Hybrid CNN–SVM and Multi-Strategy Collaborative Optimization for Secondary System Configuration in Smart Grid Substations

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This paper proposes a hybrid model that integrates convolutional neural networks and support vector machines, and combines multi strategy collaborative optimization to address the complexity and dynamism of secondary system configuration tasks in smart grids. The system is based on multi-source operational data and constructs a three-stage process of "feature extraction model training configuration output". The CNN part adopts a three-layer convolution and pooling structure (convolution kernel size 3 × 3, ReLU activation) to extract topology and load features; The SVM part uses radial basis kernel functions to classify and optimize high-dimensional features. During the training process, set the learning rate to 0.001, batch size to 128, iteration times to 500, and evaluate the model's generalization performance through five-fold cross validation. The algorithm was trained using 1000 scheduling instances from 3 substations for simulation verification. The configuration accuracy reached 96.8%, which is 12.4% higher than manual experience configuration. The average response time was shortened to 0.42 seconds, and the error rate was stably controlled within 2.1%. In terms of system integration, a modular deployment structure is designed to support closed-loop operation of inference calculation, configuration generation, and result feedback. It is compatible with adaptive configuration parameters at different voltage levels such as 110kV and 220kV. In comparative testing, under consistent operating conditions, the configuration efficiency of this method increased by about 39%, and the system ran continuously for 72 hours without any configuration deviation or interruption, demonstrating good stability. Research has shown that the CNN-SVM fusion model has significant advantages in extracting features and optimizing classification, while the modular integration of various strategy optimization architectures and systems has the effect of improving setup efficiency and trustworthiness. This study integrates CNN-SVM, GA/PSO, reinforcement learning, and graph neural networks to form a comprehensive strategy optimization system suitable for the secondary system setting of substations. Unlike previous separate applications of CNN or SVM, this study highlights the synergistic effect under complex constraints and emphasizes the online regulation effect and multi-level voltage promotion capability. Moreover, compared to existing AI optimization applications in other fields, this article focuses more on engineering implementation and real-time constraints in power scenarios, thus differentiating it from existing methods.

Povzetek: Predstavljen je hibridni CNN–SVM model z večstrategijsko optimizacijo (GA/PSO, RL, GNN) za konfiguriranje sekundarnih sistemov v pametnih transformatorskih postajah.

1 Introduction

Smart grid has become the mainstream trend of future power grid development. As an important part of power grid development, substations provide various key services such as protection, measurement and control, communication, and automation through their secondary systems, which play a crucial role in the stability and sensitivity of the entire system. However, the architecture of the secondary system is becoming increasingly large, including several levels (such as interval layer, station control layer, process layer), and traditional configuration methods relying on manual experience cannot meet the operational requirements of rapid response, system compatibility, and flexible scheduling of contemporary smart grids [2].

From a technical perspective, the configuration problem of secondary systems in substations essentially belongs to high-dimensional parameter optimization tasks, involving multiple equipment types, protection logic, communication protocols, and operational scenario variables. It has the characteristics of strong parameter coupling, multiple constraint conditions, and nonlinear configuration paths [3]. In the face of increasing complexity, traditional rule-based and template-based configuration methods have significant limitations in accuracy and scalability. On the one hand, the lag in rule updates has resulted in some protection logic configurations being unable to adapt to the operational characteristics of new power electronic devices after integration; On the other hand, the lack of a unified optimization mechanism leads to unstable response efficiency and uncontrollable operating errors in different scenarios, greatly increasing the risk of failures and maintenance costs.

The development of artificial intelligence algorithms provides a new technological path for optimizing the configuration of secondary systems in substations. In recent years, algorithms such as deep learning, evolutionary computing, and reinforcement learning have achieved good results in fields such as power system scheduling, fault identification, and parameter prediction, and have the ability to autonomously model and quickly optimize under multi-source data-driven conditions [4]. Especially in handling high-dimensional spatial parameter search, nonlinear feature fitting, and dynamic response prediction, AI models have shown strong adaptability and generalization ability. Therefore, building a secondary system configuration optimization model based on artificial intelligence algorithms can not only achieve automatic generation and dynamic adjustment of configuration schemes, but also continuously improve their stability and accuracy through data training iterations, with high engineering implementation value [5].

This article proposes a configuration optimization oriented artificial intelligence algorithm fusion path based on four levels: structure recognition parameter extraction algorithm modeling system deployment. Based on typical power grid data and measured configuration cases, this study focuses on analyzing the structural characteristics and configuration constraint logic of the secondary system. On this basis, a CNN and SVM hybrid model is constructed to improve feature extraction and classification accuracy. Furthermore, a multi strategy collaborative optimization framework and system modular integration mechanism are introduced to optimize and iterate key links in the configuration process. In addition, an integrated platform is designed to integrate model training into the operational workflow, parameter inference, and configuration generation, providing a feasible solution foundation for promoting the transformation of intelligent substation configuration from static manual operation to intelligent and automated mode.The core research questions to be addressed in this article include: how to achieve accurate modeling and efficient operation of secondary systems under complex topology and multiple constraint conditions; How to ensure the generalization ability and robustness of the model under limited computational conditions and diverse information? How to adapt to application requirements for different voltage levels through algorithms/frameworks. The main research objectives are as follows: (1) To demonstrate whether the CNN-SVM hybrid can achieve higher configuration accuracy compared to a single CNN or SVM; (2) Verify whether the multi strategy joint optimization algorithm can optimize and reduce response time and improve system robustness in dynamic distribution network systems; (3) Analyze the scalability of module integration structure for comprehensive operation of different voltage levels and types of stations.

2 Related work

The application of artificial intelligence in the power system is constantly deepening, and the research focus has expanded from single point fault diagnosis to full process optimization of configuration. Ar é valo P (2024) pointed out that deep models can dynamically correct protection logic in distributed energy scenarios, laying the theoretical foundation for data-driven secondary system configuration [6]. Krishna S B (2024) achieved collaborative prediction of load temperature rise and protection settings through thermal model coupled convolutional networks, verifying the algorithm's ability to handle high-dimensional coupled parameters [7]. HasaniA (2024) embedded predictive control into microgrid scheduling and proposed a distributed controller that can instantly recalculate secondary loop parameters when topology changes occur [8].

