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Optimization of Substation Design Based on Large Language Models: Integration of Short-Circuit Current Calculation and Intelligent Equipment Selection Recommendation

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SUMMARY: *Under the background of the new power system and the large-scale integration of new energy sources, the short-circuit current level at substations has been continuously rising, and the traditional "numerical calculation + manual table lookup" mode is unable to balance accuracy and efficiency. This paper builds a mixed integer optimization model for key equipment selection based on short-circuit current constraints, introduces a safety margin coefficient to characterize the stability of equipment, and embeds large language models in the aspects of condition analysis, simulation script generation, and candidate equipment pruning, forming a collaborative process of "short-circuit current calculation - equipment selection - result interpretation". The example results show that when the absolute error of short-circuit current remains within 0.25 to 0.30 kA, the proposed method can increase the overall safety margin of the entire station by approximately 0.02 to 0.04, reduce equipment costs by approximately 3% to 5%, and the design time for a single example is about 40% to 60% of the traditional process. The research provides a feasible path for the deep integration of large language models with power system simulation and optimization, and has certain engineering significance for promoting the intelligence and collaboration of substation design.*

Povzetek: This paper addresses the issue of significant short-circuit rise and high design difficulty in the new power system, and constructs a collaborative framework for short-circuit current calculation and equipment selection. A large language model is introduced to complete condition analysis and script generation. The results show that the current error is 0.25 to 0.30 kA, the safety margin is increased by 0.03, the cost is reduced by 3% to 5%, the design time is reduced from 120 seconds to 55 seconds, and the scheme has significant application value.

KEYWORDS: *Large language model; Substation design optimization; Short-circuit current calculation; Intelligent recommendation for equipment selection; Power system simulation*

1 Introduction

In the context of the new power system and the large-scale integration of new energy sources, the pivotal role of substations in the safe and stable operation of the power grid has become increasingly prominent. The once-connection structure has become increasingly complex, and the short-circuit current level has continued to rise, which requires substations to conduct meticulous short-circuit current calculations and strict equipment selection verification during the planning and preliminary design stages, to ensure that key equipment such as circuit breakers, disconnectors, and current transformers have sufficient thermal and dynamic stability margins [1]. At the same time, in engineering practice, there are common problems such as

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tight design cycles, numerous scheme changes, and the need to repeatedly simulate various connection methods and expansion scenarios. The traditional design mode relying on manual experience and a single software tool is increasingly unable to meet the requirements of efficient, reliable, and traceable engineering needs.

The current process for calculating short-circuit currents in substations and selecting equipment mostly adopts a sequential approach of "numerical calculation + manual table lookup / comparison with regulations": Designers use professional software to perform short-circuit current calculations, and then check the equipment parameters item by item according to national or industry standards as well as manufacturer's sample manuals to form the final configuration plan [2]. This process heavily relies on the knowledge accumulation of senior engineers. It not only involves a large amount of work and high repetition, but also is prone to omissions or misunderstandings when comparing multiple working conditions and multiple schemes. It is difficult to timely assess the comprehensive impact of different topologies and equipment combinations on short-circuit levels and investment costs. With the gradual evolution of the entire design process of substations towards three-dimensional modeling, simulation linkage, and digital delivery, how to deeply integrate short-circuit current calculation results with equipment selection logic and build an intelligent design tool that is reusable, interpretable, and scalable has become a focus of attention in both engineering and academic circles [3].

In recent years, artificial intelligence technologies represented by large language models have demonstrated outstanding capabilities in tasks such as code generation, knowledge answering, and reasoning planning. Compared with traditional algorithms, large language models can not only understand complex natural language descriptions but also conduct comprehensive reasoning on non-structured texts such as regulations, equipment samples, and historical design cases, providing suggestions with explanations and reasons for engineering problems. In the field of power systems, there have been studies attempting to use large language models to assist in fault diagnosis, operation and maintenance questions, and automatic script generation, but systematic exploration of the integrated design of short-circuit current calculation and equipment selection for substations is still insufficient, especially how to effectively couple strict electrical calculation results with uncertain language model outputs, which lacks a mature framework.

Based on this, this paper proposes a design optimization method that combines short-circuit current calculation and intelligent equipment selection recommendations for substations, through the construction of an integrated framework of "short-circuit current calculation module - equipment knowledge base - large language model - human-computer interaction interface", enabling the large language model to play a role in calculation configuration generation, regulation clause matching, equipment candidate combination screening, and scheme explanation and description, thereby improving the efficiency of scheme generation and design decision quality while ensuring safety margins and compliance with regulations. The main work of this paper includes: First, computerize the modeling of short-circuit current analysis and key equipment selection processes for substations to lay the foundation for subsequent algorithm design; Second, design a collaborative optimization process for short-circuit current calculation and equipment selection based on large language models, integrating structured calculation results with non-structured regulation knowledge in a unified framework; Third, construct engineering examples and comparative experiments to verify the effectiveness of the proposed method from multiple dimensions such as calculation accuracy, recommendation rationality, and design efficiency, providing a reference for the development of intelligent substation design tools.

2 Short-circuit Current Calculation and Large Language Model Technology Foundation

2.1 Theoretical Model and Engineering Constraints for Short-Circuit Current Analysis of Substations

The basis for calculating the short-circuit current in substations is to approximate the complex primary wiring structure as an impedance network consisting of the power source, transformers, lines, and loads, and then solve for the fault current under the given short-circuit type and fault location [4]. As shown in Figure 1, the high-voltage side power source, main transformer, and feeder lines are connected to the fault point through the equivalent impedance Z_{eq}, forming a three-phase symmetrical short-circuit equivalent network [5]. For a typical three-phase short-circuit condition, the initial symmetrical short-circuit current at the fault point under the rated voltage UN can be expressed as:

$$\mathrm{I_{sc}} = \frac{\mathrm{U_N}}{\sqrt{3}\,\mathrm{Z_{eq}}} - \frac{\mathrm{U_N}}{\sqrt{3}(\mathrm{R_{eq}} + \mathrm{jX_{eq}})} \tag{1}$$

In the per-unit system, it can be further simplified as:

$$\mathrm{I_{sc,p.l.}} = \frac{1}{\mathrm{Z_{eq,p.l.}}} \tag{2}$$

Here, R_{eq} and X_{eq} represent the equivalent resistance and reactance of each segment of equipment after being converted to the equivalent value at the fault point. By modeling different short-circuit points (busbars, line terminations, low-voltage side of transformers, etc.) and different short-circuit types (single-phase grounding, two-phase short circuit, two-phase grounding short circuit), a set of characteristic current values representing the short-circuit level of the substation can be obtained, providing boundary conditions for equipment selection [6].

