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Construction and Optimization of Knowledge Base for Commissioning Plans of New Power System Devices

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Abstract

To address the challenge of efficiently commissioning new equipment amid grid expansion, this study proposes an intelligent start-up plan generation method based on knowledge graphs. The approach first employs a bidirectional Long Short-Term Memory-Conditional Random Field model to extract entities such as equipment and operations from historical plans. This extraction process enables the construction of a structured knowledge base. Subsequently, it enhances plan standardization and reliability through multi-source data fusion and credibility analysis optimization logic. The results show that the named entity recognition model used in the study achieves an F1 score of 0.99, with an entity recognition accuracy of 92.5% for knowledge related to new power system devices commissioning plans. Testing of the proposed knowledge base reveals a knowledge coverage rate of 93.8%, which is 10.4% higher than that of traditional methods. The efficiency of plan generation significantly improves, with a rule compliance rate reaching 97%. The study provides a feasible pathway for transforming grid startup procedures from reliance on manual experience to data-driven intelligence.

Keywords: Commissioning plans; Power system devices; Knowledge graph; Named entity recognition; Data fusion; Reliability analysis

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1. Introduction

Efficient and safe commissioning of new power equipment critically ensures stable grid operation. With the rapid expansion of grid scale, the types and quantities of new equipment continue to grow. Traditional solution development heavily relies on specialist experience, which proves time-consuming, labor-intensive, and inconsistent, thus inadequate for current grid system demands [1-2].

Currently, most research on power grid equipment focuses on optimizing equipment management and fault diagnosis. Zhao S et al. addressed power equipment management challenges by integrating online sensing and data mining technologies to develop an autonomous intelligent operation and maintenance system [3]. Qin W's team leveraged a low-code platform to optimize terminal equipment management. The approach relies on active data collection and sensing systems. They proposed a power consumption information collection service system enabling efficient management of power data and equipment [4]. Nallainathan S et al. assessed grid equipment reliability by integrating climate impacts and equipment failures, developing an algorithm for microgrid reliability evaluation and validating the proposed method through case studies [5]. Weßbecher M et al. investigated energy data packet grid management in power systems, proposing three control strategies—a three-step switching controller, probabilistic range control, and packaging quantization-and testing their effectiveness in a simulated environment [6]. Feng X et al. constructed a dual-scale dataset for phased training and designed feature fusion and environmental context modeling modules, proposing a novel single-stage power equipment recognition method. Experiments demonstrated its outstanding lightness, accuracy, and robustness [7]. In summary, few studies have deeply explored the intelligent formulation of new equipment startup schemes.

Meanwhile, knowledge graph technology has demonstrated significant application potential across various domains due to its robust knowledge representation and reasoning capabilities [8]. Avdeeva Z K's team effectively expanded associative lexical information using knowledge graphs and quantified semantic distances between words, thereby integrating prior knowledge into text classification decisions to enhance the accuracy of text topic segmentation [9]. Researchers including Kabal O employed state-of-the-art open information extraction techniques, utilizing noun phrase cleaning and large language models to develop a novel information extraction method, which was subsequently tested [10]. Ivanovski A's team applied knowledge graph technology to the field of music autoplay, enriching music datasets with integrated knowledge graphs and introducing graph neural networks to enhance knowledge graph mapping, thereby providing effective retrieval recommendations [11]. Pu T et al. addressed the sparse structure, massive nodes, and heterogeneous edges characteristic of power grid knowledge graphs. They achieved rapid computation by constructing a Halki basis and introduced a multi-scale network architecture to ensure classification accuracy and generalization capability, significantly improving the accuracy of graph classification and knowledge reasoning tasks [12]. These findings demonstrate that knowledge graph technology can efficiently process massive information, establish complex relationships between entities, and generate solutions through intelligent reasoning. This offers new insights for addressing issues such as knowledge update lag and strong reliance on experience in formulating startup plans for new power grid equipment [13-14].

Building upon this foundation, this study innovatively applies knowledge graph technology to research grid new equipment startup plans. During knowledge base construction, the method employs Bidirectional Long Short-Term Memory and Conditional Random Field (BiLSTM-CRF) for named entity recognition and utilizes attention-based Bidirectional Encoder Representations from Transformers (BERT) for data fusion. The attention-based BERT model handles data fusion and provides robust data support for knowledge graph development. This study aims to deliver reliable intelligent solutions for the safe management and efficient commissioning of new power grid equipment, offering practical value for advancing the intelligent operation and maintenance management of power grids. The innovation of this study lies in: (1) proposing a knowledge extraction framework integrating a two-stage neural network, effectively addressing the precise identification of specialized entities and complex relationships within power sector texts; (2) constructing a domain knowledge graph covering the entire commissioning process, enabling unified representation and reasoning of multi-dimensional knowledge including equipment parameters, operational logic, and safety constraints; (3) designing a graph-based reasoning approach that automatically generates standardized commissioning plans while ensuring compliance with operational rules and safety requirements.

