INTELLIGENT GENERATION AND VERIFICATION OF START-UP SCHEMES BASED ON POWER GRID TOPOLOGY

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With the continuous expansion of the power grid scale, the traditional power grid startup schemes are facing challenges in terms of efficiency and accuracy. This paper proposes an intelligent startup scheme generation and verification technology based on power grid topology. By constructing a future-state power grid topology model and combining real-time power grid status information, and using knowledge graph technology to conduct safety verification of the startup schemes, the results show that this method effectively improves the generation speed and accuracy of the startup schemes, reduces manual intervention, and can significantly enhance the operational stability of the power grid.

Keywords: Power grid topology; Depth first search; Maximum common edge subgraph; Knowledge graph; Power grid start-up scheme

1. Introduction

With the rapid development of economy and the continuous progress of science and technology, the demand for electricity in society continues to rise, and the scale of power grid continues to expand [1]. The traditional manual preparation of power grid startup plan requires a lot of time and effort. The staff needs to analyze and calculate the various parameters, equipment characteristics and operation modes of the power grid in detail. The process is cumbersome and error-prone, which leads to safety hazards in the startup plan [2]. The power grid topology can

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clearly show the electrical connection relationship between power plants, substations, transmission lines and loads, providing an intuitive and effective tool for the research and management of power systems [3]. Intelligent technologies represented by Depth First Search (DFS) can analyze and predict key indicators of the power grid by real-time monitoring of the operation data of the power grid, discover potential safety hazards in advance, and realize the automatic generation of startup plans, reducing the subjectivity and uncertainty caused by manual operation [4]. Knowledge Graph (KG) technology can integrate the topological structure of the power grid with its powerful knowledge representation and reasoning capabilities, comprehensively evaluate and analyze the safety status of the power grid, and discover possible safety problems in advance [5]. Therefore, this study proposes a method for generating and verifying intelligent startup plans based on power grid topology. It is expected that it can automatically, quickly and accurately generate the startup plan of the power grid. The innovation of the research is that by combining the power grid topology model with the intelligent algorithm, the startup plan can be automatically generated by comparing the similarity of the power grid topology. At the same time, the startup plan is verified by using KG technology to ensure the safety and accuracy of the plan, providing a new intelligent idea for the preparation of the power grid startup plan.

2. Related works

Power grid topology plays a vital role throughout the entire life cycle of power system planning, construction, operation, and management. It is essential for ensuring the safety and reliability of the power industry and has been extensively studied by many researchers. Fan et al. put forward a critical node identification algorithm based on power grid topology and power flow distribution to address the issue of identifying key nodes in the grid. Experimental results showed that this algorithm identified critical nodes in the grid more accurately and effectively than existing methods [6]. Senyuk et al. proposed a transient stability analysis algorithm based on machine learning and power grid topology to tackle the problem of dynamic stability analysis in power systems. Test results indicated that their algorithm improved accuracy by 10.9% compared to the distributed gradient boosting library [7]. DFS, known for its efficiency in recursively exploring all paths in a graph, has shown clear advantages in tasks such as topological sorting and path searching, which has attracted the interest of many scholars. Guo et al. proposed a general reaction network generation approach using graph-based representation and DFS to solve the problem of constructing complex chemical reaction networks. Experimental results showed that this method reduced 116 steps compared to the complete network while achieving 94% ethanol selectivity [8]. Liu et al. developed a speaker verification model based on DFS and neural networks. The results demonstrated that the proposed model achieved a balance between performance and complexity when compared with existing models [9]. KG technology enables structured representation and reasoning of complex knowledge by constructing semantic networks of entities and relationships. It has been applied in various fields. Wu et al. proposed an intelligent fault diagnosis model for industrial equipment based on multimodal KG to address existing issues in fault detection. Experimental tests showed that the accuracy of the fault description texts generated reached 98%, outperforming standard textual approaches [10].