In engineering applications, short-circuit current calculations not only require numerical accuracy but also must satisfy a series of constraints from national standards and industry regulations [7]. For switchgear equipment such as circuit breakers and disconnectors, it is necessary to verify whether their rated short-circuit breaking current $\mathrm{I_{break}}$ and rated short-circuit closing current Imake are greater than the calculated maximum short-circuit current and its peak value:

$$\mathrm{I_{break}} \geq \mathrm{I_{sc,max}}, \quad \mathrm{I_{make}} \geq \mathrm{k_p I_{sc,max}} \tag{3}$$

Here, kp represents the peak coefficient. For equipment such as busbars, conductors, and current transformers, thermal and dynamic stability conditions must also be met [8]. For example, within the short-circuit duration tsc, there is:

$$I_{sc}^2 t_{sc} \leq I_{th}^2 t_{th} \tag{4}$$

To ensure that the temperature rise and electrical force impact remain within the allowable range. For transformers and reactors, the influence of voltage sag during short-circuit, excitation surge current and transient processes on system stability also needs to be considered.

From the perspective of computer implementation, the above equivalent networks, parameter symbols and constraint conditions can be uniformly abstracted into a set of structured data and rules: node set, branch impedance matrix, fault type code, and equipment limit parameters, etc., forming the input template for subsequent short-circuit current numerical solution and equipment verification programs [9, 10].

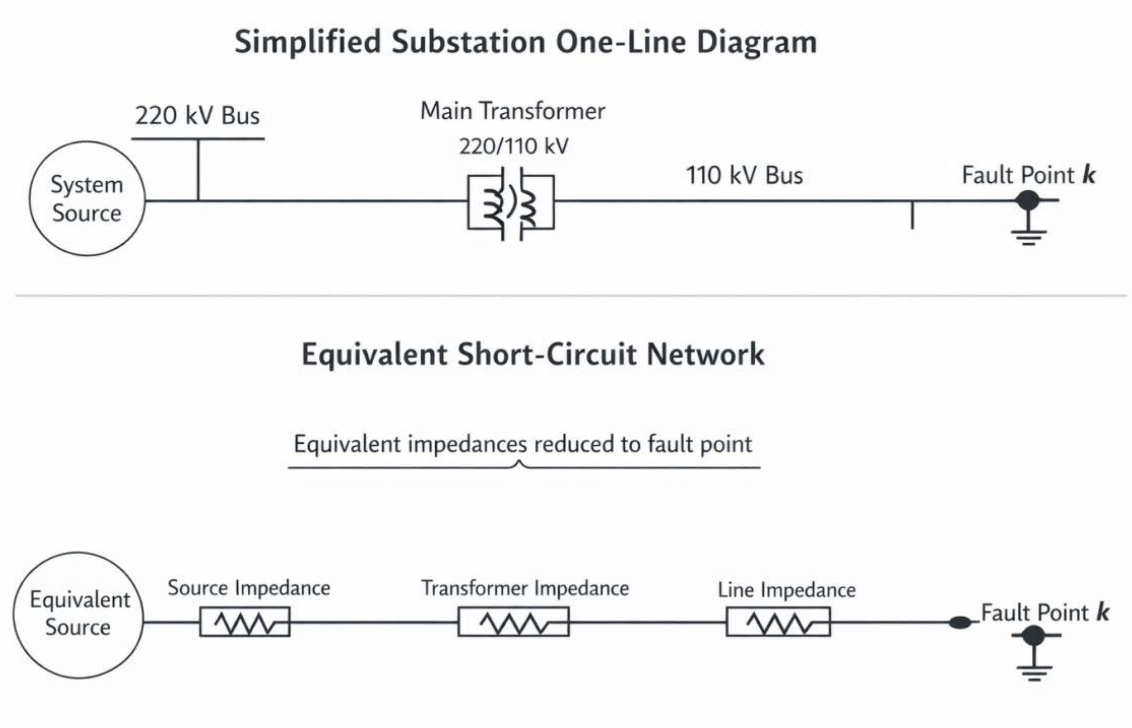

Figure 1: Schematic diagram of the equivalent network for calculating short-circuit current in a typical substation

2.2 Mechanism of application of large language models in power system calculations and knowledge reasoning

The large language model is based on a large-scale parameterized neural network. Through autoregressive modeling of massive text and code data, it learns the conditional probability distribution from the input sequence to the output sequence [11]. Given the input x (including natural language descriptions and structured features), the model outputs design suggestions or code sequences y, and its mechanism can be expressed as:

$$p_\theta(y \mid x) = \prod_{t=1}^{T} p_\theta\left(y_t \mid x, y_{<t}\right) \tag{5}$$

where θ are the model parameters, y_t is the t-th output token. By continuously predicting the next token, the large language model can automatically "translate" the description of power system requirements into formal results such as short-circuit calculation scripts, equipment selection explanations, etc.

In the power system scenario, the input not only includes textual descriptions but also includes structured data such as primary wiring topology, component parameters, short-circuit conditions, and equipment parameters. During actual implementation, these information can be encoded as feature vectors or tabular text, projected to the same semantic space through the embedding function $f_\theta(x)$, and then matched with the vector representations of regulations and historical design cases to achieve enhanced retrieval and generation based on standard and empirical knowledge [12]. For the candidate equipment combination s_i, a context c_i containing short-circuit current calculation results, equipment limit parameters, and constraints can be constructed, and the model outputs a comment text implicitly giving a score:

$$\text{Score}(s_i) = g(p_\theta(y|c_i, s_i)) \tag{6}$$

where g(·) can be approximated by a scoring function trained on keywords such as "acceptable" and "violate standard", or by training samples with human annotations, for sorting and filtering among multiple equipment combinations.

To ensure the interpretability and reusability of the reasoning results, the large language model usually works in collaboration with external power calculation programs, regulation databases, and equipment libraries: The model generates short-circuit condition configurations and solution scripts based on user's natural language instructions, and the numerical calculation module returns precise current, voltage, and power results; then the model combines the regulation clauses and equipment parameter library to provide analysis explanations on whether each candidate equipment solution meets aspects such as thermal stability, dynamic stability, insulation coordination, and economy. Table 1 provides examples of the input and output forms of the large language model in typical power system calculations and knowledge reasoning tasks, laying the mechanism foundation for the subsequent chapter to build the "short-circuit current calculation - equipment selection intelligent recommendation" integrated process.