2. Relevant theories and technologies

2.1 Knowledge graph technology

A knowledge graph is a network that processes and stores knowledge using graphs. Its core consists of triples formed by "entity-relation-entity" or "entity-attribute-attribute value." These triples enable intuitive representation of complex relationships between concepts. The construction process of knowledge graphs generally includes knowledge extraction, knowledge fusion, and knowledge storage [15]. Knowledge extraction refers to identifying data entities, relations, and attributes. Entities are denoted as shown in Equation (1).

$$S = \langle C, H, R, A \rangle \tag{1}$$

In Equation (1), C represents the set of relations, H refers to the set of class relations, R represents the set of non-class relations, and A denotes the set of axioms and rules. Knowledge integration involves consolidating and disambiguating information representing the same entity from different data sources to form a unified knowledge view. Knowledge storage entails storing processed triples in specialized graph databases to support efficient graph traversal and queries.

2.2 BiLSTM

BiLSTM consists of a forward LSTM and a backward LSTM. The forward LSTM encodes past information from left to right, while the backward LSTM encodes future information from right to left. By concatenating the forward and backward hidden state vectors at each time step, BiLSTM generates feature representations for each sequence unit that fuse the full context. The computation of the forward and backward output vectors is given in Equation (2).

$$\begin{cases} \vec{h}_{ft} = f\left(W_{ft}x_t + U_{ft}\vec{h}_{f-1t} + b_{ft}\right) \\ \overleftarrow{h}_{bt} = f\left(W_{bt}x_t + U_{bt}\overleftarrow{h}_{b-1t} + b_{bt}\right) \end{cases} \tag{2}$$

In Equation (2), $\vec{h}_{ft}$ is the forward output vector, $\overleftarrow{h}_{bt}$ is the backward output vector, f_t is the forget gate, W and

U are the weight matrices for the two directions, x_t is the input at the current time step, and b is the bias term.

2.3 BERT

BERT is a pre-trained language model based on the Transformer encoder architecture. Unlike unidirectional language modeling approaches, BERT's core innovation lies in its deep bidirectional context encoding mechanism. The model learns deep linguistic patterns through two key unsupervised pre-training tasks on large-scale, unlabeled corpora. The first task is masked language modeling. The method randomly masks portions of the input sequence and trains the model to predict the masked words based on contextual information. This approach forces the model to learn the deep semantic relationships of words within context. The second task is next sentence prediction. By determining whether two sentences appear consecutively in the original text, the model learns to understand the logical relationships between sentences.

3. Construction and optimization of knowledge base for new equipment commissioning plans

3.1 Power grid commissioning plan knowledge base based on KG

In knowledge graph construction, named entity recognition serves as a critical component of information extraction. Transformer-based models demonstrate exceptional performance in natural language processing, yet their massive parameter counts and complex training mechanisms impose stringent demands on data quality and scale. In specialized vertical domains like power grids, high-quality annotated data remains scarce and costly to acquire. This scarcity makes direct application of Transformer models prone to overfitting and excessive computational resource consumption. In contrast, the BiLSTM-CRF model, with its strong generalization capabilities and minimal parameter requirements, has become the most widely applied model in knowledge graph building processes [16]. Therefore, this study selects BiLSTM-CRF to perform entity recognition for building the knowledge base of new equipment commissioning plans in the power grid. The BiLSTM-CRF architecture comprises a word embedding, a BiLSTM, and a CRF layer [17]. The structure of BiLSTM is shown in Figure 1.

