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Intelligent Algorithms for Voltage Level Collaborative Planning and Power Supply Capacity Optimization

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Abstract. In this paper, an optimization strategy for voltage level planning using intelligent algorithms is constructed to improve the power supply capacity (PSC) and overall performance of the power grid. The Laida criterion is used to clear abnormal data, and the weighted average method is used to supplement the missing data; the adaptive Particle Swarm optimization algorithm (APSO) is used to construct a voltage-level collaborative planning model, through flexible adjustment of inertial weights and acceleration factors, to achieve a balance between global search and local fine-tuning; by combining particle swarm optimization (PSO) and Genetic algorithm (Genetic Algorithm, GA), a hybrid algorithm (PSO-GA) is formed, effectively avoiding the dilemma of local optimization by introducing random self-feedback variation and high-frequency cross-operation. The results show that the energy utilization rate and transmission efficiency of the APSO algorithm have increased to 94.3% and 92.8%, respectively; the PSC of the PSO-GA algorithm has increased by 20.61% and 22.44% under low-load and medium-load conditions, respectively. Both algorithms effectively solve the voltage planning challenges, significantly reduce energy consumption, enhance the synergy of the voltage level, and improve the maximum PSC.

Key words. Voltage level, Collaborative planning, Power supply capacity optimization, Adaptive particle swarm optimization, Genetic algorithm

1. Introduction

In the development of power systems, voltage level collaborative planning and PSC optimization have always been difficult to research. Faced with the continued growth of power demand and the increasingly complexity of the grid structure, ensuring the stable operation of the power grid, improving PSC, and reducing losses have become an important challenge in the power industry. Traditional planning methods mostly rely on empirical judgment and local optimization, and it is difficult to comprehensively consider the mutual influence between voltage levels and the overall performance of the power grid, so their planning effects are often not ideal. This study constructs a voltage level collaborative planning and PSC optimization method based on intelligent algorithms. The key to voltage level collaborative planning is to quantify the mutual influence between each voltage level to achieve optimal coordination between levels. Traditional planning methods have been difficult to cope with the complexity of modern power grids. The introduction of intelligent algorithms provides a new solution to this problem. Among them, PSO, GA, etc., have been widely used. These algorithms are drawn from evolution or group behavior in nature and can effectively deal with complex optimization problems and show strong search and adaptability [1-3]. In voltage-level collaborative planning, they can optimize power supply configuration, equipment location selection, etc., to improve the coordination and PSC of the power grid. PSC optimization is an important part of this goal, and it aims to tap the potential of the power grid by reducing losses, stabilizing voltages, and improving energy efficiency. As an invalid consumption, power loss affects the overall efficiency of the power grid. Intelligent algorithms can optimize the grid structure and strategies, reduce losses, enhance voltage stability, and thus improve PSC.

This paper solves the problem of mutual influence between multiple voltage levels and overall performance optimization that is difficult to deal with by traditional planning methods by constructing a voltage level collaborative planning model. By dynamically adjusting the inertial weight and acceleration factor, the global search capability and local fine-tuning accuracy are significantly improved, and refined regulation of the configuration of each voltage level is achieved. This greatly reduces power loss and voltage fluctuations, and also effectively enhances the stability of power grid operation. To conduct in-depth research on the optimization of PSC, this paper constructs a PSO-GA algorithm model, which combines PSO's powerful global search capabilities and GA's efficient local optimization characteristics, thus effectively avoiding the dilemma of traditional optimization methods that are prone to falling into the local optimal solution, and has significant advantages over other similar algorithms.

2. Related Work

Voltage level collaborative planning refers to the overall consideration and optimization design of power grids of different voltage levels in power grid planning to improve the reliability and economical power supply of power grids, while ensuring the power balance and voltage stability of power grids at all levels [4,5]. The details are shown in Table 1.

Table 1. Reference structure table of voltage-level collaborative planning.

Author/year	Method overview	advantages	Disadvantages	References
Deng Jiahao, 2023	Combining the risk measurement method of opportunity constraints and conditional risk value targets, evaluate the node voltage risk caused by load uncertainty	Ability to quantify risks and adapt to uncertain environments	Complex calculations may affect real-time applications	[6]
Lee Jin-Oh, 2024	Determine the optimal placement of voltage balancers in bipolar DC power distribution systems	Maintain voltage balance and improve power supply quality	Model assumptions may not match the actual network	[7]
Baviskar Aeishwarya, 2022	Research on multi-voltage level active distribution network model based on real network data	Consider the actual network data and apply new energy access	Insufficient consideration of sensitivity to extreme weather events	[8]
Makinde Kehinde Adeleye, 2021	Discuss the influence of distributed power generation technology on overvoltage problems and mitigation strategies	Provide a variety of technologies to alleviate overvoltage	Strategies need to be adjusted for specific network characteristics	[9]
Li Zheng,2022	Study the voltage adaptability of distributed photovoltaic access to distribution networks	Emphasize the importance of voltage adaptability	Insufficient discussion of large-scale distributed photovoltaic access	[10]

To satisfy the increasing demand for electricity, maintain the stability and safety of the power supply, and support the sustainable growth of the economy and society, PSC optimization aims to increase the grid's PSC and efficiency [11,12]. The details are shown in Table 2.

Table 2. Reference structure table of voltage-level collaborative planning.

Author/year	Method overview	advantages	Disadvantages	References
Wang Ning, 2023	A method for evaluating the short-term power supply capacity of microgrids considering the uncertainty of wind power, photovoltaic, and load is proposed, and each scenario is optimized and solved.	It can effectively cope with the impact of the volatility of new energy sources.	The applicability to extreme weather conditions has yet to be verified.	[13]
Fu Xiangyun, 2024	The improved small interference analysis method is used to analyze the dynamic voltage stability, and a mathematical model of the maximum power supply capacity taking into account the dynamic voltage stability index is established.	Accurately evaluate the power supply limit of the flexible interconnected power grid under dynamic operating conditions.	The complexity of the model is high and the calculation cost is large.	[14]
Zhou Xiaoming, 2022	Evaluation indicators such as supply capacity reserve and supply capacity balance are defined, and evaluation models for single-layer equipment and inter-layer equipment are established.	It comprehensively reflects the distribution of power supply capacity between equipment at different levels of the distribution network.	The application needs to be adjusted for specific network characteristics.	[15]
Wang Shunli et al., 2024	The adaptive square root cubic Kalman filter based on particle swarm optimization is used to improve the SOC estimation ability and accuracy of LIBs.	High-precision SOC estimation; strong adaptability.	The algorithm is more complex and may require more computing resources.	[16]
Wang Shunli et al., 2024	The online corrected square root traceless Kalman filtering algorithm analyzes the influence of capacity fluctuations caused by temperature.	Can be adjusted in real time to adapt to temperature changes.	The accuracy and response speed of the temperature sensor have a direct impact on the result.	[17]
Wang Shunli et al., 2024	The improved multi-feature-electrochemical thermal coupling modeling method considers the degradation of low temperature performance and real-time correction of time-varying current and temperature effects.	Accurate simulation of battery performance in low temperature environment.	The model is more complex and the parameter recognition is more difficult.	[18]

This paper first outlines the background and significance of voltage-level collaborative planning and power supply capacity optimization, and emphasizes the value of research. In the second chapter, the data preprocessing technology is studied, and the Layda criterion is used to remove abnormal data. The weighted average method is used to fill in the missing data, and the processing flow of data normalization is studied. In addition, in section 2.3, a voltage-level collaborative planning model based on APSO is constructed, and the operating mechanism of the algorithm and its application effectiveness in voltage planning are analyzed in depth; in Section 2.4, a hybrid algorithm combining PSO and GA (namely PSO-GA) is innovatively proposed for the optimization of power supply capacity, and its algorithm principle and optimization results are systematically introduced. Finally, the article comprehensively summarizes the overall research and discusses the future research direction.