Table 1: Typical application scenarios of the large language model in power system calculations and knowledge reasoning

Scenario	Primary input	Primary output	Quantitative indicators
Short-circuit condition modeling	The natural language descriptions of the primary wiring of the substation, fault types, fault locations, voltage levels, etc.	Standardized list of conditions, fault type codes	≥50 conditions per day, error rate <1%
Simulation script generation	Operating condition configuration results, component parameter table, target software type (such as a certain short-circuit calculation platform)	Executable simulation scripts/configuration files	<10 s for generating 200–500 lines of scripts, saving approximately 80% time
Regulation retrieval and verification explanation	Equipment model, short-circuit current results, target verification items (such as thermal stability, dynamic stability)	Abstract of relevant regulations, conclusion on compliance with regulations	>95% clause hit rate, response time <2 s
Equipment selection recommendation	Short-circuit calculation results, candidate equipment parameters, cost information	Recommended equipment list, sorting results and brief reasons	Consistency with expert scheme rate is approximately 85%, cost reduction of 3%–5%

3 Construction of a Coupling Framework for Intelligent Recommendation of Short-circuit Current Calculation and Equipment Selection

3.1 Modeling of Key Equipment Selection Issues for Short-Circuit Current Constraints in Substations

For the design of intelligent substations, the selection of key equipment requires a trade-off among multiple dimensions such as short-circuit current constraints, operating conditions, investment costs, and scalability [13, 14]. To connect the subsequent large language model inference with traditional numerical calculations, this section abstracts the selection of key equipment in substations into an optimization model that can be solved on a computer, and simultaneously provides a safety margin index system that is closely coupled with the short-circuit current calculation results.

(1) Abstracting the Decision Object and Data Structure

Let the set of equipment positions that need to be selected in the substation be N = {1, 2, ..., N}. For each position i, there is a candidate equipment set Ki. For any position i and candidate equipment k ∈ Ki, define binary decision variables:

$$x_{i,k}=\begin{cases}1, & device\ k\ is\ selected\ at\ positioni,\\ 0, & otherwise.\end{cases} \tag{7}$$

And also meet the mutually exclusive condition:

$$\sum_{k\in\mathcal{K}_i} x_{i,k}=1, \quad i\in\mathcal{N} \tag{8}$$

The short-circuit current calculation module provides several typical short-circuit scenarios Si for each position, and the calculated short-circuit current at position i under condition s is denoted as $I_{i,s}^{sc}$. The rated short-circuit breaking current, rated short-circuit closing current, and rated thermal stability current of the candidate equipment k are $I_{i,k}^{\mathrm{br}}$, $I_{i,k}^{mk}$, and $I_{i,k}^{th}$ respectively. All these quantities are stored in a database in a structured data table, providing a foundation for subsequent queries and combinations by the large language model.

(2) Short-circuit current constraints and safety margin indicators modeling

To avoid the simple binary judgment of "whether it can be satisfied", this paper introduces a safety margin coefficient and converts the short-circuit constraints into quantifiable indicators [15]. The opening margin of equipment k for position i under condition s is defined as:

$$\mathrm{\eta_{i,k,s}^{br}}=\frac{\mathrm{I_{i,k}^{br}}}{\mathrm{\gamma_s I_{i,s}^{sc}}} \tag{9}$$

where γ_s is a correction coefficient considering the influence of DC components and transient processes, typically ranging from 1.1 to 1.3. Similarly, the closing current margin and thermal stability margin are defined as:

$$\mathrm{\eta_{i,k,s}^{mk}}=\frac{\mathrm{I_{i,k}^{mk}}}{\mathrm{\kappa_s I_{i,s}^{sc}}} \tag{10}$$

$$\mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{th}} = \frac{(\mathrm{I}_{\mathrm{i,k}}^{\mathrm{th}})^2 \mathrm{t}_{\mathrm{i,k}}^{\mathrm{th}}}{(\mathrm{I}_{\mathrm{i,s}}^{\mathrm{sc}})^2 \mathrm{t}_{\mathrm{s}}^{\mathrm{sc}}} \tag{11}$$

where κs is the peak coefficient, tssc is the expected short-circuit duration of condition s, and ti,kth is the allowable thermal stability time of the equipment. To ensure that all constraints are satisfied simultaneously, a comprehensive safety margin is introduced:

$$\mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{safe}} = \min\left(\mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{br}}, \mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{mk}}, \mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{th}}\right) \tag{12}$$

and it is stipulated that:

$$\mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{safe}} \geq 1 + \delta, \quad \forall \mathrm{i} \in \mathcal{N}, \mathrm{k} \in \mathcal{K}_{\mathrm{i}}, \mathrm{s} \in \mathcal{S}_{\mathrm{i}} \tag{13}$$

where δ is the minimum safety redundancy coefficient required by the design. Compared with the traditional approach of only checking whether "≥ 1", the above definitions provide a continuous and optimizable safety measure for subsequent algorithms and the large language model. Table 2 presents the short-circuit current and candidate breaker safety margin data for some positions in a simple example, providing an intuitive illustration of the model meaning.

Table 2: Short-circuit Current and Candidate Breaker Safety Margin for Different Positions

Position i	Typical Condition s	$\mathrm{I}_{\mathrm{i,s}}^{\mathrm{sc}}$/ kA	Rated Breaking Current $\mathrm{I}_{\mathrm{i,k}}^{\mathrm{br}}$ / kA	$\mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{br}}$	Whether $\mathrm{\eta}^{\mathrm{br}} \geq 1.2$
220 kV Busbar	Three-phase short circuit	40.0	50	1.25	Yes
110 kV Busbar	Three-phase short circuit	31.5	40	1.27	Yes
110 kV Feeder Line End	Two-phase grounding	25.0	31.5	1.26	Yes

(3) Construction of Multi-objective Optimization Function

Under the condition of meeting safety constraints, equipment selection usually focuses on comprehensive indicators such as engineering cost, operating loss, and expansion flexibility. Let the one-time investment cost of selecting equipment k at position i be $C_{i,k}^{inv}$, and the annualized loss cost be $C_{i,k}^{loss}$. Then, the total station cost function can be written as:

$$C(\mathbf{x}) = \sum_{i \in \mathcal{N}} \sum_{k \in \mathcal{K}_i} x_{i,k} \left(C_{i,k}^{inv} + C_{i,k}^{loss}\right) \tag{14}$$

Simultaneously define the average safety margin index for the entire station:

$$\bar{\mathrm{\eta}}^{\mathrm{safe}}(\mathrm{x}) = \frac{1}{\sum_{\mathrm{i}} |\mathcal{S}_{\mathrm{i}}|} \sum_{\mathrm{i}} \sum_{\mathrm{s} \in \mathcal{S}_{\mathrm{i}}} \sum_{\mathrm{k} \in \mathcal{K}_{\mathrm{i}}} \mathrm{x}_{\mathrm{i,k}} \, \mathrm{\eta}_{\mathrm{i,k,s}}^{\mathrm{safe}} \tag{15}$$

This paper constructs the comprehensive evaluation function in a weighted multi-objective form:

$$J(\mathbf{x}) = \alpha \frac{C(\mathbf{x})}{C_{\mathrm{ref}}} - \beta \frac{\bar{\eta}^{safe}(\mathbf{x})}{\eta_{\mathrm{ref}}} \tag{16}$$

where $\mathrm{C}_{\mathrm{ref}}$ and $\mathrm{\eta}_{\mathrm{ref}}$ are normalized reference values, α and β are weight coefficients, which can be suggested by the designer or the large language model based on the project's focus. This form maintains the safety margin while making the solution process more sensitive to cost changes, facilitating the realization of "approximate optimal investment under the premise of safety" [16].

