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A Nonlinear L-SHADE Variant for Photovoltaic Parameter Estimation and Solar Power Generation Forecasting

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Abstract

Solar energy has attracted increasing attention due to its clean, renewable, and cost-effective characteristics. Among solar-related optimization tasks, photovoltaic (PV) model parameter estimation and solar power generation forecasting are two important problems for improving PV system modeling accuracy, performance evaluation, and operational management. However, both tasks involve nonlinear characteristics, coupled variables, and uncertainty caused by environmental variations, which make them challenging for conventional optimization methods. To address these issues, this paper proposes a nonlinear L-SHADE variant, termed NL-SHADE, in which a sigmoid-based nonlinear population reduction strategy is introduced to replace the linear population reduction mechanism in L-SHADE. The proposed design aims to provide a more flexible balance between exploration and exploitation while preserving the simplicity of the original framework. The performance of NL-SHADE is evaluated on six benchmark PV parameter estimation problems and 14 solar power generation forecasting datasets. For PV parameter estimation, NL-SHADE achieves highly competitive results, and the summarized Wilcoxon rank-sum results over the six benchmark problems confirm its overall advantages over most compared algorithms while maintaining strong competitiveness against DPDE and L-SHADE. For solar power generation forecasting, NL-SHADE ranks first among all compared methods according to the Friedman ranking analysis. Moreover, in 42 pairwise Wilcoxon comparisons against L-SHADE, NL-SHADE achieves 10 wins, 30 ties, and only 2 losses. These results indicate that the proposed nonlinear population reduction mechanism improves the search behavior of L-SHADE and enhances its robustness across different solar energy optimization tasks. Overall, NL-SHADE provides an effective and general optimization framework for both PV model parameter estimation and solar power generation forecasting, showing promising practical value for PV system analysis, forecasting, and operation-related decision support.



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1. Introduction

With the rapid growth of urbanization and industrial development, global electricity demand has increased substantially [1]. Meanwhile, the environmental consequences

of fossil fuel consumption, such as greenhouse gas emissions and increasingly frequent extreme climate events, have motivated countries worldwide to accelerate the transition toward clean and sustainable energy systems [2]. Among various renewable energy sources, solar energy has attracted extensive attention due to its environmental friendliness, abundant availability, and relatively low operational cost [3]. Among solar-related studies, photovoltaic (PV) systems have become one of the most widely adopted technologies because of their high energy conversion efficiency and flexible deployment characteristics [4]. Among various research topics in PV systems, PV model parameter estimation and solar power generation forecasting have received extensive attention because they directly influence system efficiency and operational reliability. Accurate parameter estimation improves PV system modeling accuracy and energy conversion efficiency, while reliable power forecasting contributes to grid scheduling and operational stability. Therefore, improving both tasks is of considerable importance for the development of intelligent solar energy systems. In recent years, research on solar energy systems has gradually expanded from power generation efficiency enhancement to intelligent monitoring, anomaly diagnosis, and performance maintenance, highlighting the growing demand for advanced optimization and data-driven techniques in practical PV applications.

PV parameter estimation aims to identify the optimal parameters of PV models under specific operating conditions [5]. Since this process can be formulated as a complex optimization problem, numerous studies have introduced Meta-Heuristic Algorithms (MHAs) to improve estimation accuracy. Classical MHAs include Genetic Algorithm (GA) [6], Particle Swarm Optimization (PSO) [7], and Gravitational Search Algorithm (GSA) [8]. Among them, Differential Evolution (DE) [9] has demonstrated highly competitive performance in PV parameter estimation. Advanced DE variants and adaptive optimization methods have further enhanced estimation accuracy through adaptive parameter control and problem-oriented search mechanisms [10–12]. Representative approaches such as DPDE have achieved promising results by incorporating PV-specific optimization strategies [13]. More recently, hybrid and adaptive metaheuristic frameworks have become an important trend in PV-related optimization, since they can integrate complementary search mechanisms and improve robustness under nonlinear and multimodal energy-system optimization scenarios. In addition, recent studies have explored hybrid metaheuristic optimization methods for renewable energy applications. By combining complementary search mechanisms from different optimization algorithms, these approaches can enhance convergence performance and solution quality. For instance, hybrid chaotic GWO–PSO algorithms have been successfully applied to maximum power point tracking (MPPT) problems in photovoltaic arrays, achieving improved tracking accuracy and dynamic response under varying environmental conditions [14]. Similar hybrid optimization strategies have also been employed in PV parameter estimation and PEMFC parameter identification, demonstrating the growing importance of advanced metaheuristic techniques in energy system optimization. Nevertheless, existing methods still face challenges in balancing problem specificity and generalization capability. Algorithms tailored for PV parameter estimation may exhibit limited applicability across different tasks, whereas general-purpose optimization frameworks may not fully exploit the nonlinear characteristics inherent in PV-related problems.

Solar power generation forecasting is another critical issue in solar energy systems because accurate prediction contributes directly to grid security and efficient energy utilization [15,16]. Unstable power generation may lead to grid imbalance and reduce operational reliability [17]. Therefore, accurate forecasting can assist system operators in generation scheduling, resource allocation, and energy management [18]. However, solar power generation forecasting is inherently challenging because generation output

is strongly affected by environmental conditions and temporal variations. Existing forecasting studies mainly rely on data-driven methods and neural network models, including ANN and LSTM [19]. Recent studies have increasingly adopted hybrid deep-learning architectures to improve the accuracy and robustness of solar energy applications. By integrating convolutional neural networks (CNNs), transformer-based models, and attention mechanisms, these approaches can effectively capture both spatial and temporal characteristics of solar-related data. For example, hybrid CNN–ViT frameworks have recently been applied to anomaly detection in solar farms, demonstrating superior monitoring accuracy and operational efficiency compared with conventional deep-learning models [20]. These developments indicate that advanced neural architectures have become an important research direction for intelligent solar energy systems. Although these approaches have demonstrated promising predictive performance, their training procedures are often computationally expensive and may struggle under rapidly changing environmental conditions. More recently, Dendritic Neuron Model (DNM) has emerged as an effective framework for time-series forecasting problems [21,22]. Since DNM can be trained using evolutionary algorithms, integrating advanced optimization algorithms with DNM may further improve prediction performance [23].

Although PV parameter estimation and solar power generation forecasting correspond to different stages of solar energy systems, they are closely related to the modeling accuracy, energy utilization efficiency, and operational reliability of PV systems. Moreover, both tasks exhibit nonlinear interactions, uncertainty, and complex search landscapes, making them difficult to solve using simple optimization strategies. Therefore, developing a unified optimization framework capable of addressing both problems is meaningful, as it can provide a more comprehensive optimization perspective for solar energy applications.

Previous studies have reported that algorithms demonstrating superior performance on IEEE CEC benchmark suites do not always achieve the best results on real-world problems [24]. Therefore, selecting optimization algorithms solely according to benchmark rankings may not be sufficient [25]. Among existing DE variants, L-SHADE has established a strong reputation because of its adaptive mechanisms and robust performance across various optimization domains. Although L-SHADE achieved competitive results in our preliminary experiments on both PV parameter estimation and power forecasting tasks, it did not consistently provide the best performance. Therefore, further improvement in L-SHADE remains necessary for solar-related optimization problems.

Many solar-related optimization problems exhibit nonlinear characteristics and complex search behaviors [26]. Therefore, introducing nonlinear techniques into optimization algorithms may provide additional advantages [4]. Motivated by this observation, this study proposes a new algorithm called NL-SHADE, which enhances L-SHADE through a sigmoid-based nonlinear strategy. The proposed design adaptively regulates population reduction behavior while preserving algorithm simplicity and computational efficiency. To evaluate the performance of NL-SHADE, six PV parameter estimation benchmark problems and solar power generation forecasting datasets are employed. Comparisons are conducted with representative optimization algorithms, prediction methods, and evolutionary learning approaches.

The main contributions of this paper are summarized as follows:

- (1) A common NL-SHADE-based optimization framework is employed to address two representative solar-energy-related parameter optimization tasks, namely PV model parameter estimation and solar power generation forecasting. In this framework, NL-SHADE is used to optimize the unknown parameters of different PV models and the parameters of the DNM-based forecasting model, allowing the optima-

tion capability of the proposed method to be evaluated across different solar energy applications under a unified parameter optimization perspective.

- (2) A sigmoid-based nonlinear population reduction strategy is introduced into L-SHADE to construct NL-SHADE. This strategy provides more flexible control over the balance between exploration and exploitation, thereby improving the adaptability of the algorithm to nonlinear solar energy optimization problems.
- (3) To further investigate the optimization behavior of the proposed method, a Population Interaction Network based analysis is introduced. Comparative analysis is conducted on the population interaction structures of SHADE, L-SHADE, and NL-SHADE to reveal how the proposed nonlinear population reduction mechanism influences the search behavior of the algorithm.
- (4) Extensive experiments are conducted on six PV parameter estimation benchmark problems and 14 solar power generation forecasting datasets. Combined with Wilcoxon rank-sum tests and Friedman ranking analysis, the experimental results verify the effectiveness, competitiveness, and robustness of NL-SHADE in both solar-energy-related optimization tasks.

This paper is organized as follows: In Section 2, the model of the relevant problem is presented. Sections 3 introduces the techniques used in NL-SHADE and describe the proposed algorithm. Section 4 presents the experimental data and comparison results, followed by an analysis of the results. Section 5 provides a discussion of NL-SHADE, including potential future applications. Finally, a conclusion is drawn in Section 6.

2. Problem Formulation

2.1. PV Parameter Estimation Model

Research on PV parameter estimation commonly involves several representative models, including the single-diode model (SDM) [27], double-diode model (DDM) [28], triple-diode model (TDM) [29], and PV module model (MM) [30]. The corresponding equivalent circuits are shown in Figure 1, where Figure 1a–d correspond to SDM, DDM, TDM, and MM, respectively [13]. These benchmark PV models can be formulated as parameter optimization problems, in which the unknown model parameters are iteratively identified by minimizing the root mean square error (RMSE) between the measured and estimated current–voltage characteristics.

The experiments considered different configurations of diodes connected either in series (N_s) or in parallel (N_p). Experimental current–voltage data were collected from a commercial RTC France silicon solar cell with a diameter of 57 mm under a temperature of 33 °C. The dataset contains 26 current–voltage pairs for SDM ($N_s = N_p = 1$), DDM ($N_s = 1, N_p = 2$), and TDM ($N_s = 1, N_p = 3$).

For MM, current–voltage datasets from three PV modules, namely Photowatt-PWP201, STP6-120/36, and STM6-40/36, were employed. The Photowatt-PWP201 module consists of 36 polycrystalline silicon cells connected in series ($N_s = 36, N_p = 1$), from which 25 current–voltage samples were obtained at 45 °C under an irradiance of 100 W/m². Similarly, the STP6-120/36 module manufactured by Schutten Solar contains the same series configuration and provides 24 measured current–voltage pairs at 55 °C. The STM6-40/36 module, also produced by Schutten Solar with an identical cell configuration, contributes 20 measured current–voltage pairs collected at 51 °C. The lower and upper bounds of parameter extraction for each model are summarized in Table 1.

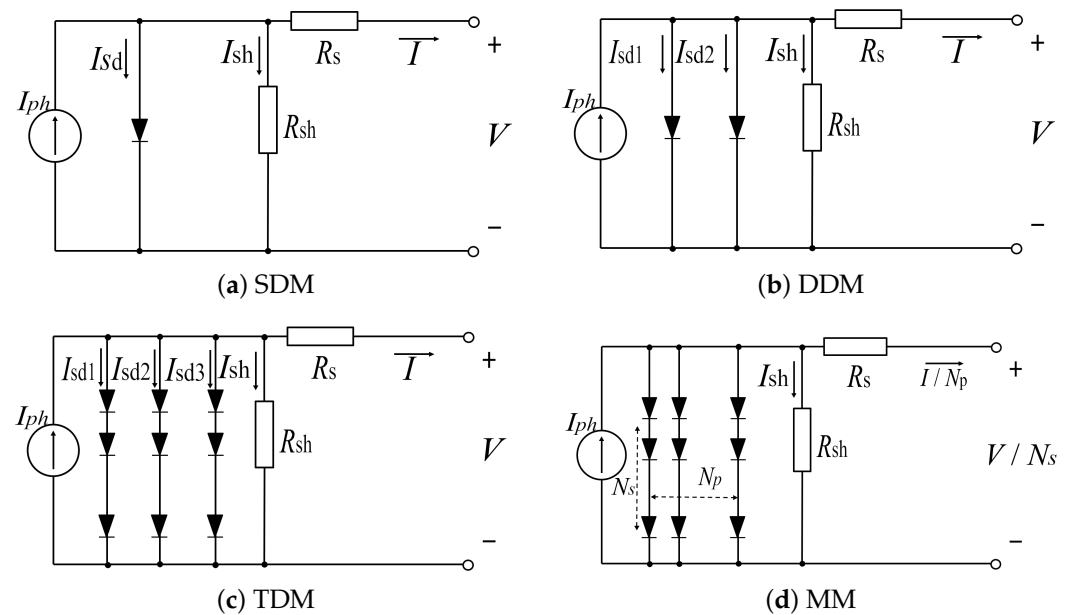


Figure 1. Equivalent circuit models of four representative photovoltaic models: (a) single-diode model (SDM), (b) double-diode model (DDM), (c) triple-diode model (TDM), and (d) PV module model (MM).

Table 1. Range of parameter estimates for PV problems.

Parameter	SDM or DDM or TDM		MM					
	lb	ub	Photowatt-PWP-201		STP6-120/36		STM6-40/36	
			lb	ub	lb	ub	lb	ub
$I_{ph}(A)$	0	1	0	2	0	8	0	2
$I_{sd}(\mu A), I_{sd1}(\mu A), I_{sd2}(\mu A), I_{sd3}(\mu A)$	0	1	0	50	0	50	0	50
$\alpha, \alpha_1, \alpha_2, \alpha_3$	1	2	1	50	1	50	1	60
$R_s(\Omega)$	0	0.5	0	2	0	0.36	0	0.36
$R_{sh}(\Omega)$	0	100	0	2000	0	1500	0	1000

Therefore, accurate parameter extraction is essential for describing the electrical characteristics and improving the modeling accuracy of PV systems.

2.2. Time-Series Prediction Model

Unlike conventional optimization problems, solving time-series prediction tasks using evolutionary algorithms generally requires artificial neural structures as learning tools. Prediction tasks, classification tasks, and many practical optimization problems are often characterized by uncertainty and the absence of explicit global optimum solutions. Therefore, directly employing evolutionary algorithms for parameter optimization may easily result in severe overfitting. A more suitable strategy is to combine optimization algorithms with artificial neural structures. Such a hybrid framework not only enhances optimization effectiveness but also provides a simpler and computationally efficient alternative compared with many existing neural models.

Figure 2 presents the Belgium-PV power generation curve adopted in this study [31]. Since publicly available datasets are generally provided only as temporal sequences, an appropriate modeling framework is required to transform the raw data into a representation suitable for optimization algorithms. For time-series prediction tasks, future outputs are typically estimated according to previous observations. Therefore, before conducting the learning process, the training data are reconstructed into temporal vectors. Specifically,

the first vector contains ordered samples from $[1, n - 1]$, while the second vector contains samples from $[2, n]$, where n denotes the total number of observations in the training set. These two vectors are subsequently combined into a two-row matrix serving as the final training input. Generally, increasing the number of input rows can improve prediction accuracy. However, practical prediction applications require both rapid learning speed and adaptive updating capability. Therefore, the adopted two-row modeling strategy achieves a favorable compromise between computational efficiency and predictive performance.