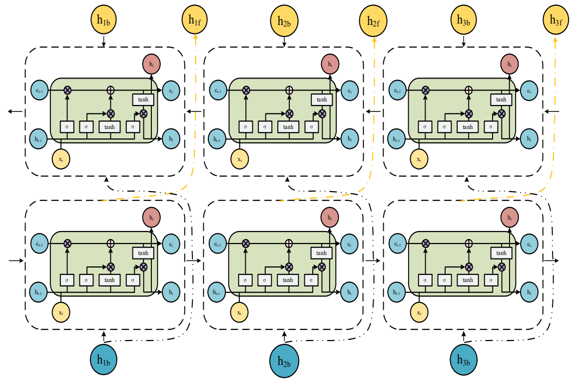

Figure 1. Basic structure of BiLSTM

As shown in Figure 1, the BiLSTM model integrates contextual information by performing both forward and backward calculations through a bidirectional LSTM network [18]. By combining the forward and backward outputs, the model state at time b step h_t is obtained, as shown in Equation (3).

$$h_t = \left[\vec{h}_{ft}, \overleftarrow{h}_{bt} \right] \tag{3}$$

The input to the CRF inference layer in the BiLSTM-CRF model is the score matrix generated by the BiLSTM layer. Let the input be $x = \left(x_1, x_2, \cdots x_n\right)$ and the corresponding label sequence be $y = \left(y_1, y_2, \cdots y_n\right)$. The score value between them is denoted as $s\left(x, y\right)$. y_o marks the beginning of the sentence, and y_1 marks the end. The scoring function is defined in Equation (4) [18].

$$s\left(x, y\right) = \sum_{i=1}^{n} \left(O_{i,yi} + T_{yi,y+1}\right) + T_{yo,y1} \tag{4}$$

In Equation (4), $O_{i,yi}$ represents the score between x_i and y_i, and $T_{yo,y1}$ denotes the transition matrix. The normalization process is described in Equation (5).

$$p\left(y \middle| x\right) = \frac{e^{s(x,y)}}{\sum_{\tilde{y} \in Yx} e^{s(x,\tilde{y})}} \tag{5}$$

In Equation (5), $\tilde{y}$ is the tag value, and Y_x represents the possible label space of $\tilde{y}$. The label sequence is optimized using maximum likelihood estimation, as shown in Equation (6).

$$\log\left(p\left(y|x\right)\right)=s\left(x,y\right)-\sum_{\tilde{y}\in Yx}e^{s\left(x,\tilde{y}\right)} \tag{6}$$

Finally, the prediction result for the sequence labeling task is calculated using Equation (7).

$$y^{*}=\arg\max_{\tilde{y}\in Yx}s\left(x,\tilde{y}\right) \tag{7}$$

In summary, this study adopts the BiLSTM-CRF model for named entity recognition, providing data support for constructing the knowledge base of new equipment commissioning plans in the power grid. The overall construction process is illustrated in Figure 2.

Figure 2 shows that the construction process of the knowledge graph-based grid new equipment startup plan comprises a modeling layer and an application layer. The modeling layer is centered on the BiLSTM-CRF entity recognition model. First, multi-source heterogeneous startup plan texts and data are collected through data acquisition. After preprocessing, the system inputs these into the BiLSTM-CRF model for named entity recognition. This process extracts key entities such as equipment, operations, and parameters. During the graph design phase, ontologies and relationship schemas are defined based on the recognition results. The system precisely defines relationship sets according to business logic, such as performing an operation (Device, Operation), possessing parameters (Device, Parameter), and having preceding steps (Operation, Operation). The system explicitly specifies the domain, range, and semantic constraints (e.g., transitivity for preceding steps) of each relationship. Subsequently, knowledge fusion is performed. This step utilizes standardized entities output by the model to integrate heterogeneous sources through similarity calculations and alignment algorithms, eliminating ambiguities. The calculation formula is shown in Equation (8).

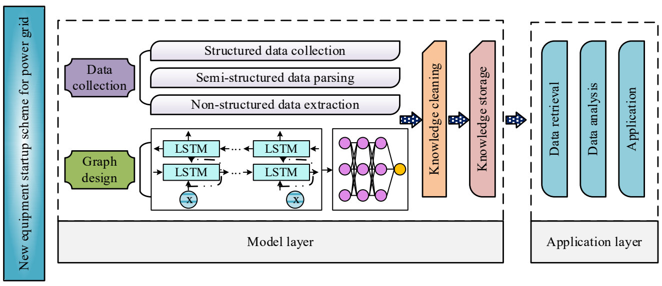

Figure 2. Construction process of commissioning plan knowledge base

$$RankScore\left(a,k\right)=\sqrt{Semantic\left(a,k\right)*Lexical\left(a,k\right)} \tag{8}$$

After completing the fusion task, the system processes the knowledge and stores the optimized content to complete the graph construction. The expression of the KG is shown in Equation (9).

$$KG=\left\langle E,R,G\right\rangle \tag{9}$$

In Equation (9), E represents the entity set, R is the relation set, and G refers to the attribute set. The application layer performs data retrieval, analysis, and application based on the constructed KG of new equipment commissioning plans. In conclusion, this study extracts and organizes historical commissioning plan data to build a knowledge base containing equipment topology models, operating procedures, and commissioning steps. The knowledge framework is shown in Figure 3.

