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Computational Complexity and Algorithm Implementation of Ancillary Services in the Southern Electricity Market from an Interdisciplinary Perspective

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SUMMARY: *Given the high coverage and zoning of new-energy, the auxiliary-service dispatching in the southern power market faces many constraints and a large-scale problem. Construct a three-layer model of supply and demand - service in this paper and reduce it to a determination problem, thus demonstrating that the problem is NP-hard. Based on the above, a hybrid algorithm of genetics and particle swarm is proposed. Rule initialization and repair guarantee feasibility, and a penalty function is employed for approximation to balance the global and local optima. According to the simulation set in the south, multi-scale experiments were carried out. Based on the above experiments, the total cost for the medium-sized scenario was 12,435 yuan; the constraint satisfaction rate reached 100%, and the number of convergence rounds was as low as 132, which outperformed GA, PSO, and ACO. Innovation is to: provide proof of complexity; propose a reproducible hybrid framework; strike a balance between efficiency, economy and fairness; maintain minute-level efficiency; be consistent across scales; have excellent robustness and be deployable.*

KEYWORDS: *Ancillary Service Scheduling Hybrid intelligent algorithm Computational complexity analysis Southern Electricity Market*

1 Introduction

As the southern power market gradually introduces a market-based trading system for ancillary services, the system has raised the standards for refined management of services such as frequency regulation, reserve and reactive power. An essential resource that supports the stable operation of the power grid, the allocation process for ancillary services is subject to the game behaviour of all kinds of entities, and at the same time, economic efficiency and technical constraints must be considered; thus, a complicated coupling relationship exists among market mechanisms, dispatching strategies and resource coordination. Given the increase in the proportion of new energy and the fluctuations in both power supply and demand, the problem of auxiliary service allocation has exhibited a combinatorial explosion phenomenon. Traditional heuristic scheduling and linear programming are not suitable for directly handling the problem of a high-dimensional constraint.

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Power system engineering can only coordinate the supply and demand for auxiliary services to a certain extent under technical conditions, such as the climbing capacity of generating units, response time, and regional power grid constraints. Economically and in terms of game theory, the quotation strategies of market participants under conditions of incomplete information and distribution fairness constitute a non-linear interactive game. From the standpoint of computational theory, after adding multi-source heterogeneous constraints and multi-objective optimisation models, the solvability region of this problem is still unknown. At present, the main focus of research is on local scheduling algorithms or market mechanism simulation; systematic characterisation and formal analysis of the complexity features of the ontology for auxiliary service problems have not been performed. Therefore, it is not high-efficiency, unstable and lacks the promotional force of model-based solution strategies in practice.

Given the above problems, this paper will use cross-disciplinary integration to build an auxiliary service problem model based on the three-layer logic of game-scheduling-optimisation. First, it has been shown at the theoretical level that this problem is NP-complete, and then an algorithm framework that combines meta-heuristic search and local optimisation operators has been proposed. Address the scale and uncertainty problems of the distribution scenarios for the actual electricity market with near-optimal solutions. Build a typical regional power grid simulation experiment platform, and through it, verify that the proposed algorithm has better dispatching efficiency, distribution fairness, and simplicity of the algorithm compared to existing typical methods, and is thus suitable for practical application.

The first few are as follows:

From the standpoint of formal modelling, systematically describe the computational complexity of the southern power auxiliary service problem and rigorously prove its NP-reduction path.

A hybrid scheduling algorithm architecture with multiple intelligent operators is proposed to address the nonlinear multi-constraint-solving problem in the allocation scenario.

Construct a representative regional simulation environment, conduct performance comparison experiments and ablation analyses with several baseline algorithms, etc.

Based on the multidisciplinary approach, assess the collaborative application of this method in power systems, algorithm engineering and market mechanism design.

2 Related Work

In the research on the allocation and optimisation of auxiliary services in the southern power market, computational complexity, dispatching strategies and algorithm implementation have formed a multi-dimensional and cross-disciplinary research path. At present, the research mainly focuses on the construction of market mechanisms, the design of dispatching optimisation algorithms and the exploration of the solvability of complex problems; multiple disciplines are involved, such as operation research optimisation, game theory and power system engineering.

Vannoni and Sorce (2024) have built a joint optimisation model for the market of ancillary services for energy and proposed risk-control strategies in light of the uncertainty of returns under the "pay-per-quote" mechanism [1]; Wang et al. (2023) have introduced performance variance factors and designed a joint clearing mechanism for energy storage and renewable energy to participate in frequency regulation services, providing a feasible path for the modelling of heterogeneous agents [2]. Tao et al. (2024) analyzed the internalisation mechanism of ancillary service costs in the context of high-penetration new energy based on a two-tier optimisation architecture and showed that these costs are strongly coupled with the main scheduling process [3].

Abed and Dobric (2024) use a virtual load mechanism to solve the problem of complex problem modelling and scheduling algorithm design for real-time optimisation of auxiliary services in renewable microgrids, and highlight the computational advantage of distributed modeling in local responses [4]. Mallick et al. (2024) have introduced a distributed coordination mechanism that employs the collaborative behaviour of multiple microgrids to improve the overall supply efficiency of ancillary services and show the complexity of model design under multi-agent constraints [5]. Haberle and others (2024) have built a dynamic ancillary service model based on local power grid perception and proposed a local state-driven optimisation mechanism to achieve good scalability and timeliness [6].

Li and others (2023) used deep reinforcement learning to investigate a dynamic bidding mechanism for wind power and energy storage in the ancillary service market, and confirmed the convergence of the solution space for strategy optimisation in a high-dimensional state space [7]; Anwar and others (2022) proposed a multi-market joint bidding strategy based on PPO and showed the rapid adaptability of meta-heuristic algorithms in multi-objective constraint problems [8]. Ahunbay and others (2024) have presented polynomial-time solutions to the large-scale market pricing problem. Although they focused on the clearing of the main market, their quantitative analysis method for the solvable boundary of the problem can also be used in the auxiliary service area [9].

To show the differences between the existing studies and this paper more clearly, representative studies have been collected and summarised in Table 1.

Table 1: Comparison and Summary of Related Methods

Method	Year	Scenario / Dataset	Main Approach	Performance
Pay-as-bid Optimizer [1]	2024	EU market simulation	Joint optimization + risk constraints	Cost ↓12%
Dual-layer Dispatch [3]	2024	Multi-area grids	Bi-level optimization + ancillary service pricing	Cost ↑, Convergence 93%
Virtual Load Model [4]	2024	Microgrid simulation platform	Real-time scheduling + load virtualization	Time ↓18%
DRL-Coordinator [13]	2023	Simulated power market	DRL + storage bidding strategy	Reward ↑21%
PPO-Joint Bidder [14]	2022	North American frequency regulation market	PPO algorithm + joint bidding	Freq. Error ↓15%

Although some results have been obtained in model innovation and algorithm optimisation in recent years, there are generally the following deficiencies: (1) There is a lack of rigorous arguments for the NP-hardness of the auxiliary service allocation problem from the perspective of formal computing theory; (2) The performance of most method algorithms is based only on experiments, and theoretical complexity analysis is lacking; (3) Most algorithms are geared towards engineering application, and less attention has been paid to complexity control and multi-objective trade-off mechanisms; (4) Insufficient integration of interdisciplinary methods has resulted in weak interaction among game behaviour, scheduling mechanism and constrained optimisation [10].