Intelligent start-up schemes for power grids use digital and automated technologies to optimize outage recovery processes, which is of great importance for enhancing power supply reliability and efficiency. Numerous researchers have explored this field. Sun Y et al. addressed the issues of long startup time and poor operational stability in traditional power grid startup schemes and proposed an intelligent power grid startup optimization strategy based on the proximal policy optimization algorithm. Test results showed that their method effectively generated schemes that met grid requirements [11]. Chopra et al. addressed the issue of low efficiency in power startup by proposing a parallel power system recovery framework. Experiments demonstrated the feasibility and effectiveness of this approach in improving start-up efficiency [12]. Tang et al. proposed a distribution optimization method based on graph convolutional networks to address the issue of optimizing the deployment of the startup power supply. Simulation results indicated that this method significantly shortened outage duration and improved recovery efficiency [13]. Znad et al. proposed a power plant start-up method using classical model predictive control to solve the problem of slow start-up in coal-fired plants. Experimental results showed that their method reduced the start-up time by 1.1 hours while meeting safety operation standards [14]. Hu et al. in response to the diversity and complexity of constraints during the generator startup process, proposed a planning method for an impedance adaptive compensation control strategy. Test results showed excellent performance in both optimality and convergence [15].

In summary, existing studies have made considerable progress in optimizing power grid start-up schemes. However, there are still few studies focusing on intelligent start-up schemes based on power grid topology. Therefore, this study puts forward a model for generating intelligent power grid start-up schemes by integrating DFS with power grid topology and uses KG to verify the safety of the schemes. The goal is to enable accurate and fast generation of start-up schemes for target grids and promote the development of smart power grids.

3. Intelligent generation and verification model for power grid start-up schemes

3.1 Design of intelligent start-up scheme generation model based on power grid topology

Power grid topology represents the connections among components in a power system through graphs. It clearly shows the electrical relationships between elements such as power plants, substations, transmission lines, and loads [16]. Therefore, a higher degree of topological similarity often indicates a more similar structure in the corresponding start-up schemes. The DFS algorithm transforms power grid topology into quantifiable and comparable feature sequences by traversing the graph. This enables similarity analysis for different grid structures or different states of the same grid [17]. The schematic diagram of the DFS structure is shown in Fig. 1.

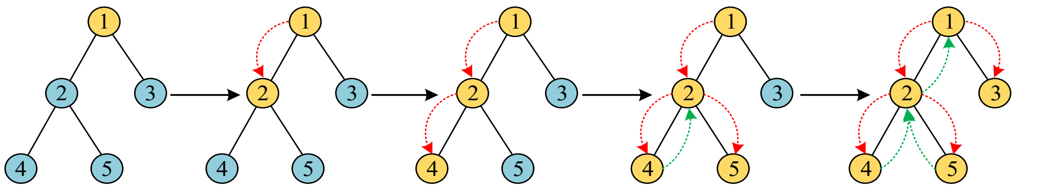


Fig. 1. DFS structure diagram

As shown in Fig. 1, the DFS algorithm starts from Node 1, first visits adjacent Node 2, then goes deeper into Node 2's child Node 4. After reaching the end, it returns to Node 2 and proceeds to visit its other child Node 5. Once that path ends, it backtracks to visit Node 3. By traversing the graph, the DFS algorithm converts the grid topology into feature sequences, providing a technical foundation for topological similarity analysis. The overall mapping expression is shown in Equation (1).

$$C(f) = C_f + C_f{}' \tag{1}$$

In Equation (1), C represents the overall mapping cost, f denotes the mapping function, C_f is the mapped power grid topology, and $C_f{}'$ is the unmapped topology. After obtaining the total mapping cost function, the similarity between grid topologies is calculated. The horizontal similarity is computed using Equation (2).

$$h_t = \alpha \sum_{i \in G} (C_t^i - \min(C_t^G) * \frac{1}{S(C_t^i)}) \tag{2}$$

In Equation (2), h denotes the horizontal similarity coefficient, t is the time index, α represents the horizontal comparison factor, G refers to the grid topology library, i is the topology index, and S represents the ranking value of the grid topology. The vertical time comparison coefficient is then calculated using Equation (3).

$$z_t = \beta \sum_{i \in G} (C_{t-1}^i - C_t^i) * \frac{1}{S(C_t^i)}) \tag{3}$$

In Equation (3), z is the vertical time comparison coefficient, and β denotes the same. Finally, the iterative coefficient for topology similarity is calculated, as shown in Equation (4).