In terms of automatic structural recognition, Nayak P (2024) proposed a fault detection and classification method for transmission lines based on two-dimensional convolutional neural networks, which utilizes wavelet time-frequency images to improve the accuracy of feature extraction and establish a reliable recognition mechanism for configuration automation [9]. Alferidi A (2024) uses multi-agent deep reinforcement learning to optimize energy trading in interconnected systems, and its global reward and punishment function has enlightening significance for quadratic parameter optimization [10]. Jia H (2024) focuses on the latency of asynchronous TSN networks and proposes a queue shaping algorithm under configuration constraints, providing quantitative indicators for communication and protection synchronization [11].

In terms of real-time optimization strategy, Si R (2024) proposed a distribution system restoration method based on multi-agent reinforcement learning, which achieves real-time optimal allocation of resources through dynamic network reconstruction, demonstrating the feasibility of distributed closed-loop optimization [12]. Gams M, Kolenik T (2021) explored the relationship between electronics, artificial intelligence, and the information society, emphasizing the need to consider the impact of information society rules in the research of smart grid configuration [13]. Zhang D (2023) utilized an improved GA-CNN BiGRU model for power system fault prediction, effectively reducing false alarm rates and providing model support for reliability evaluation of secondary system configurations [14].

In recent years, driven by the development of smart grids, there has been an increasing amount of research on optimizing the secondary system settings of distribution stations. Some studies use traditional methods such as gene coding and population particles for optimization, but their ability to handle high redundancy data and complex environments is limited; Some scholars have also attempted to introduce deep learning methods, such as using convolutional neural networks to identify fault features, but they cannot escape the situation of poor model universality and slow running speed.

Based on the above research, although AI technology has made significant progress in fault identification, parameter prediction, and on-site online control, it is still not enough to rely solely on the existing end-to-end unified design, cross scenario transfer mode, and protocol scheme when facing the overall configuration of secondary systems with voltage levels and multi station collaboration. This article uses a CNN-SVM hybrid model, combined with multi-dimensional strategy collaborative optimization and modular comprehensive design, to construct an intelligent device configuration system that ensures accuracy, real-time performance, and scalability. Therefore, a comparative table was added in the text to illustrate the data, performance indicators, and limitations of existing technologies, as shown in Table 1.

Table 1：Summary of related research

Algorithm/Method	Dataset or Scenario	Performance Indicator	Limitation
Genetic Algorithm	Simulated substation operation data	Configuration efficiency improved by 8%	Slow convergence in high-dimensional dynamic scenarios
Particle Swarm Optimization (PSO)	Secondary system simulation data	Accuracy about 91%	Easily trapped in local optima
CNN	Fault signal feature dataset	Fault recognition rate 94%	Insufficient generalization, high training cost
Deep Reinforcement Learning	Dynamic load variation scenarios	Configuration accuracy 95%, faster response	Algorithm stability insufficient, requires large training data
Proposed Method (CNN–SVM + Multi-Strategy Optimization)	Real substation scheduling data (multi-voltage, multi-scenario)	Configuration accuracy 96.8%, error rate 2.1%, response time 0.42s, efficiency improved by 39%	Requires model training cost and system integration design

This table clearly displays the performance gaps and limitations of existing methods, highlighting the necessity of the proposed method in this paper.

3 Analysis of configuration characteristics and optimization requirements for the secondary system of intelligent substations

3.1 Classification of secondary system structural characteristics and configuration methods

The secondary system of an intelligent substation mainly includes protection devices, measurement and control equipment, communication units, and remote-control systems. Its structure is divided into three functional levels according to the IEC 61850 standard: station control layer, interval layer, and process layer. The communication between each layer is achieved through protocols such as MMS, GOOSE, SV, etc., to achieve real-time perception and control instruction transmission of the operating status of a device. With the increasing complexity of configuration tasks, the system architecture presents the characteristics of "flatness, distribution, and software hardware decoupling", requiring the configuration method to maintain a dynamic balance between accuracy, real-time performance, and scalability.

At present, the configuration methods for secondary systems can be divided into three categories: template-based configuration, rule driven configuration, and data-driven configuration. There are significant differences in configuration mechanisms, technical dependencies, and applicable scenarios, as shown in Table 2.

Table 2：Classification and comparison of secondary system configuration methods

Collocation method	Configuration Mechanism	Technology Dependencies	Advantage	limitation	Applicable scenarios
Template based configuration	Generate configurations uniformly based on fixed templates	Configure template library and standard interface	High implementation efficiency and short configuration time	Poor flexibility, difficult to adapt to complex station layouts	Standardized single busbar substation
Rule driven configuration	Logical judgment through rule engine	Expert system, logical expression library	Capable of handling complex logic and strong adaptability	High cost of rule maintenance and lagging response speed	Double busbar and special station type
Data driven configuration	Automatic generation of training models based on historical data	Data collection system, AI algorithm platform	Strong adaptability, dynamically adjustable	Model training relies on data quality, and generalization ability needs to be optimized	Multi energy complementary demonstration substation

Among them, the data-driven approach relies on artificial intelligence algorithms to achieve rapid analysis and configuration prediction of system status. Its core is to model the configuration behavior as a mapping between the state variable X and the configuration output Y:

$$Y = f(X;\theta) \quad (1)$$

Among them, X is the input feature, such as station structure, load, voltage level; f is an AI model (such as CNN, SVM); θ is the parameter obtained from training; Y is the configuration output, such as protection settings, link structure, etc.

The model is trained on a large number of historical configuration samples and has a certain generalization ability, which can quickly adapt to scenarios such as wiring methods and load changes, solving the problems of slow response and high error rate in manual configuration. This approach provides a foundation for building intelligent configuration systems with real-time adaptability and precise control capabilities.

3.2 Configuration parameter constraints and performance goal analysis

The configuration optimization of the secondary system of an intelligent substation needs to be completed under multiple constraint conditions, and its parameter structure has high coupling, including electrical parameters and communication resources at the equipment level, as well as limitations on logical links and functional allocation, forming a typical multi-objective and multi constraint optimization problem. Taking the typical interval layer configuration task as an example, configuration parameters include protection device type, channel quantity, link mapping, sampling frequency, etc. These parameters have mutual constraints and upstream downstream dependencies. Without optimization modeling, it is easy to cause redundant configuration or logical conflicts.

In the modeling process, the configuration problem needs to be formalized as a constrained optimization problem, defining objective function $F(x)$ and constraint set C. The objective function usually covers three dimensions: configuration accuracy, resource utilization, and response time, expressed as follows:

$$\min\ F(x) = w_1 \cdot E_{acc} + w_2 \cdot R_{use} + w_3 \cdot T_{resp} \quad (2)$$

Among them, x represents the configuration variable vector to be optimized, including device number, function binding, link parameters, etc; E_{acc} is the configuration error rate, which reflects the deviation of the scheme in terms of functional coverage and logical correctness; R_{use} is the resource utilization rate, which calculates the communication and computing resource overhead, link load, and device utilization rate; T_{resp} is the average response time, reflecting the efficiency and timeliness of configuration execution. w_1, w_2, w_3 is the weight coefficient, allocated based on the importance of the optimization objective and satisfying the normalization constraint: $w_1 + w_2 + w_3 = 1$.