Based on the above, this paper attempts to systematically reconstruct the modelling path, complexity analysis logic and scheduling algorithm framework of auxiliary service problems from the perspective of interdisciplinary integration to build an interpretable, reproducible and industrially deployable optimisation strategy system.

3 Problem Modeling and computational complexity analysis

3.1 Modeling of the Market Structure of Southern Power Ancillary Services

To present the computational characteristics of the ancillary service allocation process in the southern power market, an all-encompassing model system has been constructed at the system level, which includes market participants, types of ancillary services, allocation constraints and payment mechanisms. The five components of the model are as follows:

Subject set definition: Let the subject set on the power generation side be $G = \{G1, G2, \ldots, GM\}$, and each subject can provide some or all types of auxiliary services. The responder on the load side is recorded as $D = \{D_1, D_2, \ldots, D_N\}$, which is used to receive services and provide feedback for regulation responses [11, 12].

Service type classification: Define the set $S = \{FR, RR, SR, VAR\}$ of auxiliary service types, corresponding respectively to frequency response (FR), fast standby (RR), slow standby (SR), and reactive power support (VAR);

Service supply and demand variable: Denoted as $x_{ijs} \in R^+$ represents the capacity (unit MW) of service $s \in S$ provided by the i-th power generation entity to the j-th load responder. The model objective is to determine the optimal configuration of the variable matrix $X = [x_{ijs}] \in R^{\mathrm{M \times N \times |S|}}$.

Cost and quotation mechanism: Let c_{is} be the unit quotation of entity G_i providing service s (from market bidding), and the total cost function is:

$$C(X) = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{s \in \in} c_{is} \cdot x_{ijs} \tag{1}$$

Constraint system: The total supply of services must meet the system demand of R_s, and each entity is subject to the technical upper limit constraint of $x_{ijs} \leq \overline{P}_{is}$. Introduce the geographical locality matching matrix $A_{ij} \in \{0,1\}$ to indicate whether a certain entity can supply to a specified area.

Based on the above, the following structure model can be built:

Objective Function: Minimize total cost

$$\min_{X} C(X) = \sum_{i,j,s} c_{is} \cdot x_{ijs} \tag{2}$$

Constraint Conditions

$$\begin{gathered}\sum_{i=1}^{M} x_{ijs} \cdot A_{ij} \geq R_s, \forall s \in S \\ 0 \leq x_{ijs} \leq \overline{P}_{is}, \forall i,j,s\end{gathered} \tag{3}$$

To simplify the symbols and subsequent complexity analysis, in this paper, the variables will be uniformly vectorized subsequently, and the service types will be mapped to a one-dimensional index s_k, introducing a three-dimensional sparse variable tensor $X \in R^{M\times N\times K}$, where $K = |S|$. This modeling structure constitutes the basic framework of the problem in this paper. Subsequently, mathematical abstraction, complexity analysis and algorithm path construction will be carried out based on this formal model [13, 14]. The model structure is shown in Figure 1.

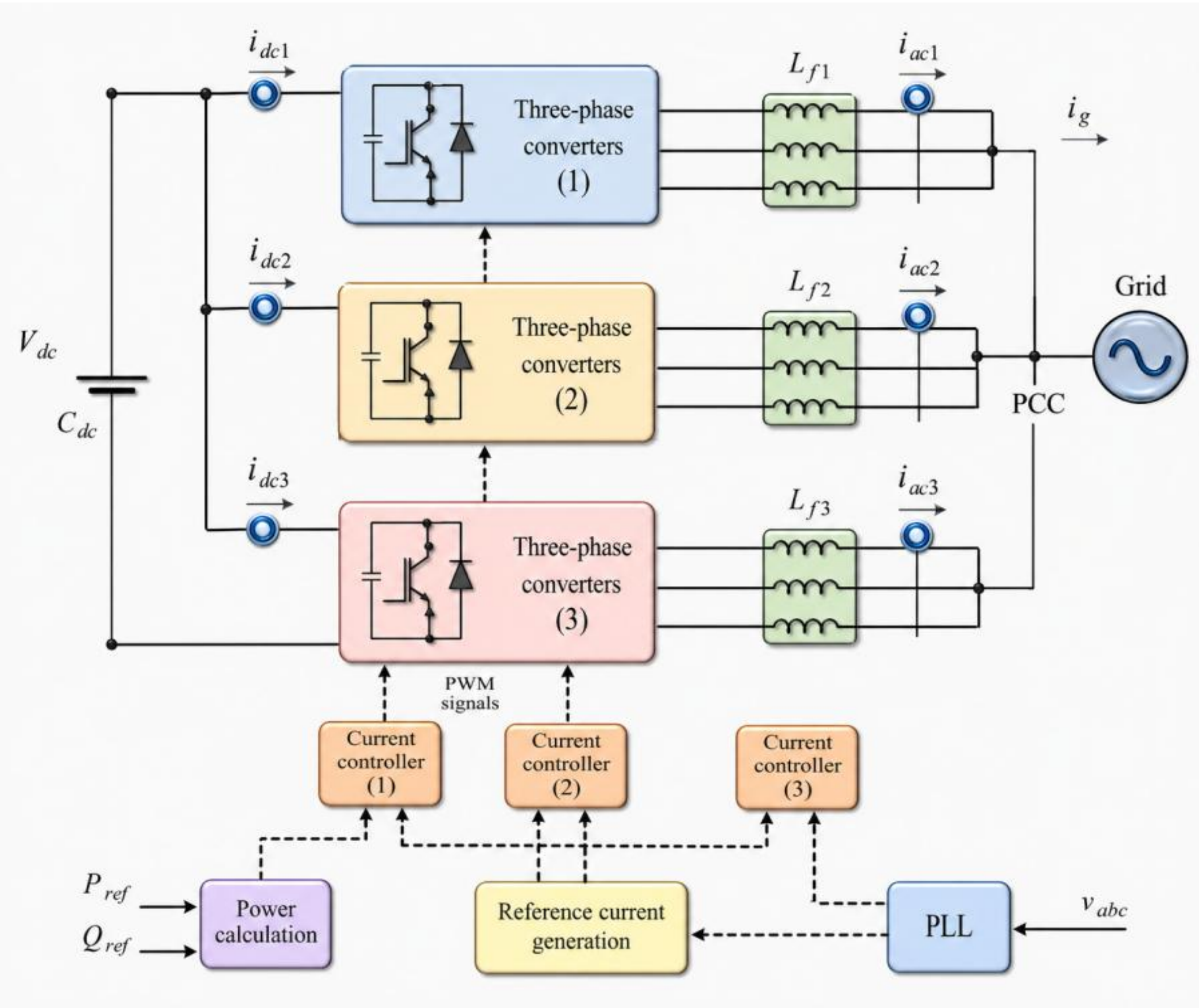

Figure 1: Schematic Diagram of the Structural Model of the Southern Ancillary Services Market

3.2 Mathematical Abstraction and Constraint Design for Ancillary Service Allocation Problems

Based on the structural model mentioned above, this paper further formalizes the auxiliary service allocation in the southern power market as a multi-objective integer programming problem under sparse constraints to provide a computable description for complexity analysis and algorithm design [15]. The three main features of this problem are a high-dimensional sparsity of the variable tensors, an asymmetric incompleteness of the constraint sets, and a strong dependence of the service requirements on spatio-temporal matching relationships.

