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Research Article

Power Transmission Network Optimization Strategy Based on Random Fractal Beetle Antenna Algorithm

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In order to optimize the performance of the transmission network (TN), this paper introduces the random fractal search algorithm based on the beetle antenna search algorithm, thus proposing the random fractal beetle antenna algorithm (SFBA). The main work of this research is as follows: (1) in the beetle antenna search algorithm, this study used a population of beetles and introduced elite members of the population in order to make the algorithm more stable and to some extent improve the accuracy of its answers. (2) Utilizing the elite reverse learning method and the leader's multilearning strategy for elites helps to strike a balance between the global exploration and local development of the algorithm. This strategy also further improves the ability of the algorithm to find the optimal solution. (3) Experiments on real experimental data show that the SFBA algorithm proposed in this paper is effective in improving TN performance. In summary, the research content of this paper provides a good reference value for the performance optimization of TN in actual production.

1. Introduction

Grid betweenness centrality is a crucial global geometric topology parameter that measures the significance and influence of key nodes and edges in the power network (PN) in the entire network (EN). For understanding the propagation mechanism of cascading faults, defending and mitigating the impact of major faults in the PN, topology optimization, PN elastic behavior and elastic optimal control, and other aspects related to the safe and stable operation (SO) and control of power systems, it is crucial to analyze and study the topology of the PN and its key nodes and edges [1]. Due to the specificity and high security requirements of the signals and business data that the power industry must transmit, it is unfeasible to use public networks such as the Internet to meet these requirements. The power communication network (PCN) is an industry-specific, dedicated communication network (CN) that primarily provides professional information services for the automatic control of the power grid (PG) and the modern management of the power enterprise in order to achieve safety and stability control of the PG basis [2]. The PCN is the second independent network after the principal PG. It contains information regarding the real-time production business of PG dispatching and the enterprise management business. If the PG dispatching center at all levels is the "brain" of the PG operation, then the PCN is the "nerve vein." The "brain" is responsible for making decisions and issuing instructions, while the "nerve vein" is responsible for transmitting the instructions and returning the effect after execution to the "brain," processing analytic data [3]. A PCN that is dependable, stable, secure, and efficient is essential for guaranteeing the SO of the PG. As power production becomes increasingly reliant on the PCN, power communication assumes an increasingly vital function within the entire power system. The PCN consists of communication lines, stations, numerous varieties of transmission equipment, access equipment, wiring connection equipment, terminal equipment, and various auxiliary equipment. The communication line includes physical carriers such as satellite, optical fiber, coaxial cable, and microwave, as well as specialized communication methods such as the power line

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carrier machine [4]. There are various channel varieties, including 2M channel, 64k low rate, IOM Ethernet, and 100M Ethernet, among others. Among them, optical fiber communication has many advantages, including high transmission capacity, strong anti-interference ability, and low loss in the transmission process, and the optical cable can be easily installed along with the power primary line, so it has become increasingly popular in the electric power industry in recent years within the CN. After years of continuous development, the power system has established a large-scale dedicated CN based primarily on optical fiber communication, supplemented by satellite, microwave, and other methods [5]. The business of power communication can be divided into two categories based on its business impact: transaction management and key operation business [6]. Key operation services, such as relay protection signals, telecontrol signals, dispatching data networks, dispatching telecommunications, and SCADA (distribution and power automation) systems, have a significant impact on the safe operation of the PG in the PCN. Substations are the core of these businesses and have extremely stringent security, dependability, and data accuracy requirements [7]. The business of transaction management refers to the internal office network, video conference, administrative telephone, diverse management information systems, and diverse application systems of electric power companies. It is characterized by a high volume of transactions, numerous data types, and significant burstiness [8]. Since SDH supports signal synchronization, diversified network topology, multiple self-healing modes, standardized network management interface and optical interface, etc., it is suitable for carrying diversified services [9]. After entering the 21st century, it is gradually applied to all levels in the PCN. Over the years, SDH communication technology has played a vital role in realizing unattended substations, digital substations, MIS (Management Information System) information transmission, and relay protection and has played a vital role in the efficient operation of the entire power system, providing a solid guarantee [10]. SDH is the abbreviation of synchronous digital hierarchy. It is a series of standardized digital transmission structures that transmit adaptive payload (PayLoad) through a physical TN [11]. It is a comprehensive information TN, including line complex connection, mapping, switching, and many other functions; its operation is managed by the network management system, which can realize effective network management and real-time monitoring of services to improve resource utilization. The goal of the SDH system is to establish a synchronous transmission system standard around the world to provide network operators with a flexible and economical network [12]. As far as transmission technology is concerned, SDH and the multiservice transmission platform (MSTP) based on SDH technology are the hotspots in the field of communication applications and are widely used in the communication backbone network [13].