(4) Computable mixed-integer optimization model and framework interface

Based on the above constraints and objectives, the selection of key equipment can be formalized as a mixed-integer programming problem:

$$\min_{x} J(x)$$

$$\sum_{k \in \mathcal{K}_i} x_{i,k} = 1, \quad x_{i,k} \in \{0,1\},$$

$$\eta_{i,k,s}^{safe}\left(I_{i,s}^{sc}, I_{i,k}^{br}, I_{i,k}^{mk}, I_{i,k}^{th}\right) \geq 1 + \delta,$$

$$i \in \mathcal{N}, k \in \mathcal{K}_i, s \in \mathcal{S}_i. \tag{17}$$

Since the short-circuit current $I_{i,s}^{sc}$ is determined by the network topology and equipment parameters, its calculation result can be regarded as an external input to the aforementioned model. On this basis, the subsequent sections in Chapter 3 will introduce a large language model. Firstly, it will be used to automatically parse the natural language description of the operating conditions and constraints into the aforementioned formal variables and constraint sets. Secondly, it will provide intelligent recommendations in the aspects of multi-objective weight setting, candidate equipment set pruning, and optimization result interpretation, forming a closed loop of "short-circuit current calculation - equipment selection - solution explanation".

3.2 Collaborative Optimization Process of Short-Circuit Current Calculation and Equipment Selection Based on Large Language Model

Based on the mathematical model presented in the previous subsection, short-circuit current calculation and equipment selection optimization can already be solved in the traditional computing environment. However, there are still problems such as cumbersome configuration of operating conditions, excessive candidate equipment space, difficulty in quantifying target weights, and unintuitive result interpretation. The large language model can understand natural language instructions, process procedural texts and equipment sample manuals, and interact with structured data, making it suitable for embedding in the complete link of "modeling - solving - interpretation" [17]. This section focuses on the collaborative optimization process, constructing a closed-loop mechanism of "person - large language model - short-circuit calculation program - optimization solver", enabling designers to complete operating condition configuration, candidate set pruning, multi-objective weight setting, and result interpretation through a conversational approach.

(1) Prompt Construction and Representation Mapping of Short-Circuit Conditions and Optimization Requirements

In practical applications, designers usually describe the planning intentions and constraint preferences of substations in natural language, such as "220 kV substation, build a 110 kV feeder line, short-circuit current not exceeding 40 kA, prioritize investment cost". To facilitate the processing by the large language model, such descriptions need to be combined with structured network data and equipment library indices to form a unified prompt vector [18]. Let the natural language description be u, and the set of structured features of the network and equipment be d. Then, through the encoding function E(·), the semantic vector is obtained:

$$z = E(u, d) \tag{18}$$

Among them, z integrates voltage levels, short-circuit current levels, expansion stages, and "cost priority" preference information. Based on this vector, the large language model selects the configuration sequence s* that best matches the current design task from the candidate short-circuit condition set S:

$$s^{*} = F_{\theta}(z) = arg \max_{s \in \mathcal{S}} q_{\theta}\,(s, z) \tag{19}$$

where q_{θ}(s,z) is the comprehensive score of the configuration s under the semantic vector z. In this way, the model can automatically complete information such as fault type, fault location number, and reference voltage, generating a complete input file for the short-circuit calculation program.

(2) Script automatic generation and consistency check for short-circuit calculation programs

After obtaining the configuration sequence s*, it needs to be converted into a specific software executable simulation script or configuration file. Let the script space of the target short-circuit calculation platform be C, and the large language model generates script candidates c based on s* and network data d:

$$c = G_{\theta}(s^{*}, d) \tag{20}$$

where Gθ represents the mapping from high-level conditions to low-level script statements. To avoid script syntax errors or parameter omissions, a consistency check operator Φ(·) is introduced, mapping the script to a Boolean variable:

$$\Phi(c) = \begin{cases} 1, & ifcpassessyntaxandrangechecks, \\ 0, & otherwise. \end{cases} \tag{21}$$

When Φ(c) = 0, the large language model automatically corrects the script based on the error information and generates again until the basic checks are passed. This ensures that the configuration entered into the short-circuit calculation module is consistent in grammar and parameter range. The short-circuit calculation program returns the short-circuit current matrix Isc for each position and each condition under the drive of script c, preparing data for subsequent candidate equipment pruning.

(3) Candidate equipment set pruning and feasible region contraction based on the large language model

In the original model, the candidate equipment set Ki at each position i often contains a large number of models, such as multiple voltage levels, breaking capacity, and frame size, which is not conducive to the rapid convergence of mixed integer optimization [19]. By leveraging the knowledge retrieval and reasoning capabilities of the large language model, obvious non-compliance with specifications or obvious redundancies can be automatically eliminated before solving, forming a more compact candidate set.

Let the short-circuit current feature vector of position i be:

$$v_i = \left(I_{i,1}^{SC}, I_{i,2}^{SC}, \dots\right) \tag{22}$$

The rated parameter vector of equipment k is:

$$\mathrm{r_{i,k}} = (\mathrm{I_{i,k}^{br}}, \mathrm{I_{i,k}^{mk}}, \mathrm{I_{i,k}^{th}}, \mathrm{C_{i,k}^{inv}}) \tag{23}$$

The large language model generates candidate masks based on v_i, $\mathrm{r_{i,k}}$ and the embedded vector w of the procedural provisions:

$$m_{i,k} = H_\theta(v_i, r_{i,k}, w) \tag{24}$$

Here, $m_{i,k} \in \{0, 1\}$ indicates whether device k is retained in the reduced candidate set at position i. After pruning, the actual decision variables involved in the optimization can be written as:

$$\tilde{x}_{i,k} = x_{i,k} m_{i,k} \tag{25}$$

Only the devices that satisfy mi,k = 1 will be solved. In this way, many small-capacity devices far below the short-circuit current level can be eliminated in advance, significantly reducing the size of the solution. Table 3 shows a comparison of the number of candidates and solution time before and after pruning in a simple example.