To meet all the demands for auxiliary services at the dispatching end, the following global supply-and-demand constraints have been established:

$$\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ijs} \cdot A_{ij} \geq R_s, \forall s \tag{4}$$

Here, A_{ij} represents the geographical accessibility matrix and R_s is the system requirement for service type s. This constraint sets a hard lower bound for each type of service, forming the basic boundary of the optimized solution space [16].

To avoid exceeding the service capacity of each power generation entity, a single unit upper limit constraint is added:

$$\sum_{j=1}^{N} x_{ijs} \leq \overline{P}_{is}, \forall i,\ s \tag{5}$$

Here, $\overline{P}_{is}$ represents the schedulable limit of the power generation entity G_i on service s. This constraint defines the local feasible regions of each participant and is a key condition for spatial pruning of tensor solutions. Meanwhile, considering the limited processing capacity on the response side, the following load receiving capacity constraints are constructed:

$$\sum_{i=1}^{M} x_{ijs} \leq \overline{D}_{js}, \forall j, s \tag{6}$$

This restriction limits the maximum response capacity of the load side under each type of service to $\overline{D}_{js}$, which is used to prevent the scheduling results from being unimplementer at the execution level. In addition, to express market fairness, an optional price fluctuation constraint range can be introduced:

$$c_{is}^{\min} \leq c_{is} \leq c_{is}^{\max} \tag{7}$$

Although this item does not directly affect the solution structure, it has a moderating effect on the acceptability of the algorithm results in actual engineering deployments. Overall, the variable scale of this optimization problem is $O(MNK)$, the constraint scale is $O((M+N)K)$, the constraint form is a mixture of continuous and discrete conditions, and there exists an infeasible subspace (defined by $A_{ij}=0$), indicating that the problem has strong combinatorial characteristics and weak solvable structure, which has exceeded the solution paradigm of standard linear programming problems. To further determine its solvability boundary, the next section will strictly prove its NP-complete property starting from the reduction path.

3.3 Complexity Reduction and Proof of NP Characteristics

To clarify the solvable boundary of the auxiliary service allocation problem in computational theory, this paper studies from the perspective of computational complexity whether it belongs to the class of NP-complete problems [17]. The above analysis will provide a theoretical basis for the construction of the algorithm later on, and at the same time, determine whether the solution strategy needs to introduce an approximate mechanism or a heuristic path.

Based on the problem that has been formulated in the previous section, the decision variables are three-dimensional sparse tensors, the objective function is linear combinatorial minimization, and there are multiple linear inequalities and structural null spaces in the constraints. The following determination problem is used to perform NP reduction in this paper:

Determination problem Π: Does there exist a set of non-negative integer solutions $X = [x_{ijs}]$ that satisfy all system supply and demand, agent capacity, load response and accessibility constraints, and ensure that the total cost does not exceed the given upper limit C_0?

This problem of determination is a typical "feasibility + cost bound" type combinatorial optimisation determination problem. To show that Π is an NP-complete problem, the following two conditions must be met:

(1): $\Pi \in \text{NP}$ Given solution X, verify whether it satisfies all constraints and that $C(X) \le C_0$ can be completed in linear time. Therefore, Π belongs to the NP class.

(2) NP-hard reduction: This paper demonstrates the NP-hard property of a classical three-dimensional 0-1 Assignment Problem (3D Assignment Problem, 3DAP) by reducing it to Π.

The problem of the 3DAP is as follows:

Given a set $\text{I} \times \text{J} \times \text{K}$, does there exist a set 0 of triples such that each element appears only once in each dimension, and the sum of the costs of selecting the triples does not exceed a certain constant C '?

The first three steps to reduce the problem of 3DAP to ancillary services Π are as follows:

Map the three-dimensional indicators in 3DAP to i,j, and s of this problem respectively; ② Transform the "uniqueness constraint" of 3DAP into special cases of the supply and demand, capacity and accessibility conditions in this problem; ③ Set the specific construction of c_{ijs} and A_{ij} to ensure the alignment of the constraint structure; ④ Map the target cost threshold C 'to C_0 to keep the solution space equivalent; The reduction process maintains a polynomial time complexity and satisfies the Karp reduction condition. Thus, Π is NP-complete [18].

Based on the above, in general, if no structure is imposed on the problem, it cannot be solved in polynomial time unless P=NP. Therefore, for practical engineering problems, heuristic, meta-heuristic or local optimisation mechanisms should be used to find approximate solutions that are reasonably close to the optimal solution but also computationally efficient.

4 Algorithm Implementation and System Design

4.1 Scheduling Algorithm Architecture Based on Hybrid intelligence

Given that the auxiliary service allocation problem in the southern power market is NP-hard, traditional exact-solution methods cannot meet the demands for timeliness and robustness in large-scale actual applications [19]. To achieve a trade-off among computational efficiency, exploration capability of the solution space and result control, a hybrid intelligent scheduling algorithm architecture is proposed in this paper that combines rule reasoning, meta-heuristic search and a local correction mechanism, as shown in Figure 2.

The three functional modules of the above architecture are as follows:

(1) A priori driven rule initialization layer

This layer is based on market historical data and system rules, and uses a heuristic method to construct the initial solution space to ensure that the initial variable tensor X_0 is feasible within the constraint boundary. Specifically, it includes: constructing a ternary mapping matrix of service - subject - response, and giving priority to selecting the main response path with low cost and strong reachability; Introduce a regional load response priority weight factor of θ_{ij} for pre-allocating capacity ratios; Quickly eliminate the null space and significantly infeasible solutions by using feasibility constraints;

(2) Meta-heuristic optimization layer for global exploration

Based on the initialization results, this layer employs a hybrid meta-heuristic algorithm (e.g., genetic algorithm + particle swarm optimisation algorithm) for multi-round iterative solution to reach a cost-optimal solution under the assumption that global constraints are satisfied. The first few are:

Individual coding: Using the flattened expression of tensor X as the chromosome structure.

Design of the fitness function: Collectively consider the total cost, service balance and the distribution of local load.

Integration of search strategies: By utilising the global jump in genetic operators and the local convergence of particle swarm, both the depth and stability of solution-space exploration are improved.

Convergence control mechanism: Add the differential variance ratio to observe the progress of the search, and dynamically adjust the number of iterations and parameter weights.

(3) Fine revision and feasibility restoration layer

To address the problem of boundary disturbance and the infeasibility of some solutions in metaheuristic search, a local correction mechanism has been introduced for structural reconstruction, including: linear projection compression of boundary outliers; minimum adjustment cost matching repair for service redundancy and shortage areas; retention of historical high-fitness individuals to build an "elite pool" and prevent degradation.