How to effectively transport multiple types of services on a single basic network has become the industry's central concern in order to accommodate the rapid development of Ethernet services. The technical concept of MSTP based on SDH technology is therefore proposed. This technology can be combined with devices such as IP edge routers and SDH multiplexers to establish a network of independent individuals [14]. In the transmission process of business data flow, the characteristics of SDH technology with low delay and the application of various recovery and protection capabilities are used to optimize the network business support layer in order to facilitate the development of multibusiness applications and to thoroughly analyze the second and third layer multitype services. The present development trend of CNs will be the intelligence of optical transmission technology ASON, viewed at a large scale. MSTP, which can allocate the bandwidth of nodes based on requirements, is one of the significant development directions. Currently, the intelligent optical node of ASON has been implemented in the base layer of a long-distance fundamental network or metropolitan area network [15]. According to the currently available technologies, SDH-based MSTP is still undergoing accelerated development, and numerous new technologies have been developed. Notable among the current research hotspots [16] is the data layer processing technology, specifically how to use the elastic packet ring and multiprotocol label switching (MPLS) in MSTP to realize the application of Ethernet services and the enhancement of networking capabilities. In addition, some scholars have introduced intelligent algorithms to optimize the operation of transmission networks. One of the more classic methods is the transmission network optimization method proposed by Thang et al. based on the random fractal search algorithm [17]. This paper focuses on optimizing the operation of transmission power networks through the application of an enhanced stochastic fractal search algorithm. The proposed algorithm aims to improve the accuracy and efficiency of finding optimal solutions for power network operation, considering factors such as power generation, transmission, and load demand. By utilizing the improved stochastic fractal search algorithm, the study aims to enhance the stability, reliability, and cost-effectiveness of power network operations. The algorithm's effectiveness is evaluated through simulations and compared with other existing optimization techniques. The results demonstrate that the improved stochastic fractal search algorithm outperforms the alternatives, leading to more effective operation strategies for transmission power networks. Overall, the paper presents a promising approach for optimizing the operation of power networks, offering potential benefits for the energy industry.

Enhance the Stability and Security of the TN. The transport network is the foundation of the EN, and its security and stability are directly related to the operation of the CN and other devices. The significance of security and stability for the PG is self-evident; therefore, enhancing the security and stability of the CN is one of the primary objectives of network optimization [18]. *Improve the TN's Dependability*. The connectivity rate of the network is used to determine the network's reliability, so the reliability also reflects the network's connectivity. In order to assure the safety and SO of the PG system as a whole, the PCN's dependability is directly

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related to whether the power system can respond correctly and quickly to potential safety hazards the first time [19]. *Optimize Information TN Channel Utilization*. How to rationally allocate resources, reduce network constraints as much as possible, balance network loads, reduce routine maintenance costs, and increase response speed as the TN scale continue to grow. With the continuous development of the PG system, the PCN's communication capacity should increase proportionally. Improving the PCN's load capacity and optimizing the network's resource utilization are crucial for the safe and secure development of the PG system and PG CN [20]. In the process of dismantling and repurposing obsolete communication equipment, various constructions must comply with applicable safety regulations and work requiring fire and power disruptions must complete work tickets in accordance with applicable regulations. The equipment room, transmission rack, power supply, optical fiber, and other conditions should be thoroughly considered, and a detailed and comprehensive circuit cutover plan should be developed to ensure the safety of the circuit cutover during the cutover process. In addition, a complete circuit cutover record should be maintained to ensure operation. *Open Circuit Protection*. During the implementation of the network optimization plan, adjustments should be made in the order of core, aggregation, and edge layers, from top to bottom. In addition to subnets and regions, structure and equipment adjustments should be divided into subnets. It has formed a ring network; after gaining experience with network optimization and adjustment [21], it can be fully extended to the entire CN after being tested out in specific areas.

This paper combines the improved stochastic fractal search algorithm to optimize the power TN model, constructs the power TN optimization model, and promotes the improvement of power transmission efficiency. The random fractal algorithm and beetle antenna algorithm can be used together to optimize the transmission and transformation network (TN) in the following ways: *Random Fractal Algorithm*. The random fractal algorithm can be used to generate a fractal structure that mimics the complexity and randomness found in nature. This can be applied to the TN to improve its robustness and resilience. The fractal structure can be used to design the network's topology and optimize its connections, resulting in a more efficient and stable TN. *Beetle Antenna Algorithm*. The beetle antenna algorithm is inspired by the behavior of beetles and their ability to locate resources efficiently. This algorithm can be used to optimize the parameters of the TN, such as the transmission power, frequency, and direction. By modeling the TN as a network of sensors, the beetle antenna algorithm can optimize the transmission and reception of signals, leading to improved network performance. By combining these two algorithms, we can design a more optimized TN that is both robust and efficient. The random fractal algorithm can provide a strong backbone for the TN, while the beetle antenna algorithm can optimize its parameters. This approach can lead to improved transmission and transformation of data, reduced energy consumption, and increased network lifetime. In addition, this approach can be applied to various types of TNs, including wireless sensor networks, ad hoc networks, and Internet of Things (IoT) networks. The main contribution of this paper is to use random fractal search algorithm [22, 23] and beetle antennae search algorithm to improve the performance of power transmission and transformation network. Experimental results show that the method used in this paper can improve the performance of the network.