$$I_t = \frac{h_t + z_t}{\lambda T} \tag{4}$$

In Equation (4), I represents the iterative similarity coefficient, λ denotes the time coefficient, and T refers to the total computation time. After calculating the similarity of the power grid topology, the numerical similarity needs to be transformed into a structured model to guide intelligent start-up scheme generation. The Maximum Common Edge Subgraph (MCES) method identifies the largest intersection of edge sets between different power grid topologies. This helps extract common start-up paths and core nodes under different topologies. The node mapping constraint function is defined in Equation (5).

$$\begin{cases} \sum_{k \in V_H} y_{nk} \le 1, \forall n \in V_R \\ \sum_{n \in V_R} y_{nk} \le 1, \forall k \in V_H \end{cases} \tag{5}$$

In Equation (5), y represents the decision variable of the node, n and k are the vertex indices, R and H refer to graph indices, and V represents the set of nodes. After determining the mapped nodes, edge mapping constraints are applied, as shown in Equation (6).

$$\begin{cases} \sum_{kl \in E_H} g_{nmkl} \le \sum_{k \in V_H} y_{nk}, \forall nm \in E_R \\ \sum_{nm \in E_R} g_{nmkl} \le \sum_{n \in V_R} y_{nk}, \forall kl \in E_H \end{cases} \tag{6}$$

In Equation (6), g represents the decision variable of the edge, nm and kl refer to the edges in the graphs, and E denotes the set of edges. By mapping both nodes and edges, a complete topological graph mapping is obtained, expressed in Equation (7).

$$F = \max \sum_{nm \in E_G} \sum_{kl \in E_H} g_{nmkl} \tag{7}$$

In Equation (7), F represents the objective function. In summary, this study first uses DFS to calculate topological similarity. Then, MCES transforms the structural comparison of power grid topology into an optimization process. It extracts common topology models and core connection features to determine common start-up paths, thus enabling intelligent generation of grid start-up schemes. Therefore, the research is based on the grid topology, combined with DFS and MCES, to construct a model for generating grid startup schemes (DFS-MCES), and its process is shown in Fig. 2.

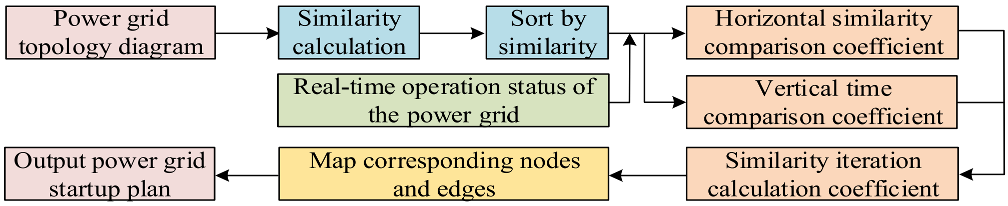


Fig. 2. Operation flow chart of DFS-MCES model

As shown in Fig. 2, the model first takes the power grid topology and real-time operational state as inputs. After similarity calculation and sorting, it identifies circuit topologies similar to the target grid. Then, it calculates the horizontal similarity coefficient and vertical time comparison coefficient to obtain the iterative similarity coefficient. With node and edge mapping, the final output is the power grid start-up scheme.

3.2 Design of power grid start-up scheme verification model based on KG

The previously constructed DFS-MCES model enables intelligent generation of power grid start-up schemes. However, the safety and compliance of these schemes still require verification. KG technology, with its capability to represent and reason over diverse knowledge such as grid topology, equipment parameters, and safety regulations, builds a semantic network that includes component attributes, connection relationships, and safety rules. This enables multi-dimensional constraint checks on generated schemes, including device operation sequences and distributed safety [18-19]. Therefore, after generating start-up schemes based on power grid topology, the method introduces KG to build a safety verification model. This ensures that the schemes comply with topological requirements and power safety standards, improving the operational stability of the power grid. The structure of KG is shown in Fig. 3. As shown in Fig. 3, structured data is integrated into a unified database, while semi-structured and unstructured data are jointly used for knowledge representation. Then, attribute correction, entity alignment, and entity construction are applied to improve the knowledge base.

