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Review Article

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A Review on Hybrid Intelligent Photovoltaic Parameter Estimation Algorithm System

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Abstract This article reviews important work in photovoltaic cell modeling and parameter estimation for photovoltaic simulation. It not only provides the advantages and drawbacks of the three main PV cell models but also the concepts and features. Analytical method and soft computing method belong to parameter estimation technique. Finally, the model is evaluated, the performance of the model is summarized, and the future research trend and direction are summarized. This article reviews the literature on PV parameter estimation and Maximum Power Point Tracking algorithms at home and abroad. The effects of different methods such as analysis, iteration, and evolutionary calculation on PV parameter estimation are evaluated. In this review, by revealing that the iterative methods in the existing literature are limited by the limitations of the precarious situation and mathematical calculations, the reasons that affect the effectiveness of the optimal PV parameter estimation for fluctuating solar radiation mode are found. Our study sheds light on evolutionary computing, such as memetic adaptive differential evolution, Coyote optimization algorithm. Because of the local minima and convergence problems of classical methods, differential evolution is of great significance in PV design parameter estimation. Due to the large and scattered literature on this topic, it is necessary to prepare a concise and comprehensive document on this topic to bring the information together for further understanding. Therefore, relevant work can help new and old relevant practitioners to get familiar with the existing field and explore the unknown field more quickly and efficiently.

Keywords Solar cell models; Parameters estimation; Optimization optimum sizing

1. Introduction

The deadly increase consumption of fossil fuels to replace renewable energy sources. Solar has the largest customer base of any renewable energy source, such as renewable, safe, and clean. Converting solar energy directly into other forms of energy is the advantage of this energy source, photovoltaic systems also occupy an important position in the power system. The photovoltaic model is an indispensable part of the development of the technical level of generating electricity from optical energy and the application of generating electricity from photovoltaic devices in related fields [4]. Meanwhile, to ensure the stability of photovoltaic model parameters under the premise of optimization of photovoltaic model parameters, we also used a model assessing the capability of the photovoltaic array is accomplished by measuring and comparing current and voltage data [5-6]. This algorithm can avoid falling into local optimal solution while accurately solving the model, and accelerating the convergence speed. In addition, the third-ranked elimination strategy can eliminate bad solution archives, but the search range of the solution obtained by NMM (Nelder-Mead simplex method) may result in getting the best RMSE (root mean square error) than the shadow (success-history establishes an adaptive anti). COA algorithm (Coyote optimization algorithm, Coyote) [7] requires fewer control parameters. Easy to implement and balance exploration and exploration with multiple mechanisms. When in the JAYA algorithm update phase, diversity of populations exploration and development capabilities of the algorithm are improved due to the integration of the logistic chaotic Chaotic mutation stage and mapping stage. However, the LCJAYA algorithm has no special parameters. From the experimental data we acquire some solar photovoltaic cells, the performance of the heuristic algorithm is evaluated. But it needs a sufficient population. HISA (Hybrid Internal Search Algorithm) [10] has appeared, the reason why the focus of the search strategy will shift from the entire search space to the search for solutions around global minima is the increasing number of iterations. Higher-order sine and cosine algorithms (the algorithm proposed in this paper ISCA is an improvement on the exploration and development of sines and cosines algorithm) [11], its disadvantage is that these steps are cumbersome and too many constraints. The IBEXOPT (This global optimization algorithm, interval branch, and bound) [12] makes three PV cell parameter estimation models are tested. The results were compared with documents found during the same situation. Experimental results of this algorithm and a meta-heuristic algorithm are analyzed from the aspects of convergence speed and result variability. But sometimes no obvious changes were observed in several runs. According to the average trend of the local similarity of the three models and the KTI (Knowledge Transfer Intensity), the SGDE result of the photovoltaic module model is significantly better than the SGDE result of the model. According to the experimental results, we believe that SSA has better performance and other effective algorithms (TLBA ITLBO, integer, ISCE, and HFAPS) single diode model and (article, ELPSO complex, BSA and ABC) double diode model [14], its scope of application is too limited. For EMSA (Enhanced moth search algorithm) [15], the reason why this algorithm is superior to other algorithms in processing the sources of optimal parameter data collected are solar panels under different conditions is that EMSA adds interference operators to the traditional MSA, the diversity of moth search algorithms has been improved. It can combine the traditional MSA algorithm with the interference operator to avoid the result falling into the local optimum. The purpose of using interference operators is to avoid landing on local sites and thus increase MSA diversity. PSFS (Perturbed Stochastic Fractal Search) [16] uses its search operator to diffuse and update to strike a balance, between global exploration and local development. ETLBO [17] achieves a balance by adjusting the parameters of the control exploration and development stage, which improves the performance of the traditional TLBO and reduces its search space. Although the existing ETLBO has the same RMSE value as the traditional TLBO, the conclusion can be drawn from the average time value of the calculation that ETLBO is faster than traditional TLB processing. LGOA (Locust optimization algorithm, which is based on Levy flight) [18] the grasshopper position of the standard GOA will be embedded by Levy flight mode (grasshopper optimization algorithm), and the fixed time delay and unavoidable in the actual system. Improved differential evolution algorithm [19]. The statistical results of the independent operation are compared with other meta-heuristic algorithms. According to literature research, not only DDM (A type of dual diode model) but also TDM (One type of three diode model) have high accuracy and reliability, so further analysis and discussion are considered. SMA not only introduces the most characteristic photovoltaic cell parameter extraction optimization methods in the literature are compared [20]. However, for these two models, it takes approximately 12,000 iterations to obtain the best solution. SAMHJ (the semi-analytical method of inference hook-Jeeves pattern search method) [21] combined with the optimization of related algorithms. These three special three key points are found on the summary graph, without sacrificing accuracy, through approximation or simplified assumptions, the dimensionality of the parameters. In addition to reducing the computational complexity, the parameters of search space can be simplified into an independent parameter is also simplified Its advantage is that there are too many steps. This kind of dynamic and efficient particle swarm algorithm DEDIW (Dynamic Inertial Weighted Particle Swarm Algorithm, based on double exponential function) is proposed traditional particle swarm optimization is used to solve the problem of premature convergence [22]. This algorithm provides excellent estimation parameters. But the maximum number of iterations is too large. DPDE (Directional permutation differential evolution algorithm) [23] makes full use of the information generated by the differential vector of direction, which belongs to the search population, and has a strong ability to break free of local optimality is applied to global exploration, but the algorithm takes too long. RLGBO (Random learning gradient-based optimization, RLGBO), [24], the method achieves parameter estimation of various photovoltaic models under fixed temperature and irradiance. In addition, the calculation workload will increase depending on the amount of correction. Proposed MLSHADE (Adaptive differential evolution based on the success history of multiple strategies) [25] and ISS (inferior solutions search, inferior solution search) technology, avoiding the first stage is the covariance matrix adaption evolution strategy population, it falls into a local optimum. Its advantage is convergence.

This article aims to introduce some algorithms to solve the parameter identification problem that belongs to the PV model. Part 2 describes the Electrical circuit models of PV cells. Part 3 describes the analysis results of relevant PV models In part 4, these results are from those found in the present literature. Part 5 discusses the conclusion and future of these algorithms.