2. Related Research

2.1. Optimization of the Power Transmission Network Problem. The optimization of power transmission networks is necessary because it can enhance the efficiency, reliability, and sustainability of the electrical systems. With the increasing energy demand and the expansion of power systems, transmission networks face numerous challenges, including load growth, voltage stability, losses, and energy wastage. By optimizing the transmission networks, we can maximize the utilization of existing resources, reduce energy losses and environmental impacts, and improve the reliability and stability of the grid. Optimization measures include rational planning of transmission lines, optimizing power transmission and distribution methods, and enhancing grid control strategies. Through these measures, we can better adapt to the demands of future energy transition, achieve efficient delivery of clean energy, and promote sustainable development. In conclusion, the optimization of transmission networks is crucial for enhancing the overall performance and sustainability of power systems.

The optimization of transmission networks is closely related to optimization algorithms, as these algorithms provide effective tools and methods for achieving optimal solutions in transmission network optimization. The objective of transmission network optimization is to maximize the efficiency and reliability of power systems by adjusting factors such as transmission line configurations, power allocation, and grid control strategies. On the other hand, optimization algorithms are mathematical and computational tools designed to solve complex optimization problems, capable of finding optimal or near-optimal solutions under given constraints. Optimization algorithms can be applied to the planning, operation, and scheduling of transmission networks. By establishing mathematical models, considering various constraints and objective functions, and utilizing algorithms for calculations and searches, optimal configurations and operating strategies for transmission networks can be obtained. Common optimization algorithms include linear programming, integer programming, genetic algorithms, and particle swarm optimization, among others. By integrating optimization algorithms with the optimization objectives of transmission networks, comprehensive optimization of power systems can be achieved, leading to improved transmission efficiency, reduced energy losses and costs, and addressing the challenges of sustainable development in power systems. Therefore, optimization algorithms play a crucial role in transmission network optimization, providing vital support in achieving optimal performance of power systems.

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2.2. Metaheuristic Search Algorithm Design. Metaheuristic search (MHS) algorithms are optimization algorithms designed to solve complex problems that are difficult to solve using traditional mathematical methods. These algorithms are inspired by natural or social phenomena and use heuristic search techniques to explore the solution space and find near-optimal or satisfactory solutions. The general steps of the search process in the MHS algorithm [24] are as follows (Algorithm 1):

The Bat search algorithm (BSA) is a metaheuristic search algorithm inspired by the echolocation behavior of bats. In BSA, the generation of the population involves the following steps:

Random initialization: Similar to other metaheuristic algorithms, BSA starts by randomly initializing the population with a set of candidate solutions.

Frequency and velocity update: Each bat in the population updates its frequency and velocity based on the previous iteration's information. This update allows bats to explore the solution space dynamically.

Local search: Bats perform a local search around their current positions to improve their solutions. This local search helps to refine the solutions and enhance their quality.

Solution update: Bats update their positions and solutions based on their updated frequencies, velocities, and the results of the local search. This step allows bats to move towards promising regions of the solution space.

By iteratively performing these steps, the population of bats in BSA explores the solution space, adjusts their positions, and refines their solutions in search of the optimal or near-optimal solutions for the given problem.

3. SFBA Algorithm

The first version of the BAS algorithm just requires one long beetle, and it is also able to produce appropriate answers to several straightforward optimization issues. However, optimization issues can be found in many other sectors, and they are becoming increasingly difficult to solve as a result of factors such as the increasing complexity of optimization variables. The BAS algorithm is frequently unable to produce a solution that satisfies the requirements when it is used to problems of this nature. In order to accomplish this goal, this paper creates a cluster of these beetles and applies the moth-flame optimization (MFO) algorithm on the population structure as a point of reference. These sorts of enhancements have the potential to render the algorithm more stable and, to some extent, boost its capacity for optimization.

The elite individual matrix **E** and its fitness value F_E are respectively shown in the formula. In addition, the following provisions are made in terms of population structure:

(1) In the elite individual matrix **E**, each beetle is sorted according to the increasing fitness value, and F_E is also sorted in this order. For minimization optimization problems, the smaller the fitness value, the better. Therefore, the first one is the best individual so far.

(2) Each individual beetle can only update its place based on the elite people in **E** who have the same order as it does. The positions of the remaining beetles are updated using the final individual in E as a reference point.

According to the regulations presented above, the beetle is permitted to hunt in the vicinity of the elite solution. Additionally, the beetle does not only search around a predetermined answer, which to some degree enhances the algorithm's ability to explore the search space. The link that exists between insects and elite persons after they have been updated is depicted in Figure 1.

If n beetles are updated each time relative to a set number of elite solutions and the elite individuals are always changing, then the capacity of the algorithm to produce potentially optimum solutions will be lowered when each iteration is updated relative to various elite solutions. This is because the ability of the algorithm to develop possible optimal solutions depends on the elite individuals. It is for this reason that, throughout the iterative process, the number of retained elite individuals undergoes a constant reduction:

$$n' = \text{round}\left(n - t \cdot \frac{n-1}{T}\right), \tag{1}$$

where t is the current number of iterations, T is the maximum number of iterations, round() is the function that symbolizes rounding, n is the number of long beetles, n' is the number of retained elite individuals, t is the current number of iterations, and T is the maximum number of iterations.