3. Voltage Level Collaborative Planning and PSC Optimization Algorithm Construction

In this paper, a typical regional power grid with complex topology, diversified power generation equipment, and load requirements in City A is selected as the data source. The time period covered by the data is from January 2023 to December 2024, and it involves the operating conditions of the power grid under different seasons and weather conditions. This helps to comprehensively analyze the dynamic characteristics of the power grid under various operating conditions, especially its ability to cope with extreme weather. To ensure the accuracy of the data, an advanced real-time monitoring system is used, including SCADA (Supervisory Control and Data Acquisition) system and PMU (Phasor Measurement Unit) equipment. The SCADA system provides the basic parameters of the operation of the power grid, which is of great significance for daily monitoring and fault diagnosis. The PMU equipment can provide high-precision phasor measurement data, can capture instantaneous voltage and current changes, and provide researchers with more in-depth information on the operating status of the power grid.

A. Data Preprocessing

The data collected initially is usually complex, multi-dimensional, and rough; the data volume is huge, and the quality is uneven. To ensure data quality, preprocessing is necessary. After collecting the required data, the collected voltage and current operation data can be ensured to be effective. Equipment errors, failures, or human factors may lead to abnormal or missing new energy historical output data and meteorological data collected. This paper uses the Laida criterion to eliminate abnormal data. This rule is based on statistical principles. By setting the threshold range, accurately identifying outliers in the data set, and calculating the mean and standard deviation of the data set, the standard range of abnormal data is determined. The expression is:

$$f_i = \frac{\left| a_i - \frac{1}{m}\sum_{i=1}^{m} a_i \right|}{\sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(a_i - \frac{1}{m}\sum_{i}^{m} a_i\right)^2}} \quad (1)$$

Among them, f_i is the degree of data offset. When $f_i \leq 3$, a_i is determined to be abnormal data and eliminated.

After removing the exception data, the missing values in the data need to be processed [19-21]. These missing values are caused by various reasons such as device failure, sensor problems, or communication interruptions. If these missing values are ignored, it can have an adverse impact on subsequent data analysis and model construction. This paper selects a weighted weighted averaging method to fill these missing data, a method based on the correlation between data sequences and their adjacent data. It takes into account known values before and after missing data points in the time series data, and then evaluates the impact of these known values on the missing values, an evaluation achieved through weighted calculations. By weighted averaging of these known data, the missing data values are estimated. Supposing the sample data set is: $A = \left[a_1, a_2, \cdots, a_m\right]$, the missing data is $H_n = \left[a_n, a_{n+1}, \cdots, a_q\right]$, where $1 < n \leq q < m$, and the filling formula is as follows:

$$a_\omega = \frac{q-i+1}{q-i+2} a_{i-1} + \frac{1}{q-i+2} a_{q-1} \quad (2)$$

Among them, $n \leq i \leq q$ and a_ω represent the data to be filled.

The distributed power generation data and various load data in the distribution network have different dimensions. If these data are directly used for model training or analysis, it may cause bias in the sample set and have adverse effects on the final result. To eliminate this effect caused by dimension differences, this paper adopts normalization, which can convert data to a unified dimension range, usually adjusting the data to an interval of [0, 1].

$$A' = \frac{A - A_{\min}}{A_{\max} - A_{\min}} \quad (3)$$

A is data without normalization processing. After normalization, the data can fall within the range of [0,1]. When these data are predicted by the prediction model, the output results can also be within the [0,1] interval. To obtain intuitive data values with actual dimensions, the output results of the prediction model need to be reverse normalized. Intuitive dimension data values can be obtained, and the expression is:

$$X_{real} = A_{min} + X_{pet}\left(A_{max} - A_{min}\right) \quad (4)$$

B. Voltage Level Collaborative Planning Indicators

The power loss of the line is an inevitable phenomenon when the power grid transmits electricity [22-24]. This loss consumes active power, and the heat generated can also damage the insulating material of the line, accelerating its aging process. To quantify this loss, specific formulas are often used to calculate the power loss of the line.

$$\Delta Q = 3I^2R = 3*\left(\frac{Q}{\sqrt{3}*\cos\phi}\right)R^2 \quad (5)$$

Among them, I is the line current; $\cos\phi$ is the power factor; R is the line resistance. The functional loss of the line is closely related to the load rate of the line. The functional loss rate of different circuits under different load rates is calculated, as shown in Table 3.

Table 3. Loss rates of different line functions under different load rates (kW).

Line load rate (%)	10kV	20kV	35kV	110kV	220kV
10	7.15	1.79	0.58	0.06	0.02
20	28.29	7.15	2.33	0.24	0.06
30	64.33	16.08	5.28	0.54	0.13
40	114.35	28.55	9.34	0.95	0.24
50	178.26	44.63	14.56	1.49	0.37
60	257.39	64.29	21.04	2.15	0.53
70	350.26	87.45	28.59	2.91	0.72
80	452.93	115.06	37.64	3.77	0.93
90	578.06	145.31	48.08	4.81	1.18
100	713.57	176.69	58.34	5.95	1.47

As shown in Table 3, when the load rate increases, the power loss of each voltage level increases significantly, and the loss of the low voltage level is significantly higher than that of the high voltage level. When the load rate is 10%, the power loss of the 10kV line is 7.15kW, while the 220kV line is only 0.02kW. When the load rate increases to 100%, the loss of the 10kV line is 713.57kW, while the loss of the 220kV line is 1.47kW. Under the same load rate conditions, the difference in power loss between different voltage levels can further expand with the increase in load rate, highlighting the economic advantages of high voltage levels in long-distance transmission and large-capacity power supply scenarios.

The transmission distance of the line is mainly limited by voltage [25,26], and the calculation formula for voltage drop percentage is as follows:

$$\Delta U\% = \frac{PY+QX}{U_M^2}*100\% = \frac{Py+Qx}{U_M^2}*L*100\% \quad (6)$$

In the formula, P and Q are the active and reactive power flowing through the distribution line. The maximum power supply distance of different lines such as 10kV, 20kV, 35kV under different load rates can be calculated, as shown in Figure 1.