2. Fundamental

The selection of the photovoltaic model and the control of related parameters are the main factors determining the performance of photovoltaic cells. The description in this section focuses on the introduction of different photovoltaic models and the description of different electrical parameters [26-28]. Some papers reveal the circuit design of mainstream photovoltaic models and their advantages and disadvantages [29-30]. The parametric characteristics of the single diode mode are considered in this experiment, as are the dual diode models [31]. Here are the details:

2.1. A type of single diode PV model

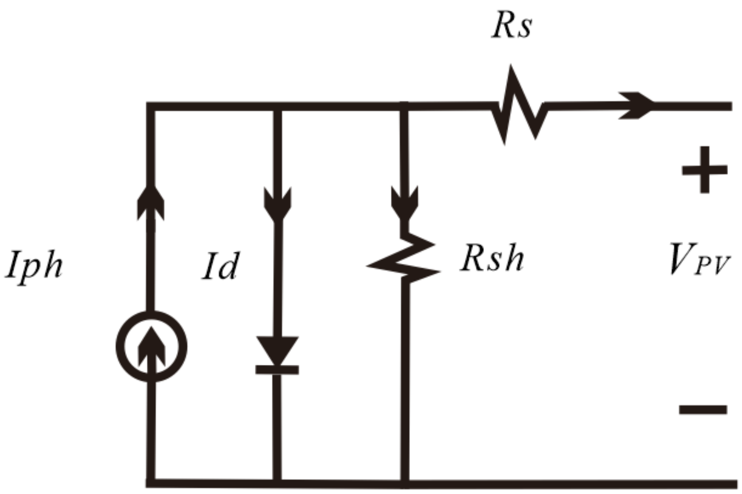

Figure 1: The circuit model of the SDM of PV cells

This is an SDM circuit model of a photovoltaic cell. The model includes a current source I_{ph}, which indicates the structure of PN is explained from the physical effect and is represented by photocurrent. A lot of resistors R_s and a parallel resistor R_{sh} are embedded in the model to consider the loss of current and voltage. Therefore, this model can be used to more accurately describe the volt-ampere characteristic curve of photovoltaic cells. Photovoltaic output current in FIG. 1 can be expressed by Kirchhoff's law as [32]:

$$I_{pv} = I_{ph} - I_d - I_p \tag{1}$$

The I_d indicates current through the diode, while I_p indicates the current through the R_{sh}. The current can be expressed by Shockley's equation as:

$$I_d = I_0 \left[\exp\left(\frac{V_{PV} + I_{PV} R_s}{aV_t}\right) - 1\right] \tag{2}$$

The I_0 indicates reverse saturation current through the diode and V_{PV} represents the output voltage of the photovoltaic model. In addition, V_t represents the ideal coefficient of the diode and the thermal voltage, which can be determined by:

$$V_t = \frac{N_s KT}{q} \tag{3}$$

N_s is the total number of batteries. K is 1.3806503×1023J/K, which is called boltzmann's constant. Q is 1.60217646×1019C, which is called electron charge. Besides, T is the junction temperature that belongs to this module. Ohm's law can be used to calculate the current in a parallel resistor:

$$I_p = \frac{V_{PV} + I_{PV} R_s}{R_{sh}} \tag{4}$$

To work out I_{PV}, we can use the following methods:

$$I_{PV} = I_{Ph} - I_0 [\exp(\frac{V_{PV} + I_{PV} R_s}{aV_t}) - 1] - \frac{V_{PV} + I_{PV} R_s}{R_{sh}} \tag{5}$$

To represent the SDM of PV modules in this way, 5 parameters need to be determined. $Param_{SDM} = [I_{ph}, I_0$, a, R_s, R_{sh}], which must be identified as modeled I-V characteristics.

2.2. A type of double diode PV model

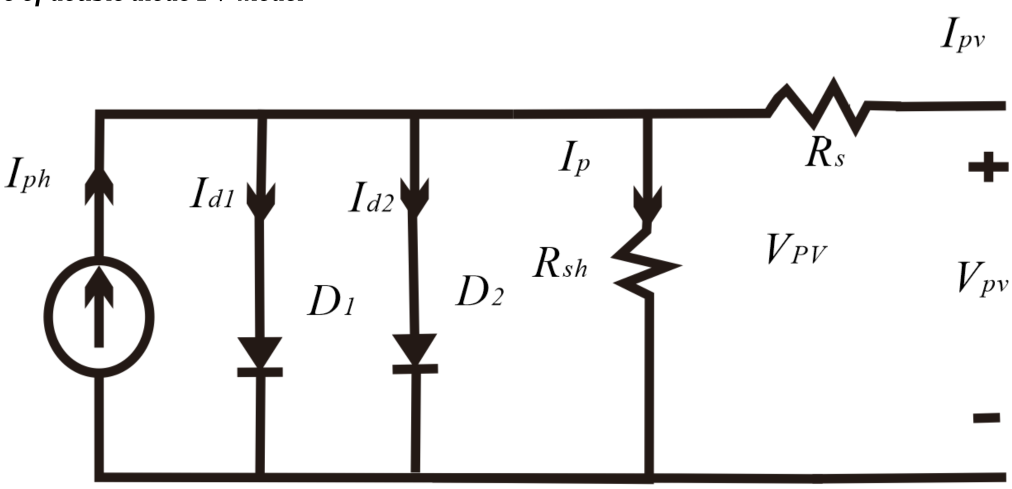

Figure 2: The circuit model of the DDM of PV cells

The photovoltaic module uses two diodes parallel to the I_{ph} current source to drive the side gate module compared with the SDM. Its digital module circuit model [33] is shown in Figure 2. To make more detailed data describing the physical effects of the PN junction we use two diodes in DDM. The first diode wants the representation of the diffusion current through the junction to be accomplished by simulating the diffusion of minority carriers. The space charge region that characterizes the second diode is the set of carriers. Therefore, a more accurate physical model can be obtained by using DDM, and the PV output current of DDM can be expressed by using different photovoltaic models such as KCl:

$$I_{PV} = I_{Ph} - I_{d1} - I_{d2} - I_p \tag{6}$$

I_{d1} indicates the currents through the diodes D1, I_{d2} indicates the currents through the diodes D2. I_{d1}, and I_{d2} can be worked out by Shockley equation:

$$I_{d1} = I_{01}[\exp(\frac{\mathrm{V_{PV}} + \mathrm{I_{PV}R_s}}{\mathrm{a_1V_t}}) - 1] \tag{7}$$

$$I_{d2} = I_{02}[\exp(\frac{\mathrm{V_{PV}} + \mathrm{I_{PV}R_s}}{\mathrm{a_2V_t}}) - 1] \tag{8}$$

$$I_{PV} = I_{Ph} - I_{01}[\exp(\frac{V_{PV} + I_{PV}R_s}{a_1V_t}) - 1] - I_{02}[\exp(\frac{V_{PV} + I_{PV}R_s}{a_2V_t}) - 1] - \frac{V_{PV} + I_{PV}R_s}{R_{sh}} \tag{9}$$

As for the parameters of DDM

$Param_{DDM} = [I_{Ph}, I_{01}, I_{02}, a_1, a_2, R_s, R_{sh}]$

To establish the I-V characteristic model must be determined. Due to the improved accuracy under low irradiance conditions, it is still an attractive option [34-35].

Problem formulation

Solar photovoltaic model parameter extraction is an optimization problem that converts the smallest fitting the data into numerical values. Root mean square error [36-38]:

$$\mathrm{RMSE}(x) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f(V_L, I_L, x)^2} \tag{10}$$

Where N represents the number of groups of I-V data.

for the SD model,

$$f(V_L, I_L, X) = I_{ph} - I_{sd} \cdot [\exp(\frac{q \cdot (V_L + R_s \cdot I_L}{n \cdot k \cdot T}) - 1] - \frac{\mathrm{V}_L + R_s \cdot I_L}{R_{sh}} - I_L$$

$$X = \{I_{Ph}, I_{sd}, R_s, R_{sh}, n\} \tag{11}$$

For the DD model,

$$f(V_L, I_L, X) = I_{ph} - I_{sd1} \cdot [\exp(\frac{q \cdot (V_L + R_s \cdot I_L}{n_1 \cdot k \cdot T}) - 1] - I_{sd_2} \cdot [\exp(\frac{q \cdot (V_L + R_S \cdot I_L}{n_2 \cdot k \cdot T}) - 1] - \frac{\mathrm{V}_L + R_s \cdot I_L}{R_{sh}} - I_L$$

$$X = \{I_{Ph}, I_{sd}, R_s, R_{sh}, n_1, n_2\}$$

(12)

3. A brief description of the most recent maximum likelihood methods used to estimate solar and photovoltaic panel parameters. The parameter hybrid intelligent algorithm mainly includes the following aspects.