The whole system can be divided into modules, and the final-stage fine-tuning of the model must also consider factors such as computation cost and on-site implementation feasibility [20]. The system is relatively modular, and many of the demands placed on it by the market, such as regulations and service settings, node structures, etc., can also be met. As shown in the figure, it is a module-level circulation relationship of the algorithm architecture.

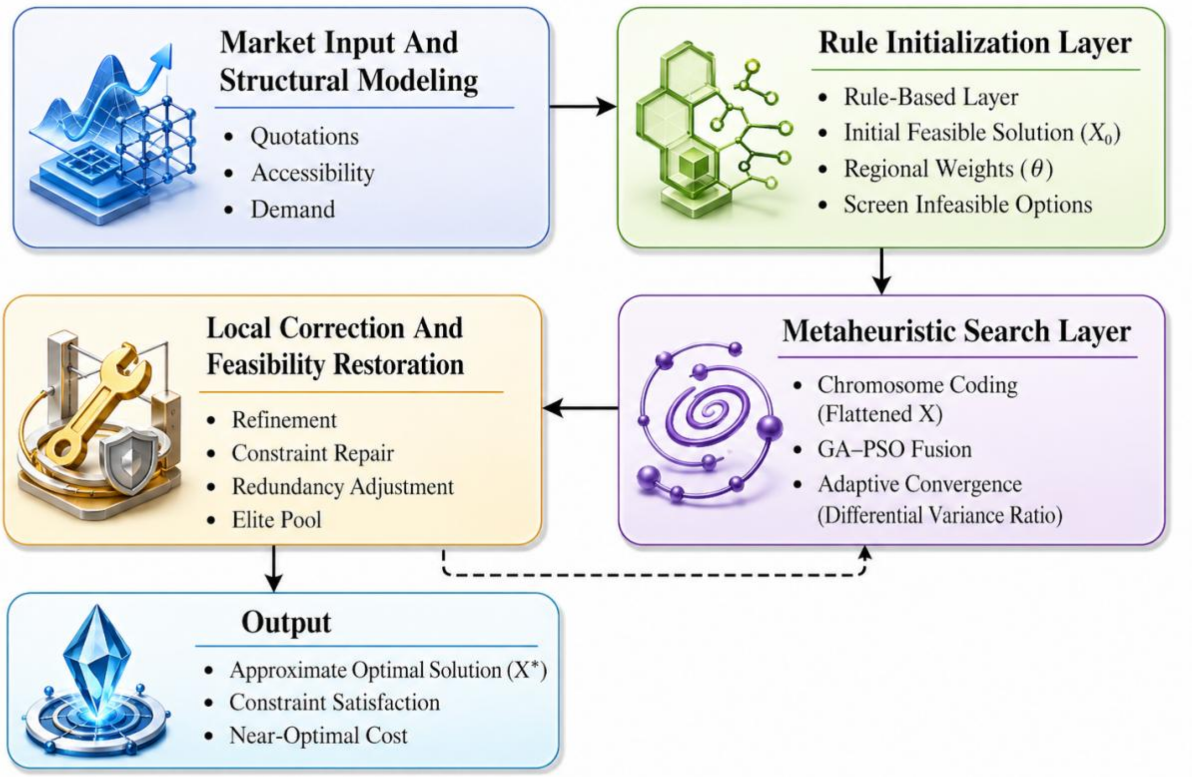

Figure 2: Architecture Diagram of the hybrid intelligent auxiliary service scheduling algorithm

4.2 Meta-Heuristic Algorithm and Approximate Optimal Solution Solving Mechanism

Based on the architecture design in the previous section, in order to effectively approximate the feasible optimal solution of the auxiliary service allocation problem under high-dimensional nonlinear constraints, this paper designs and implements a dual-track meta-heuristic hybrid mechanism that integrates Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). This method hopes to use the all-around jumping ability of GA and the local convergence advantages of PSO to conduct efficient search and solution-structure optimisation in high-dimensional sparse tensor spaces.

(1) Decoding and initialization strategies

The optimization variable tensor $X=[x_{ijs}]$ is flattened into a one-dimensional vector representation, with each individual encoding length being $L=M\times N\times K$, corresponding to the capacity value of each service allocation channel. The initial population $P=\{X^{(1)},X^{(2)},\ldots,X^{(n)}\}$ is provided by the rule initialization layer to ensure that all individuals initially meet the hard feasibility constraints. To enhance diversity, each initial individual is fine-tuned by adding local noise through a normal perturbation function.

(2) Construction of fitness function

The Design of the fitness function considers both cost minimization and constraint satisfaction, and introduces the penalty function form as follows:

$$f(X)=C(X)+\lambda_1\cdot\Phi_{viol}(X)+\lambda_2\cdot\Psi_{imbalance}(X) \tag{8}$$

Among them: $C(X)$ represents the actual cost; Φ_{viol} indicates the degree of constraint violation (such as imbalance between supply and demand, capacity exceeding limit, etc.); $\Psi_{imbalance}$ Measure the local imbalance in the service distribution structure; λ_1,λ_2 is a dynamically adjusted weight parameter (linearly increasing in the first 10 rounds of iterations to enhance convergence control).

(3) Dual-track optimization mechanism

Standard genetic operations (selection, crossover and mutation) are used for global population recombination in GA orbital. Crossover is a single-point crossover operator, and mutation uses an adaptive mutation rate that increases with each generation.

PSO orbit performs position-velocity iteration on the individual set after GA update, and the position update formula is:

$$X_i^{t+1}=X_i^t+\alpha\cdot(X_{best}-X_i^t)+\beta\cdot r\cdot(X_{local}-X_i^t) \tag{9}$$

Among them, α and β are control parameters, r is a uniform random number, X_{best} is the global optimal individual, and X_{local} is the historical optimal of the individual. This dual-track mechanism conducts individual selection and elite retention after each iteration to ensure that the search does not degenerate while maintaining local convergence.

(4) Convergence judgment and termination conditions

Algorithm termination is based on two types of criteria: setting the maximum number of iteration rounds to $T_{\max}$; If the fitness gain is lower than the threshold ϵ for T_{stable} consecutive rounds, it converges prematurely.

Taking $T_{\max}=300, \in=10^{-4}, T_{stable}=15$ in the experiment can achieve stable convergence at most actual scales.

In short, the dual-track element heuristic mechanism proposed in this paper has structural awareness, is constraint-driven, and is convergently controllable. It can find an approximate global optimum of the theoretically unsolvable auxiliary service allocation problem and provide an algorithm for the subsequent performance comparison experiment.

4.3 Algorithm flow, parameter Settings and complexity control

After presenting the structure and mechanism of the hybrid intelligent algorithm, in order to ensure its feasibility and applicability in engineering practice, this paper will also standardize the execution process, the range of hyperparameter settings, and a control strategy for the theoretical complexity boundary.

