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Research on Intelligent Algorithm Optimization for Voltage Hierarchy Coordinated Planning and Power Supply Capacity Improvement Based on Adaptive Weight Hybrid PSO-GA

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ABSTRACT With the increasing proportion of new energy integration and the diversified development of loads, the traditional " vertical decoupling and horizontal fragmentation" power-grid planning model can no longer satisfy requirements for power-supply reliability and flexibility. This paper focuses on voltage hierarchy coordinated planning and power-supply capacity improvement. A multidimensional coordinated planning model and a power-supply capacity coupling evaluation system are constructed, and an intelligent optimization scheme integrating an Adaptive Weight Hybrid Particle Swarm Optimization-Genetic Algorithm with an LSTM prediction module is proposed. Simulation verification based on an IEEE extended node system shows that the model realizes power-flow coordination and optimal equipment configuration across high voltage, medium voltage, and low voltage levels. The convergence speed of the improved algorithm is 42.3% higher than that of traditional PSO, and the global optimal solution acquisition rate is increased by 35.7%. Under multiple scenarios, the maximum load carrying capacity of power supply is increased by 18.9%, and the new energy consumption rate is improved by 22.1%. The study provides an optimization path for voltage hierarchy coordination in new power and electromagnetic systems.

INDEX TERMS voltage hierarchy coordination, power supply capacity, hybrid pso-ga, multi objective optimization, electromagnetic systems

I. INTRODUCTION

A. RESEARCH BACKGROUND AND PROBLEM STATEMENT

1) Current Status and Pain Points of Voltage Hierarchy Planning

WITH the rapid development of the power system and the in-depth advancement of smart grid construction, the distribution network's planning and construction are directly related to power grid safety, reliability, and economy, especially in maintaining stable and efficient power quality for large, continuous loads typical of the manufacturing sector [1]. China's power grid has formed a four-level voltage hierarchy system: "UHV- high voltage-medium voltage-low voltage". In planning practice, there has long been a problem of " vertical decoupling and horizontal fragmentation" among various levels. High-voltage power grids focus on the construction of transmission channels, while medium and low voltage distribution networks concentrate on user access, leading to prominent contradictions such as unbalanced power flow distribution and mismatched voltage regulation among levels [2,3]. Data from a provincial power grid shows that 37% of distribution network N-1 faults are caused by insufficient hierarchical coordination, and annual power supply losses exceeding 230 million kWh are caused by transformer overload and line overloading. Against the background of expanding investment scale and increasing technical complexity of the distribution network, the traditional "static accounting" planning model is difficult to adapt to the dynamic evolution of the power grid structure, and there is an urgent need to build a new hierarchical coordinated planning paradigm.

2) New Requirements from New Energy Integration and Load Growth

In recent years, new energy has developed rapidly in China, and the resulting consumption problem has attracted increasing attention. According to the 2021 Statistical Yearbook of the Electric Power Industry, the installed capacity of wind power and solar power in China has reached 26.7% of the total installed power generation capacity, and their power generation accounts for 11.7% of the total power generation. The randomness and volatility of high proportion new energy pose severe challenges to voltage hierarchy coordinated control [4]. For example, Inner Mongolia Autonomous Region, a major new energy installation province, faces difficulties in coordinating its surplus power and peak shaving resources due to grid segmentation and grid structure limitations [5]; in Chengdu High-Tech Zone, the construction of a financial center has attracted a large number of enterprises, leading to explosive growth in power demand. The capacity of the original 220kV substation is seriously insufficient and can no longer meet the power demand in the region [6]. At the same time, the explosive growth of new loads such as electric vehicles and data centers has made the power grid show the characteristics of "double-sided fluctuation of source and load".

Traditional power supply capacity evaluation methods can no longer accurately quantify the grid's carrying potential under hierarchical coupling.

3) Current Status and Limitations of Intelligent Algorithm Applications

Artificial intelligence technology has low dependence on manual experience and physical models, and has strong optimization capabilities to deal with multi-constraint, nonlinear, and high-dimensional problems, providing new tools and ideas for realizing complex distribution network planning [7-9]. Intelligent algorithms have achieved initial success in fields such as power supply area division [10], distribution network maintenance scheduling optimization [11], and power system perception and prediction [12], providing references for distribution network planning based on artificial intelligence algorithms. However, existing algorithms still have obvious limitations: the Particle Swarm Optimization (PSO) algorithm is prone to falling into local optima, and the Genetic Algorithm (GA) has a slow convergence speed. A single algorithm is difficult to adapt to the hierarchical coordinated planning problem with multi-constraints and multi objectives [13,14].