Table 3: Pruning Effect of Large Language Model Candidate Devices

Position Number	Before Pruning Candidate Number	After Pruning Candidate Number	Change in Linear Constraint Quantity	Change in Solution Time (Relative)
Bus-220	10	4	−60%	Approximately 0.45 of the original
Bus-110	8	3	−62%	Approximately 0.48 of the original
Feeder-1	6	3	−50%	Approximately 0.52 of the original

(4) Multi-objective Weight and Preference Modeling Driven by Large Language Models

The goal of equipment selection is often difficult to be fixed with a single weight configuration. For example, designers may be more concerned about reliability, or may place greater emphasis on investment cost or expansion reserves. Large language models can map "priority safety", "cost-sensitive", "balancing future expansion" and other vague expressions into weight vectors that can be used for optimization. Let the normalized indicator vector be:

$$\mathbf{f}(\mathbf{x}) = \left(f_{cost}(\mathbf{x}), f_{safety}(\mathbf{x}), f_{expand}(\mathbf{x})\right)^{\mathrm{T}} \tag{26}$$

The components represent the total cost, safety margin penalty, and expansion elasticity index respectively. The large language model outputs the weight vector based on the user description u:

$$\mathrm{w_\theta(u)} = \left(\mathrm{w_{cost}}, \mathrm{w_{safty}}, \mathrm{w_{expand}}\right)^{\mathrm{T}} \tag{27}$$

And through normalization, $\sum_{\mathrm{j}} \mathrm{w_j} = 1, \mathrm{w_j} \geq 0$. On this basis, the collaborative optimization objective function is constructed:

$$J_{LLM}(\mathbf{x}; u) = \mathbf{w}_\theta(u)^{\mathrm{T}} f(\mathbf{x}) \tag{28}$$

Thus, the "preference information" is explicitly embedded in the solution process. When the designer modifies the description, only u needs to be updated, and the model can adjust $w_\theta(u)$ in real time to achieve rapid switching from "safety priority" to "cost priority" and other strategies without the need to redesign the mathematical model.

(5) Iterative optimization and result interpretation mechanism for human-machine collaboration

After the candidate set pruning and weight determination, the optimization solver solves in the feasible region X(m):

$$\mathbf{x}^* = arg \min_{\mathbf{x} \in \mathcal{X}(m)} J_{LLM}(\mathbf{x}; u) \tag{29}$$

Through multiple iterations, $\{x^{(t)}\}$ gradually converges to the final solution that meets engineering experience, specification requirements, and multi-objective trade-offs under the guidance of the designer's preferences. At the same time, each iteration is accompanied by an explanation report generated by the large language model and local comparative analysis, which facilitates review and archiving.

In summary, this section constructs a collaborative optimization process centered on the large language model: the model is responsible for condition analysis and script generation at the front end, candidate set pruning and weight mapping at the intermediate stage, and provides solution result explanations and interactive adjustments at the back end, thereby integrating the traditional short-circuit current calculation and mixed integer optimization model with the intelligent dialogue system, laying the foundation for subsequent experimental verification and engineering application [20].

4 Experimental Design and Result Analysis

4.1 Engineering Examples and Data Set Construction and Short-Circuit Condition Setting

To verify the effectiveness of the proposed "Collaborative Optimization Method for Short-Circuit Current Calculation and Equipment Selection Based on Large Language Model", this paper selects three representative practical engineering examples as the research objects, corresponding to typical 220/110 kV main substations, 110/35 kV terminal substations, and 220/110/35 kV hierarchical connection substations. These three cases have significant differences in voltage levels, busbar scale, connection structure, and short-circuit current levels. They can be used to examine the applicability of the method in systems of different scales and facilitate the comparison of equipment selection strategies in high short-circuit level scenarios.

Each example is based on the existing design drawings and equipment parameters to establish a network model, which is uniformly converted to the reference capacity of 100 MVA, and a set of short-circuit conditions is generated on this basis. The fault types include three-phase short circuits, two-phase short circuits, and single-phase grounding short circuits, and the fault locations cover the busbars of each voltage level, the low-voltage side of the main transformers, and the end of the main feeder lines. For each condition s, the short-circuit current $I_{i,s}^{SC}$ at each key location i is output by the short-circuit calculation module, and the maximum short-circuit current and the corresponding condition are recorded for subsequent safety margin analysis and equipment candidate set pruning. To closely follow the engineering design process, the number of short-circuit conditions is controlled to be between 16 and 32, ensuring coverage of typical operation modes while avoiding excessive sample size that leads to long optimization times.

In terms of equipment data, a total of over 120 types of circuit breakers, disconnectors, and busbar conductors are sorted out for the three examples, including rated voltage, rated current, rated short-circuit breaking current, rated short-circuit closing current, thermal stability current, and typical quotations, and are grouped by voltage level and installation location. This not only serves as the equipment parameter library for the optimization model in 3.1, but also provides structured input for the candidate set pruning and preference modeling by the large language model in 3.2. Table 4 presents the scale characteristics and short-circuit condition statistics of the three engineering examples.

Table 4: Scale Characteristics and Short-Circuit Condition Statistics of Engineering Examples

Example Number	Voltage Level / kV	Number of Buses	Number of Branches	Number of Transformers	Number of Short-Circuit Conditions	Maximum Short-Circuit Current / kA	Number of Required Equipment Locations for Selection
C1	220/110	12	18	2	24	40.2	16
C2	110/35	9	14	2	16	31.8	12
C3	220/110/35	18	27	3	32	43.5	20

As shown in Table 4, the maximum short-circuit currents of C1 and C3 are both close to or exceed 40 kA, which impose high requirements on the breaking capacity of the circuit breaker and the thermal stability of the busbar; although C2 has a lower voltage level, it has set a large number of load branches on the feeder side, making it suitable for evaluating the trade-off between the equipment combination at the low-voltage side and cost control. The comparative experiments in Sections 4.2 to 4.4 are all based on the above three cases. Through repeated tests under different sets of working conditions and equipment libraries, the comprehensive performance of the proposed method in terms of short-circuit current calculation accuracy, the rationality of equipment selection, and the improvement of design efficiency is evaluated.

4.2 Model Training Configuration, Comparative Methods and Evaluation Index System

To objectively evaluate the effectiveness of the proposed collaborative optimization method, this paper sets up four comparison methods in a unified computing environment. All methods use the same short-circuit calculation software and the same mixed integer programming solver. The running platform is a workstation equipped with a 16-core CPU and 32 GB of memory, avoiding the influence of hardware differences on the results. M1 is the "manual configuration + traditional software" process, where the design personnel manually enter the conditions and look up tables to determine the equipment; M2 introduces a rule library and automatically generates some scripts based on the preset mapping rules, and uses the optimizer to complete the selection; M3 uses a large language model to automatically generate short-circuit condition scripts and prune the candidate set of equipment, and then submits it to the optimizer for solution; M4 is the complete collaborative framework proposed in this paper, which further utilizes the large language model to model multi-objective weights and generate result explanations based on the LLM pruning of the candidate set. The configuration and running time overview of the four methods are shown in Table 5.

