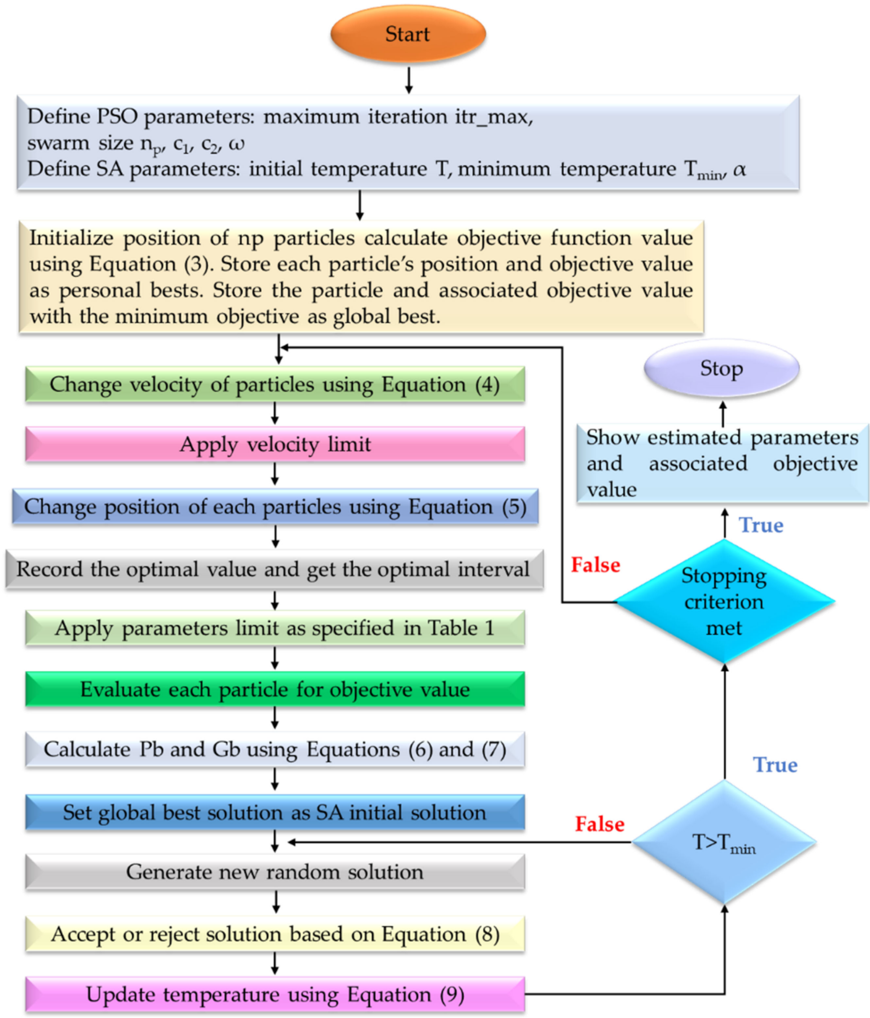

Figure 10. Process flowchart of parallel computing of HPSOSA (reprinted from Ref. [70]).

5. Qualitative Analysis

This segment compares the SI-based algorithms presented in Section 3 on the basis of key parameters for the parameter estimation of solar cells or modules. These key parameters are computational complexity, convergence speed, optimization function, computational time, and search technique. The comparison of the algorithms is shown in Table 3.

Table 3. Qualitative comparison of hybrid PSO for parameter estimation of PV cells or modules.