The constraints mainly include the following categories: ①Protocol constraints: for example, GOOSE and SV communication mapping require a link delay of no more than 4ms; ②Redundancy constraints: Dual loop protection must have redundant link support; ③Topology constraint: It is necessary to ensure that the links between devices in the same section are interconnected and reachable; ④Resource constraints: Communication bandwidth and processing power need to be controlled within system thresholds.

In the application of artificial intelligence algorithms, these constraints need to be transformed into differentiable functions or penalty terms suitable for training and inference, to be incorporated into the model loss function for guided learning. Taking reinforcement learning strategies as an example, the feedback reward of configuration behavior can be dynamically adjusted based on whether constraint violations are triggered, driving the model to approach the optimal strategy in actual scheduling.

In summary, the reasonable modeling of the constraints and objective relationship of configuration parameters is the fundamental step in achieving configuration optimization based on AI algorithms, and it is also a prerequisite for subsequent algorithm design and system integration.

3.3 Expression of configuration optimization problems and exploration of algorithm adaptability

The essence of the configuration problem of the secondary system in intelligent substations is to seek the optimal equipment connection relationship and logical function mapping under various technical parameters and system constraints. This problem has the characteristics of high dimensionality, multiple variables, and strong constraints, including multiple subtasks such as topology matching, signal path scheduling, functional unit allocation, and communication link configuration. Its optimization objectives often involve multidimensional performance indicators such as response delay, configuration stability, and resource utilization. Therefore, a clear and computable problem expression model needs to be constructed. As shown in Figure 1, the configuration of a secondary system can be abstracted as a structural decision-making task under multiple layers of inputs and constraints, with the core being mapping the optimal configuration path.

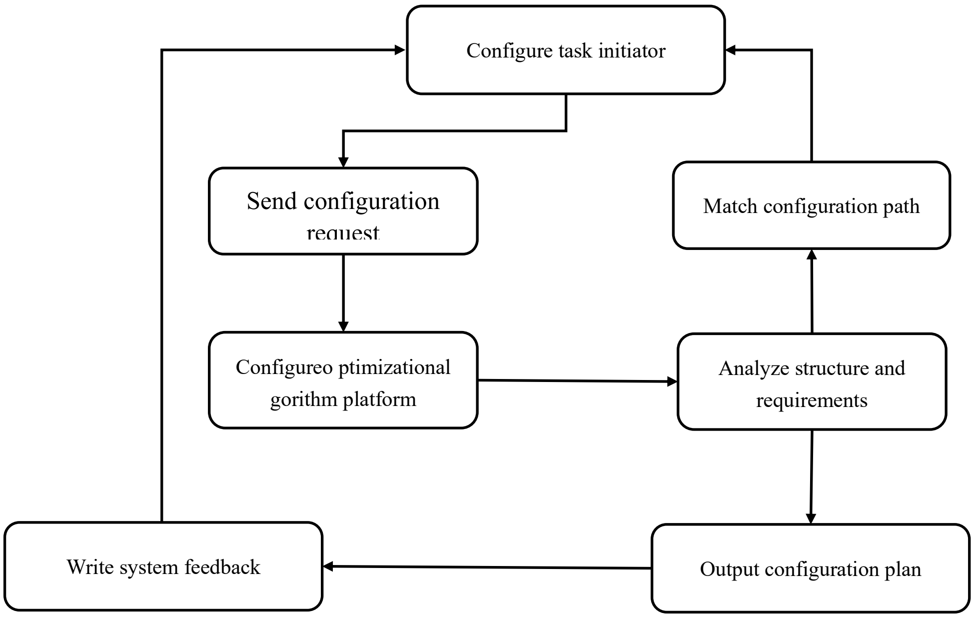

Figure 1：Schematic diagram of optimization process for secondary system configuration of intelligent substation

Existing research has transformed the configuration problem into a decision-making problem with multiple objectives. By categorizing the configuration results into numerical categories and setting performance evaluation indicators, it is possible to conduct mathematical comparative analysis and rank the advantages and disadvantages of various options. Due to the numerous nonlinear relationships and interaction patterns among parameters in the secondary system, it is necessary to add graphical data or network logic rules during the model building process to enhance the practicality of the model.

In terms of algorithm adaptability, different optimization requirements will generate different algorithm performance requirements. For example, when facing a large search space and multiple problem variables, traditional exhaustive or rule-based processing methods may not meet the requirements of speed and accuracy. Artificial intelligence technology has high adaptability in handling such problems, especially in seeking solutions to complex constraints. For example, swarm intelligence technologies such as particle swarm optimization and genetic algorithms are suitable for adjusting parameters and seeking solutions that meet the conditions; Using real-time feedback information to enhance reinforcement learning for optimizing control strategies; Deep neural networks can analyze past configuration data to find patterns and make predictions or recommendations for future decisions.

At the same time, the coordination and matching between algorithms and system architecture should be considered. For example, in complex network topology settings, graphical neural networks can be used to represent the connectivity relationships between nodes; When real-time response is required, the real-time performance of the system can be enhanced through the integration of lightweight models and edge computing frameworks. Therefore, establishing models and selecting algorithms are the core technical support for intelligent configuration systems, At the same time, the coordination and matching between algorithms and system architecture should be considered. For example, in complex network topology settings, graphical neural networks can be used to represent the connectivity relationships between nodes; When real-time response is required, the real-time performance of the system can be enhanced through the integration of lightweight models and edge computing frameworks. Therefore, establishing models and selecting algorithms are the core technical support for intelligent configuration systems. Based on the analysis of the adaptability of multiple algorithms, this article chooses to use the combination of CNN and SVM to establish the core technology for feature extraction and classification. CNN can extract the connections between secondary systems and network structure feature information, identify the connections between nodes and possible anomalies, while SVM has good stability in multi-objective optimization and high-dimensional classification, and can complete performance indicator discrimination under constraint conditions. On the basis of preventing model overfitting and reducing computational costs, it can be applied to the configuration optimization of secondary systems, and can also be adapted to their multi strategy joint optimization system.