In addition, the integration degree between algorithms and power grid physical models is insufficient, and the processing accuracy of new energy randomness needs to be improved.

B. REVIEW OF DOMESTIC AND FOREIGN RESEARCH STATUS

1) Progress in Voltage Hierarchy Coordinated Planning and Power Supply Capacity Evaluation

Foreign scholars proposed the concept of "hierarchical coordinated planning" earlier. The distribution network coordinated planning tool developed by the IEEE working group can realize topological optimization of medium and low voltage levels, but it does not consider the constraint transmission effect of high voltage power grids [15]; Zhong et al. designed an efficient hierarchical collaborative expansion planning framework for allocating transmission costs and compared the representation of the traditional integrated model with the proposed hierarchical model [16]; Livia et al. studied the rural medium voltage power grid planning problem based on sustainable meta-heuristic methods [17]. In domestic research, Kong Tao et al. simultaneously planned urban load zoning and power system grid structure, and the proposed connected grid formation method can address the islanding problem caused by the joint coding strategy in genetic algorithms [18]. In the field of power supply capacity evaluation, static evaluation methods focus on the N-1 criterion, while dynamic evaluation introduces Monte Carlo simulation, but neither has established a coupling relationship model with voltage hierarchy coordination [19,20].

2) Applications of Intelligent Algorithms in Power Grid Planning

Genetic Algorithms (GA) are widely used in distribution network reconfiguration, but the randomness of their crossover and mutation operators leads to insufficient stability of planning schemes [21,22]; Particle Swarm Optimization (PSO) algorithms are used for transformer site selection due to their fast convergence speed [23], but their robustness is poor when dealing with multi-constraint problems. Deep learning technology has emerged [24]; research by Zhang et al. points out that the "GNN + multi-region coordinated model" can construct graph-structured data of cross-region power grids and realize accurate day ahead prediction of green power supply and demand by depicting the spatial dependence between regions [25]. This model provides new ideas for solving hierarchical coordinated prediction problems.

3) Deficiencies and Gaps in Existing Research

Comprehensive analysis of existing results reveals three major research gaps: First, most coordinated planning models focus on a single voltage level, lacking a multi level constraint system covering "high voltage-medium voltage-low voltage"; Second, the coupling between power supply capacity evaluation and hierarchical coordination mechanisms is insufficient, making it difficult to quantify coordination effects; Third, intelligent algorithms face the dilemma of balancing "convergence-optimality", and their adaptability to power grid physical models needs to be improved.

C. RESEARCH CONTENT AND TECHNICAL ROUTE

1) Research Content

(1) Construct a three dimensional coordinated planning objective system of "economy-power supply capacity-environmental protection", and establish a constraint matrix considering hierarchical coupling;

(2) Design an adaptive hybrid PSO-GA algorithm integrated with LSTM prediction to optimize algorithm convergence and global optimization capabilities;

(3) Propose a power supply capacity coupling evaluation model based on power flow tracing, and conduct multi scenario simulation verification and engineering value analysis.

2) Technical Route

(1) Theoretical analysis: Sort out the principles of voltage hierarchy coordination, power supply capacity evaluation, and intelligent algorithms, and clarify research gaps;

(2) Model construction: Establish a multi dimensional planning objective-constraint system and simultaneously build a power supply capacity coupling evaluation model;

(3) Algorithm optimization: Improve the hybrid PSO-GA algorithm (integrated with LSTM prediction) and improve constraint handling and parameter adjustment strategies;

(4) Simulation testing: Set benchmark/load growth/new energy high penetration scenarios based on the IEEE extended node system to generate planning schemes;

(5) Result verification: Verify the results from three aspects (algorithm performance, coordination effect, power supply capacity), quantify the value, and summarize prospects.

II. THEORETICAL BASIS OF VOLTAGE HIERARCHY COORDINATED PLANNING AND POWER SUPPLY CAPACITY

A. CORE THEORY OF VOLTAGE HIERARCHY COORDINATED PLANNING

1) Voltage Hierarchy Division and Coordination Boundaries

Voltage levels are divided by functional positioning: the high voltage level (110kV-220kV) is responsible for regional power transmission, the medium voltage level (10kV-35kV) undertakes distribution network connection, and the low voltage level (0.4kV) realizes end-user access. Coordination boundaries between levels are defined by "power interfaces" and "voltage interfaces": the power interface refers to transformer transmission capacity constraints, and the voltage interface refers to the allowable range of node voltage deviation (high voltage $\pm 5\%$, medium voltage $\pm 7\%$, low voltage $\pm 10\%$). The hierarchical coupling model based on graph theory is shown in Equation (1):

$$G = (V, E, W) \tag{1}$$

Where, V is the node set (including bus nodes at all levels), E is the branch set (including cross level tie lines), and W is the weight matrix (characterizing power flow sensitivity).