Table 5: Comparison of different method configurations and average running time

Method Number	Method Description	Short-circuit calculation method	Equipment selection method	Whether using large language model	Individual case average running time / s
M1	Manual configuration + traditional software	Manual entry + short-circuit calculation software	Manual lookup and experience judgment	No	120
M2	Rule script + optimization	Rule generation script + the same as above	Rule library + optimization solver	No	95
M3	Large language model-assisted configuration and pruning	LLM generated script + the same as above	LLM pruning candidate set + optimization solver	Yes	72
M4	Our collaborative optimization framework	LLM generated script + the same as above	LLM pruning + preference modeling + optimization solver	Yes	55

In terms of large language model configuration, this paper selects a general language model with a parameter scale of approximately 7B as the basis. A small number of power system regulations, equipment sample manuals, and historical design reports are used for instruction fine-tuning to enable the model to better understand expressions such as "priority of safety", "control the short-circuit current not exceeding 40 kA", "considering subsequent expansion", etc. The inference stage adopts a decoding strategy with a lower temperature to ensure the stability and reproducibility of the script and the generated constraint results. The generation of short-circuit calculation scripts and the pruning of the candidate set of equipment are completed on the side of the large language model, while the numerical solution and optimization are carried out in the traditional simulation software and solver.

In terms of evaluation indicators, the short-circuit current calculation accuracy is represented by the mean absolute error (MAE) and the mean relative error (MAPE), where:

$$\mathrm{MAE} = \frac{1}{N}\sum_{n=1}^{N}\left|I_n^{pred} - I_n^{ref}\right|$$

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{n=1}^{N}\left|\frac{I_n^{pred} - I_n^{ref}}{I_n^{ref}}\right| \tag{30}$$

Among them, $\mathrm{I_n^{pred}}$ represents the short-circuit current calculated by the corresponding method, and $\mathrm{I_n^{ref}}$ represents the reference result. In terms of safety, two indicators are adopted: the average safety margin $\bar{\eta}_{\mathrm{safe}}$ of the entire station and the minimum safety margin η_{min}; in terms of economy, the cost coefficient Rcost is constructed based on the ratio of the total investment cost of the equipment to the cost of the basic scheme; in terms of efficiency, the total design time T_{design} from the input demand to obtaining the stable configuration is recorded. In addition, the consistency rate R_{match} of the recommended scheme and the expert scheme at the key equipment locations is also statistically calculated to reflect the degree of fitting of the intelligent recommendation to engineering experience.

4.3 Comparison Analysis of Short-Circuit Current Calculation Accuracy and Safety Margin

Under the unified calculation example and working condition configuration, this paper compares the performance of different methods in terms of short-circuit current calculation accuracy and equipment safety margin. The reference value of the short-circuit current is given by the traditional short-circuit calculation software after manual item-by-item verification of the working conditions. The comparison methods include rule script + optimization (M2) and the collaborative optimization framework (M4) of this paper. In M4, a large language model is introduced in the working condition configuration and script generation stages, and it plays a role in the candidate set pruning and preference modeling. The calculation accuracy is characterized by the average absolute error and average relative error, and the safety is characterized by the average safety margin ηsafe and the minimum safety margin ηmin. The statistical results are shown in Table 6.

Table 6: Comparison Results of Short-Circuit Current Accuracy and Safety Margin of Different Methods

Example Number	Method	MAE / kA	MAPE / %	Average Safety Margin $\bar{\eta}_{safe}$	Minimum Safety Margin η_{min}
C1	M2	0.32	1.05	1.24	1.15
C1	M4	0.28	0.92	1.26	1.18
C2	M2	0.27	0.98	1.22	1.13
C2	M4	0.25	0.87	1.25	1.17
C3	M2	0.35	1.10	1.23	1.14
C3	M4	0.30	0.95	1.27	1.19

From Table 6, it can be seen that in the three examples, the short-circuit current calculation error of the collaborative optimization framework M4 is overall slightly lower than that of the rule method M2. Taking C1 as an example, the average absolute error of M4 is reduced from 0.32 kA to 0.28 kA, and the average relative error is reduced from 1.05% to 0.92%; in C3, MAE and MAPE also decrease from 0.35 kA and 1.10% to 0.30 kA and 0.95%. This indicates that after the large language model participates in the working condition analysis and script generation, the short-circuit calculation results do not show numerical divergence or instability due to the introduction of the language model, but rather the uniform template and consistency verification have weakened the error caused by the manual entry differences.

In terms of safety margin, the average safety margin of M4 in all examples is not lower than that of M2, and the minimum safety margin has also been improved to a certain extent. In C2, the average safety margin of M2 is 1.22 and the minimum safety margin is 1.13; M4 in the same example reaches 1.25 and 1.17 respectively, indicating that after candidate set pruning and preference modeling, the optimization results tend to select equipment combinations with a slightly higher safety margin within the acceptable cost range. C3, as the example with the highest short-circuit level, M4 raises ηmin to 1.19, which helps to leave more sufficient margin space at high fault current levels.

Combined with the running time statistics in 4.2, it can be found that M4 significantly shortens the solution time of a single calculation example while maintaining or even slightly improving the calculation accuracy and safety margin compared to M2. This is mainly attributed to the fact that the large language model reduces the configuration of redundant working conditions during the generation stage, and eliminates the models that clearly do not meet the constraints at the candidate equipment level, enabling subsequent mixed integer optimization to be solved in a smaller feasible domain, thus balancing accuracy, reliability and efficiency.

From the perspective of engineering application, if the numerical difference in short-circuit current calculation is controlled within 1%, it usually has a limited impact on the equipment selection conclusion, while the improvement of safety margin can significantly enhance the robustness of the scheme. Experimental results show that the collaborative optimization framework, without sacrificing algebraic accuracy, through the joint modeling of working condition descriptions, regulations, and equipment parameters, guides the optimization process to automatically converge to "a more balanced safety margin and more controllable minimum margin" equipment combination, providing a reliable foundation for the subsequent 4.4 section to conduct selection effect analysis and applicability discussion.

4.4 Intelligent Equipment Selection Recommendation Effect and Engineering Applicability Evaluation

Based on the verification of short-circuit current calculation accuracy and safety margin, this section compares the applicability of different methods in engineering scenarios from the dimensions of equipment selection results, cost control and design efficiency. The comparison objects mainly include the traditional method M2 of rule script + optimization, and the collaborative optimization method M4 proposed in this paper, with M1 and M3 serving as reference baselines for efficiency and process complexity.