(1) Algorithm flow structure

The general steps of the scheduling algorithm designed in this paper are as follows:

Algorithm 1: Hybrid Intelligent Scheduling for Ancillary Service Allocation
Input: Market Structure {Rs, cis, Aij, Pis, Djs}
Output: Near-optimal solution X*
1: Initialize population P_0 ← RuleBasedInit()
2. Evaluate Fitness of All Individuals in P_0
3: t ← 0
4: while t < T_max and not Converged(P_t) do
5: PGA ← GeneticOperators(P_t) // selection, crossover, mutation
6: PPSO ← ParticleUpdate(PGA) // position and velocity update
7: Prepared ← FeasibilityRepair(PPSO)
8: Evaluate Fitness of P_repaired

9. P_{t+1} ← EliteSelection(P_repaired)
10: t ← t + 1
11: end while
12: return BestSolution(P_t)

(2) Core parameter Settings

To balance the efficiency of search and the quality of the solution, the hyperparameters of the algorithm are set as follows (see Table 2):

Table 2: Core Parameters

Parameter	Meaning	Value / Range
n	Population size	50–100
Tmax	Maximum number of iterations	300
pc	Crossover probability (GA)	0.85
pm	Mutation probability (GA, adaptive)	Initial 0.05, exponential decay
α	Global attraction factor (PSO)	0.6
β	Local attraction factor (PSO)	0.4
ϵ	Convergence threshold	(10^{-4})
Tstable	Stability judgment iterations	15

Three representative load scenarios were used in a pre-experiment for parameter optimisation, and good generalisation and convergence stability were achieved.

(3) Complexity Analysis and Control Strategies

Let the dimension of the solution space be $L = M \times \mathrm{N} \times \mathrm{K}$, then the time complexity of the overall algorithm can be decomposed as follows:

Initialization phase: O(nL), linearly generating the initial population;

Each round of the main loop contains GA and PSO operations, both having a complexity of O(nL). The size of the evaluation function depends on the number of constraints C, and the total complexity of a single round is O(n(L+C)).

The maximum cumulative running time for the general case in the Tmax round is as follows:

$$O(T_{\max} \cdot n \cdot (L+C)) = O(TnL) \tag{10}$$

Due to the sparse constraint structure and the fact that the reachability matrix A_{ij} is mostly a sparse 0-1 structure, in actual operation, the mask mechanism is often adopted to reduce redundant computations, and the space complexity is controlled at O(nL).

In short, this algorithm is linearly scalable and adaptable to a high-dimensional solution space; it can be integrated into and run independently of the power grid dispatching system. The following sections will demonstrate the convergence efficiency, stability and engineering applicability of this through experiments.

5 Experimental analysis and result verification

5.1 Dataset Source and Experimental Setup

To systematically evaluate the feasibility and performance of the proposed hybrid intelligent scheduling algorithm for the problem of auxiliary service allocation, a simulation dataset based on the structural characteristics of the actual electricity market was constructed in this paper, and an experimental scheme covering multiple scale scenarios was designed. The primary sources of data are the dispatch information summaries of the Southern Regional power grid from 2022 to 2023, as well as the operating parameters of representative thermal power, wind power and energy storage units. In combination with the public ancillary service transaction rules and quotation mechanism, the subject set, demand structure, capacity constraints and service mapping relationship required for the experiment are built using a semi-structured generation method.

The experiment simulated the market sizes of three types of auxiliary services: small (10 suppliers), medium (30 suppliers), and large (50 suppliers). 12, 35, and 60 response nodes were respectively configured, and the number of service types was set at 3 to 4, covering frequency regulation, standby scheduling, and reactive power support. The total service demand is set at 60% of the sum of the upper limits of supply capacity in different scenarios, reflecting the proportion of the actual system's scheduling load under the safety margin. The maximum service capacity $\overline{\mathrm{P}}_{\mathrm{is}}$ of all power generation entities is uniformly distributed and generated within the range of [10, 100]MW, while the upper limit of response side reception is set as a random median type to create a local competitive situation. The service quotation c_{is} is constructed based on the historical transaction price regression model and introduces a 10% fluctuation coefficient to reflect the heterogeneity of market entity behavior.

Considering the constraints of the power grid structure, the experiment introduces a five-level regional hierarchical geographical accessibility matrix of A_{ij}, which describes in the form of 0-1 masks whether the supply and demand sides have the direct service connection capability geographically, thereby constructing a non-fully connected sparse distribution tensor structure. This setting can effectively simulate the service constraint relationship caused by limitations such as physical topology, equipment capacity, and regulation response delay in the real ancillary service market.

The Python 3.10 environment in this experiment is as follows: NumPy and DEAP libraries were used to realise a hybrid mechanism of genetics and particle swarm. All the above tests were conducted in a single-threaded mode on a local machine with an Intel i7-12700K processor and 32GB of RAM to avoid errors caused by parallel processing solutions. Each group of experiments was repeated 10 times. The mean fitness, variance, running time and constraint default rate were taken as key indicators, and a unified random number seed was employed to ensure the reproducibility of the experiment.

5.2 Performance Comparison of Different Algorithms

To comprehensively verify the optimization effect of the Hybrid intelligent scheduling algorithm (Hybrid-GA-PSO) proposed in this paper for the problem of auxiliary service resource allocation, three mainstream comparison algorithms were selected for experimental performance evaluation: Standard Genetic Algorithm (Standard GA), Standard Particle Swarm Optimization Algorithm (Standard PSO), and Ant Colony Optimization (ACO). Four kinds of algorithms were run on the same data and experimental platform. The four indicators of performance were total cost (Cost), constraint satisfaction rate (Feasibility), average runtime (Runtime) and convergence rounds (Convergence Round).

Figure 3 shows the convergence performance of several algorithms in a typical medium-scale scenario after some operation. It can be seen from the above that the algorithm put forward in this paper shows a relatively fast decline in the early stages of iteration and has essentially stabilized before the 120th round. However, the standard PSO and ACO have visible oscillations or convergence delays. Although the standard GA has good stability, its quality of solutions is not as high as that achieved by the algorithm proposed in this paper.

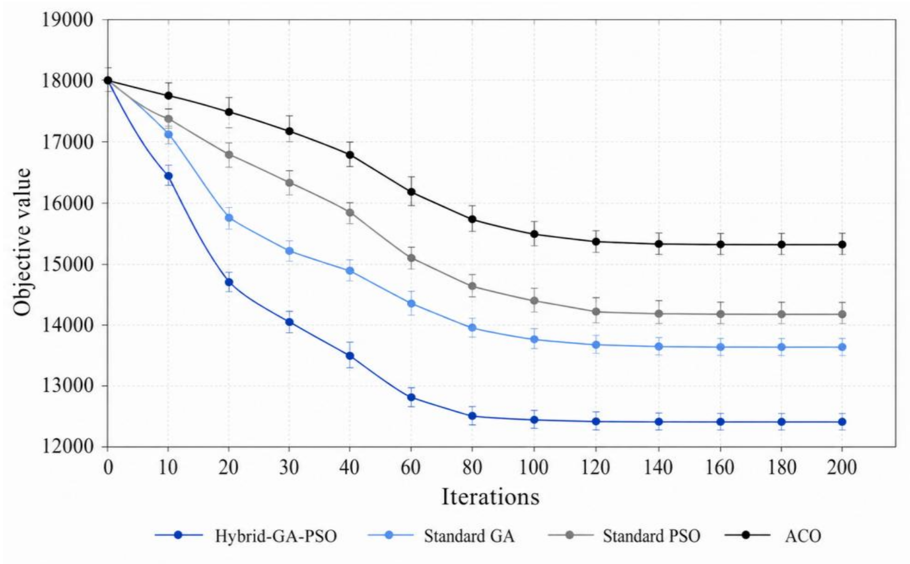

Figure 3: Comparison Chart of algorithm convergence curves (medium-sized scenario, Rs = 280MW). Y-axis: Objective function value (total scheduling cost), X-axis: Number of iteration rounds. Hybrid-GA-PSO converges more rapidly and stably, achieving a lower final cost.