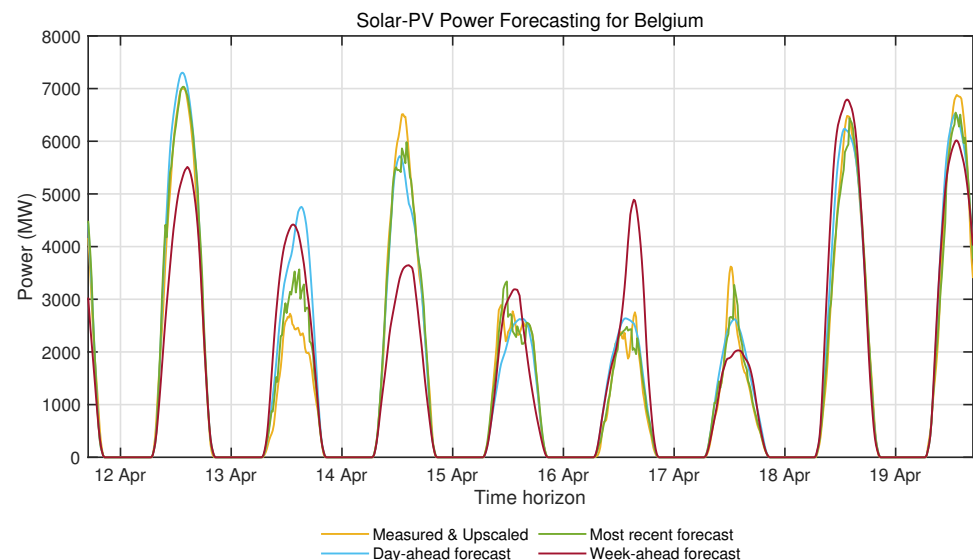


Figure 2. Belgium-PV power generation curve.

During practical deployment, prediction systems are typically evaluated through continuous forecasting and iterative error updating over time, where newly observed information can be incorporated into the training process for dynamic model updating. However, repeatedly retraining neural structures generally requires substantial computational resources. Therefore, in this study, the entire test set is directly utilized for one-time evaluation by calculating prediction errors. Although this approach slightly reduces real-time adaptability, it enables efficient assessment while preserving predictive capability. Furthermore, the dataset is divided into multiple daily sub-problems because solar power generation is strongly influenced by weather variations and environmental conditions. Recent climate fluctuations and increasingly frequent extreme weather events further increase forecasting difficulty, while the absence of solar power generation during nighttime introduces additional challenges for long-term prediction. Consequently, modeling local fluctuation patterns within shorter temporal intervals becomes more suitable for capturing dynamic characteristics and improving prediction accuracy. As discussed above, integrating optimization algorithms with lightweight neural structures enables rapid model updating and efficient prediction capability. Therefore, an effective temporal learning framework should possess both fast training ability and strong predictive performance. Motivated by these requirements, DNM is introduced as the prediction model and will be described in the following subsection.

2.3. Dendritic Neuron Model

To establish an efficient prediction framework, DNM is adopted due to its compact structure and rapid learning capability. Compared with many conventional neural structures, DNM provides a relatively lightweight architecture while maintaining favorable learning performance, making it suitable for integration with optimization algorithms.

Figure 3 illustrates the training process of DNM together with the implemented “pruning” mechanism. During information transmission from dendrites, synapses carrying a signal value of “0” are removed because they do not contribute to the training process and cannot activate the soma for problem-solving. In certain extreme situations, the dendritic structure may be simplified to a single dendrite, allowing only one signal set to be delivered to the soma. Nevertheless, under most circumstances, multiple signal sets are simultaneously transmitted to the soma. The adaptation capability of DNM is evaluated according to the error between model outputs and target values, thereby completing one iteration of the learning process.

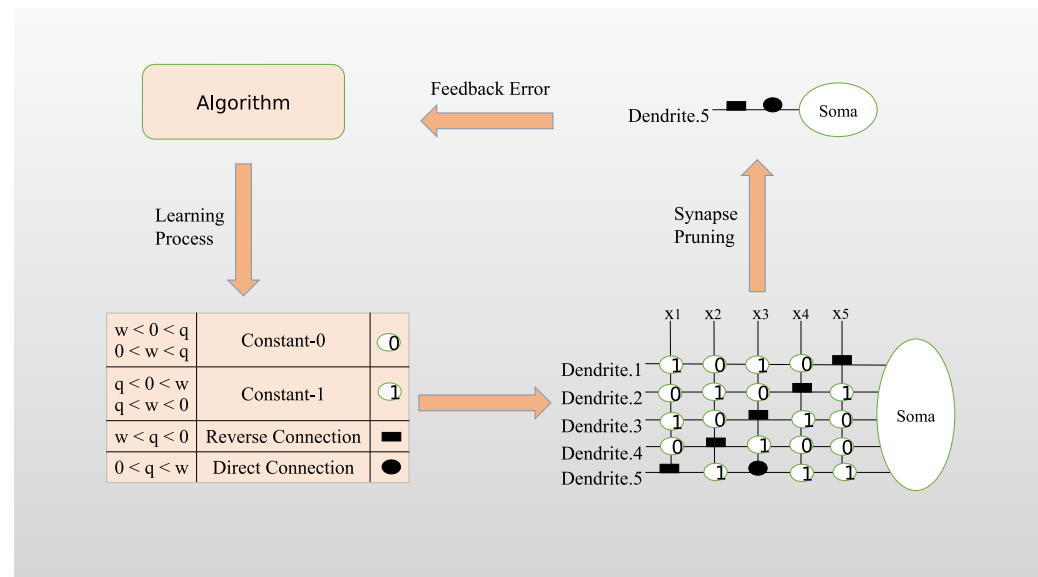


Figure 3. Training process of DNM.

DNM consists of several key structures, including synapses, dendrites, soma, and axons. Dendrites receive input signals, soma integrates incoming information and generates outputs, while axons are responsible for transmitting output signals. Through cooperation among these structures, DNM can perform complex information processing and nonlinear mapping. The mathematical operations of the synaptic, dendritic, and soma layers adopted in this study follow the standard DNM formulation reported in previous studies [32,33]. The synaptic layer is formulated as follows:

$$Y_{i,j} = \frac{1}{1 + e^{-k \cdot (w_{i,j} \cdot x_i - q_{i,j})}} \quad (1)$$

where the synaptic layer of DNM is characterized by the input index (i) and synaptic index (j). During DNM training, adaptive parameters are represented by $w_{i,j}$ and $q_{i,j}$, whereas x_i denotes normalized input data. In addition, a positive constant (k) is introduced into the formulation. Depending on the relationship between $w_{i,j}$ and $q_{i,j}$, four distinct connection patterns can be generated, namely direct, reverse, Constant-0, and Constant-1 connections, which are described as follows:

- When $0 < q_{i,j} < w_{i,j}$, a direct connection is established. Under this condition, $Y_{i,j}$ approaches 1 if $x_i > \theta_{i,j}$; otherwise, it approaches 0. Therefore, the synaptic output behaves similarly to the input signal.
- When $w_{i,j} < q_{i,j} < 0$, a reverse connection occurs. Specifically, if $x_i > \theta_{i,j}$, output $Y_{i,j}$ gradually approaches 0. Otherwise, when $x_i \leq \theta_{i,j}$, it approaches 1. Consequently, the output exhibits an inverse relationship with the input signal.

- When $0 < w_{i,j} < q_{i,j}$ or $w_{i,j} < 0 < q_{i,j}$, a Constant-0 connection is formed. In this situation, the output remains approximately zero regardless of input values.
- When $q_{i,j} < w_{i,j} < 0$ or $q_{i,j} < 0 < w_{i,j}$, a Constant-1 connection is established. Under these conditions, the corresponding output consistently approaches one.

Where $\theta_{i,j}$ is calculated as:

$$\theta_{i,j} = \frac{q_{i,j}}{w_{i,j}} \quad (2)$$

After synaptic processing, DNM performs dendritic aggregation using multiple signal branches. The cumulative multiplication of synaptic outputs can be expressed as:

$$Z_j = \prod_{i=1}^N Y_{i,j} \quad (3)$$

The multiplication results are subsequently accumulated to generate the final output of the dendritic layer. During this process, branches producing a “0” output are automatically pruned because multiplication with zero removes the influence of that branch. The accumulation process is formulated as:

$$V = \sum_{j=1}^M Z_j \quad (4)$$

Finally, an additional sigmoid function is applied within the soma layer to generate the neuron output. This process produces a pulsed electrical signal ranging from 0 to 1, where the activation threshold is controlled through soma stimulation parameter O_{soma} . The soma function is expressed as:

$$H = \frac{1}{1 + e^{-k \cdot (V - O_{soma})}} \quad (5)$$

where H represents the final output of DNM, O_{soma} denotes a positive constant associated with soma stimulation, and k is identical to the constant defined in Equation (1).

In this study, DNM is employed as a one-step-ahead forecasting model for solar power generation. To construct the prediction samples, phase-space reconstruction (PSR) is adopted for each time-series dataset. Specifically, the embedding dimension and time delay are set to $m = 2$ and $\tau = 1$, respectively. Therefore, each input sample consists of two historical observations, and the corresponding target output is the solar power value at the next time step. After sample construction, each dataset is divided into training and testing subsets with a ratio of 70%:30%.

For the forecasting model used in this study, the DNM structural hyperparameters are fixed as follows. The number of input nodes is $N = 2$, corresponding to the two reconstructed historical observations. The number of dendritic branches is set to $M = 10$. In addition, the sigmoid slope parameter is set to $k = 5$, and the soma stimulation threshold is set to $O_{soma} = 1$. Accordingly, the trainable parameter set of DNM consists of the synaptic weight matrix w and threshold matrix q , and the total optimization dimension is $D = 2 \times N \times M = 40$.

To train the DNM forecasting model, the proposed NL-SHADE is employed to optimize the DNM parameters w and q . The maximum number of function evaluations is set to 50,000. Following the default setting of NL-SHADE, the initial population size is determined as $17D$, resulting in an initial population size of 680 in the present forecasting task. During optimization, the objective function is defined as the mean squared error (MSE) between the DNM outputs and the target values on the training set. Through this

optimization process, the DNM parameters are iteratively updated until the stopping criterion is satisfied, and the optimized model is then used for solar power generation forecasting on the testing set.

3. The Proposed NL-SHADE

3.1. Differential Evolution

Differential Evolution (DE), originally introduced by R. Storn and K. Price in the late twentieth century [12], has been extensively applied to a wide range of optimization tasks because of its fast convergence behavior and efficient search capability. In recent years, numerous studies have focused on enhancing DE [34], and many variants have demonstrated competitive performance in benchmark optimization competitions. The DE framework mainly consists of four stages: initialization, mutation, crossover, and selection.

During initialization, a population consisting of N individuals is randomly generated within the predefined search boundaries, where N denotes the population size and D represents the dimensionality of the optimization problem. Following the classical DE framework [8,35], each individual corresponds to a candidate solution and can be represented as:

$$X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,D}\}, \quad i \in \{1, 2, \dots, N\}. \quad (6)$$

The population size directly affects the search behavior of DE. A larger population generally provides stronger diversity and exploration capability, while a smaller population often improves convergence efficiency. Therefore, adaptive population adjustment strategies have become an important mechanism in many advanced DE variants. Among the evolutionary stages, the selection process adopts a greedy mechanism, in which newly generated individuals are preserved only when their fitness values outperform those of their corresponding individuals from the previous generation. In classical DE, commonly used mutation strategies include DE/rand/1, DE/best/1, and DE/current-to-best/1, together with binomial crossover [8,35]. Their formulations are given as follows:

(1) DE/rand/1

$$V_{i,j} = X_{r1,j} + F \cdot (X_{r2,j} - X_{r3,j}), \quad (7)$$

(2) DE/best/1

$$V_{i,j} = X_{best,j} + F \cdot (X_{r2,j} - X_{r3,j}), \quad (8)$$

(3) DE/current-to-best/1

$$V_{i,j} = X_{i,j} + F \cdot (X_{best,j} - X_{i,j} + X_{r1,j} - X_{r2,j}), \quad (9)$$

Here, $X_{i,j}$ denotes the j -th dimension of the i -th individual in the population, while F represents the scaling factor. $X_{best,j}$ corresponds to the best individual currently available in the population. In addition, $r1$, $r2$, and $r3$ are mutually distinct integers randomly selected from $\{1, 2, \dots, N\}$. The crossover operation can be formulated as:

$$U_{i,j} = \begin{cases} V_{i,j}, & \text{if } rand < C_R \\ X_{i,j}, & \text{otherwise} \end{cases} \quad (10)$$

where C_R denotes the crossover rate of DE and $rand$ is a random number generated within $[0, 1]$. This operation controls the probability of updating each dimension according to C_R . By modifying only part of the dimensions while preserving the remaining components, individuals are encouraged to explore more diverse search directions, thereby improving the search capability of the algorithm.

SHADE extends classical DE by introducing a success-history based parameter adaptation mechanism, in which the scaling factor F and crossover rate CR are sampled from historical memories according to [36]:

$$\begin{aligned} F_i &= \mathcal{C}(M_{F,r}, 0.1) \\ C_{Ri} &= \mathcal{N}(M_{C,r}, 0.1) \end{aligned} \quad (11)$$

where $\mathcal{C}$ and $\mathcal{N}$ indicate Cauchy and Normal distributions, respectively. $M_{F,r}$ and $M_{C,r}$ denote the memory archives of F and C_R .

During evolution, successful parameter values associated with offspring that outperform their parent individuals are recorded in temporary archives. At the end of each generation, these successful values are used to update the historical memories M_F and M_C . Specifically, the updated memory entries reflect the parameter settings that contribute most to successful search steps, allowing future individuals to sample F and C_R around historically effective values. Through this success-history adaptation mechanism, SHADE can dynamically adjust its search behavior and maintain a better balance between exploration and exploitation. Such adaptive parameter adjustment helps maintain a balance between exploration and exploitation, contributing to the competitive optimization capability of SHADE on benchmark problems.

3.2. NL-SHADE Nonlinear Population Size

3.2.1. Sigmoid Function

Sigmoid-type nonlinear functions have been widely adopted in machine learning and optimization-related modeling because of their smooth nonlinear transition characteristics and flexible mapping behavior [37]. Compared with linear functions, sigmoid functions usually maintain relatively flat behaviors at both ends while producing rapid changes in the middle region. Such properties make sigmoid functions suitable for controlling gradual transition processes. Figure 4 presents four representative sigmoid functions considered in this study.

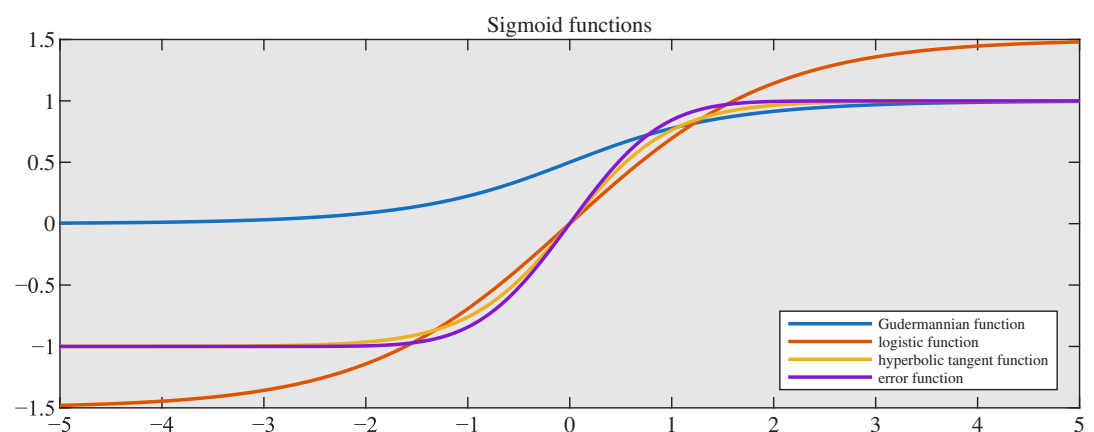


Figure 4. Distribution chart of four sigmoid functions.