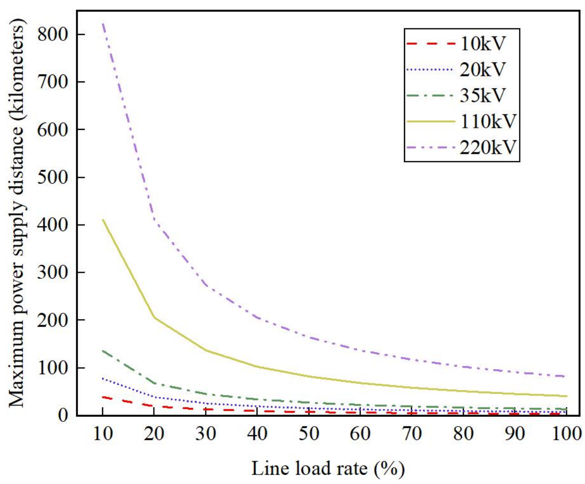

Figure 1. Maximum power supply distance of different lines under different load rates.

As shown in Figure 1, as the load rate gradually increases, the maximum power supply distance that can be achieved by each voltage level shows a downward trend. Under the condition of a load rate of 10%, the maximum power supply distance of the 10kV line can reach 38.9km. When the load rate increases to 100%, this distance is greatly shortened to 3.9km, illustrating the profound impact of high load rate on the power supply distance. High voltage levels exhibit stronger power supply due to their lower current density. Under the same load rate conditions, the maximum power supply distance of the 220kV line is always much higher than other voltage levels, demonstrating the obvious advantage of high voltage transmission. In the design process of the distribution network, the logical selection of voltage levels and load rates is a vital link in assuring voltage quality and power supply reliability.

C. Construction of Voltage Level Collaborative Planning Model

With the continuous access of new energy and the intensification of load fluctuations, the inadequacy of traditional voltage control methods has emerged, and voltage instability and power loss have gradually become problems. In this context, it becomes important to scientifically plan the voltage levels and conduct coordinated voltage control to effectively control the voltage fluctuations at each level. Voltage changes between different voltage levels in the power grid often affect each other. Therefore, it is necessary to optimize the voltage configuration at each level through collaborative planning to maintain the overall stable and efficient operation of the power grid. This study constructs a voltage level collaborative planning model based on APSO, and Figure 2 displays the particular framework diagram.

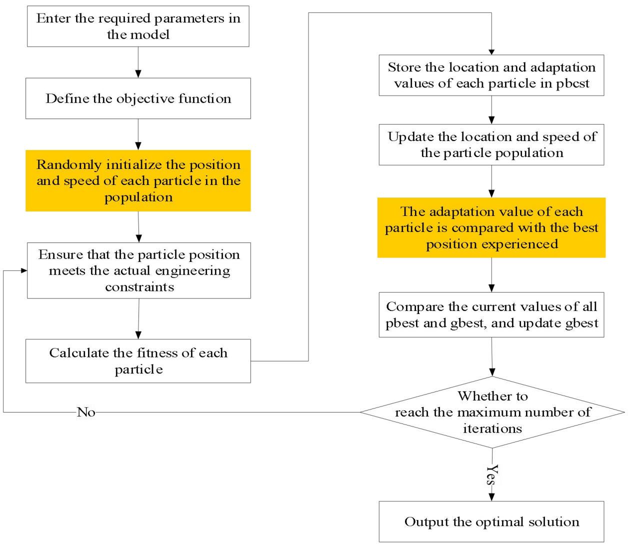

Figure 2. Framework diagram of distribution network voltage level based on APSO.

As an important advanced version of PSO, APSO has excellent global exploration and local fine-tuning capabilities. Compared with the basic PSO algorithm, the advantage of APSO is that it can dynamically adjust the inertial weight and acceleration factor of particles [27-29]. This adjustment allows the search process to more flexibly balance the global and local exploration depth, thereby reducing the risk of falling into local optimality and improving overall optimization efficiency. In the coordinated planning of the voltage level, APSO can carefully regulate the settings of each voltage level in the power grid, thereby significantly reducing voltage fluctuations and power loss. These improvements not only enhance the power supply strength of the power grid, but also greatly improve the stability of its operation. On the basis of ensuring that voltages at all levels meet the limits, APSO is committed to minimizing power loss in the power grid and stabilizing voltage fluctuations. In the process of implementing the coordinated planning of the voltage level, this paper designs a multi-objective optimization function based on various influencing factors. The objective function covers the following core components:

Load balancing means that in the power grid, the distribution of load should be as uniform as possible to prevent some lines or substations from causing risks due to excessive load.

$$L_{\text{load imbalance}} = \sum_{i=1}^{m} \left(\frac{Q_i - Q_{ref,i}}{Q_{ref,i}} \right)^2 \quad (7)$$

Among them, $Q_{ref,i}$ is the reference power load of the i -th line.

During the initialization phase, the number of individuals in the population and the dimensions of each individual must be determined first. For each particle, APSO can randomly assign it an initial velocity in the range 0 to 1, which determines the movement step rate and direction of the particle in the search space [30-32]. To ensure the broadness of the search, the starting position of each particle is also set by a random number between 0 and 1. This practice ensures population diversity and effectively avoids the algorithm's premature fall into the dilemma of local optimism. After initialization is completed, the fitness of each particle needs to be calculated, and the fitness function takes into account multiple objectives in the voltage level collaborative planning to evaluate the performance of each particle. Particle position and fitness of the optimal fitness of all particles are recorded in the global optimal position (gbest) by recording each particle's present position and fitness to its individual optimal position (pbest):

$$v_i(k+1) = r(k) * v_i(k) + c_1 * w_1 * (\text{pbest}_i - a_i(k)) + c_2 * w_2 * (\text{gbest} - a_i(k)) \quad (8)$$

$$a_i(k+1) = a_i(k) + v_i(k+1) \quad (9)$$

Among them, $v_i(k)$ and $a_i(k)$ are the velocity and position of particle i in the iteration of the k round, respectively, and $r(k)$ is the inertial weight.

Inertial weights are very important in PSO algorithms, which can balance the algorithm's global and local search capabilities. When the inertial weight is set too small, the particles can be updated very quickly, which can cause the search to focus on a local area too early, thus falling into local optimality, ignoring the possible global optimal solution [33,34]. Therefore, it is crucial to dynamically adjust the inertial weight in the process of coordinated planning of the voltage level. This can maintain a wide range of exploration in the early stage of the search, and more precise voltage setting adjustments can be made in the later stage, thereby improving the overall effect of grid optimization. In APSO, the inertial weight r can gradually decrease according to the increase of the number of iterations k. In the initial stage of search, the larger inertia weight enables particles to be widely explored throughout the solution space, effectively preventing premature convergence to local optimality. As the iteration progresses, the gradual decrease in inertia weights prompts the particles to make more refined position adjustments. This speeds up the convergence speed and avoids excessive position jumps, thus helping particles position more accurately to the global optimal solution.

$$r(k) = r_{\max} - \frac{(r_{\max} - r_{\min})}{k_{\max}} * k \quad (10)$$

Among them, $k_{\max}$ is the maximum number of iterations.