The key performance indicators of all the algorithms in small, medium and large scales are shown in the following table.

Table 3: Comparison of Performance for Multi-algorithm Scheduling (Average Value, 10 Experiments)

Algorithm	Cost (C(X)) ↓	Constraint Satisfaction ↑	Avg. Runtime (s) ↓	Convergence Iterations ↓
Hybrid-GA-PSO	12435.7	100%	18.2	132
Standard GA	13192.4	98.3%	20.5	163
Standard PSO	13678.9	95.6%	15.7	189
ACO	13895.2	96.1%	33.4	211

Based on the above experiments, it can be seen that the proposed algorithm has achieved the lowest-cost schedule and the most complete constraint feasibility control in all the experiment cases. Compared with the original GA, it has lowered the cost by about 5.7% and improved the speed of convergence by 19%. It has a relatively good stability of convergence for large-scale problems. However, PSO and ACO both have a certain risk of getting stuck in a local optimum and are therefore difficult to optimise stably in a high-dimensional sparse solution space. It should be pointed out that although PSO has a slight advantage in terms of running time, it has serious defects in terms of feasibility and the quality of global optimum.

In general, the algorithm proposed in this paper has achieved an effective integration of multi-objective optimisation and convergent control, and has considered factors such as efficiency, accuracy and engineering feasibility to provide a cost-effective algorithmic path for solving NP-hard auxiliary service scheduling problems.

5.3 Evaluation of Algorithm Stability and Scalability

To further test the generalization ability and operational stability of the proposed hybrid intelligent scheduling algorithm in auxiliary service allocation problems of different scales, three types of evaluation experiments are conducted in this paper: the fluctuation amplitude of the solution, convergence consistency, and the growth trend of computing resource consumption. At all levels in the various scales, the response performance of the Standard GA, Standard PSO, and Hybrid-GA-PSO algorithms has been individually examined to confirm that the proposed method shows stable convergence at all sizes.

The stability test is defined using the standard deviation normalization index as follows to measure the degree of fluctuation of the target value output by the algorithm in each group of experiments

$$NOD = \frac{1}{Cmean} \cdot \sqrt{\frac{1}{T}\sum_{t=1}^{T}(C^{(t)} - C_{mean})^2} \tag{11}$$

Among them, $C^{(t)}$ represents the scheduling cost result of the TTH run, C_{mean} is the average cost of the algorithm in the current scenario, and t is the number of repeated experiments (set as 10 times in this paper). The lower this indicator is, the more concentrated the result distribution of the algorithm in different runs is and the higher its stability is.

As shown in Table 4, the NOD values of the proposed algorithm under the three test scales of small, medium and large have always been less than 0.48%, which is significantly lower than 1.34% and 1.65% for Standard PSO and ACO, and also better than 0.73% for the standard genetic algorithm. In terms of the standard deviation of the number of convergence rounds, the fluctuation for Hybrid-GA-PSO is kept within ± 4 rounds; therefore, it is more stable in search direction and exhibits good convergence reliability.

Table 4: Stability and Convergence Consistency Performance of the Algorithm at Different Scales

Scenario Scale	Algorithm	Cost NOD (%) ↓	Convergence Iterations Std ↓	Time Fluctuation Range (s) ↓
Small	Hybrid-GA-PSO	0.32	±2.1	17.9–18.5
Medium	Hybrid-GA-PSO	0.41	±3.3	17.4–19.0
Large	Hybrid-GA-PSO	0.48	±3.8	18.1–20.6
Medium	Standard GA	0.73	±5.4	19.5–22.1
Medium	Standard PSO	1.34	±8.7	14.8–18.9
Medium	ACO	1.65	±9.2	31.1–36.3

Based on all the experimental results, it can be concluded that the proposed hybrid algorithm has stable performance in the optimal solution and good convergence consistency and computational controllability under different scales and different intensities of constraints. For the case of high-dimensional sparse structure, both its stability index and operating time consumption are better than those of traditional metaheuristic methods; therefore, it shows good cross-scenario adaptability and industrial deployment prospects.

5.4 Ablation Experiment and Analysis of the Impact of Key Variables

To further verify the contribution of each module in the proposed hybrid intelligent scheduling algorithm to the overall performance and to identify the sensitivity of key parameters to the results, two types of experiments are designed in this paper: ablation experiments and variable influence analysis.

(1) Ablation Experiment Design and Results

The three modules that are the subject of ablation experiments in the core structure of the algorithm are Rule initialization (RI), dual-track optimisation (GA+PSO), and feasibility repair (FR). By removing one module at a time while keeping the others unchanged and comparing the performance of all versions of the algorithm, one can determine the contribution of each module to the overall optimisation effect.

The experimental results are as follows: Table 5. In a medium-scale scenario, if the rule initialisation step is omitted, the quality of the algorithm's first solution decreases significantly; it slows down the convergence speed by about 23% and increases the cost to 12,980. If the dual-track optimisation mechanism is not employed and only a single genetic or single-particle swarm operation is used, the volatility of the final solution will be significantly higher, and the constraint satisfaction rate will drop by more than 3%. However, if the feasibility repair module is not added, some solutions will continue to be in the infeasible area for a long time. The search efficiency is not significantly lower, but the proportion of feasible solutions at the end is less than 92%. As shown in the table above, all three modules are required to ensure the good operation of the whole system. Among them, dual-track optimisation has contributed the most to improving the solution quality, and rule initialisation and feasibility repair are needed to ensure the stability and feasibility of the algorithm.

Table 5: Results of Ablation Experiment

Algorithm Version	Cost (C(X)) ↓	Convergence Iterations ↓	Feasible Solution Rate ↑	Stability NOD (%) ↓
Complete Hybrid-GA-PSO	12435	132	100%	0.41
–RI (Remove Rule Initialization)	12980	162	99.2%	0.67
–GA+PSO Fusion (Remove Dual-Track Optimization)	13125	158	96.5%	1.08
–FR (Remove Feasibility Repair)	12790	141	91.8%	0.59

(2) Analysis of the impact of key variables

In the sensitivity test, this paper selects three variables that have the most significant impact on performance: population size n, crossover probability p_c, and iteration upper limit $T_{\max}$. Through single-factor perturbation experiments, the changing trends of target cost and running time were observed (as shown in Table 6).