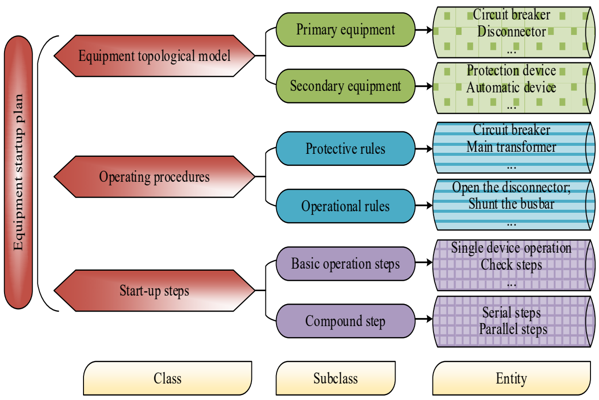

Figure 3. Knowledge framework of commissioning plans for new power system devices

Figure 3 shows that the study uses the BiLSTM-CRF model for named entity recognition to construct a domain-specific KG for new equipment commissioning plans in the power grid. The graph adopts a three-level classification system, with equipment topology models, operating rules, and commissioning steps as the core categories. Regarding equipment topology, the system incorporates both primary and secondary equipment. The primary equipment category covers components such as transformers and circuit breakers, whereas the secondary equipment includes protection systems, measurement units, and control devices. The parent category of operating rules includes subcategories such as protection rules, operation rules, and safety rules. For commissioning steps, the system categorizes basic steps into single-device operations, inspection steps, and delay delay steps. Compound steps are composed of multiple basic steps arranged in specific logic.

3.2 Optimization of new equipment commissioning plans based on reliability analysis

The newly constructed knowledge base enables intelligent management of large-scale data. However, due to the diverse sources of power system devices data, descriptions of the same entity may vary. Simple concatenation of these compromises the professionalism of the knowledge base. To address this issue, the study introduces the BERT model to integrate data from different sources and eliminate entity ambiguity. BERT uses a Transformer feature extractor to preprocess text features. The model adopts a bidirectional language approach to train deep representations of natural language based on contextual semantics, thereby improving task performance [19-20]. The Transformer feature extractor places no special requirements on input format. Before execution, it adds positional information to each token, as defined in Equation (10).

$$\begin{cases} PE_{(pos,2l)} = \sin\left(pos / 10000^{2l/d}\right) \\ PE_{(pos,2l+1)} = \cos\left(pos / 10000^{2l/d}\right) \end{cases} \tag{10}$$

In Equation (10), pos represents the annotated position and l represents the dimension. The encoder applies residual and normalization operations, and the computation is also shown in Equation (11).

$$sublayer = LayerNorm\left(x + Sublayer\left(x\right)\right) \tag{11}$$

BERT applies multi-head attention to assign different weights to position encodings, segment encodings, and character encodings in the text, helping the model understand expression order and linguistic logic. The process of data fusion using BERT begins with preprocessing multi-source data. Then, adaptive fine-tuning is used to adjust the pretrained tasks, with a power text corpus as the fine-tuning dataset. Finally, the heterogeneous data is embedded into the model, and data fusion is achieved through the model. The process of power text feature extraction using Transformer is shown in Figure 4.

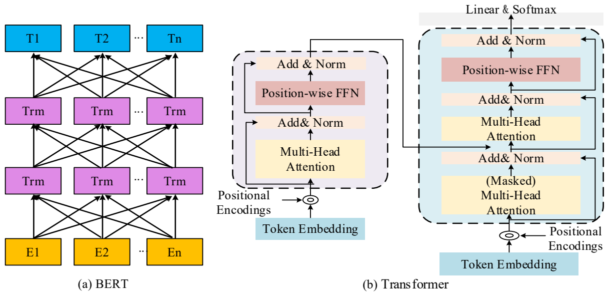

Figure 4. Schematic diagram of the BERT model and transformer feature extractor structure