- (1) Logistic sigmoid function

$$f(x) = \frac{1}{1 + e^{-x}}, \quad (12)$$

- (2) Gudermannian function

$$f(x) = 2 \cdot \arctan\left(\tanh\left(\frac{x}{2}\right)\right), \quad (13)$$

(3) Error function

$$f(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt, \quad (14)$$

(4) Hyperbolic tangent function

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \quad (15)$$

3.2.2. Nonlinear population reduction strategy

Although many optimization algorithms have been specifically designed for particular application problems, their effectiveness often relies heavily on problem characteristics and may exhibit limited generalization ability. In contrast, MHAs aim to provide robust optimization capability across different problem domains. Among advanced MHAs, L-SHADE has demonstrated competitive performance in both PV parameter estimation and time-series prediction problems. However, previous studies and preliminary experiments indicate that L-SHADE does not consistently achieve the best performance for solar energy optimization tasks. Therefore, further improving L-SHADE for solar-related applications remains meaningful.

NL-SHADE enhances L-SHADE by introducing a nonlinear sigmoid-based population reduction strategy. In L-SHADE, the population size decreases linearly during optimization, enabling a gradual transition from exploration to exploitation. However, a linear reduction mechanism may not provide sufficient flexibility for problems with different search characteristics. In practical optimization, especially for solar-related problems with nonlinear search landscapes and coupled decision variables, the early stage of the search generally requires stronger population diversity to explore multiple promising regions, whereas the later stage benefits from a more concentrated search around high-quality solutions. Therefore, instead of reducing the population at a fixed linear pace, NL-SHADE adopts a nonlinear population reduction strategy to achieve a more adaptive population evolution behavior. Since population reduction can be regarded as a smooth transition from the initial population size to the minimum population size, a logistic function is employed to regulate this evolution process. Compared with linear reduction, the proposed strategy can generate different reduction trends under various parameter settings, thereby enabling more flexible control over population diversity and convergence behavior. From this perspective, the nonlinear population schedule in NL-SHADE is designed to provide a smoother and more controllable transition between exploration and exploitation, rather than using an approximately constant reduction tendency throughout the entire optimization process.

(1) Linear population size reduction

In the original L-SHADE, the population size is reduced linearly during the optimization process using the linear population size reduction strategy proposed in [15], which can be expressed as:

$$N_{t+1} = \text{round} \left[\left(\frac{N^{\min} - N^{\text{init}}}{FES} \right) \cdot nFES + N^{\text{init}} \right], \quad (16)$$

(2) Nonlinear population size reduction

Inspired by the smooth transition property of sigmoid/logistic functions and built upon the linear population reduction framework of L-SHADE [15,37], a nonlinear population reduction strategy is proposed in this study to provide a more flexible population evolution schedule. The logistic function is adopted because it provides a smooth and monotonic transition from a relatively large population to a smaller one, which is suitable for controlling the population reduction process in DE. In particular, its curve naturally

supports a slow-to-fast reduction pattern, allowing the algorithm to preserve population diversity in the early stage while gradually strengthening exploitation in the later stage. In addition, Compared with other nonlinear functions, the logistic function is simple, interpretable, and can be conveniently controlled by the parameter p_a , making it suitable for practical implementation in the L-SHADE framework:

$$N_{t+1} = \text{round} \left[\frac{N^{\text{init}}}{1 + p_a \cdot e^{\frac{-FES}{nFES}}} \right]. \quad (17)$$

Compared with the linear population size reduction strategy adopted in L-SHADE, the nonlinear schedule in Equation (17) is introduced to provide a more flexible population evolution process. Instead of reducing the population at an approximately constant rate throughout the optimization process, the proposed sigmoid-based schedule enables different reduction rates at different search stages. Parameter p_a controls the reduction intensity of the nonlinear population schedule, allowing the population evolution behavior to be adjusted according to different search requirements. Consequently, the proposed strategy provides a smoother and more adaptive transition from exploration to exploitation than the original linear reduction mechanism.

Where N denotes the population size during optimization, N^{init} is the initial population size, N^{min} denotes the minimum population size, FES denotes the maximum number of fitness evaluations, $nFES$ denotes the current number of fitness evaluations, and $\text{round}(\cdot)$ rounds the calculated population size to the nearest integer. Parameter p_a is a control constant that regulates the reduction intensity of the nonlinear population schedule. During optimization, the current number of fitness evaluations $nFES$ gradually increases from 0 to FES , resulting in a smooth nonlinear adjustment of the population size according to Equation (17).

The rationale behind this design is closely related to the search characteristics of differential evolution. Population size directly influences the diversity of candidate solutions and the richness of differential mutation combinations. A relatively larger population is generally beneficial during the early search stage because it preserves diverse search directions, enhances global exploration, and reduces the risk of premature convergence. As the optimization proceeds and promising regions are gradually identified, a faster population reduction helps eliminate redundant individuals, concentrates the search around high-quality solutions, and improves exploitation efficiency. Therefore, compared with the original linear reduction strategy, the proposed nonlinear schedule provides a stage-aware population evolution mechanism that better coordinates the transition from exploration to exploitation.

This characteristic is particularly beneficial for the two optimization tasks considered in this work. In PV parameter estimation, the search landscape is highly nonlinear due to the coupling among multiple model parameters and the nonlinear current–voltage relationship. In solar power generation forecasting, the optimization process involves training the dendritic neuron model (DNM) using time-series data, where different optimization stages may exhibit different search characteristics. Consequently, a nonlinear population reduction strategy with adjustable reduction intensity is expected to provide better adaptability than a fixed linear population reduction rule.

Figure 5 compares the population reduction processes of NL-SHADE and L-SHADE. Compared with the linear population reduction strategy employed in L-SHADE, the proposed nonlinear schedule maintains a relatively larger population during the early search stage to preserve population diversity and strengthen global exploration. As the optimization progresses, the population size decreases more rapidly, enabling the algorithm to gradually shift its search focus toward local exploitation and convergence. Consequently,

the proposed stage-aware population evolution mechanism provides a more flexible balance between exploration and exploitation throughout the optimization process. To further verify that the performance improvement originates from the proposed nonlinear population reduction mechanism rather than an arbitrary nonlinear function, a comparative study on four representative sigmoid-based nonlinear functions is presented in Section 4.4.1. The corresponding results further support the selection of the logistic function as the nonlinear population reduction strategy adopted in NL-SHADE. In the update process of F and C_R , NL-SHADE retains the successful historical parameter adaptation mechanism inherited from SHADE and L-SHADE.

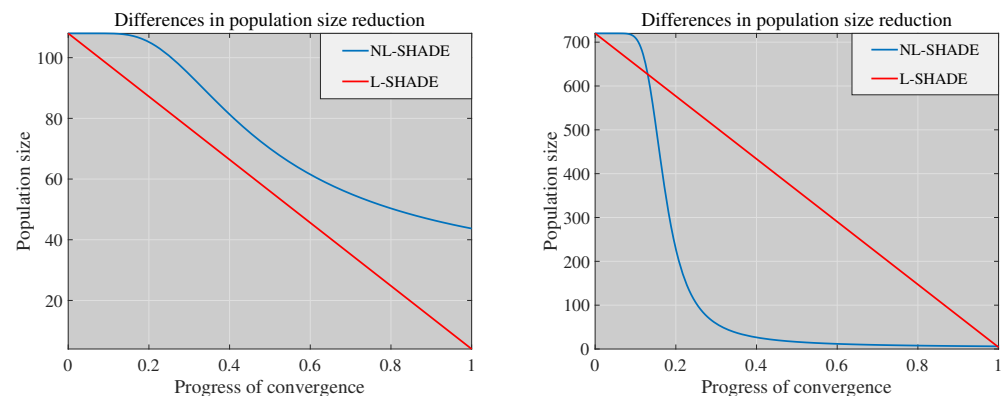


Figure 5. Population reduction process of NL-SHADE and L-SHADE.

Figure 6 presents the population reduction curves of NL-SHADE under different parameter settings. It can be observed that decreasing parameter p_a slows the population reduction process and thus maintains a larger population during optimization, whereas increasing p_a accelerates the reduction process. Therefore, parameter p_a can be used to regulate the balance between population diversity preservation and convergence pressure, providing additional flexibility for adapting NL-SHADE to different optimization tasks. A more detailed analysis of the effect of p_a and the initial population size is provided in Section 4.4.2.

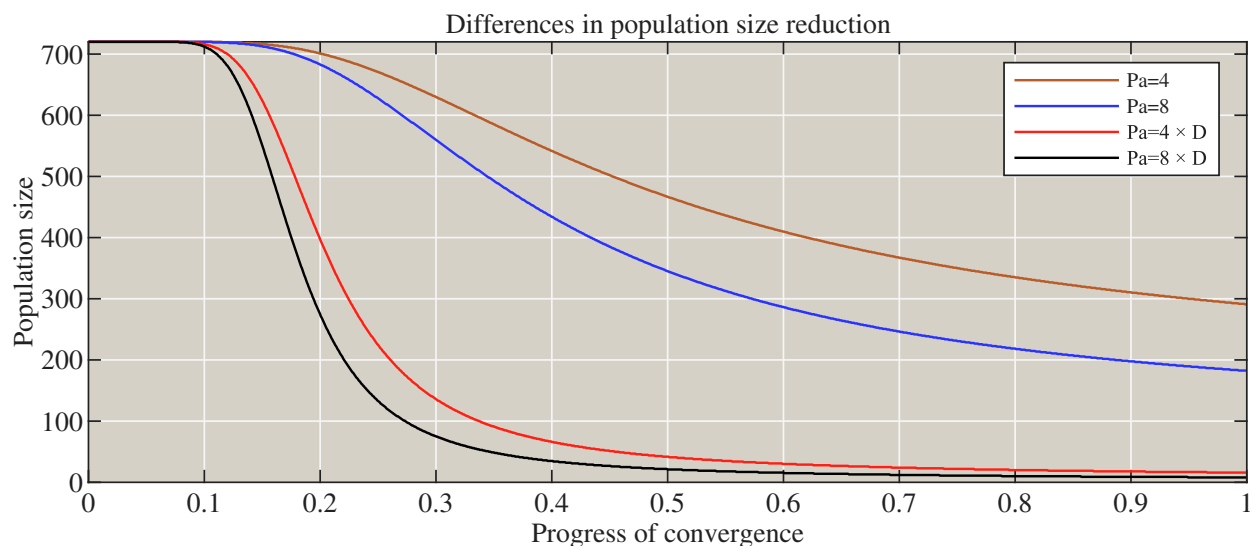


Figure 6. Population reduction process of NL-SHADE with four different parameters.

Algorithm 1 summarizes the overall procedure of NL-SHADE. The algorithm starts with population initialization and iteratively performs parameter adaptation, offspring generation, fitness evaluation, and greedy selection. After each generation, the population size

is dynamically updated according to Equation (17). Compared with L-SHADE, the primary methodological modification of NL-SHADE lies in the proposed nonlinear population reduction strategy, whereas the successful historical parameter adaptation mechanism is retained unchanged.

Algorithm 1: NL-SHADE

```

1 Input:  $FES, N^{init}, N^{min}, D, p_a$ 
2 Initialization
3  $\{X_1, X_2, \dots, X_N\}, nFES = 0$ 
4 while  $nFES \leq FES$  do
5   for  $i = 1 : N$  do
6      $F_i, C_{Ri} \leftarrow$  get the new  $F_i$  and  $C_{Ri}$ ;
7      $X_i \leftarrow$  get the new individual (Equation (9) and (10));
8     adjust the boundary of  $X_i$ ;
9      $fit_i \leftarrow$  evaluate  $X_i$ ;
10     $X_i \leftarrow$  select the new individual;
11     $nFES = nFES + 1$ ;
12  end
13  if  $N > N^{min}$  then
14     $N \leftarrow$  update the population size (Equation (17));
15     $X_i \leftarrow i \in [1, N]$  retain  $N$  individuals;
16     $fit_i \leftarrow i \in [1, N]$  retain  $N$  fitness;
17  else
18     $N \leftarrow N^{min}$ ;
19     $X_i \leftarrow i \in [1, N]$  retain  $N$  individuals;
20     $fit_i \leftarrow i \in [1, N]$  retain  $N$  fitness;
21  end
22 end
23 Return optimal
  
```

The evaluation process of NL-SHADE varies across different application scenarios. For PV parameter estimation, optimization individuals can be directly evaluated according to model errors. In contrast, for solar power generation forecasting, candidate solutions are assessed through prediction errors generated by the DNM framework. Therefore, although the optimization framework remains unchanged, the evaluation mechanism differs according to specific application tasks.

4. Experimental Results

In this section, NL-SHADE is evaluated on two representative solar energy tasks, namely PV parameter estimation and solar power generation forecasting. To assess its effectiveness, comparisons are conducted with representative optimization algorithms for PV parameter estimation and with both optimization-based DNM training methods and neural-network-based forecasting models for solar power generation forecasting. Statistical significance is evaluated using Wilcoxon's rank-sum test at a significance level of 0.05 together with Friedman ranking analysis. Detailed experimental settings, compared methods, and parameter configurations are presented in the following subsection.

4.1. Experimental Settings

For PV parameter estimation, the compared algorithms include DE-based methods, namely L-SHADE [38], DPDE [13], SHADE [11], BDE [39], and JADE [40], as well as

other metaheuristic optimization algorithms, including SIS [41], GLPSO [42], DMSIS [43], and MRSE [35]. These methods were selected because they cover both classical and advanced evolutionary optimization paradigms, and several of them, such as DPDE and L-SHADE, have already demonstrated competitive performance on PV-related optimization problems. Therefore, they provide strong and meaningful baselines for evaluating the optimization capability of NL-SHADE on PV parameter estimation tasks.

For solar power generation forecasting, two groups of comparison methods are considered. The first group consists of DNM-based training methods, including L-SHADE [38], SHADE [11], BP [44], DPDE [13], BDE [39], DMSIS [43], and MRSE [35], which are used to evaluate the effectiveness of different optimization strategies for training DNM. The second group contains representative neural-network-based forecasting models, namely MLP [45], ANFIS [45], LSTM [46], and RNN [47], which are widely used in time-series forecasting problems and therefore provide important forecasting baselines beyond optimization-based DNM training. In this way, the experimental comparisons cover classical training approaches, advanced DE-based optimizers, other metaheuristic methods, and mainstream neural forecasting models, enabling a comprehensive evaluation of NL-SHADE from both optimization and forecasting perspectives.

To ensure fairness and robustness, each algorithm was independently executed 30 times in all experiments. For optimization-based methods, the maximum number of function evaluations (FES) is uniformly set to 50,000 in both PV parameter estimation and solar power generation forecasting tasks. All experiments were conducted on a personal computer equipped with an Intel i7-9700 CPU and 16 GB RAM. For the forecasting task, 14 single-day solar power generation datasets were employed. These datasets were derived from Belgian grid PV generation records provided by opendata.elia. To facilitate reproducibility, the source codes and forecasting datasets used in this study are publicly available at https://github.com/louiseklocky/solar_energy (accessed on 8 June 2026). The parameter settings of all compared methods are summarized in Table 2.

For the Wilcoxon rank-sum test, $W/T/L$ denotes the numbers of benchmark cases in which NL-SHADE performs significantly better than, statistically equivalent to, or worse than the compared algorithm, respectively. In PV parameter estimation, the $W/T/L$ results are summarized over the six benchmark problems, while in solar power generation forecasting they are calculated over 14 datasets and three evaluation metrics, resulting in 42 pairwise comparisons for each algorithm pair. In addition, Friedman ranking analysis is employed to evaluate the overall performance of all compared methods across multiple benchmark problems or datasets.

Table 2. Parameter settings of all compared algorithms.

Parameter Estimation of Solar PV Models	
Algorithm	Parameter Settings
NL-SHADE	$N^{init} = 17 \times D$, $p = 0.11$, $p_a = 9 \times D$
SIS	$b \in (0, 0.1]$, $r = 4$
GLPSO	$\omega = 0.7298$, $pm = 0.01$, $c = 1.49618$, $sg = 7$
DPDE	$N^{init} = 18 \times D$, $p = 0.11$, $H = 5$
L-SHADE	$N^{init} = 18 \times D$, $p = 0.11$, $H = 5$
SHADE	$N = 100$, $p = 0.2$, $H = 100$
JADE	$N = 100$, $p = 0.05$
BDE	$F_0 = 0.5$, $CR_0 = 0.1$, $n = 0.05$
DMSIS	$Z = 6$, $La = 3$, $b \in (0, 0.1]$, $r = 4$
MRSE	$N = 100$, $La = 6$

Table 2. Cont.