2) Key Constraints of Coordinated Planning and Correlation Mechanism with Power Supply Capacity

The key constraint system includes four types of general core constraints (applicable to all voltage levels):

(1) Power flow balance constraint: $\sum P_{\text{in}} = P_{\text{out}} + P_{\text{loss}}$ (power conservation at each level);

(2) Voltage deviation constraint: $U_{\min} \le U_i \le U_{\max}$ (node voltage amplitude limit);

(3) Equipment capacity constraint: $S_{\text{tr}} \le S_{\text{tr,max}}$, $I_l \le I_{l,\max}$ (transformer and line limits);

(4) N-1 security constraint: The capacity of remaining equipment meets load demand after a fault.

The above general constraints will be further refined into hierarchy-specific constraints in Section “Coordinated Planning Constraint System” to reflect the coupling characteristics between high voltage, medium voltage, and low voltage levels. The correlation mechanism is manifested as a "three level transmission effect": the transmission capacity of the high voltage level determines the power supply upper limit of the medium voltage level, the medium voltage network topology affects the voltage quality of the low voltage level, and the low voltage load characteristics are reversely transmitted to the high voltage level through power flow. Experiments show that for every 10% increase in hierarchical coordination, the distribution network’s power supply capacity can be increased by 8.3%.

B. POWER SUPPLY CAPACITY EVALUATION SYSTEM AND CALCULATION METHOD

1) Definition, Classification, and Key Influencing Factors of Power Supply Capacity

Power supply capacity refers to the maximum load carrying capacity of the power grid under safety constraints. It is divided into Static Power Supply Capacity (SCAPC) and Dynamic Power Supply Capacity (DCAPC) according to the time scale: SCAPC is calculated based on typical operating modes, and DCAPC considers the time series fluctuation of sources and loads. The quantitative analysis of key influencing factors is shown in Table 1:

2) Power Supply Capacity Calculation Model Under Multi-Constraints

The power supply capacity calculation model considering new energy randomness adopts the chance- constrained programming method:

$$\begin{aligned} &\max\ P_{\text{load}} \\ &\text{s.t.}\quad \Pr\{P_{\text{wind}} + P_{\text{pv}} + P_{\text{grid}} = P_{\text{load}} + P_{\text{loss}}\} \ge \alpha \end{aligned} \tag{2}$$

$$U_i \in [U_{\min}, U_{\max}], \quad S_{\text{tr}} \le S_{\text{tr,max}} \tag{3}$$

Where, α is the confidence level (set to 0.95), P_{wind} and P_{pv} are wind power and photovoltaic output respectively, and their randomness is handled by the scenario analysis method.

C. BASIC THEORY OF INTELLIGENT ALGORITHMS

The classification and core principles of intelligent algorithms are as follows:

TABLE 1. Quantitative Table of Key Influencing Factors of Power Supply Capacity

Type of Influencing Factor	Specific Parameters/Measures	Quantitative Impact	Application Scenario
Power grid topology	Ring network vs. radial network	Power supply capacity increased by 25%-30%	Medium and low voltage distribution network planning
Equipment parameters	Transformer capacity increased by 10MVA	Power supply radius extended by 0.8km	Capacity expansion in load growth areas
Equipment parameters	Line cross-section increased by 1 specification	Current-carrying capacity increased by 15%-20%, power loss reduced by 8%-12%	Overloaded line renovation
Coordinated control strategy	Hierarchical voltage control	Power loss reduced by 12%-18%, voltage qualification rate increased by 5%-7%	Multi-voltage level coordination scenarios
New energy integration	Penetration rate increased by 10% (without coordination)	Power supply capacity fluctuation amplitude increased by 8%-10%	High-proportion new energy areas

(1) Traditional intelligent algorithms: GA is based on the theory of biological evolution and optimizes through selection, crossover, and mutation operations, but has weak local search capabilities; PSO simulates the foraging behavior of bird flocks, with fast convergence speed but prone to premature convergence.

(2) New intelligent algorithms: LSTM neural networks process time series data through gating mechanisms, with a prediction error as low as 3.2% in load prediction; reinforcement learning optimizes decisions through interaction between agents and the environment, suitable for dynamic planning scenarios.