Name of Algorithm	Computational Time	Computational Complexity	Convergence Rate	Search Technique	Merits	Demerits
FODPSO [60]	Low	High	Low	Mutation	High scalability, good diversity	Poor accuracy
NPSOPC [61]	Medium	Medium	Low	Mutation and crossover	Good at exploration	Not good at exploitation
EPSO [62]	Low	Low	High	Selection	High adaptivity	Not good for high dimension problem
PSOGWO [63]	High	High	Low	Selection	Can easily escape from local minima	Poor accuracy

Table 3. *Cont.*

Name of Algorithm	Computational Time	Computational Complexity	Convergence Rate	Search Technique	Merits	Demerits
WOAPSO [49]	Low	Low	High	Mutation and Selection	Good convergence speed for high dimensional problem	Not suitable for high-dimension problems
CIWPSO [64]	Medium	Low	High	Selection	Suitable for solving distributed optimization problem	Low diversity
CPMPSO [65]	Medium	Low	Medium	Selection	High adaptivity	Low diversity
DEDIWPSO [66]	High	High	Medium	Mutation and crossover	High diversity	Large number of tuning parameters
SAIW-PSO [67]	High	High	Medium	Mutation	Low tuning parameters	Low diversity
PSOAG [68]	Medium	Low	High	Selection	High diversity	Not suitable for high-dimension problems
CPSO [70]	Low	Low	High	Selection	Low tuning parameters	Poor accuracy
HPSOSA [70]	High	High	Medium	Selection	Good diversity and adaptability	Uncertain convergence time

Computational complexity is the system's demand for computation resources as a function of the number of parameters to be optimized. Resources are specified by the expected calculation time and computational storage needed for generating the optimized solution. Algorithms employing partitioning techniques have relatively lower computational costs.

The pace at which the algorithm can find the optimal solution is referred to as the *convergence rate*. An effective algorithm should have a fast convergence rate and be capable of avoiding local optimal solutions. Premature convergence is described as the convergence of an SI-based algorithm before obtaining a globally optimal solution, and it is typically caused by a deficiency of diversity.

Computation time is the amount of time needed to complete a computational process. A computation is represented as a set of rule applications, with computation time being related to the quantity of the rule applications.

The search technique denotes the exact method by which the algorithm solves a problem. The majority of SI-based algorithms employ one of three kinds of search techniques: crossover, mutation, and selection. The process for global exploration is a mutation, whereas selection serves two functions: one is to accept the optimal available solution in the search space, and the other is to preserve a driving factor for convergence. Lastly, a crossover broadens the search space's diversity. For the RTC France solar cell, a comparison of hybrid PSO algorithms for the parameter estimation of SDM and DDM is shown in Tables 4 and 5, respectively.

Table 4. Comparison of hybrid PSO algorithms for parameter estimation of RTC France solar cell (single-diode model).

Algorithms	I_p (A)	R_s (Ω)	R_{sh} (Ω)	I_d (µA)	a	RMSE
FODPSO	0.7609	0.0364	51.9512	0.3187	1.4806	9.7486×10^{-4}
NPSOPC	0.7608	0.0363	53.7583	0.3325	1.4814	9.8856×10^{-4}
EPSO	NA	NA	NA	NA	NA	0.0010
PSOGWO	NA	NA	NA	NA	NA	NA
WOAPSO	0.7597	0.0342	83.0131	0.499	1.5483	7.1700×10^{-4}
CIWPSO	0.7607	0.0365	53.3394	0.0312	1.4762	7.7300×10^{-4}
CPMPSO	0.7607	0.0363	53.7185	0.3230	1.4811	9.8602×10^{-4}
DEDIWPSO	0.7607	0.0365	52.8898	0.3106	1.4755	7.7300×10^{-4}
SAIWPSO	0.7607	0.0365	52.8898	0.3106	1.47559	7.7300×10^{-4}
PSOAG	NA	NA	NA	NA	NA	NA
CPSO	0.7607	0.0354	59.012	0.4000	1.5033	NA
HPSOSA	0.7608	0.0365	52.8898	0.3107	1.4753	7.7301×10^{-4}

Table 5. Comparison of hybrid PSO algorithms for parameter estimation of RTC France solar cell (double diode model).