Solar Power Generation Forecasting		
Algorithm	Parameter Settings	
NL-SHADE	$N^{init} = 17 \times D$, $p = 0.11$, $p_a = 9 \times D$	
L-SHADE	$N^{init} = 18 \times D$, $p = 0.11$, $H = 5$	
SHADE	$N = 100$, $p = 0.2$, $H = 100$	
DPDE	$N^{init} = 18 \times D$, $p = 0.11$, $H = 5$	
BDE	$F_0 = 0.5$, $CR_0 = 0.1$, $n = 0.05$	
DMSIS	$Z = 6$, $La = 3$, $b \in (0, 0.1]$, $r = 4$	
MRSE	$N = 100$, $L_a = 6$	
BP	Learning rate	0.1
BP	Dendrite number	10
MLP	Learning rate	0.1
MLP	Hidden layer number	15
ANFIS	Initial step size	0.01
ANFIS	Step size decrease rate	0.9
ANFIS	Step size increase rate	1.1
LSTM	Learning rate	0.1
LSTM	Learning rate drop factor	0.1
RNN (Elman Network)	Learning rate	0.01

4.2. Parameter Estimation of Solar PV Models

To comprehensively evaluate the effectiveness of NL-SHADE in PV parameter estimation tasks, six benchmark problems involving both solar cells and PV modules are considered in this study. These benchmark models are widely used for evaluating optimization algorithms because they contain nonlinear current–voltage relationships, coupled parameters, and multimodal search characteristics. The experimental results are summarized in Tables 3–8, where the average estimated parameters, the mean RMSE over 30 independent runs, the best RMSE obtained among 30 runs, and the corresponding *W/T/L* results are reported. In addition, Table 9 further summarizes the overall *W/T/L* comparison of NL-SHADE against all competing algorithms over the six PV parameter estimation problems.

Overall, the results indicate that NL-SHADE achieves highly competitive performance on all six PV parameter estimation benchmarks. However, it should also be noted that the difficulty of these benchmark problems is relatively limited for advanced DE-based optimizers. In particular, DPDE and L-SHADE have already been validated as strong algorithms for PV parameter estimation in previous studies, and the present results confirm that several advanced methods are able to reach very similar solutions on these problems. This phenomenon can be clearly observed from Tables 3–8, where the differences among NL-SHADE, DPDE, and L-SHADE are often extremely small, and in several cases their best RMSE values are identical within the reported precision. Therefore, the main purpose of this section is not to claim that NL-SHADE produces dramatically lower RMSE values on every PV benchmark, but rather to examine whether the proposed nonlinear population reduction strategy can provide a more stable and consistently competitive optimization behavior across multiple PV parameter estimation problems.

For the French R.T.C. solar cell models, Tables 3–5 report the results on SDM, DDM, and TDM, respectively. In Table 3, NL-SHADE, DPDE, and L-SHADE achieve exactly the same mean RMSE and best RMSE values on SDM, while all three methods also outperform the remaining competitors in terms of estimation accuracy. This result suggests that the SDM problem is relatively easy for advanced DE-based optimizers, and once the search process enters the high-quality region, multiple algorithms can converge to nearly identical

solutions. A similar phenomenon can also be observed from the estimated parameter values, where the results of NL-SHADE, DPDE, and L-SHADE are almost indistinguishable within the reported precision.

Table 3. Comparison of average estimated parameters, mean RMSE, and best RMSE values on SDM over 30 independent runs.

Algorithm	I_{ph} (A)	I_{sd} (μ A)	R_s (Ω)	R_{sh} (Ω)	α	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	0.761	0.000	0.036	53.719	1.481	0.000986022	0.000986022	
DPDE	0.761	0.000	0.036	53.719	1.481	0.000986022	0.000986022	=
L-SHADE	0.761	0.000	0.036	53.719	1.481	0.000986022	0.000986022	=
SHADE	0.479	0.000	0.236	48.704	1.356	0.000986022	0.000986022	+
JADE	0.761	0.000	0.036	0.605	1.484	0.000997057	0.000986022	+
SIS	0.497	0.000	0.264	42.403	1.469	0.002296751	0.001118865	+
GLPSO	0.761	0.000	0.035	71.318	1.528	0.001491679	0.000987823	+
BDE	0.761	0.000	0.033	78.301	1.552	0.002021292	0.001333633	+
DMSIS	0.761	0.000	0.033	62.430	1.551	0.001990302	0.001024909	+
MRSE	0.761	0.000	0.033	79.581	1.545	0.001559393	0.001056883	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

Table 4. Comparison of average estimated parameters, mean RMSE, and best RMSE values on DDM over 30 independent runs.

Algorithm	I_{ph} (A)	I_{sd1} (μ A)	R_s (Ω)	R_{sh} (Ω)	α_1	I_{sd2} (μ A)	α_2	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	0.761	0.000	0.037	55.791	1.713	4.76×10^{-7}	1.710759980	0.000988507	0.000982485	
DPDE	0.761	0.000	0.037	55.241	1.729	4.15×10^{-7}	1.687516149	0.000982822	0.000982485	+
L-SHADE	0.761	0.000	0.037	56.289	1.704	4.45×10^{-7}	1.718958704	0.001005519	0.000982485	+
SHADE	0.565	0.000	0.274	58.790	1.535	4.98×10^{-7}	1.515840047	0.001169408	0.000993787	+
JADE	0.761	0.000	0.036	62.721	1.674	2.42×10^{-7}	1.548243759	0.001140199	0.000990155	+
SIS	0.446	0.000	0.255	51.331	1.454	4.90×10^{-7}	1.428285574	0.002855786	0.001201771	+
GLPSO	0.761	0.000	0.032	87.004	1.666	5.20×10^{-7}	1.630364892	0.002233891	0.001123399	+
BDE	0.761	0.000	0.032	86.554	1.644	4.97×10^{-7}	1.638034852	0.002289994	0.001333633	+
DMSIS	0.762	0.000	0.030	57.262	1.629	6.02×10^{-7}	1.634134612	0.003172107	0.001632640	+
MRSE	0.760	0.000	0.034	79.621	1.687	3.21×10^{-7}	1.581284254	0.001566908	0.000986896	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

Table 5. Comparison of average estimated parameters, mean RMSE, and best RMSE values on TDM over 30 independent runs.

Algorithm	I_{ph}	I_{sd1} (μ A)	R_s	R_{sh}	α_1	I_{sd2} (μ A)	α_2	I_{sd3} (μ A)	α_3	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	0.761	0.000	0.037	56.630	1.696	3.10×10^{-7}	1.701437731	2.92×10^{-7}	1.681878510	0.001015634	0.000982485	
DPDE	0.761	0.000	0.037	56.454	1.591	2.68×10^{-7}	1.626287379	3.19×10^{-7}	1.746404542	0.001015548	0.000982485	+
L-SHADE	0.761	0.000	0.036	58.107	1.575	2.98×10^{-7}	1.701002895	2.73×10^{-7}	1.715739243	0.001052163	0.000982485	+
SHADE	0.488	0.000	0.299	58.567	1.446	5.29×10^{-7}	1.544397904	5.21×10^{-7}	1.462436160	0.001530931	0.001022121	+
JADE	0.761	0.000	0.035	69.932	1.682	2.18×10^{-7}	1.662373029	2.77×10^{-7}	1.667548585	0.001395313	0.001028202	+
SIS	0.560	0.000	0.296	54.310	1.481	5.53×10^{-7}	1.422962088	4.71×10^{-7}	1.518276573	0.003520675	0.001551456	+
GLPSO	0.761	0.000	0.031	88.964	1.669	5.06×10^{-7}	1.695745790	5.09×10^{-7}	1.667165644	0.002810856	0.001169145	+
BDE	0.761	0.000	0.032	88.156	1.690	4.05×10^{-7}	1.655043068	3.88×10^{-7}	1.599141245	0.002418528	0.058390393	+
DMSIS	0.762	0.000	0.030	53.868	1.676	5.32×10^{-7}	1.690372504	4.64×10^{-7}	1.666256265	0.003765729	0.001786662	+
MRSE	0.760	0.000	0.034	77.498	1.668	3.09×10^{-7}	1.728016993	2.38×10^{-7}	1.716409482	0.001518364	0.000984049	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

For the more complex DDM and TDM cases in Tables 4 and 5, the comparison becomes more subtle. In Table 4, DPDE achieves a slightly lower mean RMSE than NL-SHADE on DDM, and a similar situation also appears in Table 5 for TDM. At first glance, this may seem inconsistent with the claim that NL-SHADE is superior. However, it should be emphasized that the mean RMSE reported in Tables 4 and 5 is the average result over 30 independent runs, whereas the W/T/L results are derived from the Wilcoxon rank-sum test and therefore provide statistical evidence regarding the overall distribution of optimization performance across repeated runs. In other words, the mean RMSE reflects only the

arithmetic average of 30 runs, while the $W/T/L$ results reflect whether one algorithm tends to produce significantly better results than another in a statistical sense. Consequently, a slightly smaller mean RMSE does not necessarily imply that the corresponding algorithm is statistically more reliable or consistently better across repeated runs. In the present study, although DPDE obtains marginally smaller mean RMSE values on DDM and TDM, the differences are extremely small, and the $W/T/L$ comparisons indicate that NL-SHADE still exhibits favorable statistical performance against most competitors and remains fully competitive with the strongest baselines. Therefore, Tables 4 and 5 should be interpreted as showing that NL-SHADE, DPDE, and L-SHADE all belong to the top-performing group on these problems, while NL-SHADE maintains robust and statistically competitive behavior rather than overwhelmingly outperforming the other two methods in terms of raw RMSE alone.

A similar observation can be made for the three PV module benchmarks reported in Tables 6–8. For Photowatt-PWP201, STP6-120/36, and STM6-40/36, NL-SHADE again produces parameter estimates and RMSE values that are almost identical to those of DPDE and L-SHADE, while remaining clearly better than the other compared algorithms. In particular, on Photowatt-PWP201, NL-SHADE and DPDE obtain identical mean and best RMSE values, whereas NL-SHADE shows a better $W/T/L$ result than L-SHADE. On STP6-120/36 and STM6-40/36, NL-SHADE, DPDE, and L-SHADE again reach the same RMSE values within the reported precision. These results further support the view that the six PV parameter estimation problems do not provide a sufficiently large performance gap among the strongest DE-based algorithms, because several of them are able to locate essentially the same optimum or near-optimum solutions. Nevertheless, the fact that NL-SHADE consistently matches the best-performing algorithms while outperforming the remaining methods still demonstrates that the proposed nonlinear population reduction mechanism does not degrade the search ability of L-SHADE and can preserve strong optimization performance on representative PV parameter estimation tasks.

Table 6. Comparison of average estimated parameters, mean RMSE, and best RMSE values on Photowatt-PWP201 MM over 30 independent runs.

Algorithm	I_{ph} (A)	I_{sd} (μ A)	R_s (Ω)	R_{sh} (Ω)	α	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	1.031	0.000	0.033	27.277	1.351	0.002425075	0.002425075	
DPDE	1.031	0.000	0.033	27.277	1.351	0.002425075	0.002425075	=
L-SHADE	1.031	0.000	0.033	27.277	1.351	0.002425075	0.002425075	+
SHADE	1.128	0.000	0.949	1078.681	23.668	0.002457533	0.002425804	+
JADE	1.028	0.000	0.032	650.346	1.413	0.003142750	0.002425075	+
SIS	0.920	0.000	0.875	974.073	23.648	0.129327589	0.004617956	+
GLPSO	0.982	0.000	0.249	581.129	13.798	0.047540477	0.008660382	+
BDE	1.073	0.000	0.016	537.227	1.720	0.025819348	0.007761410	+
DMSIS	0.977	0.000	0.030	53.868	1.676	0.054149143	0.004683066	+
MRSE	1.032	0.000	0.244	1999.850	1.645	0.008340175	0.006598860	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

Table 7. Comparison of average estimated parameters, mean RMSE, and best RMSE values on STP6-120/36 MM over 30 independent runs.

Algorithm	I_{ph} (A)	I_{sd} (μ A)	R_s (Ω)	R_{sh} (Ω)	α	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	7.473	0.000	0.005	22.220	1.260	0.016600603	0.016600603	
DPDE	7.473	0.000	0.005	22.220	1.260	0.016600603	0.016600603	=
L-SHADE	7.473	0.000	0.005	22.220	1.260	0.016600603	0.016600603	=
SHADE	4.351	0.000	0.218	598.095	30.257	0.016662889	0.016600683	+

Table 7. Cont.

Algorithm	I_{ph} (A)	I_{sd} (μ A)	R_s (Ω)	R_{sh} (Ω)	α	RMSE (Mean)	RMSE (Best)	W/T/L
JADE	7.479	0.000	0.004	671.989	1.312	0.021039118	0.016600603	+
SIS	4.106	0.000	0.181	919.637	25.207	0.649501760	0.039514484	+
GLPSO	6.478	0.000	0.113	757.477	25.297	0.287183352	0.061646501	+
BDE	7.538	0.000	0.003	908.752	1.565	0.089771268	0.030186712	+
DMSIS	7.211	0.000	0.006	746.403	5.613	0.331729648	0.048001963	+
MRSE	7.525	0.000	0.003	1499.341	1.525	0.047281731	0.030394393	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

Table 8. Comparison of average estimated parameters, mean RMSE, and best RMSE values on STM6-40/36 MM over 30 independent runs.

Algorithm	I_{ph} (A)	I_{sd} (μ A)	R_s (Ω)	R_{sh} (Ω)	α	RMSE (Mean)	RMSE (Best)	W/T/L
NL-SHADE	1.664	0.000	0.004	15.928	1.520	0.001729814	0.001729814	
DPDE	1.664	0.000	0.004	15.928	1.520	0.001729814	0.001729814	=
L-SHADE	1.664	0.000	0.004	15.928	1.520	0.001729814	0.001729814	=
SHADE	0.819	0.000	0.179	468.898	30.338	0.001732722	0.001729819	+
JADE	1.663	0.000	0.003	19.292	1.565	0.002233203	0.001729814	+
SIS	0.995	0.000	0.170	489.424	30.201	0.047054891	0.005304439	+
GLPSO	1.640	0.000	0.103	329.615	19.149	0.027854029	0.012576722	+
BDE	1.678	0.000	0.003	973.608	1.966	0.029062883	0.006294787	+
DMSIS	1.671	0.000	0.003	438.849	3.327	0.030254113	0.005767741	+
MRSE	1.661	0.000	0.003	706.708	1.758	0.009834700	0.002213845	+

Note: Bold values indicate the best results. The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

To further clarify the overall comparison across all six problems, Table 9 summarizes the W/T/L results of NL-SHADE against the other algorithms. It can be seen that NL-SHADE achieves favorable overall results against all non-top baselines, including SHADE, JADE, SIS, GLPSO, BDE, DMSIS, and MRSE, with an overall score of 6/0/0 in all these comparisons. This means that NL-SHADE outperforms these algorithms on all six PV parameter estimation problems from the perspective of statistical comparison. Against the two strongest baselines, namely DPDE and L-SHADE, the competition is much closer. Specifically, NL-SHADE obtains an overall result of 2/4/0 against DPDE and 3/3/0 against L-SHADE. These results indicate that NL-SHADE does not establish an overwhelming advantage over DPDE or L-SHADE on these relatively mature PV parameter estimation benchmarks, but it remains at least comparable to them and still achieves a slight overall advantage in pairwise statistical comparisons. Therefore, the main conclusion from Table 9 is that NL-SHADE belongs to the top-performing group together with DPDE and L-SHADE, while showing clear and consistent superiority over the remaining compared algorithms across the six PV parameter estimation problems.