This paper adopts cat chaotic map with relatively good ergodicity and uniformity. The classical cat chaotic map is a two-dimensional reversible chaotic map, and its dynamic equation can be described as follows:

$$\begin{bmatrix} sx_{m+1} \\ sy_{m+1} \end{bmatrix} = \begin{bmatrix} 11 \\ 12 \end{bmatrix} \begin{bmatrix} sx_m \\ sy_m \end{bmatrix} \text{mod } 1. \tag{2}$$

Among them, sx_m is the value of the sx sequence at the mth iteration. The structure of this chaotic map is simple, so the computation is fast. In addition, the chaotic sequence generated by it is also more uniformly distributed in the interval [0, 1]. If it is assumed that the size of the beetle population is n and the dimension of the variable is d, the resulting chaotic sequences are $sx = \left\{sx_j, j = 1, 2, \cdots, d\right\}$ and $sy = \left\{sy_j, j = 1, 2, \cdots, d\right\}$, where $sx_j = \left\{sx_{i,j}, i = 1, 2, \cdots, n\right\}$ and $sy_j = \left\{sy_{i,j}, i = 1, 2, \cdots, n\right\}$. It should be noted

(1) Begin (initialization)
(2) P: Create the P-population
(3) for $i = 1$: n (the number of solution candidates)
(4) F: calculate the fitness values of members in P
(5) end
(6) while (search process lifecycle)
(7) Step 1: guide selection mechanism (create a mating pool) selection of reference positions from the P by using guide selection methods ("fitness distance balance, FDB," greedy, randomly, and roulette wheel)
(8) Step 2: search operators:
(9) Exploitation (neighborhood search around reference positions)
(10) Exploration (diversification operations in P)
(11) Step 3: update mechanism: update the P-population depending on the fitness values of solution candidates or the NSM (natural survivor method)-scores [25] of them
(12) next generation until termination criterion
(13) End

Algorithm 1: General steps of the search process in MHS algorithms.

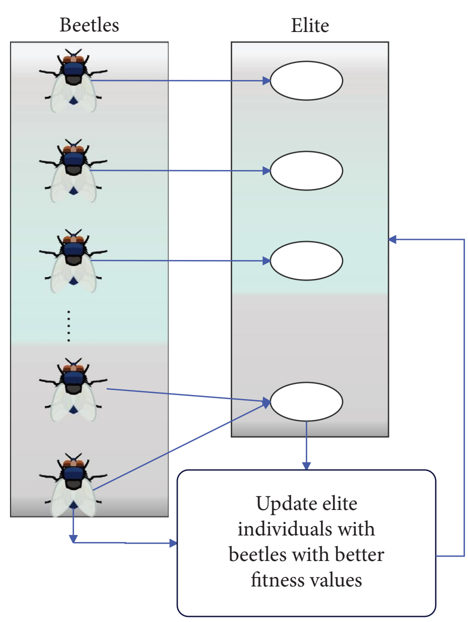

Figure 1: Updated relationship diagram of beetles and elite individuals.

that the chaotic sequence needs to be given an initial value on the interval [0, 1]. Then, for each dimension in the population, the cat chaos map can be expressed as follows:

$$\begin{cases} sx_{i+1,j} = \left(sx_{i,j} + sy_{i,j}\right) \bmod 1, \\ sy_{i+1,j} = \left(sx_{i,j} + 2sy_{i,j}\right) \bmod 1. \end{cases} \quad (3)$$

It should be noted that since the cat chaotic map has two sequences sx and sy, only sy is selected in this paper. After that, it is necessary to map the chaotic sequence into the search space to obtain the represented population X. We take $x_{i,j}$ as an example and calculate it by the following formula:

$$x_{i,j} = lb_j + sy_{i,j} \cdot \left(ub_j - lb_j\right), \quad (4)$$

where $x_{i,j}$ is the jth dimension of the ith beetle and ub_j and lb_j are the upper and lower bounds of the jth dimension of the variable, respectively.

The fundamental BAS algorithm is quite sensitive to the settings of its parameters, and the use of alternative parameters can frequently provide substantially different optimization outcomes. Alternately, a certain combination of parameters may be appropriate for one problem, but it may not be possible to solve another problem in an efficient manner. The following formula is used to compute the distance along each dimension:

$$D_{i,j}^t = \begin{cases} \left|e_{i,j}^t - x_{i,j}^t\right|, i \le n', \\ \left|e_{n',j}^t - x_{i,j}^t\right|, i > n', \end{cases} \quad (5)$$

where $x^t_{i,j}$ represents the jth dimension of the ith beetle at time t, $e^t_{i,j}$ is the jth dimension of the ith current optimal individual at time t, $D^t_{i,j}$ represents the distance between the ith beetle and the corresponding elite individuals in the jth dimension at time t, and n' represents the number of elite individuals currently reserved.