Acceleration factors w_1 and w_2 play a key role in APSO, which control how particles approach individual and global optimal solutions during search. In traditional PSO algorithms, the acceleration factor is usually fixed, which can lead to problems during the search process. In APSO, the acceleration factor is no longer fixed, but can be dynamically adjusted according to the current search state. This adjustment is mainly based on the fitness value of the particle swarm [35,36]. When the particle swarm shows a strong convergence trend at a certain stage, this indicates that the global optimal solution is relatively clear. At this time, APSO can increase the acceleration factor to accelerate the gathering of particles towards the optimal solution. On the contrary, when the search process of the particle swarm fluctuates greatly, it indicates that more exploration is needed, and APSO reduces the acceleration factor to avoid particles gathering prematurely in a local area. This dynamic adjustment strategy allows APSO to respond more flexibly to different search scenarios.

$$w_1(k) = w_{1,\max} - \frac{(w_{1,\max} - w_{1,\min})}{k_{\max}} * k \quad (11)$$

$$w_2(k) = w_{2,\max} - \frac{(w_{2,\max} - w_{2,\min})}{k_{\max}} * k \quad (12)$$

Among them, $w_{1,\max}$ and $w_{2,\max}$ are the maximum values of the acceleration factor, and $w_{1,\min}$ and $w_{2,\min}$ are their minimum values.

D. Construction of PSC Optimization Model

An essential metric for assessing the distribution network's power supply performance is its maximum PSC. It is the highest load that the distribution network is capable of supporting while adhering to node voltage and branch power constraints [37,38]. It can determine the distribution network's maximum supply capacity to load under the existing network configuration by computing this indicator. The network structure refers to the actual layout and configuration of the distribution network, that is, the various types of power equipment that make up the distribution network and their interconnection methods. This network structure is complex and changeable, and it is affected by many factors such as geography, economy, and technology. It can be transformed into an optimization problem using the following objective function in order to solve the maximum power supply:

$$\max S_{\max} = \sum_{i=1}^{M_{bus}} S_{i0} + \sum_{i=1}^{M_{bus}} u_i S_{id} \quad (13)$$

S_{i0} represents the current load supply of node i ; u_i represents the multiple of node i load growth; S_{id} represents the baseline value of node i load growth.

Despite the continuous advancement of modern grid technology, many grid systems still face the problems of insufficient PSC and low operating efficiency due to outdated equipment and continuous changes in load demand. The PSC of the power grid is often limited by insufficient voltage control, and the uneven distribution of the voltage levels can cause voltage fluctuations in each node of the grid at different times, which can in turn cause overvoltage or undervoltage. This affects the stability and safety of the power system and can also reduce the user's power quality. This paper introduces PSO and GA, combining the two (PSO-GA) [39]. This combination algorithm has strong global search capabilities and good adaptability, which can effectively avoid the local optimal solution problems that may arise in traditional optimization methods, and quickly find the optimal or near-optimal solution. Inspired by GA, this paper incorporates random self-feedback variants and high-frequency crossover operators into the particle swarm optimization process. This takes advantage of GA's advantage in maintaining individual diversity during evolution and also gives full play to the characteristics of PSO group information sharing and rapid convergence, so that it is more likely to find a better solution. The PSO-GA algorithm inherits the global optimization ability of G, and can find the global optimal solution more effectively, while also significantly improving the convergence speed compared to GA. The structure diagram of the PSC optimization algorithm based on PSO-GA is shown in Figure 3.

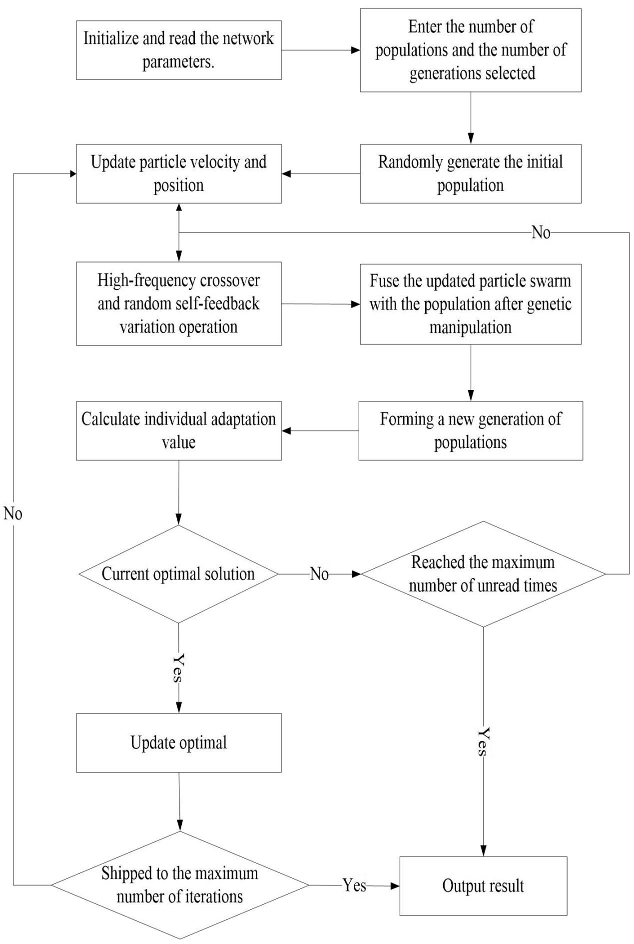

Figure 3. Structure diagram of the PSC optimization algorithm based on PSO-GA.

In actual use of traditional GA, problems often occur in the local optimality or algorithm stagnation. To effectively pick out local optimums, a feasible approach is to appropriately broaden the search space. PSO-GA can broaden the search space and control the complexity of the algorithm, which can enable the adaptive selection of inertial weights to better deal with high-dimensional and complex nonlinear problems. To achieve this combination, it is necessary to discrete the inertial weight value of PSO, divide it into multiple sub-intervals, and assign an equal number of parameters to each sub-interval, which represents a path in GA. In the design of this paper, the minimum value of the inertia weight of the particle swarm is set to 0.4. The calculation formula for discrete inertial weight is as follows:

$$\Delta d = \frac{d_{\max} - d_{\min}}{M} \quad (14)$$

Among them, M is the set number of discrete intervals.

In the PSO algorithm, particles can update their own speed and position according to the fitness function in each generation, which is the core step of the algorithm. The position of particles symbolizes the overall operating state of the power grid and covers multiple aspects. During the optimization process of PSO algorithm, particles sometimes fall into stagnation, that is, the search process may be limited to local optimal solutions. This paper can introduce GA variant operations. By randomly perturbing individuals of particles, that is, making slight random adjustments to them, the search trajectory of particles can be changed, thereby helping the algorithm escape the local optimal solution. In the context of grid optimization, this variation may involve fine-tuning of generator set scheduling schemes or changing the load distribution strategy of transmission lines, effectively preventing particle swarms from falling into the dilemma of local optimum. Cross-operation generates entirely new descendants by exchanging some characteristics of two individuals. This method allows the algorithm to combine the excellent characteristics of the parent individual to explore possible better solutions.

$$s_i(t+1) = s_i(t) + \Delta s \quad (15)$$

Among them, Δs is a small random perturbation term, representing the change in particle position. This variation strategy allows the algorithm to explore in-depth within a limited search area, mine high-quality solutions that may be overlooked, and effectively prevent solutions from converging prematurely to local optimum.