As shown in Figure 4(a), the core architecture consists of stacked multi-layer Transformer encoders. Each encoder layer incorporates a multi-head self-attention mechanism and a feedforward neural network, utilizing residual connections and layer normalization to ensure training stability. For the power grid knowledge fusion task, the model first encodes text from diverse sources-including operational procedures, work permits, and equipment manuals-using its bidirectional attention mechanism to establish cross-text semantic associations. Subsequently, the model resolves terminological ambiguities through contrastive learning and entity alignment loss. This process ultimately produces unified vector representations. As shown in Figure 4(b), the encoder transforms the received power text features into continuous sequences. The system feeds these output sequences, along with the extracted key information, into the decoder to produce prediction results. Fusing multi-source data through the BERT model improves the classification precision of entity recognition using the BiLSTM-CRF model, which in turn enhances the applicability of the knowledge base. The execution of new equipment commissioning plans also requires special attention to avoid chain reactions caused by misoperations and to prevent hidden conflicts. Therefore, this study further introduces reliability analysis to predict risks during execution. Reliability analysis quantifies expert experience into measurable indicators and improves the credibility of commissioning plans through interaction between experience and data. The expression of reliability is shown in Equation (12).

$$C\left(S\right) = P\left(S_{sage} \middle| E_{date}, K_{rules}\right) \tag{12}$$

In Equation (12), S_{sage} represents the plan to be evaluated, P is the probability of safe execution, E_{date} denotes historical evidence data, and K_{rules} represents domain knowledge rules. The reliability evaluation of commissioning plans mainly involves quantitative assessments of rule compliance, device status matching, historical similarity validation, and sequence rationality. The study adopts a multi-source evidence fusion method for quantitative evaluation. The fusion process is defined in Equation (13).

$$C = \frac{\sum \mathrm{m_i}\left(A_i\right)}{1 - \sum \Pi m_i\left(B_j\right)} \tag{13}$$

In Equation (13), A_i is the evidence set supporting the hypothesis, and B_j represents the conflicting data set. After fusion, a dynamic threshold is set to define the reliability interval for each task. Based on the interval, the system adopts different control strategies. The complete optimization process for new equipment commissioning plans with integrated reliability analysis is shown in Figure 5.

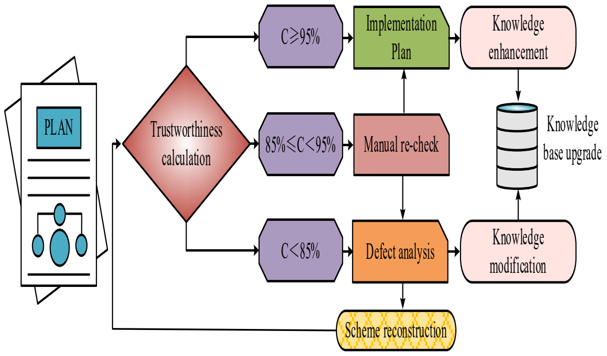

Figure 5. Optimization process of commissioning plans with reliability analysis

As shown in Figure 5, the study builds an intelligent decision-making system for new equipment commissioning plans based on reliability evaluation. The system implements hierarchical control based on the reliability score of each plan. Optimization of a cost-benefit model based on historical data determines the control threshold. This threshold integrates the generative likelihood, rule violation penalty, and uncertainty quantification value. The final objective function is synthesized using a weighted geometric mean, as expressed in Equation (14).

$$C(P)=\left(L(P)^{\alpha}\cdot(1-V(P))^{\beta}\cdot(1-U(P))^{\gamma}\right)^{\frac{1}{\alpha+\beta+\gamma}} \quad (14)$$

The weights α, β, and γ in Equation (14) are optimized via grid search on the validation set to maximize the actual execution success rate of high-confidence schemes. For plans with reliability ≥ 95%, the system automatically executes the plan and activates the knowledge enhancement mechanism. Real-time operational data is collected to continuously optimize the knowledge base. For plans with reliability < 85%, the system blocks execution immediately and performs collaborative optimization by modifying both the plan and the knowledge base. For plans with reliability between 85% and 94%, the system issues a warning. The system allows execution only after professional review and approval; otherwise, it transfers the plan to the optimization procedure.

4. Validation of entity recognition model and effectiveness of knowledge base

4.1 Validation of BiLSTM-CRF named entity recognition model

To evaluate the effectiveness of the BiLSTM-CRF model in constructing the KG for new equipment commissioning plans in the power grid, this study designed a comparative experiment under the Python 3.8 environment. The experimental settings are shown in Table 1.