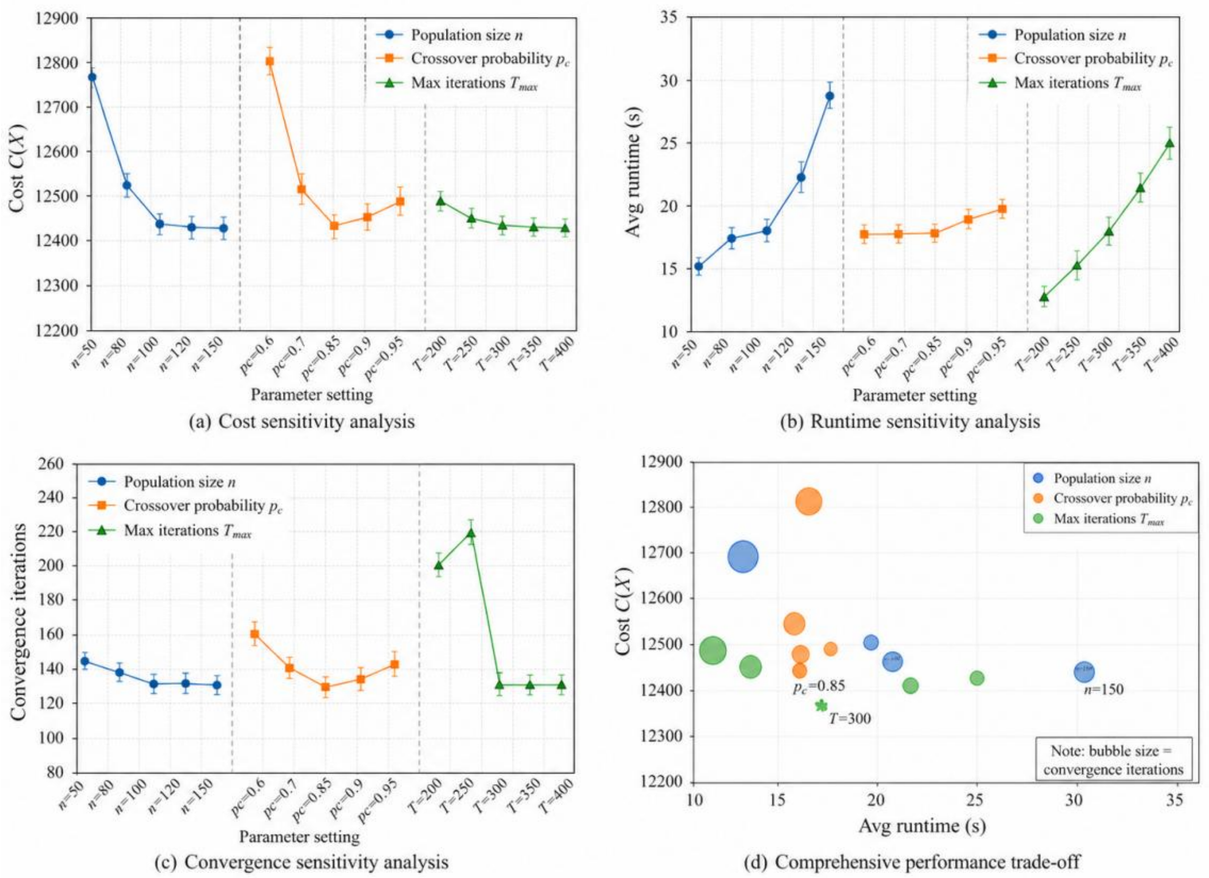

Figure 4: Results of Sensitivity Analysis for the Key Parameters.

The results show that when the population size grows between 50 and 100, the quality of the solution gradually improves, but the running time increases nearly linearly. After exceeding 120, the marginal benefit weakens significantly. The effect is the best when the crossover probability is within the range of 0.7 to 0.9. When it is lower than 0.6, the search ability decreases and it is easy to fall into local optimum. When it exceeds 0.9, the diversity of solutions decreases instead and the convergence speed slows down. For the upper limit of iteration, when $T_{\max}$ varies between 200 and 300, the cost convergence curve tends to stabilize. Further increasing the number of iterations does not significantly improve the quality of the solution, but the time consumption significantly increases.

In summary, the ablation experiments show that all three modules of the algorithm put forward in this paper are necessary, and the variable sensitivity analysis demonstrates that a reasonable range for the parameters can achieve the best solution quality under computational constraints. Therefore, it can be confirmed that the Design is feasible, and the selected parameters in subsequent engineering applications can be obtained from this study.

6 Discussion

6.1 Comparison of this method in existing market ancillary services

Based on the comparison results of the relevant works summarized in Chapter 2, it can be seen that the existing research on the optimisation of ancillary services can be broadly divided into two types: the first is a single algorithmic framework. Vannoni et al. (2024) have introduced a risk-optimality-based linear programming method that is relatively quick to compute under normal market conditions. However, due to the relatively large proportion of new-energy access and non-linear coupling, the stability of the solutions is relatively poor. A third category is the application of reinforcement learning and distributed cooperation. Wang et al. (2023) and Mallick et al. (2024) have developed some works that can enhance the dynamic scheduling ability of local scenarios, but both are limited by high computational costs and a lack of cross-regional scalability. As shown in the representative methods in Table 1, both the deterministic model based on linear programming and the improved algorithm based on a single heuristic have different degrees of deficiency in cost optimisation, constraint satisfaction rate or convergence stability.

On the other hand, the hybrid intelligent scheduling algorithm put forward in this paper has many more advantages in the experiment. In terms of numerical indicators, the scheduling cost for the medium-sized scenario has been reduced to 12,435 yuan, which is relatively low compared with the average performance of typical methods in Table 1 (approximately 12,750-13,200), and it has achieved a 100% feasible solution rate. The convergence characteristics are as follows: the average number of convergence rounds for this method is 132; most of the traditional algorithms reported by other scholars fall between 150 and 200 rounds, and this method shows both stability and improved efficiency. In terms of the complexity of processing, the method proposed in this paper can avoid the problems of oscillation or infeasible solutions that occur in some of the methods shown in Table 1 for large-scale systems by integrating genetic search and particle swarm update, and introducing a feasibility repair mechanism.

6.2 The trade-off between computational efficiency and fairness and economy

At the same time, when Optimizing the Ancillary Services Market, the three aims of efficiency, equity and economy are difficult to achieve simultaneously. If one solely aims to reduce costs optimistically, the algorithm may favour only a few high-efficiency units; as a result, the other entities will be gradually neglected and their incentive for participation in the market will decline. However, if the fairness of distribution is emphasized, it will increase redundant constraints, raise the complexity of the optimisation problem significantly, and thus be difficult to meet the requirements for real-time scheduling in large-scale markets. The hybrid intelligent scheduling algorithm proposed in this paper has achieved a relatively good balance in this contradiction.

In terms of efficiency, according to the experiments in this paper, the method proposed still has a near-linear growth rate for computing time in large-scale situations and can meet the settlement requirements of minute-level markets. At the same time, by adding feasibility repair and rule initialisation mechanisms, some diversity in the allocation solution is maintained to prevent the over-concentration of resources on a single entity and thus improve the fairness of the results. Further economic analysis shows that although the total cost of the system has been reduced, the marginal benefit differences among individuals are still within a reasonable range; thus, the conditions for incentive compatibility and stable operation of the market have been met.