The core of the mutation operation is to make random changes to the genes in the solution, which enriches the diversity of understanding and helps the algorithm escape the trap of local optimality. In the context of PSC optimization, variation means random adjustments to certain key parameters, thereby introducing new possible solutions. PSO emphasizes collaboration among groups for global optimization, while GA's cross-section mechanism quickly generates high-quality solutions through the fusion of individual information. In PSO-GA, choosing two excellent solutions to fusion can lead to better solutions. Through cross-combination, a brand new scheduling or configuration strategy is formed. This approach greatly accelerates the exploration of understanding space and helps improve the overall performance of the power grid. For discrete variables in grid optimization, by randomly selecting a certain variable and adjusting it, the flexibility of the grid in different operating states can be simulated, broadening the search range and preventing the algorithm from falling into local optimization. The variation formula can be expressed as:

$$s_i(t+1) = Crossover(s_q, s_p) \quad (16)$$

Among them, s_q and s_p are the two selected particles respectively. The cross operation combines their solutions to generate a new solution $s_i(t+1)$. This crossover strategy not only accelerates the search process of particle swarms, but also significantly improves the quality of understanding.

4. Voltage Level Collaborative Planning and PSC Optimization Model Effect Evaluation

Power loss optimization is crucial to improving the overall efficiency of the power grid. It can reduce ineffective energy consumption, reduce voltage fluctuations, and enhance coordination between voltage levels. To study the advantages of the method in power loss optimization, it is compared with PSO, Multiple-objective genetic algorithm (MOGA), improved simulated annealing (ISA) algorithm, PSO and differential evolution (DE) algorithm mixing (PSO-DE). The specific comparison results are shown in Table 4.

Table 4. Comparison of power loss optimization performance for different models.

Evaluation index	APSO	PSO	MOGA	ISA	PSO-DE
Power loss before optimization (kW)	200	200	200	200	200
Optimized power loss (kW)	148	186	173	177	162
Less power loss and damage (%)	26	7	13.5	11.5	19
Energy utilization rate (%)	94.3	82.8	88.7	86.4	84.3
Transmission efficiency (%)	92.8	84.6	90.2	89.7	88.4
Voltage deviation (V)	1.2	1.5	1.4	1.6	1.3
Stability level	High	Low	Medium	Medium	Medium

As shown in Table 4, the APSO algorithm studied in this paper performs well in power loss optimization. Compared with other algorithms, the optimized power loss of APSO is the lowest, only 148 kW, with a decrease of 26%, which is 19%, 12.5%, 14.5%, and 7% higher than the declines of PSO, MOGA, ISA, and PSO-DE, respectively. This shows that APSO has a significant effect in reducing the invalid energy consumption of the power grid and improving energy utilization. The energy utilization rate of APSO is 94.3%, which is significantly better than other methods. APSO's grid transmission efficiency is 92.8%, which is 8.2%, 2.6%, 3.1%, and 4.4% higher than the transmission efficiency of PSO, MOGA, ISA, and PSO-DE, respectively, further verifying its leading position in grid performance optimization. Regarding voltage deviation optimization, APSO has also demonstrated its strong optimization capabilities. The optimized voltage deviation is only 1.2V, which is much lower than the results obtained by other algorithms. This means that the APSO algorithm has significant advantages in enhancing the stability of the power grid and improving the quality of power supply, and can provide a strong guarantee for the safe and stable operation of the power grid. Because of its high stability, the APSO algorithm has demonstrated excellent adaptability and reliability in complex power grid environments. Compared with the low stability of the PSO algorithm and the medium performance of algorithms such as MOGA, ISA, and PSO-DE, APSO can quickly react and adjust to changes in the state of the power grid to ensure the continuous optimized operation of the power grid. This is similar to the design of a heat engine cycle and is designed to respond quickly to external changes while maintaining efficient work. Through the integration of adaptive mechanisms, APSO realizes real-time monitoring and dynamic adjustment of the power grid, providing a solid guarantee for the safety and stability of the power grid. APSO's outstanding performance in power loss optimization, energy utilization improvement, and voltage deviation control not only demonstrates its technical strength, but also reveals its profound physical connotation.

To more comprehensively verify the effectiveness and advantages of PSO-GA studied in this paper in terms of voltage-level collaborative planning and power supply capacity optimization, it is planned to conduct experimental verification on different types of power grid systems and compare with other advanced intelligent optimization algorithms, namely Grey Wolf Optimizer-Whale Optimization Algorithm (GWO-WOA) and Firefly Algorithm-Artificial Bee Colony (FA-ABC). The specific results are shown in Table 5.

Table 5. Performance comparison of different methods of different types of power grid systems.

Grid type	Algorithm name	Energy utilization rate (%)	Transmission efficiency (%)	Voltage deviation (V)	Convergence speed (seconds)
Urban power grid	PSO-GA	93.61	91.04	1.2	9.7
	GWO-WOA	87.26	84.68	1.6	16.4
	FA-ABC	86.33	85.94	1.5	20.8
Rural power grid	PSO-GA	95.61	93.04	1.2	6.4
	GWO-WOA	88.69	87.23	1.5	10.8
	FA-ABC	90.31	88.69	1.4	12.5

As shown in Table 5, for urban power grids, the PSO-GA algorithm shows significant efficiency: the energy utilization rate is 93.61%; the transmission efficiency is 91.04%; the voltage deviation is as low as 1.2V, and the convergence speed is only 9.7 seconds. The GWO-WOA and FA-ABC algorithms are not as good as each other in various indicators. In the rural power grid environment, PSO-GA also has obvious advantages, showing its excellent ability to handle dispersed loads and long-distance transmission. The experimental results show that the PSO-GA algorithm can provide efficient and stable power supply in both high-load-density urban power grids and widely covered rural power grids, and its fast convergence characteristics are more competitive in practical applications, which helps to improve the overall operating efficiency and stability of the power grid.

The power grid includes three voltage levels: high voltage, medium voltage, and low voltage. The degree of coordination is measured by calculating the degree of mutual influence between each voltage level. The main ones are high-pressure-medium-voltage coordination, high-pressure-low-voltage coordination, and medium-pressure-low-voltage coordination. These three levels are numbered according to A-C, and the experimental results are compared with other methods. The comparison results are shown in Figure 4.

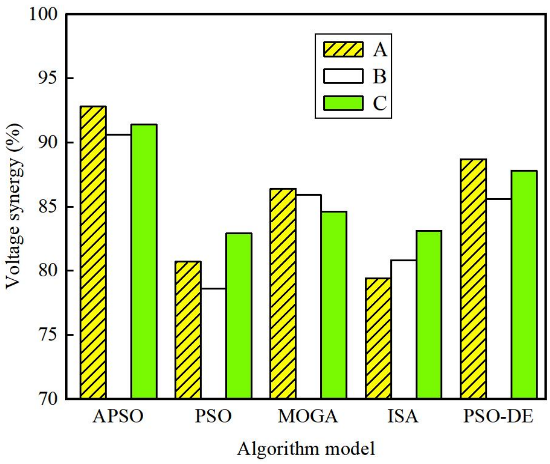

Figure 4. Comparison of the voltage level of different models.