As shown in Table 1, high-performance CPUs, GPUs, and sufficient storage space were selected to ensure the scientific validity of the experiment. The dataset used in this study comprised historical grid equipment commissioning plans from a substation over the past three years. It covered 15 typical commissioning scenarios including main transformer commissioning, busbar expansion, new line construction and renovation, and protection device replacement. All plan texts underwent systematic redaction to obscure sensitive information like station names and identification numbers, while standardizing equipment parameters and operational terminology. The study randomly selected 80 representative samples, divided into training and testing sets at an 8:2 ratio. This dataset exhibited robust diversity and engineering representativeness across equipment types, operational logic, and scenario complexity, providing a reliable foundation for model training and evaluation. Additionally, the study selected the following models for comparison: Robustly Optimized BERT Pretraining Approach with Conditional Random Field (RoBERTa-CRF), Decoupled Attention with Span-level Recognition (DeBERTa-Span), and Multi-scale attention and dependency parsing graph convolution (MADPG). The training loss during model iteration was first analyzed, and the results are shown in Figure 6.

Table 1. Experimental environment and configuration

/	Item	Parameter
Hardware	CPU	Intel Xeon E52680 v4, 14 cores, 28 threads, 2.4GHz clock frequency, dynamic acceleration frequency 5.3GHz
	GPU	NVIDIA GeForce RTX 3080, 10GB GDDR6X video memory, core frequency 1440MHz, maximum Rui frequency 1710MHz
	RAM	64GB DDR4, 3200MHz
	Storage	1TB NVMe SSD, 1TB SATA SSD
Software	Operating system	Ubuntu 20.04 LTS, 64-bit
	Programming language	Python 3.8

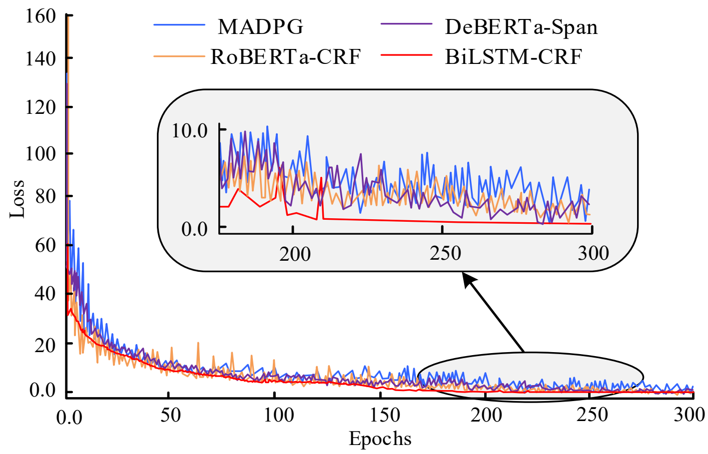

Figure 6. Training loss curves of different named entity recognition models

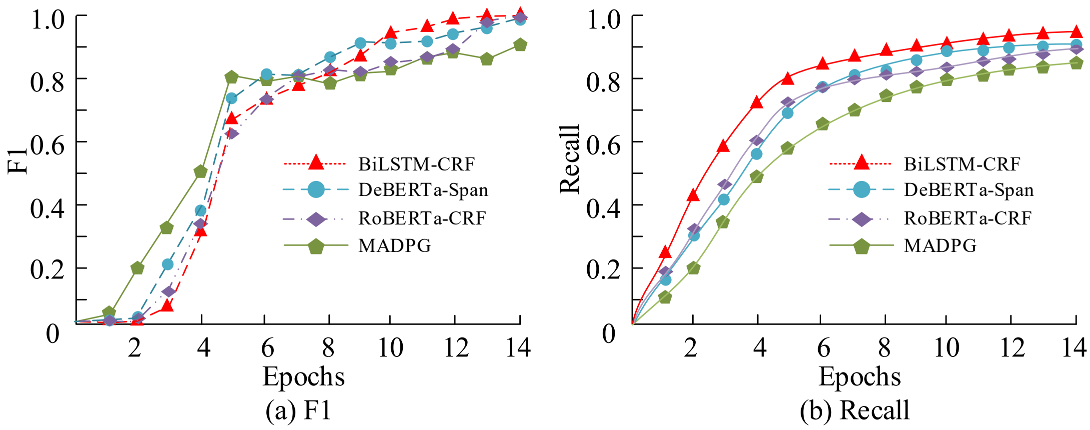

Figure 7. Comparison of F1 score and recall rate for different models

In Figure 7(a), the F1 scores of all models increased with the number of iterations. The BiLSTM-CRF model reached its highest F1 score at 12 iterations. At that point, the F1 scores of MADPG, DeBERTa-Span, and RoBERTa-CRF were 0.90, 0.98, and 0.98 respectively, all lower than that of BiLSTM-CRF. Figure 7(b) shows that when the iteration number achieved 12, the recall rate of the BiLSTM-CRF model reached 0.94, while the recall rates of MADPG, DeBERTa-Span, and RoBERTa-CRF were 0.91, 0.90, and 0.86 respectively, all significantly lower than that of BiLSTM-CRF. These results demonstrated that BiLSTM-CRF achieved the best performance in entity recognition for new power system devices and improved data processing accuracy.