After considering the random time delay, the step size is expressed as the following formula:

$$\text{step}^t_{i,j} = r_1 \cdot D^t_{i,j} + M \cdot c \cdot r_2 \cdot \left(b^{t-k}_{i,j} - x^t_{i,j}\right). \tag{6}$$

M is the delay factor, which is used to decide whether to add the delay term, and c is the acceleration coefficient. Both of these factors are discussed further. The range of possible values for k, which denotes the delay time, is $[0, t-1]$. The acceleration coefficient c found in the BAS-RDEO algorithm is conceptually comparable to the cognitive and social factors found in the PSO algorithm. An acceleration coefficient that varies over time is utilized in this piece of work. To be more explicit, it is diminishing in a linear fashion, which can be stated as follows:

$$c = c_i - \left(c_i - c_f\right) \cdot \frac{t}{T}. \tag{7}$$

Among them, c_i and c_f represent the initial value and termination value of the acceleration coefficient, respectively.

In this paper, the evolutionary factor is used to judge the evolutionary state of the population, which has been introduced. According to the size of the evolution factor and the characteristics of the search process, four evolution states can be defined: the convergence state, the development state, the exploration state, and the jumping state. Before calculating the evolution factor, the average distance I_i between each long beetle and other long beetles needs to be calculated by the following formula:

$$I_i = \frac{1}{n} \sum_{q=1}^{n} \sqrt{\sum_{j=1}^{d} \left(x_{i,j} - x_{q,j}\right)^2}. \tag{8}$$

Among these variables, n and d stand for the size of the population and the variable dimension, respectively. When all is said and done, the evolutionary factor known as EF can be defined as follows:

$$EF = \frac{I_g - I_{\min}}{I_{\max} - I_{\min}},$$
$$\xi(t) = \begin{cases} 1, 0 \leq EF < 0.25, \\ 2, 0.25 \leq EF < 0.5, \\ 3, 0.5 \leq EF < 0.75, \\ 4, 0.75 \leq EF \leq 1. \end{cases} \tag{9}$$

Among them, $\xi(t) = 1, 2, 3, 4$ represents the convergence state, the development state, the exploration state, and the hop state, respectively. Transform the abovementioned formula into the following form:

$$\begin{cases} x^t_{il} = x^t_i + \text{step}^t_i, \\ x^t_{ir} = x^t_i - \text{step}^t_i. \end{cases}$$
$$\begin{cases} f^{t+1}_{x_i} = \min\left(f\left(x^t_{il}\right), f\left(x^t_{ir}\right)\right), \\ x^{t+1}_i = \underset{x_i}{\operatorname{argmin}}\, f^{t+1}_{x_i}. \end{cases} \tag{10}$$

The concept of inverse learning has been explained. Elite reverse learning is a novel technology in the field of intelligent computing that is analogous to traditional reverse learning but is more effective. Following this, you will find a definition of the concept of elite reverse learning.

Definition (elite reverse learning): If $x^t_e = (x^t_{e,1}, x^t_{e,2}, \ldots, x^t_{e,d})$ is an elite individual in the population at time t, then its elite reverse solution is $\text{oxx}^t_e = (ox^t_{e,1}, ox^t_{e,2}, \ldots, ox^t_{e,d})$. Each dimension of ox^t_e can be obtained by the following equation:

$$ox^t_{e,j} = \omega \cdot \left(da^t_j + db^t_j\right) - x^t_{e,j}. \tag{11}$$

Among them, ω is a generalized coefficient uniformly distributed in [0, 1]; da^t_j and db^t_j are dynamically changing boundaries and can be defined as follows:

$$\begin{aligned} da^t_j &= \min\nolimits_{1\leq i\leq n}\left(x^t_{i,j}\right), \\ db^t_j &= \max\nolimits_{1\leq i\leq n}\left(x^t_{i,j}\right). \end{aligned} \tag{12}$$

However, for a given problem, a certain dimension of individual ox'_e after using elite reverse learning may jump out of the boundary $[lb_j, ub_j]$, which will make the algorithm ineffective. To avoid this situation, the following equation resets individuals outside the variable bounds:

$$ox^t_{e,j} = \begin{cases} lb_j, ox^t_{e,j} < lb_j, \\ ub_j, ox^t_{e,j} > ub_j. \end{cases} \tag{13}$$

In addition, the number n' of elite individuals decreases with the increase of the number of iterations. In view of this, this paper only selects the first individual in the elite individual matrix E for L times of elite reverse learning and sets L equal to the population size n in this paper. After the elite reverse learning, it is necessary to merge the L elite reverse solutions with the individuals in the matrix, and then select n' better individuals to replace the elite solutions in the matrix. So far, elite reverse learning has been executed. After that, it is also necessary to introduce the leader's multilearning strategy.