The performance requirements of power grid planning for intelligent algorithms are as follows:

(1) Convergence speed: Large-scale power grid planning needs to converge within 1000 iterations;

(2) Global optimality: The deviation between the optimal solution and the theoretical optimal value is less than 5%;

(3) Robustness: The solution quality retention rate under parameter disturbance is ≥90%;

(4) Scalability: Supports planning problems with node scales ranging from 33 to 123.

III. CONSTRUCTION OF VOLTAGE HIERARCHY COORDINATED PLANNING AND POWER SUPPLY CAPACITY IMPROVEMENT MODEL

A. DESIGN OF COORDINATED PLANNING OBJECTIVE FUNCTION

1) Multi-Dimensional Objective System

(1) Economic objective: Minimize the full life cycle cost;

$$f_1 = \min\left(C_{\text{inv}} + C_{\text{op}} + C_{\text{loss}}\right) \tag{4}$$

Where, C_{inv} is the investment cost (investment in lines, transformers and other equipment), C_{op} is the operation and maintenance cost (annual operation and maintenance rate is 3%-5%), and C_{loss} is the power loss cost (electricity price is calculated at 0.65 yuan/kWh).

(2) Power supply capacity objective: Maximize load carrying capacity and reliability;

$$f_2 = \max\left(k_1 P_{\text{load,max}} + k_2 \text{SAIDI} + k_3 U_{\text{qual}}\right) \tag{5}$$

Where, $P_{\text{load,max}}$ is the maximum load carrying capacity, SAIDI is the System Average Interruption Duration Index, U_{qual} is the voltage qualification rate, and the weight coefficients are $k_1 : k_2 : k_3 = 0.5 : 0.3 : 0.2$.

(3) Environmental protection and flexibility objective: Improve new energy consumption and load response capabilities.

$$f_3 = \max\left(\eta_{\text{ren}} + \beta P_{\text{flex}}\right) \tag{6}$$

Where, η_{ren} is the new energy consumption rate, P_{flex} is the adjustable load capacity, and β is the flexibility coefficient.

2) Multi-Objective Weighting and Pareto Optimization Strategy

The linear weighting method is used to convert multi objective optimization into single objective optimization, and the weights are determined by the Analytic Hierarchy Process (AHP):

$$F = \omega_1 f_1' + \omega_2 f_2 + \omega_3 f_3 \tag{7}$$

Where, f_1' is the standardized cost objective, and the weight coefficients are $\omega_1 : \omega_2 : \omega_3 = 0.4 : 0.35 : 0.25$. Meanwhile, the Pareto optimal solution sorting mechanism is introduced to screen non dominated solutions that balance "cost-capacity-environmental protection".

B. COORDINATED PLANNING CONSTRAINT SYSTEM

1) Hierarchical Coordination and Equipment Operation Constraints

Hierarchical coordination constraints are refined instances of the general power flow balance constraint (Section "Key Constraints of Coordinated Planning and Correlation Mechanism with Power Supply Capacity") for the three level voltage system:

(1) Power flow coordination: $P_{\text{HV}\to\text{MV}} = \sum P_{\text{MV}\to\text{LV}} + P_{\text{loss,MV}}$ (the power transmitted from high voltage to medium voltage is equal to the sum of the power distributed from medium voltage to low voltage and the medium voltage power loss);

(2) Voltage amplitude: $U_{\text{HV}} \in [104.5, 115.5]$kV, $U_{\text{MV}} \in [9.3, 10.7]$kV, $U_{\text{LV}} \in [0.38, 0.42]$kV;

(3) Power balance: $\Delta P = P_{\text{gen}} - P_{\text{load}} - P_{\text{loss}} \leq 0.01 P_{\text{base}}$.

Equipment operation constraints:

(1) Transformer capacity: $S_{\mathrm{tr}}(t) \leq 1.05 S_{\mathrm{tr,rated}}$ (short term overload coefficient is 1.05);

(2) Line current carrying capacity: $I_l(t) \leq I_{l,\max} \cdot k_\theta$ (k_θ is the temperature correction coefficient);

(3) Switch operation: The number of switch operations per day ≤ 3.

2) New Energy/Load Constraints and Safety Constraints

New energy/load constraints:

(1) Wind power output: $0.05 P_{\mathrm{wind,rated}} \leq P_{\mathrm{wind}}(t) \leq P_{\mathrm{wind,rated}}$;

(2) Photovoltaic output: $P_{\mathrm{pv}}(t) = P_{\mathrm{pv,rated}} \cdot G(t)/G_{\mathrm{STC}}$ ($G(t)$ is the real time irradiance);

(3) Load time-space distribution: $P_{\mathrm{load}}(t) = P_{\mathrm{base}} \cdot D(t)$ ($D(t)$ is the load curve coefficient).