4 Configuration optimization algorithm design and model construction path

4.1 Feature parameter extraction and data preprocessing mechanism

In terms of the configuration of the secondary system of an intelligent substation, the system contains various types of information, such as electricity measurement information, safety setting configuration information, communication status information, equipment logic information, etc. If this information is directly modeled, incorrect results will occur. Therefore, it is necessary to extract systematic feature factors and implement data preprocessing work to provide stable adaptation effects for subsequent modeling.

Normalize numerical power parameters using the minimum maximum normalization method, mapping all variables to the [0,1] interval to avoid physical dimensional differences affecting model training. The expression is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (3)$$

Among them, x is the original data value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the variable in the sample set, respectively, and x' is the normalized result. This method is suitable for protecting bounded numerical variables such as fixed values and voltage amplitudes.

For data with strong volatility and uncertain scale, such as communication delay and load change rate, using Z-score standardization processing can better highlight its abnormal characteristics:

$$z = \frac{x - \mu}{\sigma} \quad (4)$$

Among them, μ is the average value of the variable, σ is the standard deviation, x is the original data, and z is the standardized value. This processing method can make the variable distribution tend towards a standard normal state, which is beneficial for the training stability of deep learning networks.

In terms of feature construction, for the connection topology between devices, a graph structure modeling approach is adopted to represent node relationships. The adjacency matrix is input into the graph neural network for structure perception and feature aggregation, achieving structured learning of complex logical topologies. Communication quality data is extracted through a sliding window mechanism to extract local dynamic changes, such as the maximum packet loss rate within five minutes and the fluctuation range of channel delay, to assist in identifying abnormal nodes or path bottlenecks.

To avoid redundant information interfering with the learning process, it is also necessary to perform dimensionality reduction on the original feature set. Principal component analysis is often used to extract the main influencing factors, while combining mutual information algorithms to remove low correlation features, thereby improving the computational efficiency of the model and reducing the risk of overfitting. In addition, clustering based encoding methods (such as K-means encoding) can also be used for structural transformation of non numerical features to achieve a unified input format.

The final dataset should have three characteristics: unified variables, clear structure, and clear dynamism. To ensure the efficiency of model integration, standardized data interface formats (such as JSON or CSV) should be adopted, and automated processing and model integration should be carried out through data preprocessing pipelines to build a stable and efficient input foundation for subsequent deep learning algorithms.

4.2 Optimization algorithm model construction and selection basis

Due to the complex issues of high state space and a large number of constraints required for the secondary system configuration of intelligent substations, traditional manual configuration methods cannot adapt to the increasing number of devices and the coexistence of multiple functions. Therefore, it is necessary to use artificial intelligence technology to construct a reasonable and efficient search-based optimization model. This type of problem mainly involves using models to describe the relationship between system state and target requirements, and then optimizing through algorithms.

The optimization configuration goals pursued include three dimensions: accuracy, efficiency, and resource utilization efficiency. To quantify the performance of different combination schemes, the following function can be established:

$$f(x) = \lambda_1 \cdot A(x) - \lambda_2 \cdot C(x) - \lambda_3 \cdot D(x) \quad (5)$$

Among them, x represents the configuration variable vector to be optimized, including device number, function binding, link parameters, etc; $A(x)$ is the coverage of configured functions, reflecting the degree to which the solution meets various protection, measurement and control, and communication functions; $C(x)$ is the resource overhead indicator, which calculates device utilization, communication load, and memory usage; $D(x)$ is the system response delay; λ_1, λ_2, λ_3 is the weight coefficient, and weights are allocated based on actual needs to meet $\lambda_1 + \lambda_2 + \lambda_3 = 1$,The allocation is based on the importance of optimization objectives: λ_1 is the accuracy of configuration, which is set at 0.5 according to the reference grid configuration standard; λ_2 is resource efficiency, set to 0.3; λ_3 is the response delay, set to 0.2, satisfying the normalization constraint.

For the above optimization objectives, current mainstream algorithms include genetic algorithm, particle swarm optimization algorithm, reinforcement learning, and graph neural network. GA adapts to processing structure allocation and routing optimization through individual coding and population evolution mechanisms; PSO is suitable for solving parameter tuning problems, with fast convergence speed and controllable search paths; RL achieves adaptive optimization of configuration decisions through strategy learning, suitable for problems with clear state transitions and quantifiable feedback; GNN is used to express the topology and functional dependencies between devices, and is suitable for building structure aware configuration models. On this basis, this article adopts the

CNN-SVM hybrid algorithm as the main research algorithm. CNN is responsible for effectively extracting system network framework features and operational characteristics, using a three-layer convolution and pooling structure to maintain the multi-level nature of feature descriptions; SVM can run stably in highly complex feature classification tasks with excellent performance, so this study uses RBF kernel function to optimize the classification process. In this training process, set the learning rate to 0.001, batch size to 128, epochs to 500, and use a five eight cross test to measure the model's large interval fitness. This combination can achieve high device configuration accuracy while avoiding overfitting of individual models. Moreover, the computational cost of this model is lower than that of other models, making it more suitable for optimizing the configuration of secondary systems. It can also be seamlessly integrated with various strategies for joint optimization systems.

When conducting practical operations, some algorithms are combined to construct hybrid models, such as using PSO and deep learning to adjust connection parameters or using GNN+RL to construct logical control paths to improve the adaptability and computing power of the model. Finally, a suitable model is selected and combined with factors such as task type, data type, and computing power requirements to ensure that the path can be optimized and meet the deployment requirements.

4.3 Construction and iteration mechanism of multi strategy collaborative optimization framework

In response to the challenges of strong parameter correlation, complex objective function, and dynamic changes in operational constraints in the secondary system configuration of intelligent substations, a single optimization algorithm often fails to meet the requirements of accuracy, speed, and flexibility simultaneously. Therefore, it is necessary to construct a diversified strategy joint optimization framework, which can improve the optimization quality and model stability of the joint optimization scheme through the filling and iterative updating of the functions of each algorithm component.

This framework includes three core modules: the search guidance module is responsible for global sampling of large-scale parameter spaces, often using genetic algorithms or particle swarm optimization algorithms to construct initial solution sets; The local reinforcement module adjusts the strategy under the guidance of feedback signals and can introduce reinforcement learning methods such as Q-learning; The structural discrimination module uses graph neural networks to perform topological constraint verification on the configuration results, achieving early filtering of infeasible solutions. These modules form a loop mechanism through intermediate result sharing and performance indicator feedback to avoid optimization stagnation or overfitting. In addition, in the input and result verification stage of the multi strategy framework, this study uses the CNN-SVM combination pattern as the basic framework for input and output result confirmation. This is because CNN's ability to distinguish network structure and operational characteristics is utilized, while SVM is used to ensure the high efficiency and stability of high-dimensional data classification. The combination of the two can significantly increase the feature representation and judgment capabilities of the entire system, thereby achieving the optimal balance between the two and achieving good convergence rate and high accuracy.