As shown in Figure 4, A-C are the main three levels of high-voltage-medium-voltage synergy, high-voltage-low-voltage synergy, and medium-voltage-low-voltage synergy. Among them, the red dotted line is the mean line. The APSO algorithm shows significant advantages in all three synergy indicators.The high-pressure-medium-pressure synergy of APSO is 92.8%, which far exceeds the 80.7% of PSO, 86.4% of MOGA, and 79.4% of ISA. This shows that APSO has achieved remarkable results in optimizing the coordination and interaction between the high-pressure and medium-pressure levels. Considering the degree of coordination between the high-voltage and low-voltage levels, APSO also performs well, reaching 90.6%, which is 12%, 4.7%, 9.8%, and 5% higher than the coordination of PSO, MOGA, ISA, and PSO-DE, respectively. From the perspective of thermodynamics, improving the synergy between voltage levels can effectively reduce the energy loss in the system. According to the first law of thermodynamics, although energy does not disappear during conversion, there is always a part of the loss, and in the power system, the power loss is caused by resistance heating, etc. The APSO algorithm significantly reduces such losses by optimizing the collaborative work of the voltage levels, thereby improving the efficiency of power transmission. APSO has an average of 91.6% coordination at the three levels, which is 10.87%, 5.97%, 10.5%, and 4.23% higher than PSO, MOGA, ISA, and PSO-DE, respectively. This shows that APSO is not only outstanding in the coordination of a single voltage level, but also has a significant effect on the optimization of the overall power grid structure. For the power system, the transfer of energy between the various voltage levels is smoother, reducing the additional losses caused by uncoordinated operation.

This paper uses the PSO-GA algorithm to optimize the PSC of the distribution network. The overall performance of the PSO-GA algorithm is good, compared with the PSO, GA, GA-DE, and PSO-ant colony optimization algorithm (Ant Colony Optimization (ACO) algorithm mixing (PSO-ACO). The specific comparison results are shown in Table 6.

Table 6. Performance analysis of different algorithms.

Performance indicators	PSO-GA	PSO	GA	GA-DE	PSO-ACO
Global optimal number of times	46	25	31	36	40
Optimization probability (%)	96.7	84.6	80.8	90.7	91.5
Average calculation time (seconds)	18.5	15.2	22.4	20.3	21.7
Average number of generations selected	20.6	55.2	70.6	50.4	45
Stability of solution	High	Low	Low	Medium	Medium
Fitness improvement rate (%)	25.3	16.6	14.8	18.2	18.9

As shown in Table 6, through the analysis of the performance of the PSO-GA algorithm and other algorithms in the distribution network's power supply capacity optimization, the excellent performance of the PSO-GA algorithm is found. In terms of optimization probability, the success rate of PSO-GA is 96.7%, which is 12.1%, 15.9%, 6%, and 5.2% higher than that of PSO, GA, GA-DE, and PSO-ACO, respectively. Although the average computing time of PSO-GA is 18.5 seconds, which is higher than PSO's 15.2 seconds, its excellent optimization ability and stability are enough to make up for this small time gap. The average calculation time of the PSO-GA algorithm is 18.5 seconds, which is slightly higher than the 15.2 seconds of PSO, but its excellent optimization ability and stability are enough to make up for this small time gap. From the perspective of thermodynamics, it is difficult to achieve perfect energy conversion efficiency in the actual process, and it isl always accompanied by a certain degree of energy loss. In the field of algorithm optimization, the calculation time can be compared to “energy consumption”, while the optimization effect represents “output”. Although the PSO-GA algorithm has slightly increased its calculation time, its fitness improvement rate is as high as 25.3%, which significantly surpasses other algorithms. This shows that although more “energy consumption” has been invested, it has been exchanged for a significant performance jump. Compared with other algorithms, such as PSO, GA, GA-DE, and PSO-ACO, the fitness improvement rate of PSO-GA is 8.7%, 10.5%, 7.1%, and 6.4% higher, respectively. This data not only demonstrates that it can significantly improve the quality of the solution in the optimization process, but also highlights its efficiency and practicality in dealing with complex optimization problems. PSO-GA also shows its excellent performance in the recording of the global optimal number of times. This means that in multiple independent operations, PSO-GA can converge to the global optimal solution more frequently, further enhancing its reliability and stability in solving the problem of optimizing the power supply capacity of the distribution network. In summary, the significant advantages of the PSO-GA algorithm in multiple dimensions such as optimization probability, fitness improvement rate, and global optimization frequency make it a powerful tool to solve the problem of power supply capacity optimization of distribution networks. The robustness and reliability of this algorithm provide strong support for actual engineering applications, and it is expected to play a more important role in future distribution network optimization.

To further verify the convergence effect of PSO-GA, the training efficiency of this model is compared with other methods. By simulating the changes in the loss values of each algorithm when processing the same data set, its convergence speed is analyzed.. The specific results are shown in Figure 5.

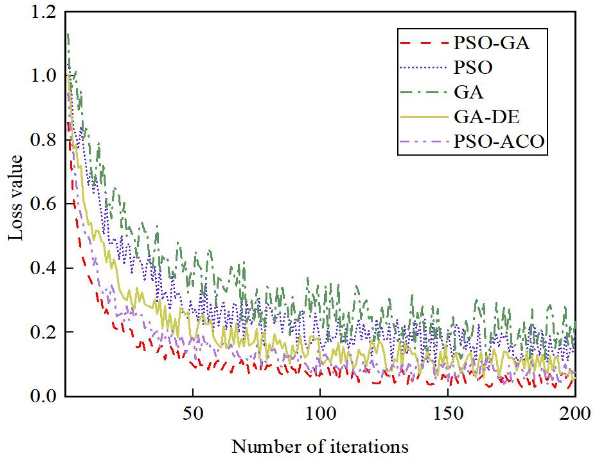

Figure 5. Convergence speed comparison of different algorithm models.

As shown in Figure 5, the PSO-GA algorithm exhibits extremely fast convergence speed and quickly approaches the optimal solution. The excellent performance of PSO-GA is due to its integration of the global search power of PSO and the local search power of GA. PSO quickly explores the solution space through group cooperation, while GA's crossover and variation operations enhance the algorithm's ability to escape local optimization, so that PSO-GA can quickly approach the optimal solution at the beginning of the iteration and deepen the search in subsequent iterations. Compared with PSO-GA, the traditional GA algorithm relies on random selection, and the search process is relatively slow. PSO-ACO combines the characteristics of PSO and ACO. Although it enhances the adaptability to path optimization problems, it is constrained by the discrete characteristics of ACO when dealing with continuous optimization problems; GA-DE combines the advantages of GA and DE, but its convergence speed is still affected by the computational complexity of DE. In general, the PSO-GA algorithm breaks the shackles of a single algorithm, so the convergence speed is relatively fast. From the perspective of thermodynamics, all actual systems inevitably face the problem of energy dissipation, and the free energy of the system cannot be completely converted into actual work output. When dealing with optimization problems, the PSO-GA algorithm can practice the principle of “maximizing energy efficiency” by streamlining calculation steps and reducing resource waste. In application scenarios such as power grid dispatching or logistics path planning, it is regarded as a method of optimizing the flow of energy or matter. Its goal is to achieve the maximum output efficiency of the system under established conditions through the most effective resource allocation. The PSO-GA algorithm continuously adjusts and optimizes the search strategy to approximate the theoretical best solution. When dealing with continuous optimization problems, the algorithm combines global and local search, which can effectively avoid the local minimum value dilemma that a single algorithm can easily fall into, so as to achieve higher “energy conversion efficiency”.