3.1. MADE (Memetic Adaptive Differential Evolution)

This algorithm uses the adaptive DE(SHEED) based on the success history proposed by [39] for global search. Second, use the leld-mead simplex method to deal with the algorithm and search optimization. Third, the elimination strategy based on sorting has resulted in a better external archiving solution. We need to compare the results of estimating the parameters of other models to evaluate the performance of the algorithm.

Experimental results show that for different photovoltaic models, make can provide very competitive results with less computing resources.

The procedure of the GA algorithm is as follows:

1. Random initialization of population number[41]
2. When the number of evaluations of the function is smaller than the number of evaluations of the maximum function, the substitution $\mathrm{S_{CR}}$ is optimal $\mathrm{CR_i}$, and the substitution $\mathrm{S_F}$ is optimal [39].
3. The number of solutions is updated to the sum of the number of solutions and the total size.
4. If it is still not optimal, update the NFE to the sum of the previous NFE and NFE consumption [42-43].

5. When the absolute value of the inferior solution is greater than the total size, the sort-based elimination strategy updates the value of the inferior solution [44].
6. Update the value of M_{CR} and M_F with memory [45].
7. Output, when the index of the storage location to be updated, is greater than the total number of entries in the historical memory

Compared with different algorithms for a type of single diode model, they conclude the best RMSE is 9.8602E−04, worst RMSE is 9.8602E−04, mean RMSE is 9.8602E−04, std RMSE is 2.74E−15, Max_NFE is 5000, CPU time (s) is 0.1267. During the single diode models, the latter table not only shows the IAE (individual absolute error) but also indicates the I-V characteristic curve combined I_{mea} with I_{cal}. The results show that the fitting degree between measured data and calculated data is good. In the comparison of the two-diode model, it can be found from the average and standard values that MADE is more robust than SHADE. These data represent the IAE value and I-V curve of this gap between theory and reality [46-52]. From the results of the PV module, it can be seen the fitting degree between measured data and calculated data is good. All comparison algorithms can have a good fit RMSE value while occupying less CPU time. It is also found that the processing results of some algorithms for RMSE are the same as those of the algorithm in this paper.

3.2. COA (Coyote Optimization Algorithm)

The algorithm is used for parameter identification [7] of a type of single diode model and a type of double diode model. This algorithm is inspired by the living habits and survival characteristics of the coyote model [53-54]. It has the advantages of fewer control parameters, easy implementation, balanced exploration, and more development mechanisms. Introducing settle parameters to keep the coyote population from being constrained deviating from the predefined search space boundary for gaining a set of physically meaningful solutions. Compared with other advanced parameter extraction methods based on environmental analysis, the optimized device has higher accuracy. In addition, when different modules of different technologies are tested under unequal radiation and temperature, the standard deviation of fitness values for both models was less than 1×105 over multiple runs. This shows that the results are extremely consistent. Because of these excellent advantages, COA is considered to be an active choice for PV cell/module parameter extraction problems.

The highly efficient and population-based Coyote Optimization Algorithm (COA) was created by Juliano and Leandro. This algorithm gets revelation about the behavior of large dog breeds that live mainly in North America. Swarm intelligence and evolutionary heuristics are part of the COA because of its special structure. N_p means several groups and N_c means one group of coyotes packs. The coyote population is the same in any population. Therefore, the population size is N_p x N_c. The social conditions of wolves determine the alternative solution X to the optimization problem.

The COA steps are as follows:

1: Randomly initializes N_P x N_C as the population coyotes in a predefined search space.

2：Coyotes' adaptation to their respective social conditions was assessed.

3：Coyotes are inclined to leave their nowadays pack for a lonely life or decide to make a living in another tribe [55]. The probability of the wolf being expelled from its population is zero, depending on the size of the pack.

4 : It improves the diversity of the population by accelerating the flexible information between coyote populations, case N$\geq \sqrt{200}$, P_e more than 1. COA keeps the number of coyotes in each package not greater than fourteen. Within each pack, the most adaptable coyote is designated as the Alpha Wolf. The solution to the minimization problem is determined by the formula.

5 : COA believes that each individual coyote will communicate with other coyotes in the group to achieve a shared social living condition because the cultural orientation of the group is defined by the information provided by its members, which can improve the survival ability of the group.

6 : The birth of a new coyote is two females randomly selected from the same population, and in order to simulate the birth and death of a coyote, we also need to take coyote age into account.

7：Different conditions of separation and aggregation will affect the structure and the overall number of coyote populations.

8 : Coyote pups have about a 10 percent chance of dying at birth, and to model what increases with age is the risk of death per coyote.

9 : Because of their superior cognitive abilities, coyotes can choose a new social environment if they find it better than before. So the overall situation of the coyote population can only get better or the same, not worse.

In order to study the property of the COA-based optimizer, these data that belong to single-diode and dual-diode models were extracted in MATLAB. In order to compare with other related work [56-57], we used two sets of voltammetric data. Not only are the exact values of the data points presented in the literature, but the paper also records the optimal performance obtained by other algorithms. It is therefore a more equitable, broad, and referable result. Parameter search range [58-59] is set according to other related work. When N_C =9， N_P =11，population is equal to 99，The average fitness of the single diode model is 0.001102101. When N_C =6， N_P =17，population is equal to 102，The average fitness of the single diode model is 0.001370024.

3.3. LCJAYA （Logistic Chaotic JAYA）

This logical chaotic genetic algorithm is proposed to improve the ability of parameter identification of this model. As the LCJAYA algorithm [8], for the improvement of population diversity in the algorithm model, we decided to introduce the Logistic chaos mapping strategy to enter the update stage, in the process of solving the JAYA algorithm [60]. The performance of LCJAYA was evaluated by standard data sets of two different photovoltaic models, and the conclusion was drawn that chaos variation was introduced as a search strategy. In addition to balancing development capabilities, search capabilities have also been enhanced. Experimental results show that compared with other heuristic algorithms, the LCJAYA algorithm achieves excellent performance for optimization accuracy and reliability [61].

The design of JAYA are as following steps:

i: Logistic chaotic map strategy: The equation [62] decides to introduce chaotic sequences instead of two random numbers.

ii: Defining the future exploration direction as choosing the optimal solution and random solution to explore more space is the previous algorithm iteration process. The role of the optimal solution and random is to find a better habitat for the species and then expand the search. The first search updating strategy uses the potential search direction is determined by an average in the late iteration process of the algorithm to update the exploration ability. The equation gives the update strategy for the second time [63].

3.4. Rao (A Heuristic Forward Search Algorithm Optimal)

The algorithms proposed in this paper are classified as algorithms for new optimization problems [64]. Combined with the experimental data collected from solar photovoltaic cells, we evaluated the performance of the heuristic method. Our algorithm is applied to various photovoltaic models, and the experimental results are compared with those of other algorithms. I can get the best and worst solution of the function very clearly. The indexes of the heuristic algorithm are better than the traditional heuristic algorithm. The article explains how the Rao-2 and Rao-3 algorithms adjust the given value to make the RMSE value more rigorous. Rao algorithm: The characteristic is to consider the maximum value of function f(x) [65]. The minimum, maximum, mean, median, and standard deviation of the experiment are the criteria for the data is shown in the table. The statistical results and comparison of other methods [64]. It is found that the performance of this algorithm is very stable in parameter estimation. RMSE shows that the minimum value given by the algorithm proposed in this paper and other algorithms is the best, and when the standard deviation of RMSE is considered, the performance of other algorithms is the worst. The results show this paper has a faster convergence rate than other algorithms. The statistical results based on the DD model show the algorithm is better than other algorithms during the above assessment indicators. If the proposed algorithm can provide a better solution, the proposed algorithm is stable and reliable, and the value of STD has been fully proved to us. At the same time, A type of dual diode model is estimated. Compared with other methods in the literature, the algorithm proposed in this paper has a faster convergence rate.