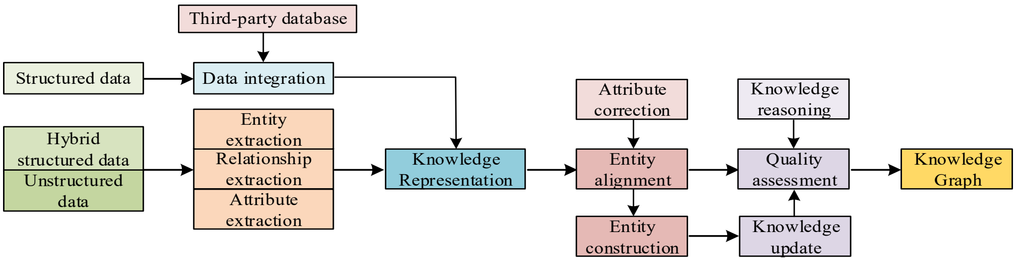


Fig. 3. KG structural diagram

After that, knowledge reasoning, quality evaluation, and knowledge updating are performed to form the KG. In this process, power grid start-up schemes are usually unstructured texts. For unstructured data, Transformer-Conditional Random Field (Trans-CRF) can be utilized for processing. With its self-attention mechanism, Trans-CRF deeply captures complex associations among elements in the data, accurately extracts semantics of each unit in the sequence, and handles long-distance dependencies [20]. The self-attention mechanism is the core of the Transformer. Its attention weight calculation equation is shown in Equation (8).

$$\begin{cases} L = XW^L \\ Q = XW^Q \\ K = XW^K \end{cases} \tag{8}$$

In Equation (8), X is the input matrix. L, Q, and K represent the value vector, query vector, and key vector, respectively, while W is the weight matrix. The input signal is multiplied by the attention weights to obtain the final output, as shown in Equation (9).

$$A(Q,K,L) = Soft\max(\frac{QK^T}{\sqrt{d_K}})L \tag{9}$$

In Equation (9), d_K denotes the dimension of the key vector, and K^T is the transpose of the key vector. The similarity score is divided by a scaling factor and then normalized to generate the weight matrix. At the same time, the CRF layer uses domain knowledge to globally constrain the output feature sequences from the Transformer. This ensures logical consistency and accuracy in label prediction. Finally, the method combines KG to construct the power grid start-up scheme verification model (KG-Trans-CRF). The process of the model is shown in Fig. 4.

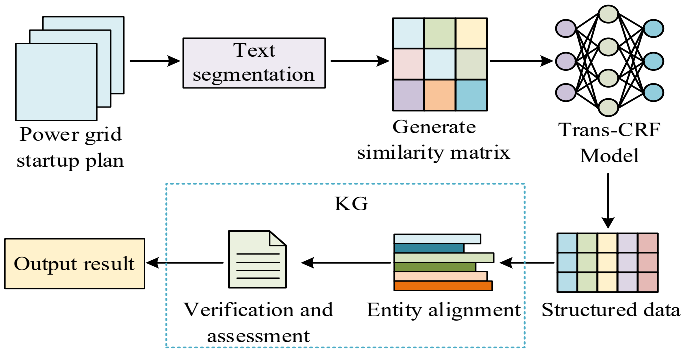


Fig. 4. Operation flow chart of KG-Trans-CRF model

As shown in Fig. 4, the power grid start-up scheme is first segmented to generate a similarity matrix. Then, the Trans-CRF model captures semantic features from the text and applies global constraints to the feature sequence to output structured data. After that, KG aligns and verifies the structured data and outputs the verification results. In this process, the feature data extracted by the Transformer is passed to the CRF inference layer. It computes the score between the input and label sequences, as shown in Equation (10).

$$s(a,b)=\sum_{d=1}^{p}(O_{d,bd}+P_{bd,b+1})+P_{b0,b1} \tag{10}$$

In Equation (10), s is the score of the input and label sequences. a and b represent the input and label sequences, O is the state feature function, P is the transition feature function, p is the sequence length, and d is the summation index. Then, the likelihood of the correct label is computed after normalization, as shown in Equation (11).