When discussing the calculation of the steady-state state of the power grid, the Newton-Rafson method is used for medium, and high-level power grids. This method can not only effectively handle the complex operation of the power grid under steady-state conditions, but also flexibly cope with different representations of the input data. Whether it is rectangular coordinates or polar coordinates, it can be accurately calculated.

An n-node power system is consideed, whose power flow equation can be expressed as:

$$\Delta P(\theta,W) = P_{\text{sepc}} - P(\theta,W) \quad (17)$$

$$\Delta Q(\theta,W) = Q_{\text{sepc}} - Q(\theta,W) \quad (18)$$

Among them, P and Q represent active power and reactive power, respectively; θ and W represent the Angle and amplitude of node voltage, respectively; sepc represents the given value.

For each node i, there are:

$$\Delta P_i = P_{i,\text{sepc}} - \sum_{j=1}^{m} W_i W_j \left(F_{ij}\cos\left(\theta_i-\theta_j\right)\right) + A_{ij}\sin\left(\theta_i-\theta_j\right) \quad (19)$$

$$\Delta Q_i = Q_{i,\text{sepc}} - \sum_{j=1}^{m} W_i W_j \left(F_{ij}\cos\left(\theta_i-\theta_j\right)\right) + A_{ij}\sin\left(\theta_i-\theta_j\right) \quad (20)$$

Among them, F_{ij} and A_{ij} are the real part and imaginary part of the node admittance matrix, respectively.

The core of the Newton-Rafson method is to construct the Jacobian matrix and update it iteratively. The Jacobian matrix consists of the partial derivative of the current equation to the state variables (i.e. voltage amplitude and angle). For nodes i and j, the Jacobian matrix elements can be written as:

For off-diagonal elements ($i \neq j$), there are:

$$J_{ij}^{\theta} = \frac{\partial \Delta P_i}{\partial \theta_j} = W_i W_j \left(F_{ij}\sin\left(\theta_i-\theta_j\right)\right) - A_{ij}\cos\left(\theta_i-\theta_j\right) \quad (21)$$

$$J_{ij}^{W} = \frac{\partial \Delta P_i}{\partial W_j} = W_i \left(F_{ij}\cos\left(\theta_i-\theta_j\right)\right) + A_{ij}\sin\left(\theta_i-\theta_j\right) \quad (22)$$

For diagonal elements ($i = j$), there are:

$$J_{ii}^{\theta} = \frac{\partial \Delta P_i}{\partial \theta_j} = -\sum_{k=1,k\neq i}^{m} W_i W_k \left(F_{ij}\sin\left(\theta_i-\theta_j\right) - A_{ij}\cos\left(\theta_i-\theta_j\right)\right) + Q_i \quad (23)$$

$$J_{ii}^{W} = \frac{\partial \Delta P_i}{\partial W_j} = \sum_{k=1}^{m} W_k \left(F_{ij}\cos\left(\theta_i-\theta_j\right) + A_{ij}\sin\left(\theta_i-\theta_j\right)\right) + F_{ii}W \quad (24)$$

The Newton-Rafson method, with its strong convergence and accuracy, plays an important role in the steady-state analysis of power grids. The details are shown in Figure 6.

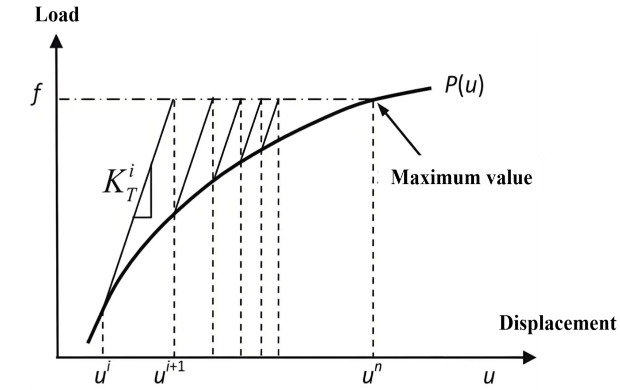

Figure 6. Schematic diagram of the application of Newton-Rafson method in power grid steady state calculation.

Under different load conditions, the PSO-GA algorithm has different optimization efficiencies for the PSC of the power grid. This paper studies the optimization efficiency under low load conditions, medium load conditions, high load conditions, and complex load conditions, and compares the experimental results with other methods. The maximum PSC of all methods before optimization is set to the same, and the effects after optimization are compared. The specific comparison results are shown in Figure 7.

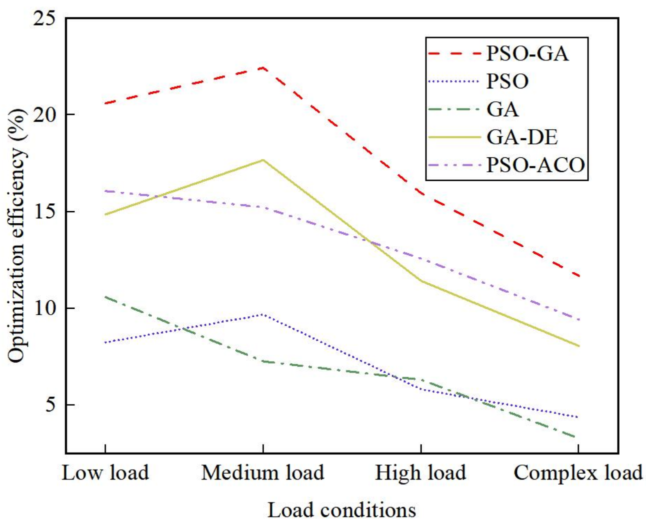

Figure 7. Comparison of PSC optimization effects under different load conditions.

As shown in Figure 6, A-D are the optimized efficiency under low load conditions, medium load conditions, high load conditions, and complex load conditions. The optimization effect of the PSO-GA algorithm on the power supply capacity of the power grid under different load conditions is significantly different, and compared with other optimization algorithms, its advantages exist in various load scenarios. In the low-load state, the PSO-GA algorithm significantly improves the power supply efficiency of the distribution network, an increase of 20.61%, far surpassing similar algorithms. This is mainly due to the precise adjustment of the matching relationship between the power supply and the load by the PSO-GA algorithm, which realizes the efficient use of electrical energy and significantly reduces energy loss. Based on the law of conservation of energy, the power system needs to ensure the balance of input and output energy and loss. Therefore, by reducing the energy loss in the system, the PSO-GA algorithm effectively improves the energy conversion efficiency of the overall system, ensuring that more electrical energy is accurately and efficiently distributed to the client. Under medium load conditions, the PSO-GA algorithm increases the efficiency of the power supply capacity to 22.44%, demonstrating its excellent dynamic adaptability. This is similar to the rate control step in a chemical reaction. The key nodes in the power grid are optimized by the PSO-GA algorithm. With the help of a catalyst, it accelerates the transmission and distribution of electricity. The PSO-GA algorithm also intelligently adjusts the collaborative working mode between the voltages of various levels, minimizing the energy loss caused by the entropy increase, and ensuring that the power grid can still maintain an efficient power supply state under high load conditions.