3.5. HISA (Hybridized Interior Search Algorithm)

This paper describes a hybrid optimizer for parameter estimation [65]. These experimental results show the five case studies that estimated the single and dual cell models of photovoltaic cells/modules from characteristics of a single I-V cell, thin-film-based photovoltaic technology, and specific insights based on the PV model [66-67]. The evaluation of HISA modeling performance found that the evaluation criteria for the experimental results obtained from these experimental data are the RMSE of the experiment, the experiment weighting, and the experiment mean absolute error. Through a comparative study of 34 documents, five case studies including analysis, determinism, and meta-heuristic methods have found that the parameter estimation method based on HISA is more effective.

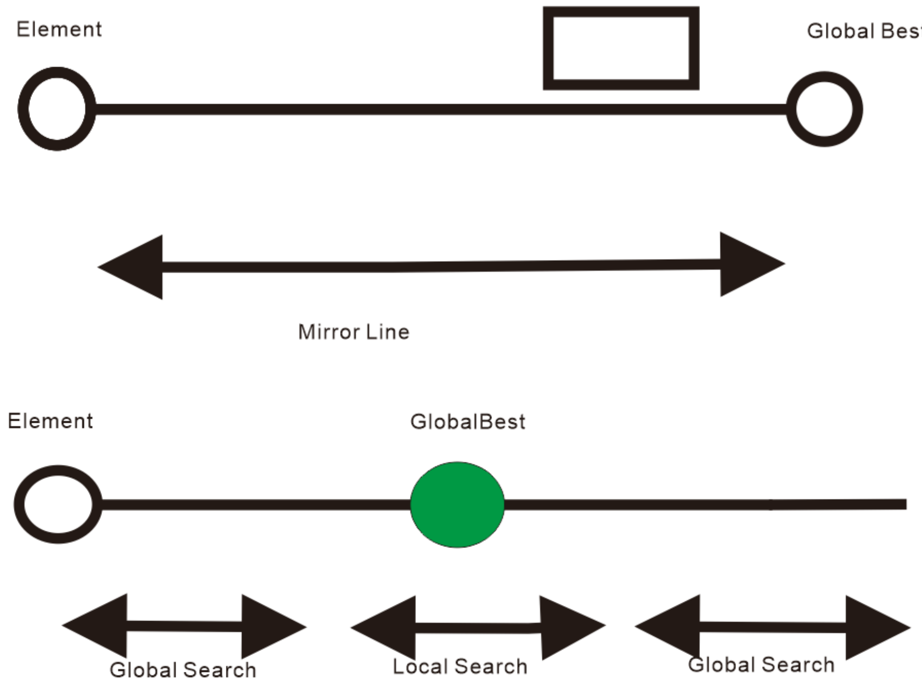

Figure 3: Mirror work search part of algorithm

The algorithm steps are as follows:

i: The function of the internal search algorithm: The ISA method is used to improve the overall aesthetic of the interior design by arranging the items in the room according to the requirements and limitations set by the client. Images placed near the world's best locations can be used for local search or enhancement by mirror search or observed as global search or diversification [67].

ii: Mutation used mutation strategy DE/best/1,

$$V_i = X_{gBest} + W(X_P - X_Q)$$

In this work [68], Setting the value of W to 1 is to generate as many mutant individuals as possible. The condition $i \neq g_{Best}$ Elitism is about ensuring that solutions don't change, which is critical to preserving existing information about the best solution. It is worth noting that, compared with exponential crossover, binomial crossover or unified crossover strategy is usually used, because the latter requires the connection between adjacent decision variables. Therefore, the best solutions never involve cross-border strategies. This allows the current algorithm to retain the best solution for the crowd while using the crossover to modify specific solutions and improve its relative fitness.

The comparison of parameter estimation performance of PVM 752 GaAs photovoltaic cell [71] SDBM shows that the RMSE is 1.592555E−4 and the MAE is 1.37567E−4.

3.6. SCA (Sine Cosine Algorithm)

ISCA proposed in this paper is characterized by an exploratory and exploitable core construction based on SCA, which combined the Nelder-Mead simplex concept with OBL [73], The NMs method can ensure species cluster reduction and improve development capabilities in ISCA[74]. In addition, a learning program based on the opposition can promoting population diversity and simplify the steps of algorithmic theory to ensure a more stable balance between development and exploration [76], the experimental results of one type of SD model and one type of DD model show their ability of unrecognized parameters of photovoltaic modules the accuracy and convergence are the advantages of ISCA in the algorithm field rate of the conclusion solution. The proposed algorithm has mentioned a is as follows:

I: Basic sine cosine algorithm:

SCA uses equations based on sines and cosines to update positions. Initialize the search parameters and liberate each search into the objective function. Use equations to update the optimal solution objective function, these parameters, and the location of each search solution agent. Returns the best solution until less than the maximum number of iterations.

II: NMs (Nelder-Mead simplex method)

This method can work out the derivative-free function. For example, if there is an E-dimensional minimization function, NMs will start from formed by E+1 initial vertices. In the process of iteration, you find that the new vertices are worse, you get a simplex and that's what happens every iteration, the simplex gets closer to the optimal solution because of the iteration.

III: OBL mechanism

This has also proved to be a feasible strategy to humanize the search trend of the meta-heuristic optimizer. This technique is used to obtain a parameter with better fitness, and it can also estimate the matching dual base agent.

IV：The proposed algorithm

SCA can do a good job attribute between detection and development, and the NMs method can be used as an effective local search technology to further search the neighborhood. The OBL mechanism can dig deep into the entire decision space while avoiding local optima. To promote the trend of exploration and expand the scope of the search space, we used the OBL mechanism in the original SCA.

Finally, the algorithm first executes the basic strategy or evolution group of SCA and then transfers to the implementation of the OBL mechanism. After the OBL runs, the best agent in the current group is selected to construct the master simplex. After many tests, select the value D+1 and then use the simplex method is performed on the μ iteration, switching back to the original SCA.

To fully verify the capability of ISCA, we start to use the best algorithms to compare the problems existing in the accuracy of parameter estimation in various PV models. IAE values are under 2.508E−03 , while RE's values are during[−2.00E−02, 1.47E−01] . According to the absolute errors of current and power, the detailed statistical results of experimental data and simulation data are obtained on SDM. SDM ensures the accuracy of the estimated parameters and realizes the best solution for this task. ISC and ISCA have an obvious advantage and a faster convergence rate over other algorithms, respectively. The ISCA mentioned above can be used to accurately estimate the actual performance of DDM. In this paper, after a series of acoustic emission experiments on DDM, the sum of IAE values measured are 1.66E−05 and 1.86E −06 respectively. Therefore, compared with other algorithms, this algorithm has a faster convergence speed. All IAE values of the PV model are no more than 4.8328E−03. The results verify that the behavior of the result is very accurate.