$$\log(q(a\,|\,b))=s(a,b)-\sum_{b'\in B_a}^{p}s(a,b') \tag{11}$$

In Equation (11), P denotes the conditional probability, b' is any label sequence, and B represents the set of possible labels. After that, the predicted label sequence with the highest total score among all sequences is selected, as shown in Equation (12).

$$\tilde{b}=\arg\max s(a,b') \tag{12}$$

In Equation (12), $\tilde{b}$ denotes the optimal label sequence. In summary, this study builds the DFS-MCES-KG model for power grid start-up scheme generation and verification based on DFS-MCES and KG-Trans-CRF. The complete process is shown in Fig. 5.

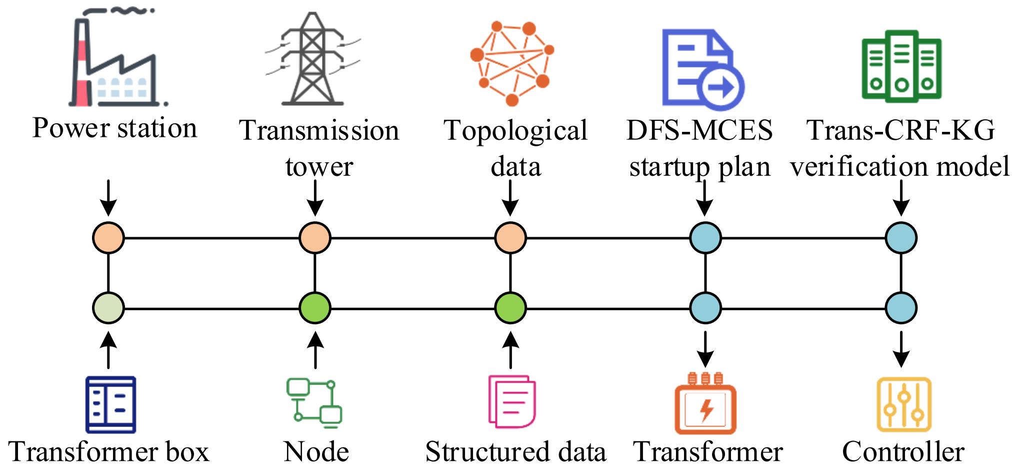


Fig. 5. Operation flow chart of DFS-MCES-KG model

In Fig. 5, the model first uses the DFS-MCES model to calculate the similarity of the input power grid topology, matches the most similar topology, and generates the corresponding start-up scheme. Then, the KG-Trans-CRF model transforms the scheme into structured, quantifiable data. Through data integration and comparison, it verifies whether the generated scheme meets safety standards and whether the operation flow is reasonable. If not, the process iterates until convergence conditions are met. Finally, a compliant start-up scheme is output.

4. Performance analysis of the DFS-MCES-KG model for power grid start-up scheme generation and verification

4.1 Performance evaluation of the Trans-CRF-KG model

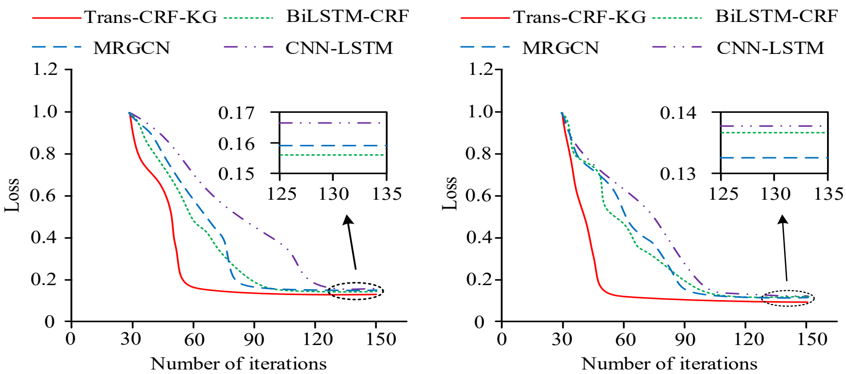
To evaluate the superiority of the Trans-CRF-KG model for power grid start-up scheme verification, the study compared it with Bidirectional Long Short-Term Memory Network-Conditional Random Field (BiLSTM-CRF), Multi-relational Graph Convolutional Network (MRGCN), and Convolutional Neural Network-Long Short-Term Memory Network (CNN-LSTM). The experiments were conducted on a Windows 10 system with an Intel Core i7-10700K @ 3.8GHz CPU, NVIDIA RTX 3090 (24GB) GPU, 32GB RAM, using the PyTorch deep learning framework and the Adam optimizer. The experiment used the historical power grid startup schemes of City A and City B in southern China to create the test dataset. The power grid topology diagram was based on the actual power grid structure of City A and City B in southern China and was constructed using the standard node-edge model. The core parameters are shown in Table 1.