The leader learns to randomly select one dimension of the globally optimal individual. For example, if the jth dimension is chosen, it can be expressed as $e^t_{1,j}$. The reason for choosing only one dimension is because the local optimum is most likely to have a better solution in a certain dimension. After selecting a dimension, leader multilearning is carried out through the following 3 formulas:

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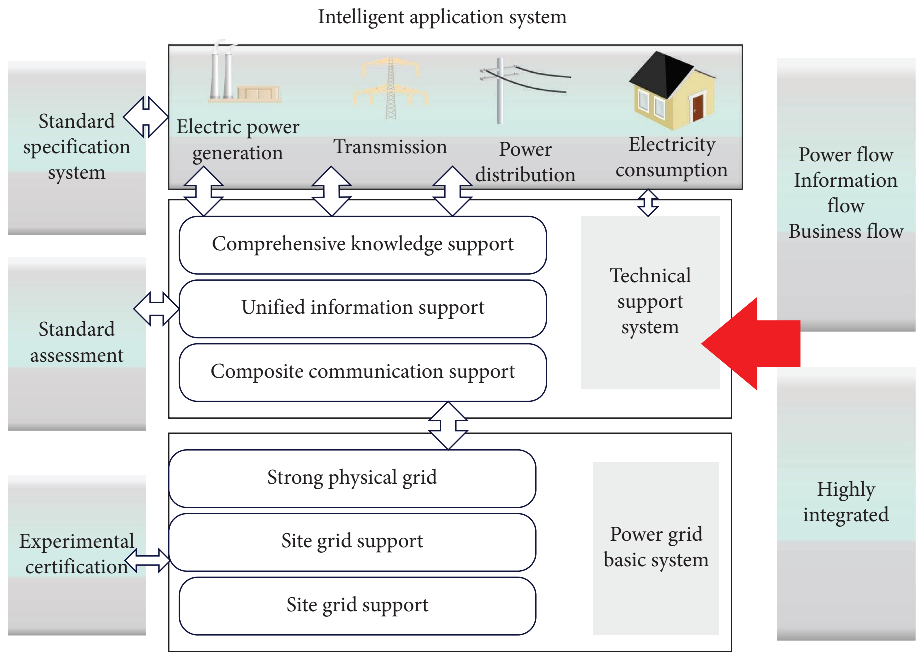

FIGURE 2: Schematic diagram of the basic architecture of the smart grid.

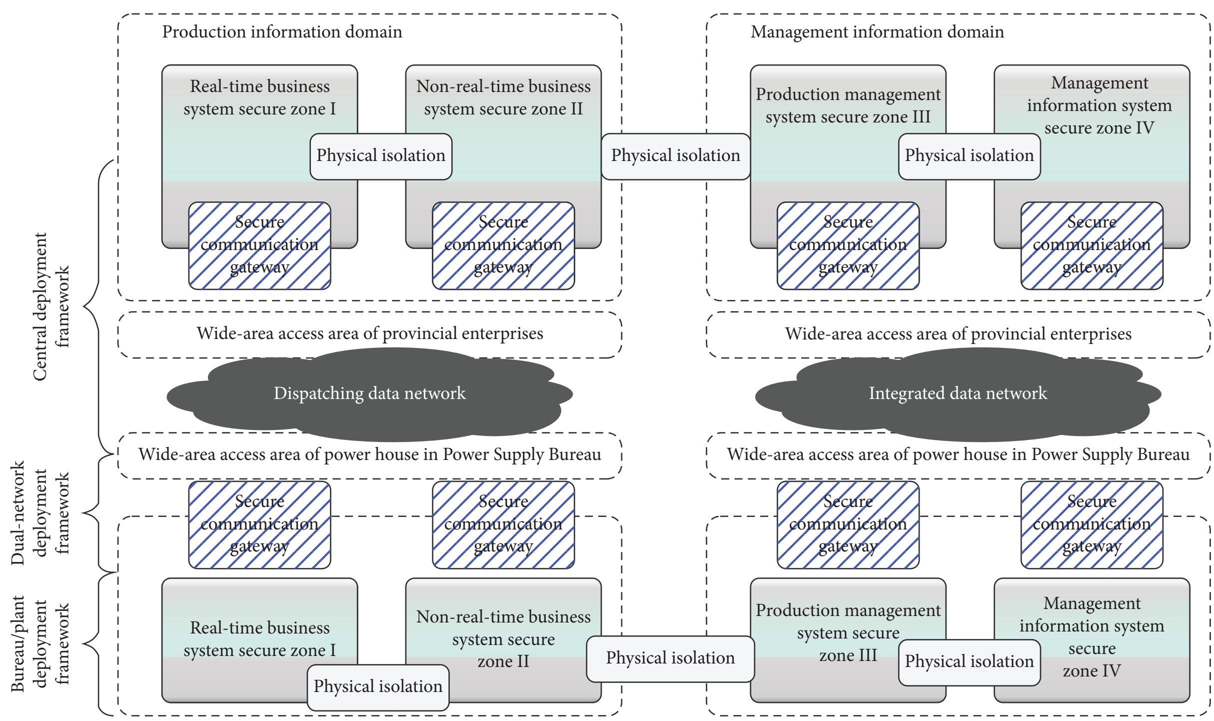

FIGURE 3: The dual-network power safety communication infrastructure of the dispatching data network and the integrated service network.

$$e_{1,j}^{t} = e_{1,j}^{t} + \left(\left(ub_j - lb_j\right) \cdot \text{rand} - ub_j\right) \cdot R_1, \tag{14}$$

$$e_{1,j}^{t} = e_{1,j}^{t} + \left(\left(\lambda_{1,j} - \lambda_{2,j}\right) \cdot \text{rand 2} - \lambda_{1,j}\right) \cdot R_2, \tag{15}$$

$$e_{1,j}^{t} = e_{1,j}^{t} + \left(\left(\eta_1 - \eta_2\right) \cdot \text{rand 3} - \eta_1\right) \cdot R_3. \tag{16}$$

Among them, rand1, rand2, and rand3 are random numbers in [0, 1]; η_1 and η_2 are the maximum and minimum values of all dimensions of the globally optimal individual e_1^t in each generation. R_1, R_2, and R_3 are the search radius of the multilearning method. Obviously, formula (14) is used to improve the global exploration ability, while formulas (15)

Table 1: Parameter settings.