4.2 Validation of knowledge base and optimization results

After validating the BiLSTM-CRF model, this study further tested the effectiveness of the constructed knowledge base for new equipment commissioning plans. To do so, the study used historical commissioning plans from a substation as the dataset. The study applied the proposed method to construct the knowledge base and used traditional manual compilation and rule engine methods as comparison groups. To evaluate the quality of the knowledge base, this study analyzed entity recognition accuracy and KG coverage. The results are shown in Figure 8.

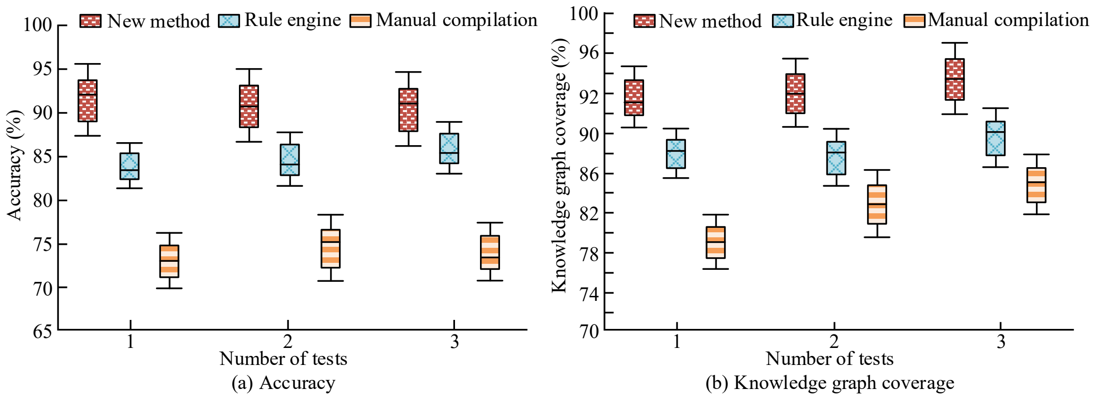

Figure 8. Comparison of entity recognition accuracy and graph coverage

In Figure 8(a), the proposed method significantly improved entity recognition accuracy. For example, in the first group of experiments, the manual method achieved an accuracy of 73.2%, the rule engine achieved 83.0%, while the proposed method reached 92.5%, which was significantly higher than the others. As shown in Figure 8(b), the maximum coverage rate of the KG using manual methods was 85.0%. In contrast, the proposed method achieved an average coverage rate of 92.4%, which was clearly higher. These results indicated that the proposed KG-based approach significantly improved both entity recognition accuracy and knowledge coverage. To further evaluate the effectiveness of plan optimization, this study assessed the efficiency of new equipment commissioning plan generation based on the above experiments. It analyzed both the time required for plan generation and the compliance rate with rules. The results are shown in Figure 9.