Table 1

Grid topology parameters

Parameter category	Specific indicators	Range of values / Standards
Node parameters	Node type	Power plant / Substation / Load node
	Node voltage level	110kV/220kV/500kV
	Node capacity	100MVA~2000MVA
Transmission line parameters	Line resistance	0.01Ω/km~0.05Ω/km
	Line reactance	0.4Ω/km~0.45Ω/km
	Line length	1km~150km
	Rated current capacity	500A~2000A
Topological structure parameters	Total number of nodes	City A: 87; City B: 112
	Number of transmission lines	City A: 103 roads; City B: 138 roads
	Connectivity	0.85 ~ 0.92

Subsequently, the study tested the loss values of the four models, and the results are shown in Fig. 6.



(a) The test results of different models on the dataset of City A

(b) The test results of different models on the dataset of City B

Fig. 6. Loss test results of four models

As shown in Fig. 6(a), the Trans-CRF-KG model gradually converged after 60 iterations on the City A dataset. At 120 iterations, the loss value reached 0.13. Fig. 6(b) shows that on the City B dataset, the loss value reached 0.11 at 120 iterations. The MRGCN model stabilized after 90 iterations, while the BiLSTM-CRF and CNN-LSTM models showed relatively stable loss curves after 120 iterations. In summary, the Trans-CRF-KG model maintained good convergence and fast convergence speed across different datasets. To further validate the performance of the Trans-CRF-KG model, the study tested the verification accuracy of all four models. The results are shown in Fig. 7.

As shown in Fig. 7(a), on the City A dataset, the accuracy of the Trans-CRF-KG model in 10 tests was consistently above 90%, with a maximum of 93.5% and a minimum of 90.7%. The BiLSTM-CRF model achieved a maximum accuracy of 91.3% and a minimum of 85.7%. The MRGCN model had a maximum accuracy of 90.5%, with the highest fluctuation in performance. The CNN-LSTM model had the lowest accuracy at 83.9%. Fig. 7(b) shows that the Trans-CRF-KG model achieved the highest precision at 94.4%, while the BiLSTM-CRF, MRGCN, and CNN-LSTM models achieved 92.0%, 91.4%, and 86.5%, respectively. In summary, the Trans-CRF-KG model verified power grid start-up schemes more accurately and with less fluctuation than the other models.