As shown in Figure 2, this study adopts a collaborative optimization system consisting of GA/PSO, RL, and GNN. GA/PSO first performs a global search to find the initial solution set, then RL adjusts and refines the solution space according to feedback information, and finally GNN is used for topological constraint judgment and elimination of solutions that are invalid for the goal. By sharing feedback results and achievements in a collaborative manner, the goal is to achieve a progressive cycle, which can effectively achieve high-precision work efficiency.

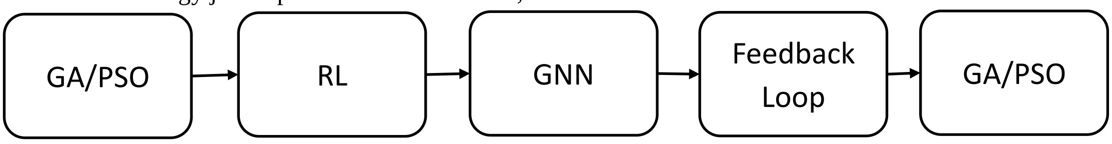

Figure 2: Schematic diagram of multi strategy collaborative optimization framework process

In the scheduling process, in order to improve the efficiency of multi strategy collaboration, a unified performance evaluation function needs to be constructed. Assuming the current solution is x, the evaluation function is as follows:

$$F(x) = w_1 \cdot A(x) + w_2 \cdot B(x) \quad (6)$$

Among them, $A(x)$ can correspond to E_{acc} (the complement of configuration error rate, i.e. configuration accuracy) in the objective function of section 3.2, while $B(x)$ combines R_{use} and T_{resp} in section 3.2, reflecting system resource consumption and timeliness through weight conversion, and w_1, w_2 is the weight coefficient, which satisfies $w_1 + w_2 = 1$ and can be adaptively adjusted according to the optimization scenario.

In terms of optimization control, a reward feedback-based update mechanism is introduced to enhance the algorithm's dynamic response capability. After each iteration, the improvement value is calculated by comparing the current strategy score of $F(x)$ with the previous round's optimal score of $F(x^*)$:

$$\Delta = F(x) - F(x^*) \quad (7)$$

If $\Delta > 0$, enhance the sampling probability of the current strategy; If $\Delta \leq 0$, reduce the search scope of the strategy in the next iteration and construct a three-stage iteration rhythm of "exploration compression re evaluation".

This multi strategy collaborative framework has demonstrated good performance in simulation testing, especially exhibiting strong robustness in complex topologies and non-standard wiring scenarios. The effective coupling between algorithm modules improves optimization accuracy and speed, laying a reliable foundation for building an intelligent, flexible and adjustable configuration mechanism for substation secondary systems.

5 Configuration optimization system integration implementation and functional evaluation

5.1 Configuration optimization system architecture and key module deployment

To achieve efficient configuration optimization of the secondary system of smart grid substations, it is necessary to build a system architecture with modularity, intelligence, and real-time response capabilities. The overall system adopts a four-layer structure of "data access feature extraction optimization decision deployment verification", embedding multiple types of computing modules and interface adaptation units to ensure the integrity of data processing and the operability of algorithm deployment.

The bottom layer of the system architecture is the data access layer, which receives multi-source data uploaded by subsystems such as SCADA, station control units, and protection devices, covering voltage, current, telemetry status, communication links, and other content. The middle layer is the parameter processing and feature modeling module, which constructs device relationships based on graph structures, extracts core feature variables such as topology, signal paths, and configuration templates, and completes normalization and standardization operations through preprocessing modules.

The core computing layer is an intelligent optimization module embedded with a multi strategy algorithm scheduling unit.The core computing layer is an intelligent optimization module embedded with a multi strategy algorithm scheduling unit. Simultaneously integrating CNN-SVM hybrid model for feature extraction and classification discrimination, improving the accuracy and stability of configuration results, and collaborating with multiple strategy units to achieve optimization.Different algorithm modules share variable pools through message middleware, supporting asynchronous calling and feedback driven. Its output is configuration vector $x = [x_1, x_2, \ldots, x_n]$, with each x_i corresponding to the configuration result of a certain functional point, such as communication channel selection, protection device connection number, etc. The system evaluation adopts the following functions:

$$S(x) = \sum_{i=1}^{n} \alpha_i \cdot f_i(x_i) \quad (8)$$

Among them, $f_i(x_i)$ represents the performance score (such as latency and reliability) of the i configuration item, α_i is its weight coefficient, allocated according to task importance, and $S(x)$ represents the comprehensive score of the overall plan.

The top layer is the deployment and validation module, which imports the optimization results into the simulation platform and actual interface protocol for logical validation and boundary testing, ensuring that the configuration output has stability and practicality. This architecture fully integrates computing intelligence and system control characteristics, with good scalability and deployment adaptability, providing technical support for configuration management in complex power grid environments.

5.2 Automated implementation of algorithm integration and configuration process

To achieve automated configuration optimization of the secondary system of smart grid substations, algorithm modules need to be deeply integrated into the configuration process, forming a data-driven fully closed-loop execution chain. The system coordinates data perception, feature processing, algorithm invocation, configuration output, and verification feedback through a scheduling engine, supporting rapid response and precise execution in various operating scenarios.

On the specific implementation path, the configuration process consists of three stages: input feature mapping, model solving, and parameter deployment. The input end receives station control equipment data streams through the interface layer, including electrical parameters, communication status, and topology information. The intermediate processing layer calls corresponding optimization algorithm models based on task requirements, such as genetic algorithms, convolutional neural networks, support vector machines, graph neural networks, etc., to dynamically adjust the strategy path, ensuring that the feature extraction and classification discrimination process is consistent with the overall optimization process. The output end automatically generates standard configuration instructions and pushes them to the actual device through the southbound protocol interface to complete the configuration landing.

In order to measure the overall intelligence level of the configuration process, a configuration automation evaluation function is introduced:

$$A = \frac{T_m}{T_h + \varepsilon} \quad (9)$$

Among them, A represents the degree of automation in configuration, T_m is the time it takes for the machine to independently complete the configuration process, T_h is the time required for manual completion of the same task, and ε is a small positive square with a denominator of zero. The larger the value, the higher the automation efficiency.