Algorithm	Detail
FPA	Population size: 50 Iterations: 1000 Search range/limits: [−5, 5] for each variable Fitness function: mean squared error Mutation rate: 0.2 Termination criterion: 6000
GWO	Population size: 30 Iterations: 500 Search range/limits: [−10, 10] for each variable Fitness function: Rosenbrock function Mutation rate: 0.1 Termination criterion: 5000
WOA	Population size: 50 Iterations: 1000 Search range/limits: [−100, 100] for each variable Fitness function: sphere function Mutation rate: 0.5 Termination criterion: 6000
KH	Population size: 100 Iterations: 2000 Search range/limits: [−50, 50] for each variable Fitness function: Ackley function Mutation rate: 0.2 Termination criterion: 7000
PSO-TVAC	Population size: 40 Iterations: 800 Search range/limits: [−1, 1] for each variable Fitness function: Rastrigin function Termination criterion: 6000
BAS	Population size: 50 Iterations: 1000 Search range/limits: [−5, 5] for each variable Fitness function: Griewank function Mutation rate: 0.2 Termination criterion: 8000
BAS-RDEO	Mutation rate: 0.3 Radius: 0.1 Encircling rate: 0.5 Termination criterion: 6000

and (16) are used to improve the local development ability. It should be noted that the search radii R_1, R_2, and R_3 are determined by the Markov chain $\gamma^t\,(t > 0)$:

$$P\left\{\gamma^{t+1} = j \mid \gamma^t = i\right\} = \alpha_{ij}^t, i, j = 1, 2, \ldots, N. \tag{17}$$

Among them, $\alpha_{ij}^t \geq 0\,(i, j \in S)$ is the transition probability from i to j. The number of states set in this paper is $N = 2$. At the same time, this paper assumes that the values of R_1, R_2, and R_3 are the same, namely, $R_1 = R_2 = R_3$. Therefore, when choosing the value of the search radius, we only take R_1 as an example. When the state is $\gamma^t = 1$, R_1 is taken as $\rho_1 = 1$. When the state is $\gamma^t = 2$, the value of R_1 is $\rho_2 = 0.1$. It should be pointed out that the adopted probability transition matrix Γ^t is time-varying and can be expressed as follows:

Table 2: Performance comparison of various optimization algorithms.

Function	Algorithm	Average optimal value	Standard deviation
$f_{\text{Spherical}}(x)$	FPA	0.1716	0.0328
	GWO	0.1322	0.0234
	WOA	0.1632	0.0257
	KH	0.1278	0.0263
	PSO-TVAC	0.1037	0.0189
	BAS	0.0863	0.0195
	BAS-RDEO	0.0631	0.0176
$f_{\text{Rosenbrock}}(x)$	FPA	56.37	9.7634
	GWO	45.82	9.1733
	WOA	49.10	7.9348
	KH	39.62	8.2542
	PSO-TVAC	37.07	6.7230
	BAS	36.62	6.8123
	BAS-RDEO	33.28	5.7913
$f_{\text{Rastrigin}}(x)$	FPA	58.91	8.1932
	GWO	54.37	7.2749
	WOA	55.68	7.1828
	KH	43.13	5.9732
	PSO-TVAC	40.19	5.2764
	BAS	42.04	4.8345
	BAS-RDEO	39.83	4.0273

$$\Gamma^t = \begin{pmatrix} \alpha^t 1 - \alpha^t \\ \alpha^t 1 - \alpha^t \end{pmatrix}. \tag{18}$$

Among them, α^t is a time-varying probability variable whose value decreases linearly in the iterative process and can be expressed as the following formula:

$$\alpha^t = \left(\alpha_i - \alpha_f\right) \cdot \frac{T - t}{T} + \alpha_f. \tag{19}$$

Among them, α_i and α_f are the initial and final values of α^t, respectively. In this paper, they are set to $\alpha_i = 1$ and $\alpha_f = 0$. Therefore, ρ_1 occurs more frequently than ρ_2 in the early stages. However, in the late period, ρ_1 rarely occurs and ρ_2 occurs frequently. It should be noted that in leader multilearning, if the new position is better than the previous global optimal individual, the new position is accepted. Otherwise, the previous global optimal individual remains unchanged.

4. Power TN Optimization Experiment

In order to provide high-reliability and uninterrupted communication services for power systems, power communication must meet and adapt to the features that power cannot be stored, and that production, supply, and sales are all finished at the same time. A basic architecture of a smart grid is depicted in a schematic form in Figure 2, which may be seen here.