Table 7 presents several examples of equipment selection results under M2 and M4 at typical positions. It can be seen that at the 220 kV busbar position of C1, both methods choose a circuit breaker with a rated short-circuit breaking current of 50 kA, and M4, while maintaining a higher safety margin, selects a model of the same series with slightly lower investment cost; at the 110 kV busbar and the 110 kV feeder of C2, M4 also tends to select a cost-optimized equipment combination while meeting safety constraints. Overall, the configuration given by M4 is consistent with M2 in key parameters such as voltage level and breaking capacity, while only presenting optimization effects in specific models and costs, indicating that the collaborative optimization framework can explore more cost-effective combinations without changing the basic configuration concept.

Table 7: Comparison of equipment selection results of different methods at typical positions

Location	Method	Recommended device model	Rated short-circuit breaking current / kA	Safety margin η_{safe}	Investment cost / 10,000 yuan
C1 220 kV busbar	M2	CB-220-50	50	1.22	48.0
C1 220 kV busbar	M4	CB-220-50L	50	1.25	45.5
C1 110 kV busbar	M2	CB-110-40	40	1.23	32.0
C1 110 kV busbar	M4	CB-110-40E	40	1.26	30.5
C2 110 kV Feeder Line 1	M2	CB-110-31.5	31.5	1.20	26.0
C2 110 kV Feeder Line 1	M4	CB-110-31.5N	31.5	1.24	24.8

To depict the trade-off relationship between cost and safety under different preferences, this paper sets three types of preferences within M4: "Safety Priority", "Balanced Weight", and

"Cost Priority". Through the natural language description parsed by the large language model, the corresponding weights are obtained, and the cost–safety margin curve is drawn, as shown in Figure 2.

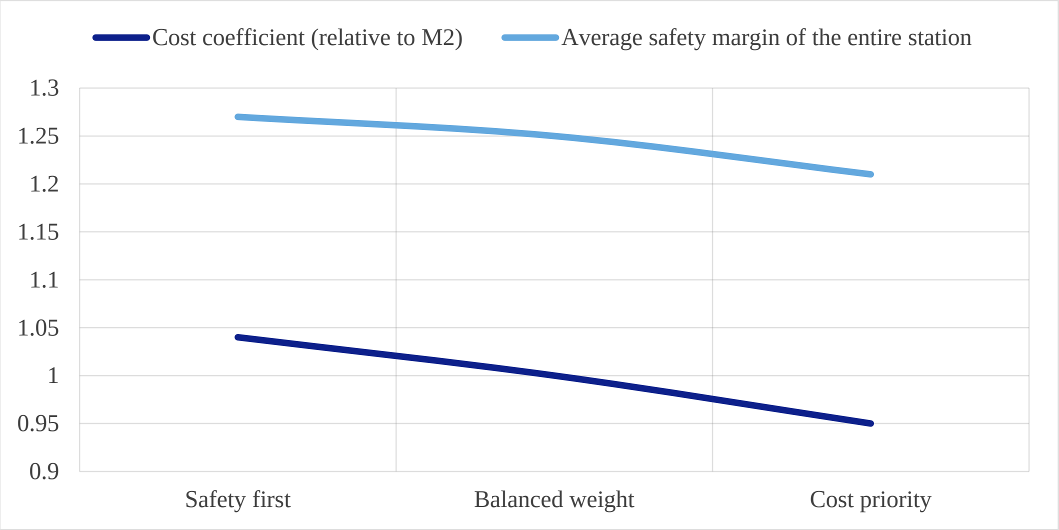

Figure 2: Relationship between cost coefficient and average safety margin under different preference weights

The results show that compared with the "safety priority" setting, under the "cost priority" setting, the total cost can be reduced by approximately 4% to 6%, while the average safety margin remains above 1.20; when using the "balanced weight", the cost and safety indicators are both close to M2, corresponding to a compromise solution set. This indicates that by adjusting the preference description, large language models can achieve continuous adjustment between cost and safety constraints without changing the structure of the optimization model.

In terms of engineering efficiency, this paper uses a bar chart to compare the average design time and iteration rounds of M1, M2, M3, and M4 in a single case, as shown in Figure 3.

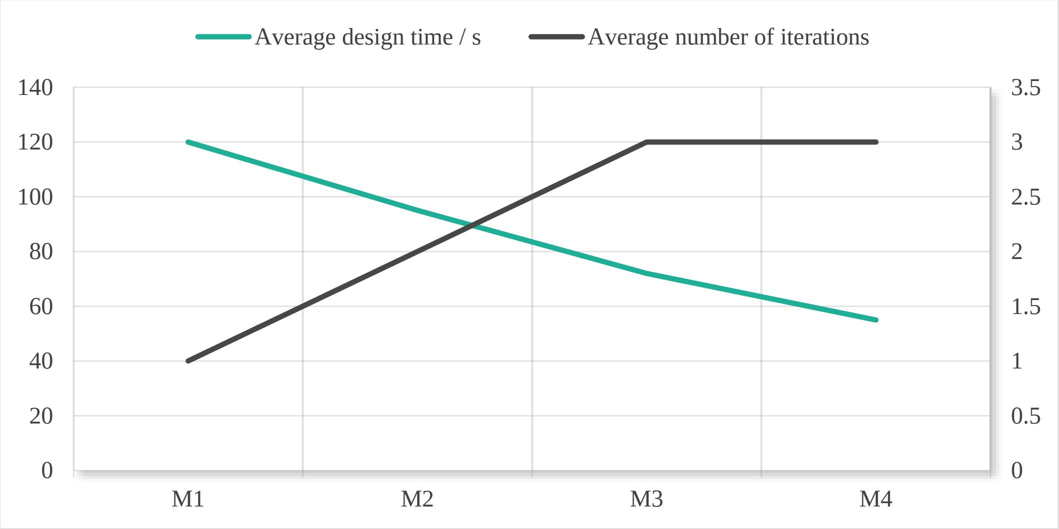

Figure 3: Comparison of average design time and iteration rounds for different methods

The results show that compared with the fully manually-configured M1, M2, which uses rule scripts, reduces the average design time by approximately 20%; on this basis, M3 and M4, which introduce large language models for condition analysis and candidate set pruning, further reduce the time cost to 40% - 60% of the traditional manual process. Among them, although M4 increases a certain amount of model inference time in the preference modeling and result interpretation stages, due to the significant reduction in the feasible domain and more concentrated parameter adjustments during the iteration process, generally speaking, the total design time still has a significant advantage over M2.

From the results in Table 7, Figure 2, and Figure 3, it can be seen that the proposed large language model collaborative optimization method achieves simultaneous improvement in equipment investment cost and design efficiency while ensuring that the short-circuit current calculation accuracy and safety margin are not lower than those of traditional methods: On one hand, the average equipment cost at typical positions is reduced by approximately 3% - 5%, and in the high short-circuit current level examples, the minimum safety margin of the entire station still remains above the set threshold; on the other hand, the time for scheme generation and iteration adjustment is significantly shortened, making it more suitable for multi-scheme comparison and frequent changes in engineering design scenarios. This indicates that embedding large language models in the short-circuit current calculation and equipment selection process is a feasible path for the intelligent and collaborative design of substations.