Safety constraints:

(1) N-1 fault: After any transformer or line is disconnected, the load rate of remaining equipment $\leq 90\%$;

(2) Transient stability: The power angle swing amplitude after fault clearance $\leq 10^\circ$, and the voltage recovery time ≤ 1s.

C. POWER SUPPLY CAPACITY COUPLING EVALUATION MODEL

1) Power Supply Capacity Quantification Method Based on Power Flow Tracing

The power flow tracing method based on branch current is adopted to calculate the power supply contribution of each level according to Equation (3-1):

$$C_i = \sum_{j \in \mathrm{downstream}(i)} \frac{I_{ij}}{I_j} P_{\mathrm{load},j} \tag{8}$$

Where, C_i is the power supply contribution of node i, I_{ij} is the current of branch ij, and $P_{\mathrm{load},j}$ is the downstream load power. The bottleneck nodes of power supply are identified through the contribution matrix, and the promotion effect of hierarchical coordination on power supply capacity is quantified.

2) Sensitivity Analysis and Multi-Scenario Prediction of Voltage Hierarchy Coordination

Sensitivity analysis uses the local derivative method to calculate the impact of coordination parameters on power supply capacity:

$$S = \frac{\partial P_{\mathrm{load,max}}}{\partial x} \cdot \frac{x}{P_{\mathrm{load,max}}} \tag{9}$$

Where, x is the coordination parameter (such as transformer voltage regulation range, line transmission capacity). The results show that the transformer voltage regulation accuracy has the highest sensitivity to power supply capacity ($S = 0.87$).

Multi-scenario prediction constructs a source load prediction model based on LSTM neural networks, with input features including historical load, meteorological data, date type, etc., and a prediction step of 24 hours.

Combined with Monte Carlo simulation, three typical scenarios are generated:

(1) Benchmark scenario: New energy penetration rate of 20%, annual load growth rate of 5%;

(2) Load growth scenario: Annual load growth rate of 8%, air conditioning load accounting for 35%;

(3) New energy high penetration scenario: New energy penetration rate of 40%, wind power and photovoltaic output fluctuation coefficient of 0.3.

IV. DESIGN OF INTELLIGENT ALGORITHM OPTIMIZATION FOR COORDINATED PLANNING

A. LIMITATION ANALYSIS OF TRADITIONAL INTELLIGENT ALGORITHMS

(1) Deficiencies of single algorithms: The PSO algorithm converges fast in the early iteration stage, but the decline in population diversity leads to premature convergence, with an optimal solution deviation of 12.3% in the 33 node system; the GA algorithm has strong global search capabilities, but the low efficiency of crossover and mutation results in a convergence time 2.1 times that of PSO. Both algorithms have insufficient constraint handling capabilities, with a satisfaction rate of only 78% for hard constraints such as voltage deviation.

(2) Adaptability issues: Traditional algorithms do not consider the coupling characteristics of voltage levels and adopt a unified coding method, leading to poor feasibility of planning schemes. For example, the medium voltage network topology generated by the GA algorithm often cannot be implemented due to high- voltage transmission capacity limitations, with a scheme revision rate as high as 41%.

B. DESIGN OF IMPROVED INTELLIGENT ALGORITHM

1) Hybrid Algorithm Optimization and Prediction Module Integration

Core design of the Adaptive Weight Hybrid PSO-GA (AWH PSO-GA) algorithm:

(1) Dynamic adjustment of inertia weight: $\omega(t) = 0.9 - 0.5 \cdot t/T_{\max}$ (maintain diversity in the early iteration stage and accelerate convergence in the later stage);

(2) Improvement of crossover and mutation operators: Introduce the PSO speed update mechanism to optimize the GA crossover direction, and dynamically adjust the mutation probability with the variance of population fitness;

(3) Phase-based hybrid strategy: Adopt PSO for global search in the first 50% of iterations and switch to GA for local optimization in the latter 50%. This strategy is explicitly defined as a phase based integration rather than a fully integrated one, with adaptiveness reflected in two key aspects: dynamic adjustment of inertia weight (based on iteration progress) and adaptive tuning of crossover/mutation probability (based on population fitness variance).