3.7. IBEXOPT (Interval Branch and bound global optimization algorithm)

IBEX, a library of open-source c++ for real number to constraint, completes the IBEXOPT structure of the algorithm used in this paper [82]. The language selection for a specific stage is defined by Minibex [83]. The binaries are generated by IBEXOPT based on the design of the computational solution set. It is a solution technique from numerical method to constraint programming. Its minimum value is calculated using the interval branch-and-bound algorithm [84-85]. It is based on interval analysis. Think of the search space as an interval, and express the objective function in terms of I to n. The proof that its solution is globally optimal is that it traverses the search space. The search tree can be used to explore the search space of the algorithm. The problems are represented as children of the parent node in the tree. To reduce the field of variables, you need to partition the selected field in the subproblem [86-87]. You can use Abound as a goal function to eliminate bad space of search to find the optimal value of the objective function more quickly. After reduction, the box can be empty, which means that not equal to LOUP [88]. The characteristic of the new solution is to determine whether the box is empty, and then check its width if so. The condition for LOUP updates is that if the data we get is not precise enough we can split the box and push it. Update the loop in each cycle, and evaluate all current boxes with the minimum value of the objective functions in the graph to summarize the global process. Flow chart of the algorithm. The optimal value for SDM is 1.0e−7 for the SSE function [89].

3.8. SGDE (Similarity-Guided Evolutionary)

Algorithms that can be used to extract the parameters of the photovoltaic model at the same time are called evolutionary multi-task optimization algorithms [90]. The reason why this algorithm can improve the resulting quality and convergence speed of the group is that it can adjust the strategy in time and adjust it continuously according to the feedback in the calculation process and evaluate the algorithm by extracting three parameters. The algorithm has good accuracy and robustness. The main steps are to set the total number of iterations and population size. In the initial search space, we can generate the initial population P [91]. As for P_i, when assign randomly skills factor and evaluate P_i. When calculating factorial rank and scalar fitness, it is necessary to combine the defined P and the defined C will change to the temporary population. Take the best one as the next generation of new P [92].

The IAE values of current and power in the single-diode model are no more than 2.507E-03 and no less than 1.463E-03, so the parameter extraction results are very accurate [93-94]. For the dual diode model, the current IAE value is less than 2.517E-03, and the power IAE value is less than 1.468E-03, which proves that SGDE can realize high-precision parameter identification.

3.9. SSA (Salp Swarm Algorithm)

In order to study the parameter estimation problem of SD and DD solar photovoltaic models, the Salp group algorithm (SSA) will be used for operation while considering the uncertainty of measures [95]. The method includes three steps, namely, the parameters are retrieved according to the conventional method, and then the uncertainty of each parameter is determined. Finally, the parameters are determined results of previous steps. Firstly, the algorithm is applied to several problems to obtain a conclusion to verify the proposed theory. To take these results compared with the existing algorithms and it is found mentioned algorithms perform better. The content of the algorithm is described as follows, obtain experimental I-V data set and set of SSA control parameters. Apply the SSA algorithm for equations for SDM and equation for DDM. Extract of parameters for SDM and DDM. Define the new search interval of parameters using conditions. The equation can extract the instantaneous values of parameters and display the calculation results. The instantaneous solar cell parameter extraction scheme [96-98] shows very satisfactory parameter estimation results, because the instantaneous RMSE of the silicon solar cell RTC is between [9.6435E-13 1.2309E08], and the instantaneous RMSE of the STP6-120/36 solar module Between [7.0275E-11 8.9004E-08]. These comparison results show that the algorithm has a more powerful data processing ability than existing algorithms.

The algorithm considers the measurement uncertainty and instantaneous value of each parameter. We apply it to work out the parameter estimation problem of multiple unknowns in different fields and find that this method has better performance and is also a more effective PV parameter estimation tool.

3.10. EMSA (Enhanced Moth Search Algorithm)

The ITAE of this paper, which named integral time absolute error. It is between the experimental current and the calculated current of the three-junction photovoltaic panel. The simulation was carried out in Simulink to study the panel performance under different solar radiation conditions and shadow effects [104]. It is compared with other technologies. The operating efficiency of the proposed EMSA in the first and second modes is 99.66% and 99.89%, respectively. The superiority and reliability of the method are verified. This paper considers the three-junction model [105], which has higher efficiency compared with single-junction solar cells. EMSA used the objective function to evaluate the quality of each moth after producing new solutions. ITAE stands for absolute error and is used when calculating the current of an objective function and when simulating the experimental current. Using traditional MSA operators to update the solution until the stop condition, relative error, and other statistical parameters compare the performance of each algorithm; The root symbol represents the efficiency of the sum of squares of error.

The global maximum power of the experiment is 571.2143 W; the suggested method is successful

The obtained GMPP is 570.9369W, and the result is the best. The proposed EMSA rejected the null hypothesis for the two shadow modes at the 1% significance level. The mixed-method proposed to reject the null median hypothesis in the Wilcoxon test gives a significance level of 5% and H ¼1. In addition, the proposed EMSA scheme provides an important solution for the two shadow modes and is of great help for holm-Bonferroni correction. Statistical parameters of EMSA in different shadow modes are better than other methods.

3.11. SFS (Stochastic Fractal Search)

SFS is a kind of MHA recently developed by Salimi [106] inspired by the random phenomena of natural growth fractals. Diffusion and update are two main processes used in the SFS algorithm. Each particle diffuses around its position and performs developmental tasks, each particle updating according to the position of the other particles. This completes the exploration of attributes.

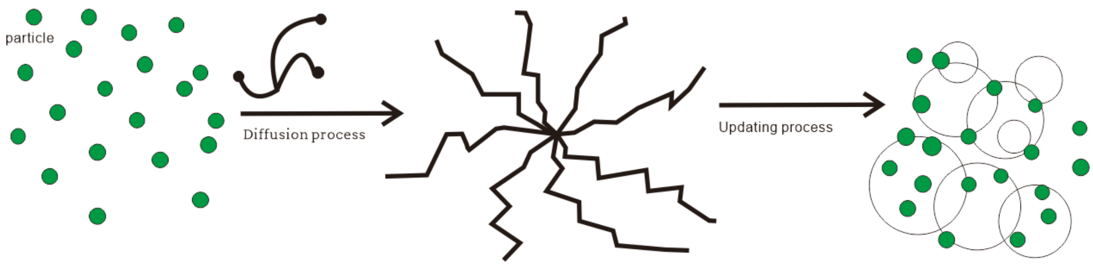

Figure 4: The main procedure of SFS algorithm

The main process of the pSFS is as follows. We need to initialize the population before we find the best location. Once the terminated condition is met, output the optimal solution, or particle p in the population. Take k from 1 to MDN. Select a Gaussian walk to generate a new point while creating the best point created by the Gaussian walk. Then sort all the particles and take each p in the population. Update using formula. Rand all particles, if $r_i \leq$ rand(0,1) update p using equation ,or for each particle p in the population .Find the optimal solution P and execute the chaotic elite perturbation strategy.

During the results of single diode mode [107], the existing pSFS, SFS, and TLABC reached the best RMSE value. Root mean square error is the only measure that can show the accuracy of the algorithm, then the estimation accuracy of pSFS, SFS, and TLABC is the highest. CLPSO and BLPSO have relatively poor performance. The results of the PV module model can be combined with five estimated PV module model parameters to further evaluate the estimation accuracy.

3.12. ETLBO (Enhanced Teaching–Learning-Based Optimization)

The optimization algorithm ETLBO is proposed to enhance the ability of traditional TLBO, which can be used in the estimation of photovoltaic cell parameters to reduce the search space to achieve appropriate balance [111-113]. This paper also verifies the algorithm with real data sets of photovoltaic single and dual diode models. Experimental verification was carried out on two data sets of actual photovoltaic windsurfing boards. The results of this algorithm are compared with those of other algorithms and it is found that this algorithm has certain effectiveness and superiority.

The goal of meta-heuristic algorithms is to strike a proper balance between exploration and development to ensure that the optimal global minimum solution is found in the search space. Exploration and development have the ability to search and find localized solutions in the solution space, respectively. ETLBO is to choose an appropriate balance point between the exploration phase and the development phase. Firstly, this balance is achieved by controlling the sine and cosine functions of the parameters, and the search space is explored in a predetermined iterative process, and then local mining is performed around the optimal solution to quickly converge to the global solution.