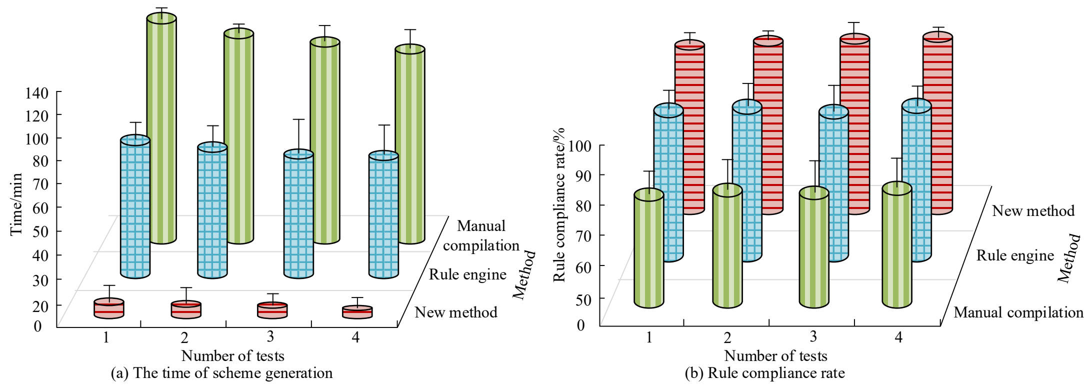

Figure 9. Comparison of plan generation time and rule compliance rate

As shown in Figure 9(a), the time required by the proposed method to generate a commissioning plan ranged from 11 min to 17 min. In comparison, the manual method required between 103 min and 128 min, and the rule engine method took between 60 min and 67 min. Figure 9(b) shows that the rule compliance rate of the manual method ranged from 75% to 79%. The rule engine method achieved 87% to 90%, while the proposed KG-based method reached up to 97%. The key factor contributing to this performance was the highly accurate entity recognition model. These experimental results demonstrated that the proposed method significantly improved the efficiency of commissioning plan generation and enhanced the standardization of the plans. Finally, to systematically evaluate the generalization capability of the proposed method, the study conducted generalization experiments across diverse scenarios. These scenarios encompassed commissioning plans for two common types-busbar expansion and new line construction-while also introducing two novel scenarios: main transformer commissioning and protection device replacement. This approach validated the method's adaptability to unknown tasks. The experimental results are presented in Table 2.

Table 2: Comparison of method generalization performance across different scenarios

Test Scenario	Voltage Level	F1/ %	Rule Compliance Rate /%	Exact Match Rate/ %
Bus Expansion	220kV	94.7 ± 0.5	88.2± 0.9	85.0± 1.2
New Line Commissioning	220kV	93.8 ± 0.7	87.5± 1.1	82.5± 1.5
Main Transformer Energization	220kV	88.3 ± 1.2	81.6± 1.8	62.0± 2.5
Protection Device Replacement	220kV	85.1 ± 1.5	79.4± 2.2	58.4± 2.8

Table 2 shows that the proposed method demonstrated stable performance in busbar expansion and new line construction scenarios covered by the training set, achieving F1 scores of 94.7% and 93.8% respectively, with rule compliance rates exceeding 87%. In scenarios not included in training—namely main transformer commissioning and protection replacement—the model still demonstrated reliable generalization capabilities. It achieved F1 scores of 88.3% and 85.1% respectively, with rule compliance rates exceeding 79%. This indicated that the constructed knowledge graph effectively supported solution generation in novel scenarios. However, the exact match rates for these two new scenarios dropped significantly to 62.0% and 58.0%. This drop indicated limitations in the model's ability to reproduce fine details. Nevertheless, it established an engineering foundation for generating safety-compliant solution frameworks.

5. Conclusions

To address the operational pressure of deploying new equipment resulting from grid expansion, this study proposes an intelligent generation method for startup plans based on knowledge graphs. By integrating the BiLSTM-CRF model with a BERT fusion mechanism, the study constructed a domain knowledge base covering multidimensional relationships—including equipment, operations, and parameters. This knowledge base achieved a maximum coverage rate of 93.8%, providing structured knowledge support for plan generation. Experiments demonstrated that the proposed method achieved outstanding performance on key metrics, including 92.5% entity recognition accuracy and 97% rule compliance in knowledge inference. Compared to traditional manual compilation methods, it significantly enhances plan generation efficiency. More importantly, the system embeds a credibility assessment mechanism that enables risk prediction and tiered control for generated plans. This mechanism ensures operational safety and decision reliability while improving efficiency. Although the study achieved certain results, significant challenges remain in terms of robustness within dynamic power grid environments and practical engineering deployment. Current systems exhibit insufficient adaptability to complex scenarios. These scenarios include sudden topology changes, new equipment integration, and multi-device coupling. Their ability to handle ambiguous conflict data requires enhancement. Adversarial testing and incremental learning mechanisms can improve environmental adaptability. Simultaneously, the system must address deployment challenges. These challenges include data interface compatibility with existing production systems, integration with operational workflows, and long-term maintenance costs. Future efforts will focus on three key areas. First, the study will develop closed-loop online learning frameworks to enhance dynamic robustness. Second, it will design modular integration solutions. Third, it will create automated operations and maintenance tools to advance the technology toward highly reliable, maintainable practical systems.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: Zheng Yaopu and Lin Xiongfeng; methodology: Peng Shifeng; software: Lin Xiongfeng; validation: Zheng Yaopu, Huang Yunsheng and Huang Jian; formal analysis: Peng Shifeng; investigation: Deng Guangyu; resources: Huang Jian; data curation: Zheng Yaopu; writing—original draft preparation: Huang Yunsheng; writing—review and editing: Peng Shifeng; visualization: Huang Yunsheng; supervision: Zheng Yaopu; project administration: Zheng Yaopu; funding acquisition: Deng Guangyu. All authors have read and agreed to the published version of the manuscript.

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