Algorithms	I_p (A)	R_s (Ω)	R_{sh} (Ω)	I_{d_1} (µA)	I_{d_2} (µA)	a_1	a_2	RMSE
FODPSO	0.7609	0.0365	52.7589	0.3857	0.2664	1.9999	1.4654	9.7334×10^{-4}
NPSOPC	0.7607	0.0366	55.1170	0.2509	0.5454	1.4598	1.9994	9.8208×10^{-4}
EPSO	NA	NA	NA	NA	NA	NA	NA	0.0010
PSOGWO	NA	NA	NA	NA	NA	NA	NA	NA
WOAPSO	0.7601	0.0311	100	0.5	0.5	1.5755	1.7314	9.8412×10^{-4}
CIWPSO	0.7608	0.0379	60.9400	0.1353	8.0314	1.4022	NA	7.1837×10^{-4}
CPMPSO	0.7607	0.0367	55.4854	0.7493	0.2259	2	1.4510	9.8248×10^{-4}
DEDIWPSO	0.7608	0.0379	60.9353	0.3523	8.0117	1.4027	2.4999	7.1823×10^{-4}
SAIWPSO	0.7608	0.0377	56.2704	0.0703	1.000	1.3627	1.7943	7.4193×10^{-4}
PSOAG	NA	NA	NA	NA	NA	NA	NA	NA
CPSO	NA	NA	NA	NA	NA	NA	NA	NA
HPSOSA	0.7608	0.0374	55.5392	0.1119	0.8559	1.3959	1.8201	7.7583×10^{-4}

6. Discussion

Here, we discussed the application of hybrid PSO algorithms for the parameter optimization of PV cells. Hybrid PSO algorithms are also applicable for various other applications: maritime transportation [74], space trusses [75], Internet of Things [76], managing deliveries of pharmaceuticals [77], load dispatching [78], power quality improvement [79], economic emission dispatch problems [80], pressurized water reactors [81], the partial shading of PV systems [82], the stability of security systems [83], the control of hybrid energy storage systems [84], the operation of integrated energy systems [85], the control optimization of an inverted pendulum [86], optimal chiller loading [87], and many more [73,88–93].

PSO algorithms are widely useful for microwave engineering [94], parameter optimization in electromagnetic shields [95,96], saving energy in antennas [97], saving energy in electromagnetic conductors [98] and many more [99]. Thus, scholars and researchers are encouraged to conduct further research on the theory and applications of PSO algorithms in forthcoming years. The following years will almost certainly see further refinement of the methodology and its incorporation with different procedures, such as applications moving out of the exploration lab into industry and trade. Further comprehension is required of the overall qualities of PSO and different methods, and of the difficulties in sending a PSO-based framework. PSO is a welcome expansion to advancement tool kits. The future exploration of planning mind-boggling issues in multilevel-headed (or many-objective) optimization issues and tackling them with appropriate parallelization procedure could be invaluable directions. Additionally, for issues with few factors or huge information issues, parallelization could adequately upgrade the proficiency and execution by utilizing equal adaptations of heuristics.

7. Conclusions

Hybridization is a developing area of intelligent framework research that means to consolidate the advantageous properties of various ways of relieving their singular shortcomings. This paper presents a bird's eye view of hybrid PSO algorithms applied for the parameter assessment of PV cells or modules. The algorithms were compared on the basis of the used objective function, type of diode model, irradiation conditions, and types of panels. The qualitative analysis of algorithms was performed on the basis of computation time, computational complexity, convergence rate, search technique, and merits and demerits. Several hybrid PSO algorithms were proposed and employed for various applications apart from the parameter assessment of PV cells. However, this review article studied hybrid PSO algorithms employed for the parameter assessment of PV cells during 2020–2022, namely, the FODPSO, NPSOPC, EPSO, CPMPSO, DEDIWPSO, PSOG-WO, WOAPSO, CIWPSO, HPSOSA, PSOAG, and SAIW-PSO algorithms. The hybridization of basic PSO with additional methods significantly enhances the efficiency of parameter assessment.

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Conflicts of Interest: The authors declare no conflict of interest.

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