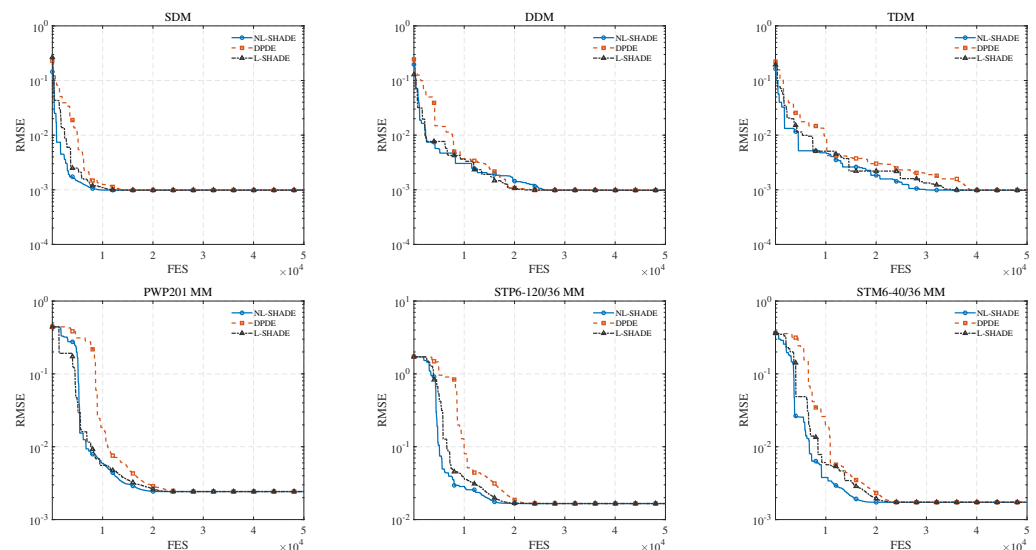
From a broader perspective, the results in Tables 3–9 suggest that NL-SHADE maintains top-level optimization performance across all six PV parameter estimation problems. Although the margins over DPDE and L-SHADE are not large in terms of final RMSE, NL-SHADE remains statistically competitive with these two strongest DE baselines while showing clear superiority over the remaining compared algorithms. To provide a more intuitive comparison of the search behavior of the three algorithms, Figure 7 presents the RMSE convergence curves of NL-SHADE, DPDE, and L-SHADE on the six PV parameter estimation benchmark problems. It can be observed that all three algorithms eventually converge to very similar final RMSE values on most problems, which is consistent with the numerical results reported in Tables 3–8. This indicates that for these PV parameter estimation tasks, especially the relatively easier cases, several advanced DE variants are

Table 9. Summary of *W/T/L* results of NL-SHADE against the compared algorithms over six PV parameter estimation benchmark problems.

Problem	DPDE	L-SHADE	SHADE	JADE	SIS	GLPSO	BDE	DMSIS	MRSE
SDM	=	=	+	+	+	+	+	+	+
DDM	+	+	+	+	+	+	+	+	+
TDM	+	+	+	+	+	+	+	+	+
PWP201 MM	=	+	+	+	+	+	+	+	+
STP6-120/36 MM	=	=	+	+	+	+	+	+	+
STM6-40/36 MM	=	=	+	+	+	+	+	+	+
ALL	2/4/0	3/3/0	6/0/0	6/0/0	6/0/0	6/0/0	6/0/0	6/0/0	6/0/0

Note: The symbols “+”, “=”, and “−” denote win, tie, and loss, respectively.

all capable of locating near-optimal solutions. Therefore, the main difference among the compared algorithms is not only reflected in the final best value, but also in the convergence process, including how quickly low-RMSE regions can be reached and how stably the search proceeds toward the final solution.

**Figure 7.** Convergence curves of NL-SHADE, DPDE, and L-SHADE on six PV parameter estimation benchmark problems.

More specifically, NL-SHADE generally exhibits a faster convergence tendency in the early and middle stages of the search. On SDM and DDM, the three algorithms show similar final performance, but NL-SHADE reaches the low-error region earlier and maintains a competitive convergence trajectory throughout the optimization process. On TDM, where the search space is more complex because of the increased number of parameters, the advantage of NL-SHADE becomes clearer. Its RMSE decreases more rapidly and remains below or close to the other two algorithms during most of the search process. Similar behavior can also be observed on the three PV module models, especially STP6-120/36 MM and STM6-40/36 MM, where NL-SHADE enters the sharp descent stage earlier and approaches the final stable RMSE region faster than DPDE and L-SHADE. These results suggest that the proposed nonlinear population reduction strategy helps NL-SHADE improve search efficiency, particularly in problems with relatively more complicated parameter interactions.

Another observation from Figure 7 is that the convergence curves of NL-SHADE are generally smoother in the later search stage. Since the final RMSE values of the three algorithms are often very close, this smoother convergence behavior is important

because it indicates that NL-SHADE can approach the final solution with less unnecessary fluctuation while maintaining competitive accuracy. In other words, the advantage of NL-SHADE on PV parameter estimation is not that it always produces dramatically lower final errors than DPDE or L-SHADE, but that it can more efficiently drive the search toward high-quality solutions and often reaches the final accuracy level earlier. This observation is consistent with the statistical comparisons in Tables 3–9, where NL-SHADE shows overall competitive accuracy together with favorable robustness across the six benchmark problems.

Overall, the PV parameter estimation results indicate that NL-SHADE belongs to the top-performing group together with DPDE and L-SHADE, while showing consistently favorable statistical performance and competitive convergence efficiency across the six benchmark problems. However, these six PV parameter estimation benchmarks are relatively mature test problems, and several advanced DE variants are already able to obtain nearly identical final solutions on them. Therefore, although the above experiments verify the effectiveness of the proposed nonlinear population reduction strategy on PV model parameter estimation, they do not fully reveal the performance differences among advanced optimization algorithms in more challenging solar-energy-related tasks. For this reason, the next subsection further evaluates NL-SHADE on solar power generation forecasting, where it is used to train DNM and is compared with representative optimization-based and neural-network-based forecasting methods under a more complex time-series prediction setting.

4.3. Solar Power Generation Forecasting

Following the PV parameter estimation experiments in Section 4.2, solar power generation forecasting is further investigated to provide a more comprehensive evaluation of NL-SHADE. Compared with the six PV parameter estimation benchmarks, where several advanced DE-based algorithms often achieve very similar RMSE values and even identical best solutions, forecasting tasks provide a more discriminative scenario for evaluating optimization performance. This is because solar power forecasting not only depends on the search capability of the optimization algorithm, but also reflects its effectiveness in training the Dendritic Neuron Model (DNM) for nonlinear time-series modeling and generalization. Therefore, this subsection further examines whether NL-SHADE can maintain competitive and robust performance when applied to DNM-based solar power generation forecasting.

For the forecasting task, NL-SHADE is used to train DNM for single-day solar power generation prediction. To provide a comprehensive evaluation, three groups of comparison methods are considered. First, Table 10 compares NL-SHADE with L-SHADE, SHADE, and BP, where L-SHADE and SHADE are included to evaluate the effect of the proposed nonlinear population reduction strategy, and BP is adopted as a classical training baseline for DNM. Second, Table 11 compares NL-SHADE-DNM with several representative neural-network-based forecasting models, including MLP, ANFIS, LSTM, and Elman Network. Third, Table 12 reports the forecasting results of four optimization algorithms, namely DPDE, BDE, DMSIS, and MRSE, which are also used to train DNM under the same forecasting setting. In these three tables, *MSE*, *MAPE*, and *MAE* denote the mean squared error, mean absolute percentage error, and mean absolute error, respectively. The reported mean and standard deviation values are calculated over 30 independent runs to evaluate both forecasting accuracy and robustness. In addition, two statistical analyses are employed in this subsection. Specifically, the *W/T/L* results are obtained by pairwise comparisons over 14 datasets and 3 evaluation metrics, resulting in 42 comparisons for each algorithm pair, while the Friedman ranking is used to evaluate the overall performance of all compared methods across the forecasting benchmarks.

Table 10. Comparison of single-day power generation forecast results.

	Metrics	NL-SHADE		L-SHADE		SHADE		BP	
		Mean	std	Mean	std	Mean	std	Mean	std
Antwerp	MSE	14.3344	18.3377	10.9889	4.0685	34.9295	24.2130	350.7398	815.4377
	MAPE	0.0028	0.0020	0.0036	0.0022	0.0066	0.0029	0.0136	0.0167
	MAE	2.8486	1.4515	2.8337	0.7393	4.6042	1.9084	10.1438	14.4017
Belgium	MSE	20.4953	20.7114	18.9552	11.8415	35.6381	32.5902	558.6980	945.1239
	MAPE	0.0032	0.0022	0.0057	0.0026	0.0056	0.0025	0.0161	0.0155
	MAE	3.3177	1.6701	3.8320	1.3867	4.6788	1.9400	14.3838	16.5286
Brussels	MSE	13.8779	14.2834	10.6447	2.7495	38.8677	24.8284	27.4233	22.2214
	MAPE	0.0030	0.0021	0.0036	0.0018	0.0067	0.0030	0.0068	0.0030
	MAE	2.8857	1.3117	2.7634	0.5252	4.9125	1.9776	4.3353	1.9058
EastFlanders	MSE	17.8117	17.3638	11.6182	4.3609	30.6593	21.6702	357.2271	829.8711
	MAPE	0.0035	0.0025	0.0035	0.0024	0.0058	0.0019	0.0130	0.0166
	MAE	3.2826	1.5613	2.8871	0.7686	4.2285	1.5940	10.3463	14.4207
Flanders	MSE	17.3806	22.0109	13.3487	7.5473	29.4122	17.3105	571.4060	969.6398
	MAPE	0.0031	0.0020	0.0045	0.0021	0.0052	0.0019	0.0158	0.0163
	MAE	3.0943	1.6632	3.1702	0.9848	4.3341	1.3250	14.2799	16.9891
FlemishBrabant	MSE	13.1037	13.2679	12.4764	9.7029	39.4845	30.0752	600.3505	1030.8233
	MAPE	0.0026	0.0018	0.0038	0.0028	0.0072	0.0034	0.0175	0.0202
	MAE	2.7646	1.2975	2.9580	1.1758	4.8523	2.0025	14.4036	17.9280
Hainaut	MSE	19.3131	16.3143	14.8384	8.2763	41.0794	28.5308	334.6169	771.3393
	MAPE	0.0036	0.0020	0.0047	0.0023	0.0060	0.0019	0.0114	0.0124
	MAE	3.3744	1.5052	3.3321	0.9991	4.9475	1.7414	10.1008	13.5457
Lige	MSE	14.1097	10.6406	13.4946	7.7925	34.6777	19.3084	314.2402	728.0874
	MAPE	0.0028	0.0020	0.0051	0.0019	0.0056	0.0020	0.0121	0.0144
	MAE	3.0230	1.0894	3.2322	0.9715	4.5887	1.5664	9.6615	13.3573
Limburg	MSE	21.4609	20.6506	12.7821	11.8637	40.6928	29.4444	482.4721	898.4665
	MAPE	0.0042	0.0026	0.0044	0.0026	0.0067	0.0038	0.0159	0.0179
	MAE	3.5458	1.6872	2.9766	1.2055	4.9430	1.9643	12.7044	16.1357
Luxembourg	MSE	18.8332	21.2566	16.2710	9.4950	34.1809	18.1010	150.9341	468.8140
	MAPE	0.0034	0.0020	0.0055	0.0023	0.0061	0.0017	0.0088	0.0096
	MAE	3.2375	1.6237	3.5481	1.1970	4.8381	1.4460	6.7574	9.0828
Namur	MSE	17.0885	13.4750	13.2568	7.5293	29.0487	19.6267	166.3446	521.2632
	MAPE	0.0034	0.0019	0.0047	0.0025	0.0057	0.0025	0.0097	0.0108
	MAE	3.2247	1.2806	3.1294	1.0722	4.3687	1.6433	6.9864	9.7775
Wallonia	MSE	15.7899	15.3606	12.6125	6.8603	30.9170	23.6557	246.9911	658.4800
	MAPE	0.0029	0.0018	0.0043	0.0025	0.0063	0.0027	0.0105	0.0132
	MAE	3.0076	1.4143	3.0202	1.0682	4.4041	1.8736	8.3124	12.0407
WalloonBrabant	MSE	26.9360	30.7370	11.9435	5.2685	38.1536	25.3862	271.8572	728.5165
	MAPE	0.0043	0.0023	0.0038	0.0024	0.0061	0.0026	0.0107	0.0146
	MAE	3.9054	1.8192	2.9396	0.8763	4.7920	1.9665	8.4537	12.9075
WestFlanders	MSE	22.2650	25.1964	17.3077	9.4040	43.1703	54.8292	355.7590	817.4665
	MAPE	0.0036	0.0027	0.0054	0.0027	0.0062	0.0032	0.0122	0.0129
	MAE	3.3699	1.9559	3.5426	1.1511	4.6794	2.3672	10.5263	13.9765
W/T/L		-/-/-		10/30/2		42/0/0		40/2/0	
Rank		2.00		2.12		6.48		8.64	

Note: The bold values indicate the best results among all compared algorithms for each performance metric.

Table 11. Comparison of single-day power generation forecast results.

	Metrics	MLP		ANFIS		LSTM		RNN (Elman Network)	
		Mean	std	Mean	std	Mean	std	Mean	std
Antwerp	MSE	130.2636	155.1062	36.3767	0.0000	14.6741	7.1993	28.7373	14.7913
	MAPE	0.0126	0.0110	0.0096	0.0000	0.0050	0.0016	0.0073	0.0033
	MAE	8.5039	4.8859	5.6923	0.0000	3.5037	0.8033	4.9027	1.4725
Belgium	MSE	132.0765	117.8210	37.4747	0.0000	13.0057	8.4767	23.4355	13.4862
	MAPE	0.0123	0.0074	0.0094	0.0000	0.0037	0.0016	0.0056	0.0024
	MAE	8.8699	4.4876	5.7866	0.0000	3.1302	0.9933	4.4614	1.4125
Brussels	MSE	100.3474	72.7086	36.8671	0.0000	14.6117	6.1934	31.4162	16.1467
	MAPE	0.0121	0.0073	0.0096	0.0000	0.0043	0.0012	0.0080	0.0025
	MAE	7.8975	2.8063	5.7212	0.0000	3.3636	0.6878	5.2497	1.3441
EastFlanders	MSE	116.0040	104.2974	37.7105	0.0000	15.3476	13.8955	28.9906	13.4913
	MAPE	0.0119	0.0078	0.0098	0.0000	0.0041	0.0021	0.0074	0.0030
	MAE	8.2393	3.5571	5.7835	0.0000	3.3118	1.1951	5.0245	1.3503
Flanders	MSE	142.6487	113.0799	37.7187	0.0000	13.9965	9.7087	25.3624	16.3355
	MAPE	0.0112	0.0064	0.0096	0.0000	0.0039	0.0013	0.0058	0.0029
	MAE	9.0245	3.6360	5.7919	0.0000	3.2692	0.9757	4.5079	1.6754
FlemishBrabant	MSE	87.1222	100.7200	37.9797	0.0000	12.6170	6.0549	30.9594	18.4011
	MAPE	0.0087	0.0076	0.0095	0.0000	0.0042	0.0016	0.0077	0.0032
	MAE	6.7967	3.8682	5.8132	0.0000	3.2206	0.6772	5.1477	1.7649
Hainaut	MSE	111.0598	76.7019	39.0702	0.0000	18.1402	18.0942	28.4351	17.0680
	MAPE	0.0089	0.0065	0.0094	0.0000	0.0042	0.0023	0.0063	0.0027
	MAE	7.9242	3.0296	5.8640	0.0000	3.4571	1.4826	4.8847	1.6364
Lige	MSE	163.5245	155.5002	36.8236	0.0000	11.9141	6.9664	26.6698	15.6455
	MAPE	0.0129	0.0079	0.0088	0.0000	0.0038	0.0012	0.0064	0.0029
	MAE	9.6658	4.8337	5.8073	0.0000	3.0621	0.7304	4.7306	1.6220
Limburg	MSE	137.9427	124.0955	36.9067	0.0000	15.8920	12.0499	24.3515	12.5340
	MAPE	0.0141	0.0077	0.0091	0.0000	0.0047	0.0016	0.0064	0.0027
	MAE	8.9889	3.8201	5.7672	0.0000	3.5334	1.0550	4.5524	1.4054
Luxembourg	MSE	150.6641	160.9361	33.4861	0.0000	15.5015	9.5319	24.6680	15.1241
	MAPE	0.0109	0.0076	0.0079	0.0000	0.0036	0.0016	0.0060	0.0024
	MAE	9.0980	4.5839	5.5657	0.0000	3.3224	0.9059	4.5488	1.5033
Namur	MSE	122.5845	152.0998	35.2945	0.0000	18.8682	17.2232	30.6982	16.8674
	MAPE	0.0111	0.0078	0.0088	0.0000	0.0043	0.0020	0.0073	0.0034
	MAE	8.1331	4.8880	5.6568	0.0000	3.6687	1.3730	5.0687	1.6228
Wallonia	MSE	127.9075	163.0084	36.9912	0.0000	12.4888	7.5701	26.7597	16.5577
	MAPE	0.0099	0.0074	0.0089	0.0000	0.0038	0.0012	0.0065	0.0036
	MAE	8.3308	4.6279	5.7898	0.0000	3.0966	0.8280	4.6217	1.7355
WalloonBrabant	MSE	150.7566	170.0870	38.6746	0.0000	12.0258	6.6703	31.4092	17.9839
	MAPE	0.0131	0.0104	0.0095	0.0000	0.0033	0.0011	0.0076	0.0036
	MAE	9.1125	5.6369	5.8660	0.0000	3.0411	0.7544	5.1329	1.6454
WestFlanders	MSE	123.4507	134.0029	39.6585	0.0000	14.0477	10.5355	31.0346	16.0785
	MAPE	0.0088	0.0090	0.0098	0.0000	0.0037	0.0017	0.0068	0.0028
	MAE	8.1654	4.3361	5.9140	0.0000	3.1464	1.1047	5.1289	1.5833
W/T/L		42/0/0		42/0/0		12/27/3		42/0/0	
Rank		9.33		11.21		2.31		6.79	

Note: The bold values indicate the best results among all compared algorithms for each performance metric.