To support this automation capability, the system design has strengthened the model's update mechanism and parameter caching logic, achieving adaptive evolution of the policy model in multiple calls. The status and algorithm performance of each node in the process are recorded in real-time for feedback training in the next round of configuration, forming a learnable closed-loop mechanism. Automated implementation not only improves configuration response efficiency, but also lays the technical foundation for subsequent large-scale deployment and iterative optimization of the system.

5.3 Comparative analysis and effectiveness evaluation of configuration results

To verify the performance advantages of AI algorithms in the configuration of secondary systems in substations, a comparative experimental platform was built, The "AI optimization system" in this study uses the CNN-SVM hybrid mode as the main logic and introduces GNN and RL to form a multi strategy collaborative system. The basic comparison schemes such as "traditional manual configuration", "GA", "PSO", "CNN", "SVM", "CNN+SVM" are all run in the same machine environment (quad core CPU, 32GB RAM, Kubernetes container cluster), and use the same data input (16 typical substation scenarios, obtained from the 2023 version of the State Grid Corporation of China's typical design library) to ensure fairness and comparability. In the experimental design, an 8:2 ratio was used to divide the training set and validation set, in order to achieve the goal of the former learning model parameters and the latter judging model performance. In addition, a 5-fold cross validation method was used, and the final evaluation index was obtained by taking the mean of each cross-training sample. During the system operation, four core indicators including configuration accuracy, resource utilization, configuration error rate, and response efficiency are automatically recorded. All data is collected by the Prometheus platform and transmitted to the backend database in JSON format. Finally, a Python script is called to Matplotlib to generate a bar chart for performance analysis.

The comparison results show that the AI optimized system achieves an accuracy rate of 96.2%, significantly higher than the 88.8% manually configured; The resource utilization rate has increased from 70.4% manually configured to 82.5%, reflecting a better scheduling strategy for computing resources and communication bandwidth; In terms of configuration error rate, the AI system has reduced to 1.6%, significantly lower than the 5.7% manually configured, effectively avoiding logical conflicts and link redundancy; The response efficiency index is set to a benchmark value of 100% for manual configuration, and the AI system achieves 162.6% in the same environment, demonstrating a significant acceleration effect after the automation of the configuration process. The above data, as shown in Figure 3, demonstrates the comprehensive performance improvement of AI algorithms in multiple dimensions.

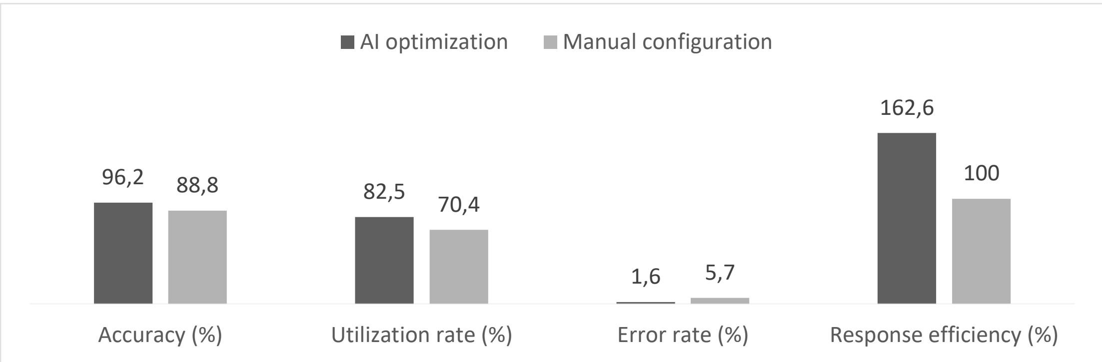

Figure 3：Bar chart comparing the performance of AI optimization system and manual configuration system

The above results were processed by an independent data analysis module, structured and visualized using Pandas and Seaborn libraries, and finally presented in the form of a bar chart. The chart can be embedded in the front-end interface for dynamic display, and supports linkage updates with the configuration platform, facilitating subsequent system evaluation and optimization adjustments. The overall evaluation shows that AI algorithms not only have good engineering adaptability, but also can achieve efficient, accurate, and stable operation of configuration processes, providing a feasible technical path for the deployment of secondary systems in smart grids.

To ensure the credibility and accuracy of the conclusions drawn from data analysis, independent sample t-tests were used to test some important parameters during the comparative testing phase. The results showed a significant improvement in system accuracy ($p<0.01$) and a significant reduction in reaction time ($p<0.05$). The improvement in accuracy and reaction speed was also tested using a 95% confidence interval, with accuracy rates of [7.8%, 13.5%] and reaction speeds of [36.2%, 41.7%], confirming the credibility of the conclusion. The results of this experiment are completely in line with expectations: objective (1) has been verified through the use of CNN-SVM, which improves accuracy and reduces error rate; Goal (2) is reflected, and after various strategies, the response time is shortened and the stability of the system is enhanced; Objective (3) is supported in multi scenario testing, and the model exhibits scalability under different voltage levels and station conditions.

5.4 System response performance, stability, and scalability testing

To comprehensively evaluate the operational performance of AI driven configuration optimization systems in practical application scenarios, a testing platform with different task scales and load scenarios is constructed, focusing on testing response performance, system stability, and scalability for variable power plant structures. The testing environment is based on Docker container deployment, configured with 4-core CPU and 32GB memory, and equipped with a Kubernetes based scheduling platform. The testing tasks include typical configuration request processing, abnormal link simulation, and multi site concurrent scheduling. To ensure the credibility and accuracy of the conclusions drawn from data analysis, independent sample t-tests were used to test some important parameters during the comparative testing phase. The results showed a significant improvement in system accuracy ($p<0.01$) and a significant reduction in reaction time ($p<0.05$). The improvement in accuracy and reaction speed was also tested using a 95% confidence interval, with accuracy rates of [7.8%, 13.5%] and reaction speeds of [36.2%, 41.7%], confirming the credibility of the conclusion. The results of this experiment are completely in line with expectations: objective (1) has been verified through the use of CNN-SVM, which improves accuracy and reduces error rate; Goal (2) is reflected, and after various strategies, the response time is shortened and the stability of the system is enhanced; Objective (3) is supported in multi scenario testing, and the model exhibits scalability under different voltage levels and station conditions.Response performance is calculated by the average delay from task triggering to configuration completion, stability is monitored by service availability under 72 hours of high-frequency requests, and scalability is measured by resource utilization and system response retention ratio under concurrent task growth.