The RMSE given in the article is the estimated parameter of the mentioned ETLBO algorithm and others. In a word, the proposed ETLBO has the lowest RMSE value in the SD model and the DD model.

3.13. LGOA (Locust Optimization Algorithm Based on Levy Flight)

This article is to show us the improved locust optimization algorithm (LGOA) based on Levy flight to reckon the PV model parameters. This algorithm embeds the Levy flight pattern in the position of the locust not only improves the diversity of understanding but also enhances the algorithm's exploration ability [108-109]. The algorithm has better performance and detection ability [110]. An improved Grasshopper optimization algorithm based on Levy flight is mentioned to improve the global performance of GOA. These steps' size of Levy flight is derived from Levy distribution, which is a random non-Gaussian walk first proposed by Paul Levy. The main feature of Levi's flight simulates the flight behavior of many insects in nature. The flight tracks are a combination of short-range search (development) and occasional long-range search.

Levy flight trajectory not only ensures efficient search space but also ensures local optimization of data processing by providing diversification of search agents.

The results are obtained by LGOA and GOA algorithm using root mean square error on SD and DD models. They are 1.0944E-03 and 9.9691E-04, respectively. Besides, the figure shows objective function curves obtained by LGOA and GOA algorithms on one type of single-diode model and one type of dual-diode model experiments. It indicates that LGOA has obvious convergence advantages and can find better solutions faster than GOA.

3.14. IDEA (Enhanced Differential Evolutionary Algorithm IDEA)

The algorithm optimizes the experimental data without any assumptions and intuitions to get all the parameters of PV cells. The best solution, a collection of parameters, from several PV modules, running individually. It also describes a data sheet from the manufacturer containing many possible solutions. DE algorithm contains parameter sets describing real vectors [111]. At the beginning of the whole exploration, different vectors in the population need to be randomly set up. The process of generating and selecting the test carrier has to be repeated in order to obtain the specific termination criteria. The population size N_p is constant in the optimization process of the traditional DE algorithm [112]. The random vector constitutes the initial value of the population and applies crossover and mutation processes to populations. The child vector competes with the parent vector to choose the largest vector for the offspring. In one array of the DE algorithm the current population needs to be stored, and the second array needs to store the vectors needed for the second-generation selection, forming the parallel form of the algorithm [113]. The array dimension is represented by (N_p, D).

By comparison, it is found that the number of iterations of the existing algorithm is the same as the FES number because it implements the number of fitness assessments per iteration. We compared these results obtained through a variety of different algorithms and found that PSO, GA, and IDEA algorithms are more efficient. In the case of SSA and RA algorithms, the maximum error value is between 10-11 and 10-9. Therefore, the error can be ignored, and it can be concluded from these tests [114-115] that the PV module can achieve specific results at the operating point V_{oc}, I_{sc}, V_{mpp}, and I_{mpp}. No matter what algorithm is applied, various PV module parameter sets will be used.

3.15. SMA (Sime Mould Algorithm)

The main contribution of the slime mold algorithm (SMA) is the introduction of an application of optimization methods [116]. The algorithm is characterized by high precision and a rapid photovoltaic cell parameter determination program. The slime mold stochastic optimization algorithm uses adaptive weights to provide a unique mathematical model for the optimization problem. The process of slime mold generating positive feedback and negative feedback in propagating waves are simulated by these adaptive weights. In the field of solar photovoltaic cell parameters, it can accurately extract its global optimal value. It can handle the nonlinear and multi-modal characteristics of photovoltaic cells. Therefore, it provides a generalized solution that can be used to determine the technical parameters of various photovoltaic cells. The proposed slime mold algorithm is compared with the existing methods to extract photovoltaic cell parameters and it is found that the mentioned slime mold algorithm is better. The step flow chart of the proposed SMA method is as follows. Input the PV module data and PV specifications from the experimental data set [117-118]. Set the boundary of each parameter in SDM and DDM. Set the fitness function. Initialize the parameter population of the SMA method and the maximum number of iterations. The initial location of slime molds was determined according to the description in the article, and then the optimal location was updated according to the formula. Show the best parameter set and performance indicators. Estimates of RMSE and MAE are for SMA and ACT. The proposed SMA method has a root mean square error is $7.803 \times 10{-}4$ at SDM and $7.6105 \times 10{-}4$ at a type of DDM. In the meantime, the minimized RMSE belonging to the SMA method is $8.3839 \times 10{-}4$ at SDM. Besides, the MAE of SMA is $6.4026 \times 10{-}4$ and of SDM is $6.4109 \times 10{-}4$ at a type of DDM. And MAE belongs to ACT method is $6.92832 \times 10{-}4$ SDM. The consistency between the estimation of the data set and the experiment is shown in the SMA method to determine the best coefficients of SDM and DDM are both 0.9999 [119-120].

3.16. SAMHJ (Hybrid Method to Identify the Parameter Rand Performance Estimation of PV Modules)

The analysis expression is combined with the optimization algorithm. When performing dimensionality reduction, four equations need to be used to solve five independent parameters. It is necessary to find an initially determined parameter before estimating the parameter under any working condition the dependence is mainly for the surrounding environmental conditions. I-V curves derived from numerous experimental data drawn by a large amount of data prove the effectiveness of the method. This method not only has higher accuracy, but its output performance estimation results are better than other methods. Therefore, this makes a significant contribution to the modeling and accurate estimation of I-V characteristics under different working conditions and provides users with a faster and more efficient working model.

In this paper, we introduce an algorithm that can not only identify the diode model with unknown parameters but also estimate the output performance of PV models under un similar circumstances. Combining the simplified equivalent circuit model with the curve fitting method, and then reusing the three key points on the IV curve, there are several steps to test the accuracy of algorithm, so that the dimensionality of the search space can be reduced to that by the accuracy of the algorithm cannot be sacrificed under the premise of approximating or simplifying the hypothesis. In this case, an independent parameter should be introduced to eliminate the interference of complexity and accuracy. The second step uses optimization methods to determine the optimal parameters. , Compared with the traditional calculation method of translation value, this method significantly improves the prediction accuracy of electrical performance. After an in-depth study of the accuracy of the algorithm is affected by the change of reference conditions, it is found that reference conditions with higher irradiance should be given priority.

The analysis method usually uses three commonly used I-V equations, derived from equations describing some important special points [121]. It turns out that this algorithm takes less time to get more accurate data.

3.17. DEDIW (Double Exponential Function-Based Dynamic Inertia Weight Particle Swarm Optimization)

The double exponential dynamic inertia weight PSO algorithm proposed in this paper it can not only be used in a type of single diode element, a type of double diode element, but also in the parameter estimation of the module [130] is inspired by reducing the rate of the exponential function. The reason why the convergence speed is improved is that the fast characteristic of the exponential function maintains the trade-offs between global and local search cases.[131-132].

The main steps of the algorithm are to initialize the random population, set the particle swarm optimization parameters, determining the best solution requires modifying the solution based on the best solution to calculate the average value of each design variable. The average value of RMSE belongs to the proposed method in 30 times is 7.730062×10^{-4}, the minimum value is 7.73062×10^{-4}, and the maximum value is 7.730062×10^{-4}. The root mean square error standard for 30 runs. The difference is 2.486129×10^{-6}, and the comparison with other methods shows that this method is effective.

3.18. DPDE (Directional Permutation Differential Evolution Algorithm)

Differential evolution algorithm and meta-heuristic algorithm are the data to be processed, we found from the experimental results, DPDE algorithm can improve the optimization ability because of the fusion of useful information from individuals. Therefore, DPDE has strong global exploration capabilities, especially in the early stages of the search. Compared with existing optimization algorithms, it is found that DPDE has the best performance.