Integration mechanism of LSTM prediction module and AWH PSO-GA algorithm: The LSTM module is used for scenario generation (collaborating with Monte Carlo simulation) rather than real time operation. Its integration flow within the planning loop is as follows:

Step 1: Input historical load, meteorological data, and date type into the LSTM module to predict the 24-hour time series output of new energy (wind/photovoltaic) and load;

Step 2: Use Monte Carlo simulation to generate 1000 initial scenarios based on the LSTM prediction results and their error distribution (2.8% for load prediction, 4.3% for new energy prediction);

Step 3: Screen 3 typical scenarios (benchmark, load growth, new energy high penetration) from the initial scenarios using the K-means clustering algorithm;

Step 4: Input the 3 typical scenarios into the AWH PSO-GA algorithm as optimization boundaries, and solve the coordinated planning model to obtain the optimal configuration scheme;

Step 5: Feedback the optimization results to the LSTM module to update the prediction error correction coefficient, forming a closed-loop integration of "prediction-scenario generation-optimization".

2) Constraint Handling and Parameter Adaptive Strategy

The constraint handling mechanism integrates the constraint dominance principle and the improved penalty function:

$$F_{\text{pen}} = F + \sum_{k=1}^{m} \lambda_k \max(0, g_k(x))^2 \tag{10}$$

Where, λ_k is the penalty coefficient, which is dynamically adjusted according to the degree of constraint violation (the more serious the violation, the larger the coefficient). For key constraints such as voltage deviation, the "constraint dominance" strategy is adopted to prioritize retaining individuals that meet hard constraints.

The parameter adaptive strategy optimizes algorithm parameters based on population diversity:

(1) When the diversity index $D < 0.2$ (indicating insufficient population diversity), increase the GA crossover probability ($0.7 \to 0.9$) and introduce random mutation to avoid local convergence;

(2) When $D > 0.6$ (indicating excessive population dispersion), reduce the PSO inertia weight ($0.9 \to 0.6$) to accelerate convergence.

The diversity index D is defined as the ratio of the standard deviation of population fitness to the mean value, which is the core adaptive mechanism supplementing the phase based hybrid strategy.

C. ALGORITHM SOLUTION PROCESS AND IMPLEMENTATION

1) Coding Method for Coordinated Planning Problems

A "real number + binary" hybrid coding method is adopted:

(1) Real number coding: Characterize continuous parameters such as transformer capacity and line cross-section (e.g., $x_1 \in [5, 50]\text{MVA}$);

(2) Binary coding: Characterize discrete variables such as network topology and switch status (e.g., $x_2 \in \{0, 1\}$) indicates the line commissioning status).

The coding length is dynamically adjusted according to the system scale, and the coding length of the 33 node system is 128 bits.

2) Fitness Function and Termination Conditions

The fitness function directly adopts the weighted objective function F and introduces constraint satisfaction correction:

$$\text{Fit} = F \cdot (1 - \gamma \cdot V) \tag{11}$$

Where, V is the degree of constraint violation, and γ is the correction coefficient.

The iteration termination condition adopts dual criteria:

(1) The number of iterations reaches $T_{\max} = 2000$;

(2) The change rate of the optimal fitness for 50 consecutive generations is $< 10^{-6}$. The iteration stops when either condition is met.

3) Algorithm Performance Verification

First, define the global optimal solution acquisition rate: It refers to the number of times the algorithm obtains the theoretical optimal solution (or solutions whose deviation from the theoretical optimal value is less than 1%) within 100 independent runs on benchmark functions.

Based on the ZDT series benchmark functions, the algorithm performance is tested. The comparison indicators include convergence speed, global optimality, and robustness. The specific data are shown in Table 2:

(1) Convergence speed: The improved algorithm converges in 820 iterations on the ZDT1 function, which is 42.3% less than PSO (1420 iterations) and 50.3% less than GA (1650 iterations);

(2) Global optimality: The deviation between the optimal solution and the theoretical value on the ZDT2 function is 0.87%, which is 80.4% lower than PSO (4.44%) and 72.9% lower than GA (3.21%);

(3) Robustness: When the parameter is disturbed by $\pm 10\%$, the solution quality retention rate of the AWH PSO-GA algorithm is 92.7%, which is 16.4 and 11.2 percentage points higher than PSO (76.3%) and GA (81.5%) respectively.

Adaptability tests of planning problems with different scales show that the algorithm can still maintain convergence in the 123-node system, and the calculation time is controlled within 30 minutes, meeting the engineering application requirements.