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Table 3: The effect of each comparison algorithm in power TN optimization.

Model	Number	1	2	3	4	5	6	7	8
[26]	Optimization effect	87.433	90.833	84.872	82.192	85.234	88.263	83.753	80.364
[27]	Optimization effect	88.872	89.251	82.374	81.233	83.4988	85.721	82.3612	79.213
[28]	Optimization effect	88.891	89.376	82.763	82.124	84.243	86.263	83.171	79.721
[29]	Optimization effect	89.082	90.163	82.979	83.457	84.799	87.108	84.589	80.823
BAS-REDO	Optimization effect	89.260	91.278	84.689	83.445	86.095	87.935	84.601	81.070

Figure 3 illustrates the design of the PCN's two fundamental networks, which are the integrated service data network and the dispatching data network. Figure 3 also illustrates the PCN's overall structure.

To validate the performance of the proposed method in power TN optimization, the experimental setup in this paper is mainly conducted from two perspectives. Firstly, it verifies the optimization performance of the proposed method, and secondly, it applies the method to optimize the power transmission network.

Firstly, to validate the performance of the proposed algorithm, this paper will conduct a comparative analysis of solution accuracy and convergence using several typical test functions. Specifically, a classic single-peak spherical function and two multipeak functions, Rosenbrock and Rastrigin, will be employed for testing. The functional forms of these test functions are as follows:

$$f_{\text{Spherical}}(x) = \sum_{i=1}^{n} x_i^2,$$
$$f_{\text{Rosenbrock}}(x) = \sum_{i=1}^{n-1}\left(100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right), \tag{20}$$
$$f_{\text{Rastrigin}}(x) = \sum_{i=1}^{n}\left(x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right).$$

The parameter settings of each algorithm are shown in Table 1.

Based on the parameter settings provided in Table 1, the experimental results obtained by each algorithm are shown in Table 2.

According to the experimental data shown in Table 2, it can be observed that the proposed BAS-RDEO algorithm outperforms other algorithms in both the average optimal value and standard deviation indicators. This indicates that the proposed algorithm has shown significant improvements in both computational accuracy and stability. Moreover, the BAS-RDEO algorithm is more adept at locating the global optimum in the solution space.

In order to further compare and analyze the performance of the model in this paper and similar algorithms, this paper selects [26–29] as comparison algorithms. The parameter settings of each model are the same as in references. The effect of each algorithm in the optimization of the power TN is shown in Table 3.

From the experimental results shown in Table 2, it can be seen that in most cases, our method obtains the optimal effect, and the average optimization effect is 86.067. There are two sets of data in [26] that exceed our method, and the average obtained was 85.368. The experimental results obtained by [28, 29] are relatively close, and their mean values are 84.567 and 85.375, respectively, which are lower than the experimental data obtained by the algorithm in this paper. Our method utilizes random perturbations and self-similarity to explore the solution space effectively. It can escape local optima by introducing randomness and adapt its search strategy to different scales within the problem domain. The algorithm requires minimal problem-specific information, making it versatile for various optimization problems. In comparison, the gaining-sharing knowledge-based algorithm emphasizes knowledge exchange among individuals in a population, promoting collective intelligence and exploration. However, when focusing on the advantages of the stochastic fractal search algorithm, it stands out in its ability to efficiently explore the solution space, especially in high-dimensional problems and noisy environments. Its simplicity of implementation, robustness, and adaptability to diverse problem domains contribute to its practicality. In addition, the algorithm's stochastic nature and self-similarity enable it to overcome local optima and discover global optima. In general, our method provides an efficient and flexible solution for optimization tasks that demand efficient exploration, adaptability, and ease of implementation. This makes our method suitable for a wide range of optimization problems. In comparison to the strategy described in [27], our approach demonstrates clear and convincing advantages. This demonstrates that nonparametric statistical methods function satisfactorily in general when it comes to the optimization effect of transmission networks.

5. Conclusion and Future Directions

The graphical connection relationship between each electrical component in the PN is referred to as the "PN topology," and it is described here. The topological structure and system function of the PN are its two fundamental qualities, and the two are interrelated and affect each other in the following way: the structure places restrictions on and determines the size, type, and boundary of the power system function; the structure also sets the size of the PN. The function of the power system is the exterior manifestation of its structure, and the change in function is typically accompanied by a change in the system's structure. Both the structure of the PN and the stability of the power system are directly impacted by the essential nodes and edges that make up the PN. In this study, an enhanced stochastic fractal search technique is used with the power TN model in order to achieve optimal results. The empirical research demonstrates that the improved stochastic fractal search method

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that was suggested in this paper is able to successfully increase the optimization effect of the power TN, and that it also has a beneficial effect on enhancing the efficiency of power transmission. This paper has some shortcomings that need to be addressed. To give just one illustration, the identification of the model's ideal parameters necessitates several iterations, each of which takes a considerable amount of time and contributes to an increase in the algorithm's level of complexity about the passage of time. The main work of this paper in the future will be carried out to address the abovementioned limitations.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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