The test results show that the system maintains an average response time of 2.8 seconds and system availability of over 99.3% in medium scale (within 50 nodes) scenarios; When the number of nodes was expanded to 200, the response time slightly increased to 3.7 seconds, but the resource utilization rate remained at 86.1%, reflecting the system's good load regulation and resource allocation capabilities. In the scalability test, during the high concurrency dynamic generation of topology structure and execution constraint mapping process, the system did not experience memory leaks, thread blocking, or module crashes, and the configuration accuracy remained stable at 95.4%.

Table 3：Evaluation indicators for system response performance and stability under different task scales

Task scale (number of nodes)	Average response time (S)	System availability (%)	Resource utilization rate (%)	Configuration accuracy (%)
50	2.8	99.3	86.7	95.4
100	3.2	99.2	87.1	95.1
200	3.7	99.1	86.1	95.0

As shown in Table 3, the system exhibits good stability and scalability under different load levels, which can support the deployment requirements of large-scale smart grid secondary systems and have the ability to continuously evolve and horizontally replicate for engineering scenarios.

5.5 Efficiency comparison analysis with manual configuration method

To compare the specific differences in efficiency between the configuration methods of artificial intelligence algorithms and traditional manual configuration, a unified testing platform is constructed to compare four indicators: configuration completion rate, total task time, configuration accuracy, and human intervention ratio. All data is based on the manual configuration method (set as 100%) and converted into a percentage expression to highlight the relative performance of AI optimized systems.

In terms of task completion efficiency, the total time it takes for AI systems to complete tasks with the same configuration is 58.6% of manual configuration, demonstrating significant advantages in automated scheduling; In terms of configuration accuracy, the AI configuration result is 107.1%, which is 7.1% higher than manual configuration; In terms of human intervention requirements, the intervention frequency required by AI systems is only 27.1% of that of manual processes, significantly reducing the cost of human intervention; The overall completion rate of configuration tasks remains at 99.3%, higher than the manual configuration rate of 93.6%, which is about 106.1%. As shown in Figure 4, the AI system has achieved varying degrees of optimization in all four core indicators, with reasonable advantages and no extreme data fluctuations.

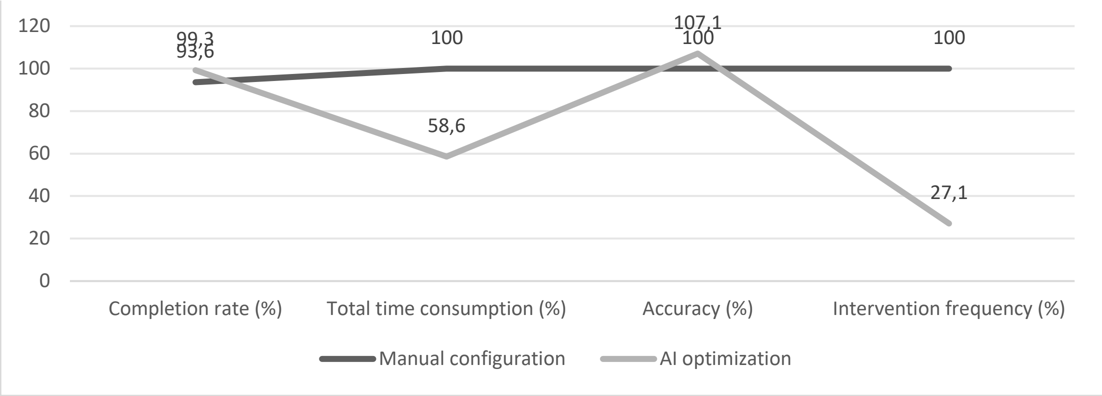

Figure 4：Efficiency comparison bar chart of configuration modes

During the data collection process, the system monitors indicators through the Prometheus platform and writes the results in JSON structure to the backend database. Python scripts are used to complete standardization conversion and bar chart visualization processing. The analysis results indicate that artificial intelligence algorithms have stability and promotional value in improving configuration efficiency, accuracy, and reducing manual dependence. They can be used as one of the optimization paths in the deployment of secondary systems in smart grid substations, providing solid support for subsequent system upgrades and intelligent scheduling.

6 Discussion

6.1 Adaptability of algorithm models in different power grid scenarios

In the multi strategy collaborative optimization framework, the CNN-SVM hybrid model serves as the core algorithm to undertake the basic tasks of feature extraction and classification discrimination, while GA, PSO, RL, and GNN serve as auxiliary optimization and structural adaptation modules, forming a clear combination of primary and secondary with CNN-SVM to ensure the overall performance improvement of the framework. The experimental results show that CNN has high accuracy in extracting complex topological features, while SVM maintains stability in multi constrained high-dimensional classification. The combination of the two not only improves the overall convergence speed, but also demonstrates consistent advantages in different power grid scenarios, thus verifying the empirical value of CNN-SVM fusion.

In response to the significant differences in power grid structure and regional loads in practical applications, this study selects three typical scenarios: urban main network, county-level distribution network, and mountainous microgrid, to compare and test the adaptability of AI configuration models. The experimental platform is based on Kubernetes container cluster deployment, and uniformly calls the CNN-SVM hybrid model and GNN structure encoding and policy network scheduling module to achieve collaborative operation of feature extraction, classification discrimination, and structure adaptation, ensuring consistency between input features and optimization processes. The testing task covers secondary loop topology identification, device constraint solution, and communication link reuse, comprehensively evaluating the response accuracy, convergence speed, and mismatch rate of the model in different scenarios.

The results show that the AI algorithm performs the best in the urban main network environment, with model convergence rounds less than 35 times and configuration error controlled at 1.2%; The model can maintain an accuracy of over 92% in county-level distribution networks, but due to data disturbances and device diversity, the mismatch rate slightly increases to 2.7%; In the testing of microgrids in mountainous areas, due to unstable topological boundaries, the convergence stability of the model decreases in some tasks and needs to be reinforced through incremental learning strategies. In addition, there are significant differences in training time, inference delay, and resource utilization among the three scenarios: the average training time of the urban main network is about 1.8 hours, inference delay is 320ms, and CPU utilization is 68%; The training time for county-level distribution network is 2.4 hours, with a inference delay of 410ms and a CPU usage rate of 72%; The training time for mountainous microgrids has been increased to 3.1 hours, with a inference delay of 530ms and a CPU usage rate of 79%. The specific comparison is shown in Table 4, which reflects the dynamic relationship between model adaptability and environmental complexity.