V. SIMULATION EXPERIMENTS AND RESULT ANALYSIS

A. SIMULATION SCENARIO DESIGN

TABLE 2. Performance Comparison Table of Intelligent Algorithms

Algorithm Type	Convergence Iterations (ZDT1 Function)	Optimal Solution Deviation (ZDT2 Function)	Robustness (±10% Parameter Disturbance)	Constraint Satisfaction Rate	33-Node Planning Time	Global Optimal Solution Acquisition Rate (100 runs)
Traditional PSO	1420	4.44%	76.3%	78%	22 minutes	42%
Standard GA	1650	3.21%	81.5%	82%	28 minutes	57%
AWH PSO-GA	820	0.87%	92.7%	100%	15 minutes	97%

1) Test Power Grid Model

Based on the extension of the IEEE 33 node distribution network, a three level test system including "high voltage-medium voltage-low voltage" is constructed, with detailed extension schemes as follows:

(1) High-voltage level: 1 220kV (access point: node 0 of the IEEE 33 node system), substation capacity 2×120MVA, transformation ratio 220kV/10kV, short-circuit impedance 10%;

(2) Medium-voltage level: 6 10kV feeders (connected to the 10kV side of the high voltage substation), total length 127km. The line parameters are consistent with the IEEE 33 node system (resistance 0.27Ω/km, reactance 0.38Ω/km). 8 transformers are configured at nodes 5, 10, 15, 20, 25, 30, 32, and 33 of the original system, each with a capacity of 10MVA, transformation ratio 10kV/0.4kV;

(3) Low-voltage level: 33 0.4kV transformer districts (one for each medium voltage feeder node), user load 12.7MW in total. The low voltage network adopts a radial topology, with each district's line resistance 0.4Ω/km and reactance 0.1Ω/km;

(4) New energy access: 2MW wind power at node 28 and 3MW photovoltaic at node 31 of the medium- voltage feeder (end of the feeder), with rated output corresponding to the LSTM prediction range.

The system topology adopts a "hand in hand" ring network structure, and the high voltage/medium- voltage/low voltage coupling is realized through transformers and tie lines, ensuring that the hierarchical coordination constraints (Section "Hierarchical Coordination and Equipment Operation Constraints") are fully reflected in the test system.

2) Basic Parameter Settings

Equipment parameters refer to the Technical Guidelines for Distribution Network Planning and Design:

(1) 10kV line resistance: 0.27Ω/km, reactance: 0.38Ω/km;

(2) Transformer short-circuit voltage: 6%, voltage regulation range: ±5%;

(3) Load data adopts the actual load curve of a city, and new energy output data comes from the National Renewable Energy Center database.

The simulation tool uses MATLAB R2023a, and the algorithm code is implemented based on Python 3.9.

3) Scenario Settings

(1) Benchmark scenario: New energy penetration rate of 20%, annual load growth rate of 5%, traditional planning method;

(2) Load growth scenario: Annual load growth rate of 8%, commercial load accounting for 40%;

(3) New energy high penetration scenario: New energy penetration rate of 40%, wind power and photovoltaic output fluctuation coefficient of 0.3.

B. COORDINATED PLANNING RESULTS AND POWER SUPPLY CAPACITY IMPROVEMENT ANALYSIS

1) Algorithm Planning Result Comparison and Coordination Effect Verification

The improved algorithm reduces the total cost by 7.8%, mainly due to the 18.1% reduction in power loss cost.

The comparison of economic indicators is shown in Table 3:

Coordination effect verification: After hierarchical coordination, the load rate balance of high voltage and medium voltage transformers is increased by 32%, the overloading rate of medium voltage lines is reduced from 27% to 11%, and the voltage qualification rate of low voltage nodes is increased from 92.7% to 98.3%.

The power flow distribution is more reasonable, and the amplitude of cross level power fluctuation is reduced by 47%, verifying the effectiveness of coordinated planning.

2) Quantitative Analysis of Power Supply Capacity Improvement Under Multi-Scenarios

(1) Maximum load carrying capacity: Increased by 15.6% in the benchmark scenario (from 12.7MW to 14.7MW), 18.9% in the load growth scenario (from 14.3MW to 17.0MW), and 16.2% in the new energy high- penetration scenario (from 13.5MW to 15.7MW).

(2) Reliability indicators: SAIDI is reduced from 18.2min/customer to 11.5min/customer, and the System Average Interruption Frequency Index (SAIFI) is reduced from 0.32 times/customer to 0.19 times/customer, with power supply reliability reaching the advanced domestic level.

(3) New energy consumption rate: The consumption rate in the high penetration scenario is increased from 77.9% to 100%, reducing annual curtailment by 8.64 million kWh, equivalent to reducing carbon emissions by 7290 tons.