The maximum Photowatt-PWP201 belongs IAE I is 4.833E-03, and belongs to IAE P is 7.9858E-02. From an intuitive point of view, These values are the largest ones in one is called SDM algorithm, which means the method of parameter estimation [139] module is more efficient and performs better. The worst IAE I was 4.43E-02, which data was tested on the STP6-120/36 device, and its IAE P was 7.126E-01. Although the data is small, these IAE results are already larger than other models, including Current-voltage and power-voltage characteristic curves [140-141]. The identification parameters of a series of the model are shown in the figure, which shows that DPDE also has a good performance on these complex models.

3.19. RLGBO (Random Learning Gradient-based Optimization)

More and more people expect to be able to identify the parameters in various fields for more convenient and efficient data processing in machine learning. A gradient-based optimizer combined with a random learning mechanism is introduced to solve the problem of parameter identification of photovoltaic models. The GBO method surprises people because it can directly observe the results.

From the optimization steps of the model [143-145], its use process can be deduced. The two core processes of the optimizer include the application of local escape operators and the application of gradient search rules. Not only can effective learning be achieved by introducing a new mechanism to the existing GBO to alleviate the GBO's tendency to fall into the local optimum, but also improve the processing power of algorithmic data. Encouraging continuous learning and sharing among different individuals is the process of a random learning mechanism. We can apply RLGEB to various types of photovoltaic module models to complete the parameter evaluation of RLGBO performance. Through experiments, we found that RLGBO has a strong ability. Apply RLGBO to different models to solve the parameter identification problem. So we get the conclusion that RLGBO has high accuracy in parameter estimation. Therefore, the algorithm proposed in this paper can become a good calculation tool, which is convenient for people in various fields to operate and use.

The result of the single diode mode [146-148], the average value of the single diode in the RLBO experimental data is 9.86465E-04 and the standard deviation of the single diode is 1.38939E-07. RLGBO's overall performance is the best. This article enumerates the use of RLBBO and other mentioned algorithm and finds that the current results of using RLBBO have the highest accuracy. The maximum RMSE of a dual diode mode is 1.42736-04, the minimum root mean square error of the dual diode mode is 9.82776E-04, the average RMSE of the dual diode mode is 1.07389E-03, and the standard of the dual diode mode The RMSE of the difference is 1.79165 e-04.

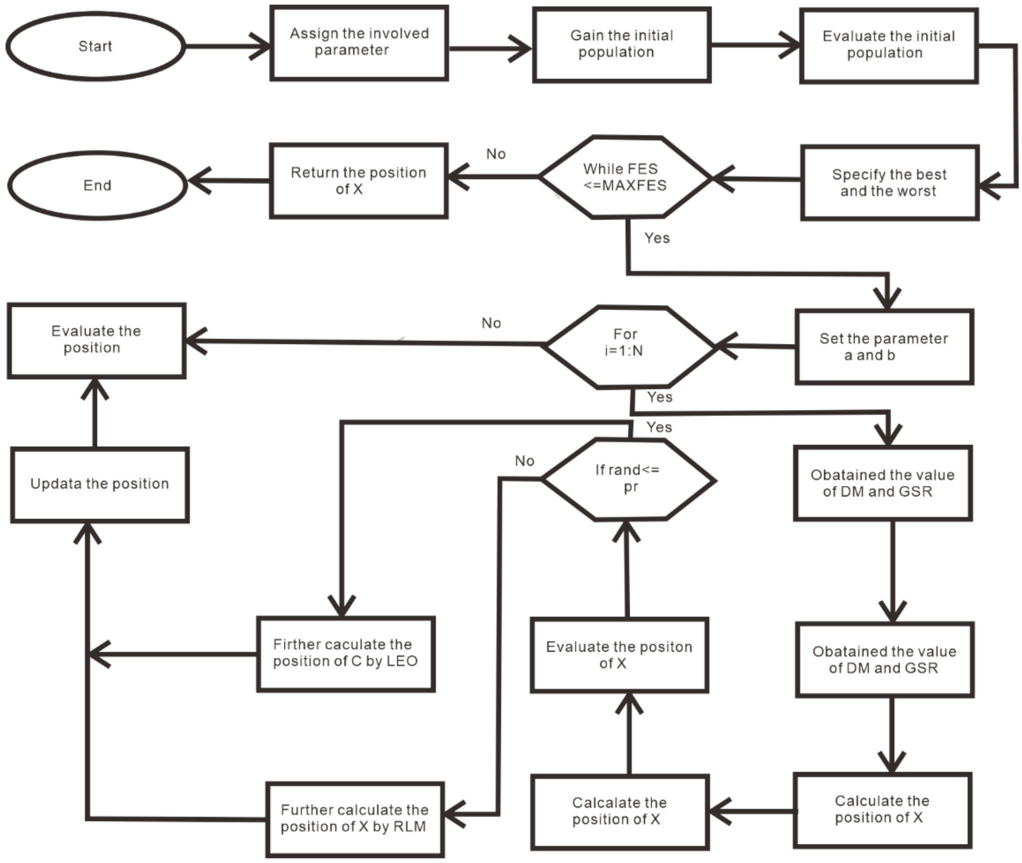

Figure 5: The flow chart of RLGBO

3.20. MLSHADE (Multi-Strategy Success-History-Based Adaptive Differential Evolution)

This article is to introduce an LSHADE algorithm. Thus solving the problem of PV model parameters due to it. Its characteristics are as follows:

I: LSAHDE and CMA-ES are two important elements of this algorithm.

Two: MLSHADE adopts a strict mutation strategy to improve algorithm simplification ability in order to enhance exploration ability. The development of the balance ability is compared on the basis of the semi-parametric enhancement of LSHADE's C-ES (ELSHADESPACMA) [30]

Three: To solve the parameter problem, the algorithm proposed in this article can be used

IV: The aging of our TSO involves the comparative experiment of the 2018CEC test service and experimental results on the identification of different parameters. The processing capability of this algorithm for single-even models is the same as MLSHADE, NRO, and MLBSA in terms of accuracy. Regarding the processing power of MLSHADE's standard components, all comparison algorithms of MLSHADE's minimum RMSE are the same, except for TLBO. At the same time, MLSHADE did very well in terms of the overall minimum RMSE.

4. Discussion and Future Researches

In order to select the optimal combination to meet the scale constraints, it is very necessary to test the reliability and analyze the cost of the system. In photovoltaic systems, to control power reliability and system cost, it is necessary to achieve a mutually adaptive combination of goals.

Table 1 summarizes the research work of hybrid intelligent algorithm applied to parameter estimation. Besides, Table 2 illustrates the main pros and cons.

You can see not only the advantages of each algorithm that have been summarized but also the limitations of applying each method.