Under complex load conditions, the PSO-GA algorithm increases efficiency by 11.68%. In the face of various uncertainties in the operation of the power grid, the algorithm exhibits a high degree of stability and adaptability under complex load conditions. In the intricate chemical reactions, in order to maintain a stable reaction efficiency, it is necessary to have a strong ability to resist external interference. The PSO-GA algorithm combines the wide-area search of particle swarm optimization and the fine adjustment of genetic algorithms, so that it can react quickly when the state of the power grid changes dynamically, and accurately find the optimal solution. From the perspective of energy management, this means that even in non-ideal environments, the algorithm can efficiently control the energy flow in the system and minimize energy loss, thereby ensuring that the power supply efficiency is maintained at a high level. In summary, through in-depth analysis of the optimization effectiveness of the PSO-GA algorithm under different load conditions, combined with the relevant principles of chemistry and thermodynamics, it is not only possible to more thoroughly understand the practical significance represented by these data, but also to deeply understand the key role of this algorithm in improving the overall performance of the power grid.

In discussing the effectiveness of the research methods in this paper, comparative experiments are designed, and the methods with the literature [16], [17], and [18] are compared from different research indicators. The specific research results are shown in Table 7.

Table 7. Comparison results of different optimization algorithms on key performance indicators.

Experimental indicators	APSO	PSO-GA	Literature [16] Method	Literature [17] Method	Literature [18] Method
SOC estimation accuracy (%)	98.5	97.8	96.2	95.5	97.0
Power status evaluation error (%)	2.3	2.8	3.5	4.0	3.1
Standard deviation of power status evaluation	0.5	0.7	1.0	1.2	0.8
Grid optimization time (hours)	1.2	1.5	2.0	2.5	1.8
Algorithm convergence speed (number of iterations)	50	60	75	85	70

According to the data in Table 7, APSO has reached 98.5% SOC estimation accuracy, which is higher than 97.8% of PSO-GA, and significantly higher than the methods in the literature [16], [17], and [18]. This shows that APSO has significant advantages in improving the accuracy of lithium-ion battery state of charge (SOC) estimation, which can more truly reflect the battery charge and discharge status, and provide a solid foundation for the stable operation of the power system. In terms of power state evaluation error, the error rate of APSO is 2.3%, which is better than the 2.8% of PSO-GA, and much lower than the other three methods. This proves that APSO is not only excellent in SOC estimation, but also very competitive in power state evaluation, which helps to improve the overall efficiency of the power system. The standard deviation of APSO is only 0.5, which is much lower than other methods, showing high stability and reliability. In terms of power grid optimization time, APSO only takes 1.2 hours, which is faster than PSO-GA's 1.5 hours, and much faster than the method of more than 2 hours in the literature, indicating that APSO and PSO-GA are significantly faster than traditional methods in processing speed and can quickly respond to changes in the power grid. Finally, in terms of the convergence speed of the algorithm, APSO quickly reaches the optimal solution in 50 iterations, demonstrating excellent search and convergence capabilities. Although PSO-GA is slightly slower, it is still much faster than the literature method, reflecting the balance between global and local search of the hybrid algorithm. The successful application of APSO and PSO-GA provides new ideas and solutions to solve related problems and promotes progress in related fields.

In the process of collaborative voltage level planning, it is necessary to comprehensively collect power grid-related data, covering line details, load conditions, and new energy access information for each voltage level. Using these data, the APSO algorithm is used to construct a voltage-level collaborative planning model.

When setting the model, the parameters of the APSO algorithm, such as inertial weights, acceleration factors, etc., must be carefully adjusted in combination with the actual power grid and the characteristics of the algorithm to find the best balance. During the operation of the model, the optimization process of the APSO algorithm should be closely monitored to ensure that the voltage level configuration is continuously optimized. In view of possible algorithm convergence problems, strategies need to be adjusted in time to improve efficiency. For the optimization of power supply capacity, the PSO-GA algorithm is used to construct the corresponding model. In this process, the algorithm parameters need to be reasonably set based on key data such as load prediction and power distribution of the power grid.

During the model operation phase, the PSO-GA algorithm gives full play to its advantages of global search and local optimization to explore the best power capacity configuration. To ensure the efficient operation of the algorithm, its status needs to be evaluated regularly and adjusted in time. The actual optimization results of the power grid are combined to verify the optimization results to ensure the feasibility and effect of its actual application. In actual operation, it is necessary to pay attention to the complexity and variability of the power grid and respond flexibly; the new developments in power grid technology are continuously focused on, and models are constantly updated and optimized to meet future challenges. Through these measures, the research results can be transformed into a boost for the actual power grid planning and operation, and the overall performance and power supply capacity of the power grid can be effectively improved.

5. Conclusions

The purpose of this paper is to realize the collaborative planning of the voltage level and the optimization of the power supply capacity through intelligent algorithms. With the large-scale access of new energy sources, it is difficult for traditional voltage regulation methods to adapt to the complex needs of modern power grids. In this paper, APSO is used to construct a voltage-level collaborative planning model. By dynamically adjusting the inertial weight and acceleration factor of the particles, the model finds an effective balance between global search and local fine-tuning, thereby significantly reducing voltage fluctuations and power loss. This paper also innovatively combines PSO and GA to form a new hybrid algorithm (PSO-GA) for optimizing power supply capabilities. The APSO algorithm has advantages in power loss optimization. The optimized power loss is only 148kW, which is 26% lower than other algorithms; the algorithm achieves 94.3% energy utilization and 92.8% transmission efficiency, which is significantly better than other algorithms. According to the second law of thermodynamics, there is always part of the energy in the actual process that cannot be effectively utilized due to entropy increase, but APSO greatly reduces this energy loss by intelligently regulating the state of each voltage level, thereby ensuring higher energy utilization and transmission efficiency. The PSO-GA algorithm significantly improves the power supply capacity under different loads. At low loads, it improves the power supply efficiency of the distribution network by 20.61%, far surpassing similar algorithms. At complex loads, it also has an 11.68% increase, demonstrating a strong processing power for complex problems. With the increasing complexity of power systems and technological progress, the role of intelligent algorithms in power grid optimization has become more and more important. In the future, it is necessary to develop smarter and adaptive algorithms that combine big data to monitor and predict the status of the power grid in real-time. In short, through continuous innovation, intelligent algorithms are expected to provide strong support for the construction of an efficient and sustainable smart grid, and promote the continuous progress of the power industry.

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Consent to Publish

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Author Contribution

Xinxiong Wu: Conceived and designed the research, conducted experiments, and analyzed data. Drafted and revised the manuscript critically for important intellectual content.

Huafeng Su, Yan Xue: Contributed to the acquisition, analysis, and interpretation of data. Provided substantial intellectual input during the drafting and revision of the manuscript.

Shaoquan Li, Yulai Li: Participated in the conception and design of the study. Played a key role in data interpretation and manuscript preparation.

All authors have read and approved the final version of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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