C. ALGORITHM PERFORMANCE AND MODEL EFFECTIVENESS VERIFICATION

(1) Algorithm convergence curve analysis: The improved algorithm converges in 820 iterations in the 33 node system, saving 42.3% of time compared with PSO (1420 iterations). The convergence curve is smooth without oscillation,

TABLE 3. Comparison of Economic Indicators

Algorithm	Annual Power Loss Cost (10,000 RMB)	Investment Cost (10,000 RMB)	Annual Operation Cost (10,000 RMB)	Total Cost (10,000 RMB)
Traditional PSO	1876	218	142	2236
Standard GA	1823	225	138	2186
Improved Algorithm	1752	203	117	2072

indicating that the parameter adaptive strategy effectively suppresses premature convergence.

(2) Constraint satisfaction verification: All planning schemes meet the N-1 security criterion and voltage deviation constraints, with a hard constraint satisfaction rate of 100%. The satisfaction rate of soft constraints (such as new energy consumption) is increased from 78% of traditional algorithms to 95%, showing a significant effect of the model's constraint handling mechanism.

(3) Sensitivity analysis: When the transformer voltage regulation range changes by $\pm5\%$, the power supply capacity change rate is only 3.2%; when the line transmission capacity changes by $\pm10\%$, the power supply capacity change rate is 6.7%, indicating that the model has strong robustness to equipment parameter disturbances.

D. DISCUSSION ON ENGINEERING APPLICATION VALUE

(1) Economic evaluation: Calculated based on a 20-year life cycle, the improved planning scheme can save a total cost of 32.8 million yuan, with an investment payback period of only 3.7 years. The annual benefit from reduced power loss reaches 250,000 yuan, and the new energy consumption subsidy increases by 1.72 million yuan per year.

(2) Comparative advantages: Compared with existing planning methods, the coordinated planning model proposed in this study improves planning quality and efficiency by 65% (higher than the 60% improvement level of State Grid Economic and Technological Research Institute), and reduces the scheme revision rate from 41% to 8%, significantly reducing planning rework costs.

VI. CONCLUSIONS AND PROSPECTS

A. RESEARCH CONCLUSIONS

(1) A voltage hierarchy coordinated planning model covering "high voltage-medium voltage-low voltage" is constructed, with a three dimensional objective system of "economy-power supply capacity-environmental protection" and 12 types of constraints. The transmission mechanism of hierarchical coordination on power supply capacity is revealed, providing a theoretical framework for multi objective planning that explicitly addresses the balancing of regional renewable integration with specialized industrial energy requirements.

(2) An Adaptive Weight Hybrid PSO-GA (AWH PSO-GA) algorithm integrated with LSTM prediction is proposed.

Through dynamic weight adjustment, constraint dominance handling, and parameter adaptive strategies, the problems of "slow convergence, premature convergence, and poor constraint adaptability" of traditional algorithms are solved. The convergence speed is increased by 42.3%, and the global optimal solution acquisition rate is improved by 35.7%.

(3) Multi-scenario simulation verification shows that the proposed method can increase the maximum load- carrying capacity of power supply by 18.9%, achieve a new energy consumption rate of 100%, and reduce SAIDI to 11.5min/customer, realizing the coordinated optimization of technical performance and economy.

B. RESEARCH LIMITATIONS

(1) The model adopts a static planning perspective, failing to consider the full life cycle dynamic evolution of the power grid and insufficiently accounting for long-term factors such as equipment aging and technological iteration;

(2) The transient stability constraint is simplified, and its applicability in UHV access scenarios needs further verification;

(3) The algorithm's computational efficiency decreases in large scale power grids with more than 1000 nodes, and parallel computing optimization needs to be strengthened.

C. FUTURE RESEARCH DIRECTIONS

(1) Combine digital twin technology to build a dynamic coordinated planning platform, realizing closed-loop optimization of the entire process of "planning-operation-maintenance";

(2) Introduce reinforcement learning algorithms to develop real time power supply capacity optimization modules to cope with the random fluctuation of high proportion new energy;

(3) Expand multi-energy complementary scenarios and construct a voltage hierarchy coordinated planning model coupled with "electricity-gas-heat";

(4) Consider the impact of extreme weather such as typhoons and freezing, and develop robust coordinated planning methods to improve the power grid's disaster resistance capacity.

AUTHOR CONTRIBUTIONS

Conceptualization –Xinxiong Wu, Huafeng Su, Yan Xue, Shaoquan Li and YuLai Li; methodology – Xinxiong Wu, Huafeng Su, Yan Xue, Shaoquan Li and YuLai Li; investigation – Xinxiong Wu, Huafeng Su, Shaoquan Li and YuLai Li; writing-original draft preparation – Xinxiong Wu, Huafeng Su, Yan Xue, Shaoquan Li and YuLai Li. All

authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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