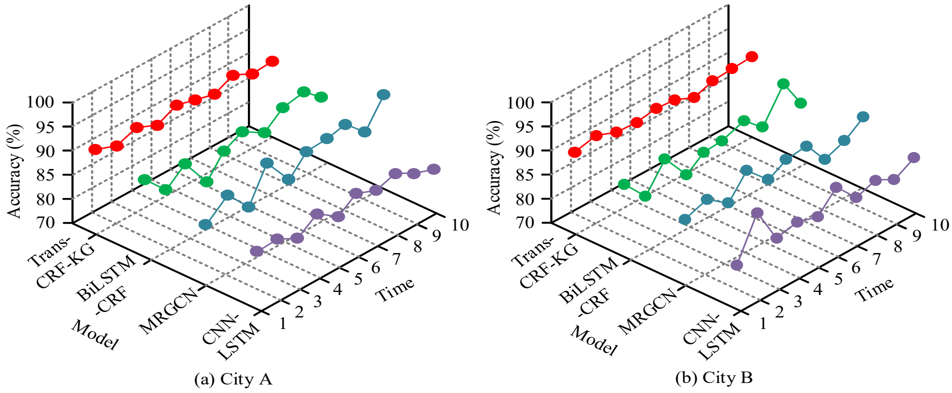


Fig. 7. Verify accuracy test results

4.2 Performance evaluation of the DFS-MCES-KG model

After validating the performance of the Trans-CRF-KG model, the study further evaluated the combined DFS-MCES-KG model by comparing it with Particle Swarm Optimization-Genetic Algorithm (PSO-GA), Residual Network-Knowledge Graph (RseNet-KG), and Random Forest-Support Vector Machine (RF-SVM). Historical start-up schemes from City A and City B were again used as test datasets. The study tested scheme generation time and verification accuracy for all four models, and the results are shown in Fig. 8.

In Fig. 8(a), on the City A dataset, the accuracy curve of the DFS-MCES-KG model became stable after a generation time of 4 s. At 8 s, the accuracy reached 94.6%, which was higher than all three comparison models. Fig. 8(b) shows that on the City B dataset, when the generation time reached 10 s, the accuracy of the DFS-MCES-KG model was 95.3%, while RseNet-KG, RF-SVM, and PSO-GA achieved 90.6%, 89.1%, and 92.4%, respectively. These results demonstrated that the DFS-MCES-KG model could accurately generate power grid start-up schemes in a relatively short time. To further validate its performance, the study compared the F1 score and Area Under Curve (AUC) value. The experimental results are shown in Fig. 9. As shown in Fig. 9(a), the F1 score of the DFS-MCES-KG model reached 91.4% at 120 iterations, significantly outperforming the comparison models. The F1 score gradually stabilized after 90 iterations. At 150 iterations, the F1 scores of the RseNet-KG, PSO-GA, and RF-SVM models were 83.9%, 85.6%, and 82.4%, respectively. As seen in Fig. 9(b), the ROC curve of the DFS-MCES-KG model was closest to the upper left corner, with an AUC value of 0.895.