Table 1: Summary of the hybrid intelligent algorithm for parameter estimation

References and Year	Method	Main Result
(Y. Chen et al. 2019)2019[6]	MADE	SD：RMSE 9.8602E−04 DD：RMSE 9.8608E−04
(Jack and Salam 2019) [7]	COA	SD：RMSE 7.7301E−04 DD：RMSE 7.3265E-04
(Jian and Weng 2020) [8]	LGJAYA	SD: RMSE 9.8602E-04 DD: RMSE 9.8308E-04
(Premkumar et al. 2020) [9]	Rao	SD: RMSE 9.8602E-04 DD: RMSE 9.8308E-04
(Kler et al. 2019) [10]	HISA	SS：RMSE 1.592555E−4 DD：RMSE 5.694015E−5
(H. Chen et al. 2019) [11]	ISCA	SD：RMSE 7.23043E−04 DD：RMSE：9.83800E−04
(Chenouard and El-Sehiemy 2020) [12]		SD：RMSE 1.2071e−3 DD：RMSE 1.2187e−3
(Liang et al. 2020) [13]	SGDE	SD:RMSE 9.8602187789E-04 DD:RMSE 9.84413E-04
(Messaoud 2020) [14]	SSA	RMSE 1.2993e-08
(Fathy et al. 2019) [15]	EMSA	RMS 0.07832
(X. Chen, Yue, and Yu 2019) [16]	pSFS	SS:RMSE 9.8602E-04 DD:RMSE 9.8255E-04
(Ramadan et al. 2020) [17]	ETLBO	SD:RMSE 9.86022 9 10-4 DD:RMSE 9.8241 9 10-4
(Mokeddem 2021) [18]	LGOA	SD:RMSE1.0944E-03 DD:RMSE9.9691E-04
(Shankar, Saravanakumar, and Indu Rani 2020) [19]	IDEA	SD:RMSE 4.058E-13 DD:RMSE 3.641E-12
(Mostafa et al. 2020) [20]	SMA	SD:RMSE 7.803E−4 DD:RMSE 7.6105E−4
(Lang and Zhang 2020)[21]	PIPE	SD:RMSE 3.21E-3 DD:RMSE 1.1E-2
(Kiani et al. 2020) [22]	DEDIW	SD:RMSE 2.039992E−3 DD:RMSE 2.039992E−3
(Gao et al. 2021) [23]	DPDE	SD:RMSE9.86021877891470E-04 DD:RMSE9.824848E-04
(Zhou et al. 2021) [24]	RLGBO	SD:RMSE 9.86022E-04 DD:RMSE 9.82776E-04
(Hao et al. 2020) [25]	MLSHADE	SS:RMSE9.8602E-04 DD:RMSE9.8248E-04

Table 2: Summary of the pros and cons of the hybrid intelligent algorithm for parameter estimation

Algorithm	Advantages	Disadvantages
MADE	I: SHADE avoids jumping into local optima. II: Elimination strategies based on rankings can eliminate poor solutions in the archive.	NMM obtains the solution beyond the search range may cause the best RMSE obtained by MADE to be slightly lower than in the SHADE.

COA	I: The number of control parameters is too little. II: Diversified exploration and development balance mechanisms and facilitated implementation.	It needs enough population.
LCJAYA	I: In the solution update phase of the JAYA algorithm, the chaotic mutation strategy and the mapping strategy belonging logistic chaotic are introduced. It can increase the diversity of algorithm results and avoid falling into local optimal solution.	LCJAYA algorithm has no specific parameters.
Rao	I: The Rao-1 algorithm is simple and does not contain algorithm-specific parameters. II: The RAO-1 algorithm can accurately estimate model parameters, and the operation is simple and suitable for practical industrial applications.	It needs enough population.
HISA	I: HISA has tested and verified the effective modeling of PV cells. II: Five case studies have fully investigated the modeling performance of HISA, including photovoltaic cells and modules using monocrystalline, polycrystalline and thin-film photovoltaic technologies.	During the process, the progress and focus of iteration will be gradually lost and the search strategy will shift from the explore the minimum solution, searching the global space
ISCA	I: A new enhanced method to work out the problem of PV parameter identification is proposed. To trade off a stable balance between the user's exploration ability and development ability.	The steps are tedious.
IBEXOPT	I: A new optimization method was proposed, and three photovoltaic cell parameter estimation models were tested. II: Compare the meta-heuristic algorithm and analyze the performance of this algorithm is not only in convergence speed but also in a variation of results	Deterministic algorithms, IBEXOPT, sometimes fail to see significant changes over several runs.
SGDE	I: SGEMTO transfer knowledge transfer degree is based on local similarity ability. It shows the amount of useful knowledge.	According to the average trend of the local similarity of the three models and the KTI, the SGDE result of T3 is significantly better than DE.
SSA	I: The model performance of this algorithm is better than others.	The scope of application is too limited.

EMSA	I: The best way to prevent it from flying is that the traditional moth search base adds interference operators, so the interference operator of MSA is improved. II: It proves that EMSA has performance in terms of the best parameters of three-junction solar panels in complex situations.	The purpose of using interference operators is to increase the diversity of MSA. This algorithm combines traditional MSA with interference operators to avoid them falling on local points.
pSFS	I: Use your own search operations the reason for realizing global exploration and block development is to balance diffusion and renewal. II: The reason why the search performance is improved is that the chaos elite perturbation strategy is introduced	IJAVA has the fastest convergence rate.
ETLBO	I: The reason why ETLBO improves the performance of TLBO reduces the search space of TLBO by adjusting parameters to achieve the appropriate balance. II: The control parameters are determined by the sine and cosine functions in the iterative process is the main feature of the ETLBO proposed in this article.	ETLBO is faster than traditional TLB in the average time value of data processing.
LGOA	I: The strategy of the LGOA meta-heuristic algorithm is to embed Levy flight patterns after finding specific locust locations in GOA II: Compared with GOA, LGOA improves the diversity of solutions and provides a better trade-off between exploration and development mechanisms.	In actual systems, the time lag is inherent and inevitable.
IDEA	I: Develop a simple error function using data table information II: The method of extracting feasible parameters is to use IDEA to optimize the established error function III: It is found that the statistical results obtained by independent operations have superior performance in comparison with the results of other meta-heuristic algorithms	According to literature research, the reason why the experimental results need to be further analyzed and discussed is that DDM and TDM have high-precision and high-reliability computing capabilities.

SMA	I: The algorithm uses adaptive weights in the process of global optimal search. II: The performance of the SMA optimization method is more outstanding in PV cell parameter extraction.	For these two models, it takes approximately 12,000 iterations to obtain the best solution.
SAMHJ	The method to reduce the computational complexity and cost of this method needs to be based on a simplified form, and the analytical method and optimization method are combined to reduce the dimensionality of the search space to an independent parameter.	Too many steps.
DEDIW	I: In view of the premature problem of the traditional particle swarm algorithm, this algorithm provides a dynamic and efficient strategy for parameter estimation-dediwpso, which makes the calculation result in an optimal, efficient, and accurate solution II: The computational intelligence (CI) method was used to estimate the parameters.	The maximum number of iterations is too large.
DPDE	I: DPDE makes full use of the information generated the algorithm has a strong ability to search globally and avoid local optimal solutions. This is because the algorithm increases the differential vector of the search group and the search direction	The algorithm takes too long.
RLGBO	I: The method of this algorithm to improve the performance of GBO is to design a new random learning mechanism II: The feature of the GBO algorithm is that it has a random learning estimation mechanism for the PV model parameters.	According to the modification, the calculation workload may increase.
MLSHADE	I: For the first-stage differentially evolved population, the way to increase population enrichment capacity is to adopt a new weighted mutation strategy. II: The feature Gaussian random walk strategy is added into the second stage of calculation to avoid the bad fitting degree of the results caused by the data falling into the local optimal solution.	Slow convergence.

4.3. Some future works

This article brings together various meta-heuristic methods for extracting photovoltaic cell parameters. But there are some issues that have not been considered.

1) Due to the hybridization of multiple convolution stages, the complexity of the algorithm is increased, thereby increasing the calculation and time.

2) Compared with recent analysis methods, unreasonable performance enhancement.

3) The reason why the parameter extraction performance is not the best is that it converges to the local minimum prematurely.

4) The reason why there are few or no terms for verifying the applicability of the extracted parameters is that the estimated parameters are too sensitive to small changes in known constant values, however, some important precision values are not available for us to study.

5) There are few PV specific technology analyses to fully verify the solution of mentioned method and test the feasibility of the extracted parameters.

5. Conclusion

For parameter hybrid algorithms, different optimization methods are used to find the optimal scale. Parameter mixture algorithm is a good technique for extracting solar PV model parameters. This article reviews parameter mixing algorithms and studies the most common criteria for finding the best solution for system size. In future research, it is also very efficient to use parameter hybrid algorithms to deal with such as energy dispatch, optimal allocation of distributed power generation, economic load dispatch, and other energy optimization issues.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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