Since single-day solar power generation data usually exhibit periodic patterns, several forecasting methods can achieve acceptable fitting performance on individual datasets. However, the overall results still reveal clear differences in prediction accuracy, robustness, and generalization performance. Table 10 reports the comparison among DNM-based training methods. It can be observed that NL-SHADE achieves the best Friedman ranking of 2.00, followed by L-SHADE with 2.12, while both methods clearly outperform SHADE and BP, whose rankings are 6.48 and 8.64, respectively. This result indicates that DNM training benefits significantly from advanced DE-based optimization strategies, whereas the classical BP training mechanism is much less effective for this forecasting task. Moreover, compared with SHADE and BP, NL-SHADE achieves overwhelmingly favorable *W/T/L* results of 42/0/0 and 40/2/0, respectively, showing that the proposed method consistently outperforms these two baselines across almost all forecasting cases. A more careful comparison between NL-SHADE and L-SHADE further clarifies the contribution of the proposed nonlinear population reduction strategy. Although both algorithms achieve highly competitive forecasting performance, the statistical results still indicate a clear overall advantage for NL-SHADE. Specifically, the *W/T/L* result of 10/30/2 means that, out of the 42 pairwise comparisons conducted over 14 datasets and 3 evaluation metrics, NL-SHADE performs better than L-SHADE in 10 cases and worse in only 2 cases, yielding a net advantage of 8 wins. This result suggests that the superiority of NL-SHADE is not merely reflected by isolated best values, but is supported by a broader statistical advantage across the forecasting benchmarks. In addition, the Friedman ranking further places NL-SHADE ahead of L-SHADE (2.00 versus 2.12), which is consistent with the *W/T/L* comparison and confirms that the proposed nonlinear mechanism improves the overall training quality of DNM. Therefore, although the difference between the two methods is not dramatic, the proposed nonlinear population reduction strategy still provides a measurable and consistent improvement over the original L-SHADE framework. This result is also in line with the observations in Section 4.1, where NL-SHADE remained highly competitive with L-SHADE on PV parameter estimation while preserving stable overall performance.

Table 12. Comparison of single-day power generation forecast results.

	Metrics	DPDE		BDE		DMSIS		MRSE	
		Mean	std	Mean	std	Mean	std	Mean	std
Antwerp	MSE	27.8582	23.1673	51.2125	50.4427	25.6039	28.1342	24.9965	17.6181
	MAPE	0.0050	0.0028	0.0067	0.0047	0.0060	0.0039	0.0042	0.0022
	MAE	4.0116	1.8608	5.1895	2.9551	4.0555	1.8224	3.9228	1.5531
Belgium	MSE	31.2480	19.0719	33.8191	31.8436	60.7799	67.3144	37.2752	51.2816
	MAPE	0.0058	0.0022	0.0043	0.0032	0.0079	0.0051	0.0043	0.0041
	MAE	4.5638	1.5237	4.3099	2.1949	5.9119	3.2579	4.3636	2.9659
Brussels	MSE	40.9651	25.9399	40.5442	48.3642	45.5515	46.9121	27.0121	25.6608
	MAPE	0.0069	0.0029	0.0050	0.0041	0.0076	0.0051	0.0040	0.0027
	MAE	5.0948	1.7676	4.7475	2.4292	5.1364	2.3974	3.9447	1.8492
EastFlanders	MSE	30.9584	23.3618	31.9828	36.5946	58.3769	86.8220	31.1520	21.4711
	MAPE	0.0058	0.0029	0.0044	0.0038	0.0078	0.0059	0.0051	0.0031
	MAE	4.3599	1.8270	4.2834	2.2696	5.6252	3.1548	4.4892	1.6692
Flanders	MSE	35.0253	22.5879	40.0509	24.8856	37.6537	36.0906	25.4088	16.0034
	MAPE	0.0060	0.0031	0.0047	0.0025	0.0057	0.0026	0.0037	0.0020
	MAE	4.8044	1.8716	4.9884	1.7353	4.8142	2.1051	3.9584	1.3545
FlemishBrabant	MSE	29.9913	22.0276	45.0962	45.2443	43.6824	52.2625	29.4689	16.4783
	MAPE	0.0054	0.0024	0.0056	0.0032	0.0068	0.0034	0.0052	0.0026
	MAE	4.3161	1.6897	4.9502	2.4280	5.1414	2.4439	4.4242	1.3233

Table 12. Cont.

	Metrics	DPDE		BDE		DMSIS		MRSE	
		Mean	std	Mean	std	Mean	std	Mean	std
Hainaut	MSE	42.8521	23.8639	41.5334	50.3031	52.9268	85.6540	37.1887	35.6819
	MAPE	0.0062	0.0025	0.0048	0.0033	0.0066	0.0056	0.0045	0.0032
	MAE	5.3122	1.8738	4.8230	2.1730	5.4472	3.9635	4.6083	2.2998
Lige	MSE	37.6873	23.9227	51.1307	47.4184	51.9890	75.1270	33.3826	22.8124
	MAPE	0.0065	0.0027	0.0052	0.0034	0.0069	0.0052	0.0052	0.0032
	MAE	5.0358	1.7483	5.3866	2.5006	5.4086	3.1957	4.6702	1.8941
Limburg	MSE	30.3689	24.1651	51.8986	66.6605	29.1476	26.0206	30.6603	28.5608
	MAPE	0.0057	0.0024	0.0055	0.0043	0.0054	0.0029	0.0049	0.0021
	MAE	4.3073	1.7833	5.1022	2.9185	4.3437	1.8357	4.2876	1.5844
Luxembourg	MSE	34.8334	23.9636	40.2125	52.2573	34.2071	27.8473	21.1370	18.0193
	MAPE	0.0061	0.0033	0.0047	0.0036	0.0057	0.0027	0.0038	0.0029
	MAE	4.7906	2.0222	4.7054	2.5987	4.8624	1.9006	3.6042	1.7315
Namur	MSE	34.0649	20.3547	29.4806	25.9617	31.5179	31.8479	34.3563	34.1031
	MAPE	0.0067	0.0022	0.0043	0.0034	0.0060	0.0034	0.0050	0.0029
	MAE	4.7906	1.6341	4.1173	1.9677	4.5313	2.1916	4.5762	1.9603
Wallonia	MSE	44.6046	26.9836	38.9055	54.4886	59.8283	97.1364	34.6367	37.3730
	MAPE	0.0068	0.0031	0.0043	0.0042	0.0078	0.0059	0.0046	0.0036
	MAE	5.4340	2.0391	4.4046	2.6139	5.8252	3.8558	4.4160	2.2234
WalloonBrabant	MSE	39.1177	28.1436	42.8801	44.9880	39.7007	40.8276	24.5953	20.2905
	MAPE	0.0066	0.0030	0.0059	0.0053	0.0065	0.0033	0.0042	0.0029
	MAE	5.0186	2.0167	4.9563	2.6556	4.9810	2.1703	3.9167	1.6473
WestFlanders	MSE	34.6222	20.4032	54.5892	47.9839	35.9194	35.8505	24.7865	17.2238
	MAPE	0.0062	0.0017	0.0059	0.0030	0.0065	0.0031	0.0035	0.0022
	MAE	4.8324	1.5202	5.4708	2.5316	4.8050	2.0599	3.8311	1.4886
W/T/L		41/1/0		32/10/0		41/1/0		27/15/0	
Rank		7.10		6.71		8.05		4.57	

Note: The bold values indicate the best results among all compared algorithms for each performance metric.

Table 11 provides a broader comparison between NL-SHADE-DNM and several representative neural-network-based forecasting models. According to the Friedman ranking results, NL-SHADE achieves the best overall rank of 2.00, outperforming LSTM (2.31), Elman Network (6.79), MLP (9.33), and ANFIS (11.21). This result is particularly meaningful because LSTM is one of the most widely used deep-learning models for time-series forecasting and is generally regarded as a strong baseline for capturing temporal dependencies. Therefore, the fact that NL-SHADE achieves a better overall rank than LSTM demonstrates the effectiveness of combining DNM with the proposed optimization strategy for solar power forecasting. In addition, the *W/T/L* results show that NL-SHADE obtains dominant advantages over MLP, ANFIS, and Elman Network, with comparison results of 42/0/0, 42/0/0, and 42/0/0, respectively. Against LSTM, the *W/T/L* result is 12/27/3. Although this indicates that LSTM remains competitive on several datasets, NL-SHADE still wins more cases than it loses, and the Friedman ranking also favors NL-SHADE by a clear margin (2.00 versus 2.31). Therefore, from the perspective of both overall ranking and pairwise comparisons, NL-SHADE can be regarded as one of the most effective forecasting methods among the neural-network-based approaches considered in this study.

Table 12 further reports the forecasting performance of DPDE, BDE, DMSIS, and MRSE when they are used to train DNM under the same experimental setting. According to the

Friedman ranking results, MRSE achieves the best overall rank among these four algorithms, followed by BDE, DPDE, and DMSIS. However, pairwise statistical comparisons show that NL-SHADE still maintains favorable overall performance against all of them. Specifically, the $W/T/L$ results indicate that NL-SHADE achieves 41/1/0 against DPDE, 32/10/0 against BDE, 41/1/0 against DMSIS, and 27/15/0 against MRSE. Since each comparison is conducted over 42 forecasting results, these statistics indicate that NL-SHADE wins in the majority of cases against all four algorithms. In particular, the comparisons against DPDE and DMSIS are especially convincing, as NL-SHADE loses only one case in each of the two comparisons. Although MRSE exhibits relatively strong forecasting performance among these optimization algorithms and achieves the best Friedman rank within this subgroup, NL-SHADE still obtains a clearly favorable $W/T/L$ result against it. This observation indicates that even when some algorithms perform competitively in terms of average ranking, NL-SHADE still demonstrates stronger robustness and broader superiority across multiple datasets and evaluation metrics.

Overall, compared with the PV parameter estimation benchmarks in Section 4.2, solar power forecasting provides a more challenging and more discriminative scenario for evaluating optimization algorithms. In the PV parameter estimation problems, several advanced algorithms can often obtain nearly identical best solutions, which makes the performance differences relatively difficult to distinguish. In contrast, when DNM training and time-series prediction are jointly considered, the forecasting task reveals more substantial differences in optimization effectiveness. The results in Tables 10–12 demonstrate that NL-SHADE can effectively train DNM, achieve highly competitive prediction accuracy, and maintain favorable statistical performance across 14 solar power forecasting datasets. In particular, NL-SHADE achieves the best Friedman ranking among the DNM-based DE training methods in Table 10, and also maintains a favorable $W/T/L$ result of 10/30/2 against L-SHADE, indicating that the proposed nonlinear strategy provides a consistent overall improvement over its linear counterpart in DNM training. Moreover, NL-SHADE achieves the best Friedman ranking among the neural-network-based forecasting methods in Table 11, and obtains statistically favorable $W/T/L$ results against all compared optimization algorithms in Table 12. Therefore, by combining the results of Sections 4.2 and 4.3, it can be concluded that NL-SHADE not only remains highly competitive in PV parameter estimation, but also exhibits stronger comprehensive applicability in solar power generation forecasting. Figure 8 further presents representative training and prediction curves for visual comparison.

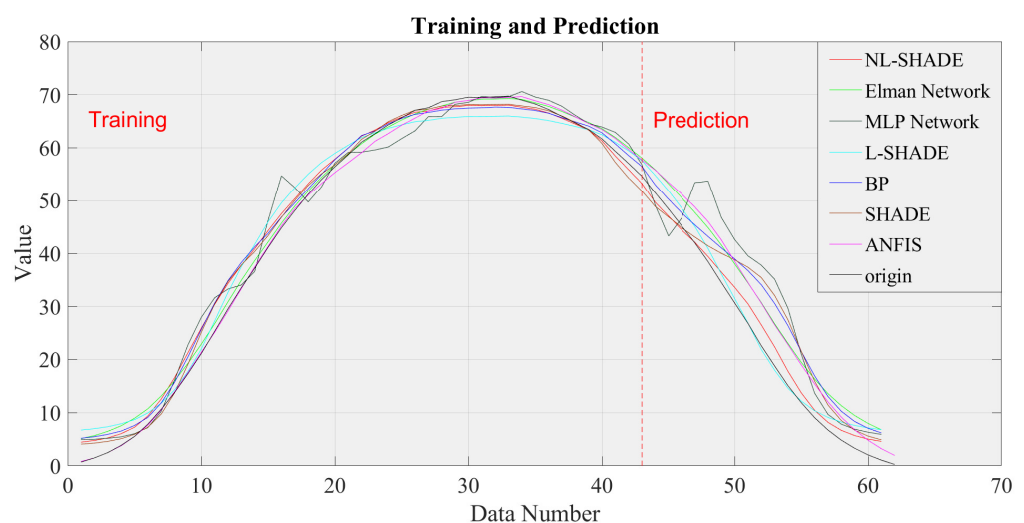


Figure 8. Training and prediction plots for 7 methods in time series prediction.

4.4. Ablation Studies

4.4.1. Effect of Nonlinear Population Reduction

To investigate the effect of the proposed nonlinear population reduction strategy and to justify the choice of the sigmoid function adopted in NL-SHADE, an ablation study is conducted on six PV parameter estimation benchmark problems. In this experiment, the original linear population reduction strategy in L-SHADE is replaced by four sigmoid-based nonlinear reduction schemes, namely Logistic, Gudermannian (Gud), Error function (Erf), and Hyperbolic tangent (Tanh). Their comparative results are reported in Table 13. It can be observed that the choice of sigmoid function has a clear influence on optimization performance. Among the four candidates, Logistic achieves the best overall results. Specifically, it obtains the best mean RMSE on SDM, TDM, PWP201 MM, STP6-120/36 MM, and STM6-40/36 MM, while remaining highly competitive on DDM. In contrast, Gud and Erf show consistently inferior performance, with $W/T/L = 6/0/0$ against Logistic, indicating that Logistic outperforms them on all six benchmark problems. Tanh is relatively competitive and produces identical or very close results to Logistic on several problems, but its overall comparison result is still weaker, with $W/T/L = 3/3/0$ against Logistic. These results indicate that although different sigmoid functions can all be incorporated into the nonlinear reduction framework, their induced population evolution behaviors are not equivalent, and Logistic provides the most suitable reduction pattern for the six PV parameter estimation problems considered in this study.