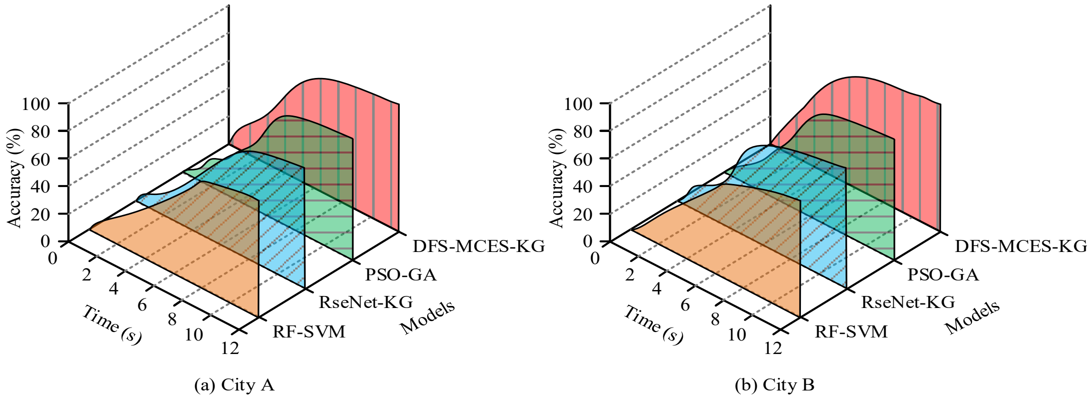


Fig. 8. Solution generation time and calibration accuracy test results

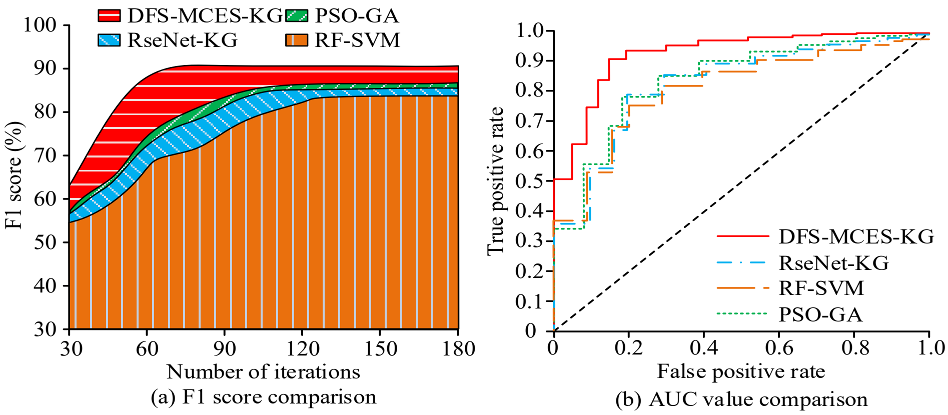


Fig. 9. F1 score and AUC value test results

This was higher than those of the RseNet-KG, PSO-GA, and RF-SVM models, which were 0.833, 0.847, and 0.814, respectively, indicating better accuracy for the DFS-MCES-KG model. To further analyze the performance of the DFS-MCES-KG model, the study also compared the precision and recall of the four models. The test results are shown in Table 2.

Table 2

Precision and recall test results

Dateset	Model	Precision(%)	Recall(%)
City A	DFS-MCES-KG	91.26	89.31
	PSO-GA	88.64	85.45
	RseNet-KG	87.52	86.38
	RF-SVM	87.63	86.72

City B	DFS-MCES-KG	92.63	90.07
	PSO-GA	89.64	88.96
	RseNet-KG	87.83	87.01
	RF-SVM	86.39	85.47

As shown in Table 2, on the City A dataset, the DFS-MCES-KG model achieved a precision of 91.26% and a recall of 89.31%. On the City B dataset, the precision reached 92.63%, while the precision values of PSO-GA, RseNet-KG, and RF-SVM were 89.64%, 87.83%, and 86.39%, respectively. Compared to PSO-GA and RseNet-KG, the recall of the DFS-MCES-KG model improved by 1.11% and 3.08%, respectively. In summary, the DFS-MCES-KG model maintained strong precision across different datasets and accurately generated power grid start-up schemes that met practical requirements.

5. Conclusion

In view of the low efficiency and error-proneness of the traditional manual preparation of power grid startup plans, this study proposed an intelligent startup plan generation and verification model based on power grid topology. The model was built upon power grid topology and integrated the DFS and MCES algorithms with real-time grid status information to realize the automatic generation of startup plans. In parallel, a startup plan verification model was developed by combining KG with the Transformer-CRF framework to perform safety verification on the automatically generated startup plans. Experimental results showed that the loss value of the proposed Trans-CRF-KG verification model did not exceed 0.13 on the two test datasets, and the model gradually converged after 60 iterations. In ten groups of tests, the verification accuracy of the Trans-CRF-KG model exceeded 90%, with a maximum value of 94.4%. Further testing demonstrated that the proposed DFS-MCES-KG model achieved accuracies of 94.6% and 95.3% on the City A and City B datasets, respectively, along with an F1 score of 91.4% and an AUC value of 0.895. Compared with models such as PSO-GA and RseNet-KG, the proposed model improved precision by 2.62% to 6.24% and recall by 1.11% to 3.08%. Moreover, the DFS-MCES-KG model stably generated solutions within 8 s, with a significantly shorter runtime and faster loss convergence compared to the baseline models. In summary, the DFS-MCES-KG model improved the efficiency and accuracy of startup plan generation by integrating power grid topology with intelligent algorithms, reduced manual intervention, and provided an innovative technical path for the intelligent development of power grid startup plans. Although the proposed model was tested under ideal conditions, its adaptability to complex power grid scenarios still requires further validation. In the future, its robustness under extreme conditions can be explored to promote the intelligent upgrade of the entire power grid startup planning process.

Acknowledgment:

This work was supported by the project: Research on and Application of Technology for One-Click Generation of Startup Schemes Based on Power Grid Topology. Project Number: 032000KC24070030 (GDKJXM20240568).

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