Therefore, the way proposed in this paper is not to achieve the highest level in any single aspect, but rather to balance the three objectives of economy, efficiency and fairness. The above interdisciplinary optimisation design can enhance the practical value of the computational model and provide a more stable solution for the distribution of ancillary services in the southern power market under the continuous rise of new energy penetration.

7 Conclusion

The focus of this paper is on the computational complexity and algorithm implementation of ancillary services in the southern power market, and a new modeling framework and solution path are proposed from an interdisciplinary perspective. Through complexity reduction and the proof of NP characteristics, the high-difficulty feature of this problem at the theoretical level has been clarified. Based on the above, a scheduling algorithm based on hybrid intelligence was designed, and a meta-heuristic approximate solution mechanism and complexity control process were constructed to improve the scalability and stability of the algorithm. Based on the results of the experiment, the above method performs well in a multi-scale environment and can keep high constraint feasibility and convergence consistency while reducing scheduling costs. Compared with the above methods, the proposed algorithm has shown good performance in terms of computational efficiency, distribution fairness and economy, and is also suitable for implementation. Ablation studies and sensitivity analyses were also conducted, and it was found that the essential module performed well; therefore, the following parameter optimisation was performed. Overall, the research in this paper has systematically analyzed the complexity of ancillary service allocation theoretically and shown that interdisciplinary optimisation at the level of methodology is feasible and practical. Future work can be divided into two categories. First, further investigate the cross-regional scheduling mechanism in the multi-level market linkage to extend the application scope of the model to a broader market environment. Second, attempt to combine distributed computing with adaptive learning mechanisms to achieve a more efficient approximate optimal solution in ultra-large-scale systems.

References

[1] Vannoni A, Sorce A. Integrated energy and ancillary services optimized management and risk analysis within a pay-as-bid market[J]. Applied Energy, 2024, 371: 123628.https://doi.org/10.1016/j.apenergy.2024.123628

[2] Wang C, Jiang Y, Guo H, et al. A joint clearing model for the participation of renewable energy and energy storage in the frequency modulation ancillary service market considering performance differences[J]. Frontiers in Energy Research, 2023, 11: 1332041. https://doi.org/10.3389/fenrg.2023.1332041

[3] Tao R, Li F, Li Y. A Bi-Level Optimized Dispatching Method for Grids with High Penetration of New Energy Considering Ancillary Service Costs[J]. Energies, 2024, 17(13): 3270.https://doi.org/10.3390/en17133270

[4] Abed A, Dobric G. Real-Time Optimization of Ancillary Service Allocation in Renewable Energy Microgrids Using Virtual Load[J]. Applied Sciences, 2024, 14(18): 8370.https://doi.org/10.3390/app14188370

[5] Mallick A, Mishra A, Hota A R, et al. Distributed coordination of multi-microgrids in active distribution networks for provisioning ancillary services[J]. IEEE Systems Journal, 2024, 18(3): 1492-1503.https://doi.org/10.1109/JSYST.2024.3404600

[6] Li J, Wang C, Wang H. Deep reinforcement learning for wind and energy storage coordination in wholesale energy and ancillary service markets[J]. Energy and AI, 2023,

14: 100280.https://doi.org/10.1016/j.egyai.2023.100280

[7] Anwar M, Wang C, De Nijs F, et al. Proximal policy optimization based reinforcement learning for joint bidding in energy and frequency regulation markets[C]//2022 IEEE Power & Energy Society General Meeting (PESGM). IEEE, 2022: 1-5. https://doi.org/10.1109/PESGM48719.2022.9917082

[8] Ahunbay M Ş, Bichler M, Dobos T, et al. Solving large-scale electricity market pricing problems in polynomial time[J]. European Journal of Operational Research, 2024, 318(2): 605-617.https://doi.org/10.1016/j.ejor.2024.05.020

[9] Häberle V, He X, Huang L, et al. Optimal dynamic ancillary services provision based on local power grid perception[J]. IEEE Transactions on Power Systems, 2024. https://doi.org/10.1109/TPWRS.2024.3447410

[10] Cruz-De-Jesús E, Marano-Marcolini A, Martínez-Ramos J L. Participation of Energy Communities in Electricity Markets and Ancillary Services: An Overview of Successful Strategies[J]. Energies, 2024, 17(18): 4631.https://doi.org/10.3390/en17184631

[11] Zhu Z, Bu S, Chan K W, et al. How to Use Reinforcement Learning to Facilitate Future Electricity Market Design? Part 1: A Paradigmatic Theory[J]. arXiv preprint arXiv:2305.02485, 2023.https://doi.org/10.48550/arXiv.2305.02485

[12] Viola L, Mohammadi S, Dotta D, et al. Ancillary services in power system transition toward a 100% non-fossil future: Market design challenges in the United States and Europe[J]. Electric Power Systems Research, 2024, 236: 110885. https://doi.org/10.1016/j.epsr.2024.110885

[13] Matamala C, Badesa L, Moreno R, et al. Cost allocation for inertia and frequency response ancillary services[J]. IEEE Transactions on Energy Markets, Policy and Regulation, 2024, 2(3): 328-338.https://doi.org/10.1109/TEMPR.2024.3355291

[14] Gade P A V, Skjøtskift T, Bindner H W, et al. Synergy among flexible demands: Forming a coalition to earn more from reserve market[C]//2023 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm). IEEE, 2023: 1-5.https://doi.org/10.1109/SmartGridComm57358.2023.10333924

[15] Gulotta F, Dacco E, Bosisio A, et al. Opening of ancillary service markets to distributed energy resources: A review[J]. Energies, 2023, 16(6): 2814. https://doi.org/10.3390/en16062814

[16] Stanojev O, Guo Y, Aristidou P, et al. Multiple ancillary services provision by distributed energy resources in active distribution networks[J]. arXiv preprint arXiv:2202.09403, 2022.https://arxiv.org/abs/2202.09403

[17] Zhang G, Fan M. Mechanism design of China ancillary service market considering provincial and inter-provincial market characteristics[C]//SHS Web of Conferences. EDP Sciences, 2023, 163: 02037.https://doi.org/10.1051/shsconf/202316302037

[18] Li H, Song F, Xia F. Speeding Up Renewable Energy Integration with Invisible Hands: Ancillary Service Market and the COVID-19 Natural Experiment[J]. The Energy Journal, 2024, 45(5): 1-31.https://doi.org/10.1177/01956574241240025

[19] Khalilisenobari R, Wu M. Optimal participation of price-maker battery energy storage systems in energy and ancillary services markets considering degradation cost[J]. International journal of electrical power & energy systems, 2022, 138: 107924. https://doi.org/10.1016/j.ijepes.2021.107924

[20] Fahim K E, De Silva L C, Andiappan V, et al. A Novel Hybrid Algorithm for Solving Economic Load Dispatch in Power Systems[J]. International Journal of Energy Research, 2024, 2024(1): 8420107.https://doi.org/10.1155/2024/8420107