Table 13. Ablation comparison of four sigmoid functions used in the nonlinear population reduction strategy on six PV parameter estimation benchmark problems.

Problem	Logistic		Gud		Erf		Tanh	
	Mean	std	Mean	std	Mean	std	Mean	std
SDM	9.860×10^{-4}	2.682×10^{-17}	1.167×10^{-3}	4.004×10^{-4}	1.051×10^{-3}	1.825×10^{-4}	9.860×10^{-4}	2.161×10^{-17}
DDM	9.885×10^{-4}	3.213×10^{-5}	1.257×10^{-3}	7.216×10^{-4}	1.738×10^{-3}	2.999×10^{-3}	9.843×10^{-4}	4.350×10^{-6}
TDM	1.016×10^{-3}	1.504×10^{-4}	1.449×10^{-3}	7.948×10^{-4}	1.463×10^{-3}	7.627×10^{-4}	1.140×10^{-3}	3.305×10^{-4}
PWP201 MM	2.425×10^{-3}	2.605×10^{-17}	2.987×10^{-2}	6.618×10^{-2}	2.483×10^{-2}	6.423×10^{-2}	2.425×10^{-3}	1.580×10^{-17}
STP6-120/36 MM	1.660×10^{-2}	1.162×10^{-16}	1.124×10^{-1}	2.704×10^{-1}	1.131×10^{-1}	2.855×10^{-1}	1.660×10^{-2}	7.873×10^{-17}
STM6-40/36 MM	1.730×10^{-3}	1.133×10^{-17}	1.208×10^{-2}	2.491×10^{-2}	1.520×10^{-2}	3.768×10^{-2}	1.730×10^{-3}	7.869×10^{-18}
W/T/L	N/A		6/0/0		6/0/0		3/3/0	

The superiority of Logistic can be understood from the shape of its population reduction curve. Compared with linear reduction, the Logistic-based schedule maintains a relatively slow reduction rate in the early stage of the search, which helps preserve population diversity and supports broader exploration of the search space. As the optimization proceeds, the reduction speed gradually increases, allowing the algorithm to shift more efficiently from exploration to exploitation. Such a smooth “slow-fast” transition is beneficial for PV parameter estimation problems, whose search spaces usually involve nonlinear parameter interactions and multiple local optima. By contrast, Gud and Erf lead to less effective reduction trajectories under the same framework, resulting in weaker robustness and inferior average RMSE values. Tanh provides a more competitive nonlinear schedule than Gud and Erf, but its overall performance is still slightly less stable than that of Logistic. Therefore, the selection of Logistic in NL-SHADE is not empirical only, but is supported by comparative experimental evidence as well as by its more suitable exploration–exploitation transition behavior.

This ablation study also clarifies the methodological motivation for introducing nonlinear population reduction into L-SHADE. The purpose of NL-SHADE is not simply to replace the original linear rule with an arbitrary nonlinear function, but to provide a more flexible population evolution process that better matches the search requirements of solar-related optimization problems. In L-SHADE, the population is reduced at an

approximately constant rate throughout the search, which is simple and effective but cannot explicitly regulate different search stages. In contrast, the proposed sigmoid-based reduction strategy introduces a controllable nonlinear transition, enabling the algorithm to maintain a relatively larger population in the early stage and to accelerate convergence in the middle and later stages. Therefore, the advantage of the proposed strategy lies not in increasing algorithmic complexity, but in providing a smoother and more adaptive exploration–exploitation transition within the same L-SHADE framework. Based on the above observations, the Logistic function is selected as the final nonlinear population reduction model in NL-SHADE. The sensitivity of its control parameter p_a and the initial population size is further analyzed in Section 4.4.2.

4.4.2. Hyperparameter Analysis

To further justify the role and the selection of parameter p_a in Equation (17), a dedicated hyperparameter analysis is conducted on the solar power generation forecasting problem. In particular, two factors are investigated: the initial population size and the parameter p_a in the proposed nonlinear population size reduction scheme. In Equation (17), p_a is the key parameter controlling the reduction intensity of the population size during the search process. Specifically, a relatively small p_a results in a milder reduction effect and therefore maintains a larger population for a longer period, which is beneficial for preserving diversity and enhancing exploration. In contrast, a larger p_a leads to a stronger reduction effect, which can accelerate convergence but may also increase the risk of premature convergence due to the faster loss of population diversity. Therefore, p_a plays an important role in balancing exploration and exploitation, and its value should be carefully selected. To analyze the effects of the initial population size and p_a separately, the hyperparameter study is carried out in two stages. In the first stage, p_a is fixed at $8D$, while the initial population size is varied from $15D$ to $20D$ to determine a suitable population scale. In Table 14, the notation $15D$ indicates that the initial population size is set to $15D$ with $p_a = 8D$ in Equation (17); similarly, $16D$, $17D$, $18D$, $19D$, and $20D$ follow the same setting. In the second stage, after identifying the most promising population size, the value of p_a is further adjusted while fixing the initial population size at $17D$. Accordingly, $17Dp6$, $17Dp7$, $17Dp8$, $17Dp9$, and $17Dp10$ denote that the initial population size is fixed at $17D$, while p_a is set to $6D$, $7D$, $8D$, $9D$, and $10D$, respectively.

From the results in Table 14, it can first be observed that the initial population size has a more pronounced influence on optimization performance than p_a . When p_a is fixed at $8D$, the average rank changes from 5.45 to 6.45 as the initial population size varies from $15D$ to $20D$. Among these settings, $17D$ achieves the best overall rank of 4.90, followed by $15D$ and $19D$ with ranks of 5.45 and 5.52, respectively, whereas both smaller and larger population sizes generally lead to inferior performance. This tendency can also be observed from the three error indicators. For example, the values of MSE, MAPE, and MAE obtained by $17D$ are generally more competitive than those of the neighboring settings, indicating that this population size provides a more balanced performance across different test instances rather than achieving improvements only on a few cases. These results suggest that an excessively small initial population may limit the search diversity in the early stage, while an overly large population may introduce redundant search efforts and slow down convergence. Therefore, an intermediate population size, namely $17D$, provides a better balance between exploration capability and search efficiency for the considered forecasting problem.

Table 14. Hyperparameter analysis of the initial population size and parameter p_a in NL-SHADE.

	15D	16D	17Dp6	17Dp7	17Dp8	17Dp9	17Dp10	18D	19D	20D
MSE	13.0993	15.7466	18.3758	15.2384	14.7732	14.3344	13.4361	14.3278	15.6973	18.2406
	17.4686	16.3881	19.8077	20.1351	15.0109	20.4953	15.8778	18.1984	14.1241	20.6185
	20.4857	17.4033	16.6024	19.0859	22.3156	13.8779	21.0171	21.5182	19.0839	20.7279
	15.5987	15.9307	19.6835	20.5400	16.7634	17.8117	14.9341	20.7097	14.5108	30.2697
	13.6816	17.7265	15.1036	15.5466	19.9203	17.3806	16.7265	16.3041	29.3585	16.6118
	19.1073	14.8697	16.6338	28.2568	17.5326	13.1037	17.2102	16.4333	20.5291	22.4374
	25.9550	23.9301	19.1427	20.1892	20.6708	19.3131	19.8661	23.8870	22.8181	20.9461
	25.7537	23.1096	18.4155	20.5358	16.5698	14.1097	17.7356	18.6351	21.9063	16.0293
	10.5829	23.6511	17.4301	19.8953	23.7550	21.4609	19.4941	23.8047	15.1179	15.6019
	21.9645	17.5309	14.7594	11.3919	17.1665	18.8332	22.1183	15.6888	17.3436	20.9229
	24.3905	19.3320	17.1319	16.7638	17.6956	17.0885	22.7051	23.1465	22.4976	16.7786
	17.7139	21.7749	19.7706	19.0879	16.9572	15.7899	15.5308	15.1270	32.7815	21.4111
	23.8225	14.8613	21.2248	17.8693	18.9709	26.9360	24.0850	20.6956	14.0707	15.4943
	18.8337	24.3603	22.7957	24.0466	17.0761	22.2650	18.0511	20.2916	16.0416	19.4892
MAPE	0.0028	0.0037	0.0036	0.0035	0.0030	0.0028	0.0028	0.0030	0.0034	0.0040
	0.0032	0.0031	0.0038	0.0035	0.0028	0.0032	0.0032	0.0038	0.0029	0.0038
	0.0038	0.0036	0.0039	0.0036	0.0037	0.0030	0.0035	0.0041	0.0041	0.0039
	0.0031	0.0033	0.0037	0.0039	0.0037	0.0035	0.0033	0.0037	0.0032	0.0046
	0.0029	0.0035	0.0030	0.0027	0.0033	0.0031	0.0032	0.0030	0.0046	0.0031
	0.0036	0.0030	0.0037	0.0045	0.0037	0.0026	0.0031	0.0034	0.0034	0.0043
	0.0037	0.0040	0.0034	0.0035	0.0033	0.0036	0.0034	0.0038	0.0035	0.0036
	0.0038	0.0038	0.0034	0.0039	0.0029	0.0028	0.0032	0.0037	0.0041	0.0031
	0.0024	0.0041	0.0037	0.0038	0.0046	0.0042	0.0031	0.0039	0.0031	0.0031
	0.0037	0.0030	0.0032	0.0025	0.0033	0.0034	0.0039	0.0032	0.0036	0.0035
	0.0038	0.0038	0.0033	0.0030	0.0034	0.0034	0.0038	0.0038	0.0037	0.0034
	0.0034	0.0038	0.0035	0.0038	0.0035	0.0029	0.0031	0.0032	0.0043	0.0037
	0.0041	0.0028	0.0040	0.0037	0.0036	0.0043	0.0034	0.0041	0.0032	0.0033
	0.0033	0.0040	0.0037	0.0042	0.0033	0.0036	0.0033	0.0035	0.0033	0.0035
MAE	2.7039	3.1036	3.3172	3.0908	2.9353	2.8486	2.8643	2.8894	3.0133	3.2850
	3.1676	3.1113	3.4931	3.3838	2.9736	3.3177	3.1380	3.3574	2.8254	3.5398
	3.5011	3.2368	3.2167	3.1725	3.3823	2.8857	3.3296	3.6003	3.4554	3.4990
	3.0228	3.1202	3.3359	3.4912	3.2330	3.2826	3.1118	3.3920	2.9667	3.9949
	2.8073	3.2794	3.0146	3.1037	3.3978	3.0943	3.1250	3.0239	4.1265	3.1247
	3.3525	2.8646	3.2926	3.8585	3.2564	2.7646	3.1260	3.0993	3.3936	3.7096
	3.7984	3.6991	3.4899	3.3381	3.4129	3.3744	3.3713	3.7435	3.5918	3.5240
	3.8620	3.6831	3.3257	3.5378	3.1262	3.0230	3.2674	3.4759	3.6587	3.1287
	2.5717	3.6036	3.2101	3.4329	3.7607	3.5458	3.0845	3.6886	3.0295	3.0389
	3.4144	3.2853	2.9133	2.6669	3.2089	3.2375	3.6203	3.0668	3.2656	3.4962
	3.6529	3.4994	3.2436	3.1949	3.2615	3.2247	3.5819	3.7016	3.5759	3.2124
	3.3446	3.4521	3.4588	3.3735	3.2221	3.0076	3.0777	3.0169	4.0590	3.4613
	3.6861	2.9028	3.6487	3.3111	3.3461	3.9054	3.6790	3.5970	2.9136	3.1098
	3.2651	3.7434	3.4286	3.7612	3.0698	3.3699	3.1433	3.3325	3.1231	3.3462
Rank	5.45	6.05	5.50	5.67	4.90	4.55	4.71	6.19	5.52	6.45

Note: The bold values indicate the best results among all compared algorithms for each performance metric.

After fixing the initial population size at 17D, the influence of p_a is further examined. It can be seen that the variation caused by different p_a values is relatively smaller than that caused by the initial population size, indicating that NL-SHADE is not overly sensitive to p_a within a reasonable range. Specifically, the average rank values of 17Dp6, 17Dp7, 17Dp8, 17Dp9, and 17Dp10 are 5.50, 5.67, 4.90, 4.55, and 4.71, respectively. Among them, 17Dp9 achieves the best overall rank, while 17Dp10 and 17Dp8 also show competitive performance. This result indicates that the value of p_a should not be set too small or too large.

When p_a is too small, the reduction effect becomes overly weak, causing the population to remain large for too long and thereby reducing the convergence pressure in the later search stage. On the other hand, an excessively large p_a leads to a more aggressive reduction of population size, which may weaken diversity preservation and increase the risk of premature convergence. The superior performance of 17Dp9 suggests that this setting provides a more suitable reduction intensity, allowing the algorithm to preserve sufficient diversity in the early stage while still gradually strengthening exploitation in the later stage. Moreover, the performance around the best-performing parameter region exhibits a relatively smooth variation trend, suggesting that the proposed nonlinear population size reduction strategy has a certain degree of robustness within a reasonable parameter interval. Based on the above observations, the final parameter setting used in this paper is determined as an initial population size of 17D and $p_a = 9D$. Overall, the experimental results demonstrate that the initial population size is the dominant factor affecting optimization performance, while p_a serves as a fine-grained control parameter for the reduction intensity of the nonlinear population schedule. This analysis not only provides empirical justification for the parameter setting in Equation (17), but also offers useful guidance for applying NL-SHADE to other optimization problems.

4.5. CPU Time

In addition to solution quality and statistical performance, computational cost is also an important criterion for evaluating the practical applicability of optimization algorithms. Therefore, this subsection further analyzes the total CPU time of the compared methods on both PV parameter estimation and solar power generation forecasting tasks. The corresponding results are shown in Figure 9 and Figure 10, respectively.

For the six PV parameter estimation benchmark problems, Figure 9 shows that the CPU times of all compared optimization algorithms fall within a relatively narrow range, indicating that these methods have broadly comparable computational complexity under the same experimental settings. Among them, GLPSO achieves the lowest total CPU time, followed by SIS and SHADE, whereas L-SHADE and NL-SHADE require relatively more computational time. Specifically, the total CPU time of NL-SHADE is 87.977 s, which is very close to that of DPDE (87.040 s) and L-SHADE (88.920 s). This suggests that the introduction of the nonlinear population reduction strategy does not lead to a substantial increase in computational cost compared with the strongest DE-based baselines. More importantly, when the CPU-time results are considered together with the statistical comparisons in Table 9, a clearer picture emerges. Although some algorithms, such as GLPSO, SIS, and SHADE, consume slightly less computational time, their overall optimization performance is clearly inferior to that of NL-SHADE, as reflected by the $W/T/L$ results. In particular, NL-SHADE achieves an overall score of 6/0/0 against SHADE, SIS, and GLPSO, indicating consistent superiority over these faster but less competitive methods across the six PV parameter estimation problems. In contrast, the two strongest competitors, DPDE and L-SHADE, show CPU times very close to that of NL-SHADE, while their statistical comparison results with NL-SHADE are 2/4/0 and 3/3/0, respectively. Therefore, although NL-SHADE is not the fastest algorithm in terms of raw CPU time, its computational overhead remains moderate and comparable to the strongest baselines, while its optimization performance stays within the top-performing group.