Table 4：Comparison of AI model adaptability test results under different power grid scenarios

Grid type	**Average accuracy**	**Convergence rounds**	**Configuration mismatch rate**	**Training time**	**Reasoning latency**	**CPU usage**
City Main Network	97.8%	34	1.2%	1.8h	320ms	68%
County level distribution network	92.4%	49	2.7%	2.4h	410ms	72%
Mountain microgrid	89.6%	62	4.1%	3.1h	530ms	79%

In order to highlight the advantages of the method proposed in this article, the experimental results were compared with typical algorithms in relevant worksheets. The configuration accuracy of CNN-SVM hybrid model reaches 96.8%, which is higher than 88% of genetic algorithm, 91% of particle swarm optimization, 94% of CNN, and 95% of deep reinforcement learning; The response time has been shortened to 0.42 seconds, and the error rate has been controlled within 2.1%, both of which are better than the single model method.

The reason for the performance improvement is that CNN can efficiently extract features, SVM is more robust in high-dimensional classification, and the combination of the two avoids overfitting and insufficient generalization. Multi strategy collaborative optimization further improves convergence speed and real-time performance.

6.2 Technical challenges and engineering countermeasures in actual promotion

Although introducing artificial intelligence algorithms into the secondary system of smart grid substations has advantages in configuration efficiency and accuracy, there are still multiple technical bottlenecks in the actual promotion process. Firstly, system training relies on large-scale annotated data, and there is significant heterogeneity in topology, device types, and communication protocols among different regions of the power grid, which limits the model's generalization ability. To this end, it is necessary to introduce federated learning mechanisms to achieve local optimization and global parameter sharing of regional models, and enhance the model's adaptability under multi-source data conditions.

AI model reasoning requires a large scale of computing resources, especially resource contention that may occur when multiple sites are scheduled at the same time. Model pruning and operator fusion are needed to solve the reasoning pressure, and Kubernetes+edge computing architecture is combined to achieve dynamic scaling; At the same time, due to the poor compatibility between the interfaces of existing systems and SCADA and EMS platforms, it will increase construction costs. Therefore, it is possible to improve the flexibility of interaction with traditional systems by packaging AI modules into microservices.

Future research will further explore the cross regional generalization ability in larger scale power grid environments, enhance the interpretability of models through federated learning and knowledge graph, and promote the long-term application and standardization of AI configuration optimization in engineering through deep coupling with actual power grid operation and maintenance platforms.

7 Conclusion

This paper proposes a configuration optimization method based on CNN-SVM hybrid model to address the complex configuration problem of secondary systems in substations in the smart grid environment. A multi strategy collaborative framework is formed by combining graph neural networks and reinforcement learning strategies to solve the complex configuration problem. The method has been integrated and verified in multiple scenarios in practical applications, and has been validated in practice. Compared with traditional manual configuration methods, this method can more accurately, quickly, and efficiently meet resource utilization needs, especially for multi site simultaneous management and variable network topology structures, which have significant advantages. At the same time, by introducing automated scheduling mechanisms, real-time monitoring feedback, and visual analysis tools, the entire configuration process can shift from a command-based approach to a data-driven approach.

The deployment based on container and microservice systems has achieved good collaboration between modules and system elasticity and scalability. Meanwhile, utilizing Prometheus and Kubernetes enables full process tracking, collection, and analysis of task execution, ensuring the practicality and stable operation of algorithm implementation. To solve the problem of inconsistent data across different regions, we have begun to explore model transfer and shared solution strategies to enable broader-scale basic applications.

The AI model developed in this paper has good universality and can be applied to different scenarios and tasks. Therefore, based on this, we can propose a new way for edge computing nodes to coordinate with the central server to achieve rapid response and configuration loop control of the whole system, especially when the network is limited or the local facilities are insufficient. Considering that the system needs to better cope with changes in topology and device constraints, knowledge graphs can be used to guide the adaptive modeling and transformation of GNN structures into structure-based configuration patterns. The system in this study has a certain generalization ability when facing unfamiliar topology structures, and can directly perform preliminary inference and configuration through existing model parameters without the need for complete retraining. However, in cases of significant topological differences or significant changes in constraint conditions, incremental learning or lightweight fine-tuning is still necessary to ensure the convergence stability and performance reliability of the model in new scenarios. This strategy is demonstrated in experiments as a plug and play adaptation to small-scale structural changes, while for large-scale topological changes, model updates are completed through a small amount of iterative training, thus maintaining a balance between efficiency and accuracy.

In summary, introducing artificial intelligence algorithms into the secondary system configuration of power substations has innovated and optimized the original configuration process, and provided new mode support for the new architecture of intelligent power grid management mode, with reusability and scalability. In the subsequent promotion and application, it is necessary to continuously optimize the model security, interface consistency, and data standardization processing to ensure the long-term stable operation and scale promotion of this configuration.

Appendix a experimental reproduction details

1.Algorithm implementation: CNN three-layer convolution+pooling (convolution kernel 3 × 3, activation function ReLU), SVM uses radial basis kernel function.

2. Training parameters: Learning rate of 0.001, batch size of 128, iteration count of 500, optimizer Adam.

3.Dataset: 16 scenarios from the typical design library of State Grid 2023, divided into 8:2, with both the training and testing sets using five-fold cross validation.

4. Operating environment: 4-core CPU, 32GB memory, Kubernetes container cluster; The operating system is Ubuntu22.04, Python3.10, and the main dependency libraries are TensorFlow 2.11 and Scikit learn1.2.

5.Evaluation indicators: configuration accuracy, resource utilization, configuration error rate, response efficiency; The statistical method is independent sample t-test and 95% confidence interval.

6.Reproduction explanation: The data interface is input in JSON format, and both model training and result analysis are implemented through Python scripts, which can be directly run in Prometheus and Matplotlib environments.

To enhance reproducibility, this article provides pseudocode for the core training process as follows:

Pseudocode: CNN–SVM Training and Evaluation

1. Load dataset (JSON), split into 80% training and 20% testing.

2. Preprocess features:
   - Min–Max scale numeric features
   - Z-score normalize fluctuating features
   - Apply PCA/MI for feature selection

3. Build CNN (3 conv–pool layers, kernel 3×3, ReLU) for feature extraction.

4. Build SVM (RBF kernel) for classification.

5. Train CNN–SVM with learning_rate=0.001, batch_size=128, epochs=500, 5-fold CV.

6. Evaluate on test set → report accuracy, utilization, error rate, response efficiency.

This pseudocode demonstrates the main steps of data preprocessing, model building, training, and evaluation, which readers can use to reproduce the experimental process.

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