5 Discussion

Based on the short-circuit current constraint, this paper formalizes the selection problem of key equipment in the substation as a computable mixed-integer optimization model, and introduces a large language model to construct a collaborative optimization process. From the experimental results, under the premise that the calculation accuracy of short-circuit current is basically equivalent to the traditional method, the proposed framework can maintain or even slightly improve the safety margin of the entire station, while achieving certain improvements in equipment investment cost and design efficiency [21]. The large language model, through natural language parsing, script generation, candidate equipment pruning, and preference modeling, transforms several key steps that rely on manual experience into repeatable calculation processes, forming a relatively smooth computerized channel between short-circuit current calculation, equipment selection, and design intent expression, which has positive significance for the standardization and intelligence of the substation design process.

From the perspective of engineering application, the advantages of the collaborative optimization framework mainly lie in three aspects: First, it reduces the repetitive and mechanical manual work in the configuration of operating conditions and script writing, reducing the probability of manual input errors; second, by leveraging the comprehensive processing capabilities of the large language model for regulations and equipment samples, it expands the selection space while ensuring the satisfaction of constraints, facilitating the discovery of more cost-effective equipment combinations; third, by expressing multi-objective weights and preferences in natural language form, it enables designers to more intuitively adjust the balance between cost and safety, enhancing the friendliness of human-computer interaction and the flexibility of scheme iteration.

At present, this research still has certain limitations and requires further improvement in subsequent work. On one hand, although the large language model has undergone rule constraints and consistency checks in script generation and constraint interpretation, it may still have understanding deviations for some boundary operating conditions and complex wiring, and the reliability of the model verification on larger-scale engineering libraries is still insufficient. On the other hand, the structured quality of the equipment library and the text of regulations directly affects the reasoning effect and pruning efficiency of the model. How to construct a device knowledge graph and improve the data update mechanism is a problem that the collaborative framework must consider for long-term operation. Moreover, the experiments in this paper are mainly based on static short-circuit calculation scenarios of several typical voltage levels and have not covered more complex situations such as new power systems with a large number of power electronic devices, transient processes, and multi-station collaborative planning.

Future research can be carried out in several directions: First, for power system-specific tasks, conduct more systematic domain pre-training or fine-tuning for the large language model, and introduce uncertainty assessment and result confidence quantification mechanisms; second, combine existing optimization models with Monte Carlo simulation, sensitivity analysis, etc., to evaluate the robustness of equipment selection under load fluctuations and uncertain output of new energy; third, explore deep integration with 3D design platforms and digital twin systems, enabling the visualization of short-circuit current calculation and equipment selection results directly in 3D models, achieving integrated linkage from scheme generation to collision checking and construction drawing design. Through these expansion efforts, the substation design optimization method based on the large language model is expected to play a role in more extensive engineering practices.

6 Conclusion

This paper addresses the practical demand of the continuous rise in short-circuit current levels and the significant increase in design operating conditions under the new power system, proposing a substation design optimization method that combines short-circuit current calculation and intelligent recommendation of key equipment selection. Through unified modeling of the equivalent network of primary wiring, short-circuit conditions, and equipment limit parameters, a mixed-integer optimization model with safety margin coefficients is constructed, achieving collaborative selection of circuit breakers, busbars, and feeder equipment under thermal and dynamic stability constraints, providing a strict electrical calculation basis for the participation of the large language model in optimization. Based on this, this paper designs a collaborative optimization process driven by a large language model, which jointly encodes the planning requirements described in natural language with structured network data, equipment libraries, and procedural clauses, achieving automatic construction of short-circuit conditions and generation of simulation scripts. Through a consistency check mechanism, it ensures the grammatical correctness and parameter rationality of the input configuration. The large language model further completes the pruning of candidate equipment sets and the reconstruction of multi-objective preference models, mapping "safety priority", "balanced weights", and "cost priority" and other fuzzy preferences into weight vectors that can be used for optimization solving, coupling the short-circuit current calculation results, equipment parameters, and design preferences within a unified framework, forming an iterative human-machine collaborative design loop.

Engineering examples and comparative experiments show that the proposed method maintains the accuracy of short-circuit current calculation while achieving comprehensive improvements in safety, economy, and efficiency. In three practical examples, compared with the rule script + optimization method, the collaborative optimization framework, under the condition of controlling the average absolute error of short-circuit current calculation within 0.25-0.30 kA and the average relative error below 1%, improves the average safety margin of the entire station by approximately 0.02-0.04, and the minimum safety margin increases to 1.17-1.19; the average investment cost of typical position equipment is reduced by approximately 3%-5% under different preference weight settings, and the total cost can be smoothly adjusted within the ±4%-6% range, while the safety margin always remains above 1.20. In addition, through automatic condition analysis and candidate set pruning, the single-case solution generation time is reduced from 120 s in the manual process to approximately 55 s, and the overall design time is about 40%-60% of the traditional method, verifying the potential of the large language model in improving the efficiency of solution generation.

It should be noted that the current work still has several limitations: First, the large language model is mainly fine-tuned based on typical procedural clauses and limited equipment samples, and its adaptability to extreme operating modes, complex wiring structures, and new power grid scenarios containing a large number of power electronic devices needs further verification; Second, the structured degree of the equipment knowledge base and procedural database directly affects the effect of candidate set pruning and preference modeling, and it is necessary to construct a unified equipment knowledge graph covering more manufacturers and improve the data update and version management mechanism; Third, the experimental scenarios are concentrated on static short-circuit calculations, and factors such as transient processes, uncertain output power, and multi-station collaborative planning have not yet been incorporated into a unified framework.

Future work can be deepened in three aspects: First, conduct more systematic pre-training of large language models for specific tasks in the power system and safety-constrained fine-tuning, introduce uncertainty quantification and output confidence assessment mechanisms to improve the controllability of the model in key design stages; Second, combine existing optimization models with sensitivity analysis and Monte Carlo simulation to systematically evaluate the robustness of equipment selection schemes under load fluctuations and random output power of new energy; Third, explore deep integration with 3D design platforms, digital twin systems, and distribution network dispatch simulation platforms to achieve an integrated closed-loop from condition configuration, short-circuit calculation, equipment selection to 3D visualization and operation strategy simulation. Through the above expansions, the optimization method for substation design based on the large language model is expected to be applied in larger-scale and multi-scenario engineering practices, providing more intelligent, flexible, and reliable technical support for the design of key infrastructure of the new power system.

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