For the solar power generation forecasting task, the CPU-time results in Figure 10 show a much larger difference among the compared methods than that observed in PV parameter estimation. In particular, ANFIS and BP require the least computational time, while Elman Network exhibits by far the highest runtime (3346.58 s), and LSTM also incurs a relatively large computational cost (147.88 s). Compared with these neural-network-based

forecasting models, the optimization-based DNM training methods are concentrated in a much narrower range. The runtime of NL-SHADE is 54.55 s, which is slightly higher than that of L-SHADE (50.87 s) and SHADE (45.42 s), but lower than those of DPDE (63.15 s), BDE (80.57 s), DMSIS (63.10 s), and MRSE (78.19 s). Therefore, from the perspective of computational efficiency alone, NL-SHADE can still be regarded as a relatively efficient optimization-based training method for DNM. More importantly, this runtime should be interpreted together with the forecasting accuracy and statistical results reported in Tables 10–12. As shown in Table 10, NL-SHADE achieves the best overall Friedman rank (2.00) among the four methods in Table 10, and also obtains a favorable $W/T/L = 10/30/2$ against L-SHADE, indicating a slight but meaningful statistical advantage over its closest DE-based competitor despite only a modest increase in computational time. In comparison with the additional optimization algorithms in Table 12, NL-SHADE not only requires less runtime than BDE and MRSE, but also achieves clearly better forecasting performance than these methods. When compared with the neural-network-based models in Table 11, NL-SHADE is substantially more efficient than MLP, LSTM, and Elman Network, while simultaneously delivering much stronger prediction accuracy and ranking performance. These results indicate that the computational cost of NL-SHADE remains well controlled in the forecasting task and is justified by its superior predictive performance across the 14 datasets.

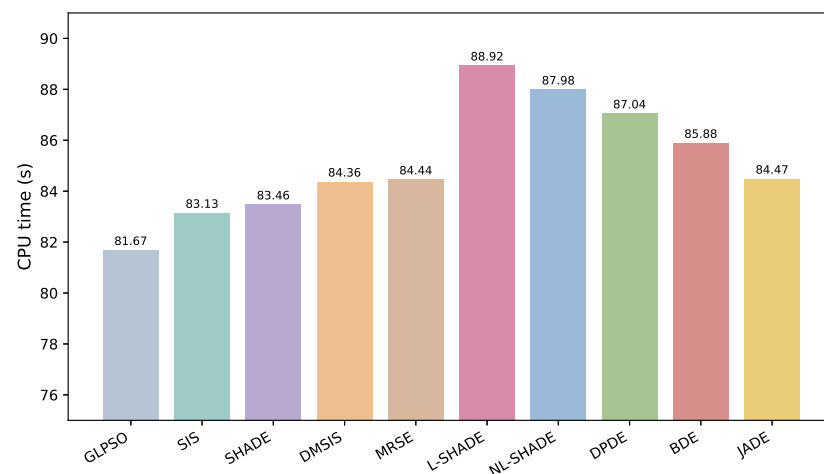


Figure 9. Total CPU time of the compared algorithms over six PV parameter estimation benchmark problems.

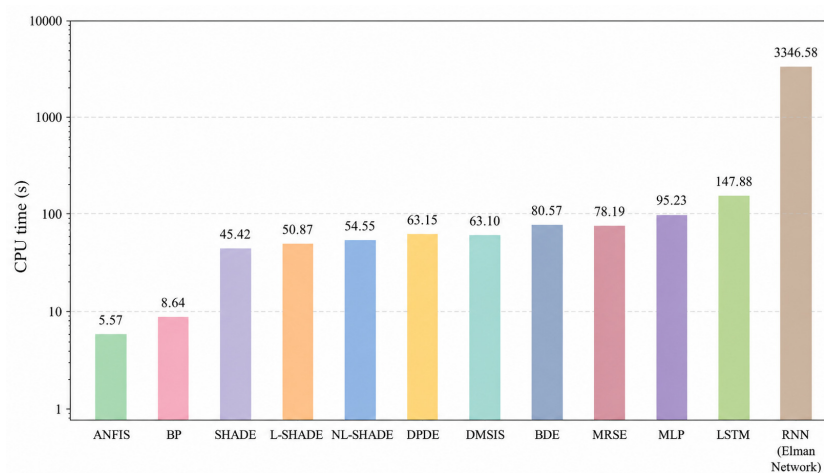


Figure 10. Total CPU time of the compared algorithms and forecasting models over 14 single-day power generation forecasting datasets.

Overall, the CPU-time analysis shows that NL-SHADE achieves a favorable balance between computational cost and solution quality on both solar-energy-related tasks. In PV parameter estimation, its runtime remains close to those of the strongest DE-based baselines while maintaining top-level statistical competitiveness. In solar power generation forecasting, although NL-SHADE is not the fastest method in absolute terms, it provides a more attractive trade-off between runtime and forecasting performance than most competing optimization algorithms and neural forecasting models. Therefore, rather than simply minimizing computational time, NL-SHADE demonstrates practical value by achieving strong optimization and forecasting performance within an acceptable computational budget.

5. Discussion

5.1. Population Interaction Network

To investigate the underlying mechanisms responsible for the superior performance of NL-SHADE in photovoltaic parameter estimation and solar power generation forecasting, the Population Interaction Network (PIN) is employed as the primary analysis tool in this study. PIN is a network-based framework used to characterize information interactions among individuals during the optimization process. By recording interaction relationships and information transmission patterns, PIN can reveal hidden structural properties of population evolution and provide valuable insights into the exploration and exploitation behaviors of evolutionary algorithms [48].

Figure 11 illustrates the PIN topology structure of L-SHADE. To generate the current individual X_i^{t+1} , four individuals from the previous generation are involved in the evolutionary process. Black connections indicate reference relationships among individuals, while red connections represent comparison relationships used during fitness evaluation. When the current individual is not selected as the optimal solution, it may participate multiple times in offspring generation, archive updating, and fitness comparison, resulting in different interaction frequencies among individuals. These interaction relationships collectively form the PIN topology and reflect the information flow characteristics during the optimization process.

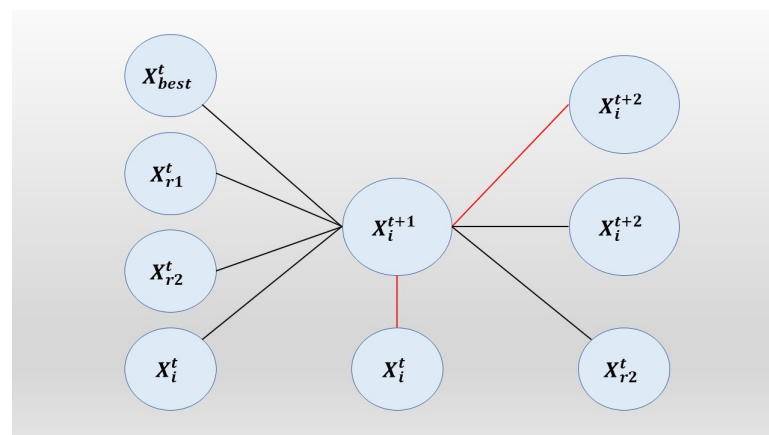


Figure 11. PIN topology structure of L-SHADE.

5.2. PIN Statistical Analysis Procedure

Based on the constructed PIN, statistical analysis is performed to quantitatively investigate information transmission characteristics during the evolutionary process. Specifically, unique labels are assigned to individuals, and interaction relationships are recorded throughout optimization. The occurrence frequency of each label is then counted to construct the corresponding Probability Distribution Function (PDF), which reflects the distribution of information interactions within the population. Furthermore, the Cumu-

lative Distribution Function (CDF) is employed to analyze the cumulative distribution characteristics of interaction frequencies.

To further characterize the structural properties of the network, several mathematical distributions are fitted to the statistical results derived from PIN. The fitting quality is evaluated using the sum of squared errors (SSE) and the coefficient of determination (R^2). Through these analyses, the information propagation patterns and evolutionary dynamics of NL-SHADE can be systematically investigated and compared with those of other algorithms.

5.3. Distribution and Structural Analysis

Since the primary purpose of PIN in this study is to reveal subtle evolutionary differences among closely related DE variants, the PIN analysis is focused on SHADE, L-SHADE, and NL-SHADE. For algorithms with substantially different optimization paradigms, the resulting PIN structures would be strongly influenced by their inherently different update rules and information-sharing mechanisms. Therefore, such cross-paradigm PIN comparisons are less suitable for explaining the performance improvement brought by the proposed nonlinear population reduction strategy.

Based on the PIN analysis framework introduced above, the interaction characteristics of SHADE, L-SHADE, and NL-SHADE are further investigated from both distribution and structural perspectives. Distribution analysis focuses on examining whether the statistical characteristics of PIN are associated with algorithm performance, while structural analysis aims to reveal how individual interaction patterns influence optimization behavior. Through combining these two perspectives, it becomes possible to provide a more comprehensive explanation of why NL-SHADE demonstrates favorable performance in solar power generation prediction tasks. The corresponding fitting results and PIN structures are presented in Table 15 and Figure 12, respectively.

Table 15. Fitting results of three algorithms on PIN under seven candidate distributions.

		Normal	Gamma	Poisson	Exponential	Weibull	Logistic	Power-Law
L-SHADE	SSE	2.1415	1.2066	1.9841	1.1247	1.1751	1.1507	0.7238
	R^2	0.5744	0.7706	0.7237	0.7364	0.7470	0.6904	0.0979
NL-SHADE	SSE	11.1351	1.5840	2.4881	1.5776	1.3893	1.5026	0.4788
	R^2	0.1137	0.7013	0.6918	0.6821	0.6488	0.7179	0.0478
SHADE	SSE	0.3839	0.1875	0.1314	1.1342	0.3584	0.1142	0.3389
	R^2	0.9434	0.9749	0.9824	0.7144	0.9451	0.9841	0.0815

Note: The bold values indicate the best results among all compared algorithms for each performance metric.

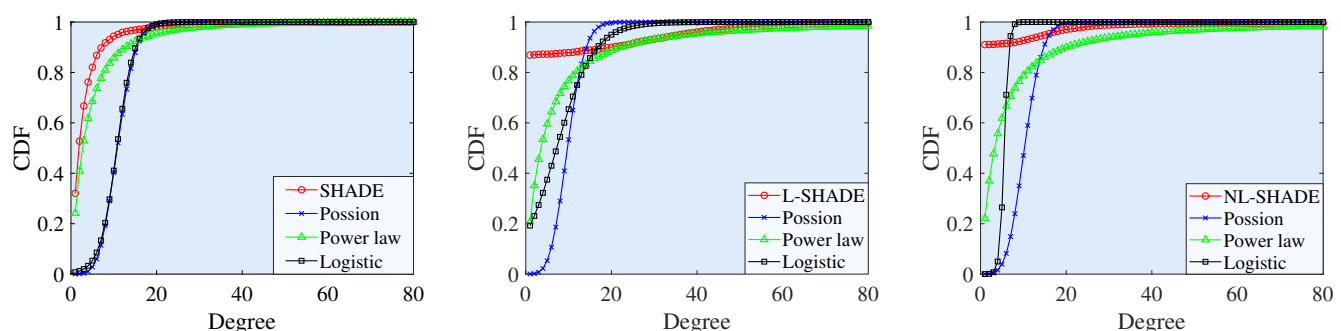


Figure 12. PIN structures of SHADE, L-SHADE, and NL-SHADE in the solar power generation forecasting task.

5.3.1. Distribution Analysis

Table 15 presents the fitting results of three algorithms under different mathematical distributions. Previous studies suggested that algorithms with PIN distributions closer to power-law characteristics generally achieve better optimization performance. However, different observations are obtained in this study. Although SHADE exhibits the closest power-law behavior, it achieves the worst prediction performance, whereas NL-SHADE obtains superior results despite exhibiting larger deviations from Poisson distributions. These findings suggest that conclusions derived from benchmark functions may not directly generalize to practical prediction problems.

5.3.2. Structural Interpretation

To further explain the superior performance of NL-SHADE, structural characteristics of the algorithms are investigated. According to the iteration mechanisms of SHADE, L-SHADE, and NL-SHADE, six connections are generated whenever a new individual is updated. Under the greedy update strategy, when offspring outperform parent individuals, the connection number of previous individuals becomes fixed at 8 (non-optimal individual: six initial connections with two additional references during offspring generation) or 9 (optimal individual: six initial connections with three additional references).

Combined with Figure 12, it can be observed that more than 80% of individuals in L-SHADE belong to the same update category, indicating that nearly all newly generated individuals outperform previous solutions. Compared with L-SHADE, NL-SHADE exhibits a larger number of individuals with identical update frequencies, implying a greater probability of continuous improvement.

Combining PIN distribution theory and structural characteristics, it can be concluded that better performance is not solely determined by similarity to power-law distributions. Structural behavior of the algorithm must also be considered. In NL-SHADE, PIN distributions remain relatively close to power-law characteristics while maintaining continuous individual updates throughout the optimization process. This indicates that NL-SHADE maintains continuous evolutionary activity throughout optimization. Therefore, NL-SHADE exhibits more favorable structural characteristics for solar power generation prediction tasks.

6. Conclusions and Future Works

In this paper, a nonlinear population reduction strategy is introduced into Differential Evolution (DE), resulting in the proposed NL-SHADE algorithm for solar energy-related optimization problems. Unlike conventional approaches that separately address PV model parameter estimation and solar power generation forecasting using different optimization frameworks, NL-SHADE provides a unified optimization framework capable of handling both tasks. Experimental results demonstrate that the proposed method achieves competitive and stable performance in both PV parameter estimation and solar power generation forecasting problems, indicating its effectiveness for solar energy applications. Furthermore, accurate photovoltaic parameter estimation can provide more reliable PV models for system design, performance evaluation, and fault diagnosis, while improved solar power generation forecasting can support energy scheduling, grid integration, and operational decision-making in smart energy systems. Therefore, NL-SHADE offers a practical and flexible solution for improving the efficiency, reliability, and sustainability of photovoltaic energy utilization in real-world applications.

In addition, the findings obtained from PIN analysis provide a useful complement to traditional PIN-based studies. By combining algorithm structures with PIN statistical characteristics, it becomes possible to provide additional guidance for algorithm selection

and improvement in real-world optimization problems. These findings also help explain the superior optimization behavior of NL-SHADE from the perspective of information transmission and population evolution. Although NL-SHADE demonstrates promising performance, several aspects still require further investigation. First, additional PV benchmark models can be considered to further evaluate the generalization capability of the proposed method. Second, more challenging forecasting scenarios, such as unusual weather conditions and long-term forecasting tasks, may be investigated to examine the robustness of the algorithm under more complex environments. Furthermore, future work will focus on developing more effective nonlinear optimization mechanisms and extending the proposed PIN-based analysis framework to broader optimization scenarios.

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Nomenclature

Nomenclature of the main variables and symbols used in this manuscript.

Symbol	Description
PV model variables	
I_{ph}	Photogenerated current
$I_{sd}, I_{sd1}-I_{sd3}$	Diode saturation current(s) in SDM, DDM, and TDM
R_s, R_{sh}	Series and shunt resistances
$\alpha, \alpha_1-\alpha_3$	Diode ideality factor(s)
N_s, N_p	Numbers of cells/diodes in series and parallel
RMSE	Root mean square error
DNM variables	
x_i	Input of the i -th synapse
$w_{i,j}, q_{i,j}, \theta_{i,j}$	Synaptic weight, threshold-related parameter, and synaptic threshold
$Y_{i,j}, Z_j, V, H$	Outputs of the synaptic layer, dendritic branch, aggregation layer, and soma
M, k, O_{soma}	Number of dendritic branches, sigmoid slope, and soma stimulation threshold
DE/NL-SHADE variables	
N, N^{init}, N_{min}, D	Population size, initial population size, minimum population size, and dimension
$X_i, x_{i,j}, V_{i,j}, U_{i,j}$	Target individual, component, mutant component, and trial component
$F, CR, M_F, M_{F,r}, M_{CR}, M_{CR,r}$	Scaling factor, crossover rate, and their historical memory values
r_1, r_2, r_3, X_{best}	Randomly selected indices and current best individual
$nFES, FES, p_a$	Current evaluations, maximum evaluations, and nonlinear reduction parameter

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