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A fusion topology method for generating new equipment startup schemes for power grids

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New grid equipment startup programs are widely used in various countries to regulate the commissioning of new equipment; these programs have unique differences in terms of strictness, information asymmetry, and complexity relative to other types of startup programs. With respect to rule-based generation methods, because the method of revising the rules weakens their migration ability, it is difficult to adapt these methods to the *status quo* of high-speed power grid construction; moreover, most of the current generation methods based on deep learning improve upon the rule-based methods but do not eliminate the rules of the constraints. Therefore, this paper presents a fusion topology for generating a new grid equipment startup scheme, which generates the scheme from end to end. The method utilizes the powerful processing capabilities of the GATv2 model and the ERNIE-GEN model for topology and text, respectively. The device type-based coding strategy and the scheme complexity-based self-attention layer selection strategy are used in the GATv2-based device identification model to address information asymmetry and complexity variability, and the device information modification strategy is applied to solve the strictness variability problem in the ERNIE-GEN-based scheme generation model. Finally, through the testing and verification of field data from four types of new equipment startup schemes in real power grids, it is verified that the method can effectively generate new equipment startup schemes for power grids, and the reasonableness and efficiency of the three strategies are verified through ablation experiments, which verify that the method can effectively generate new equipment startup schemes for power grids that meet the requirements of real power grids.

KEYWORDS

GATv2, ERNIE-GEN, new equipment operation, start-up plan, deep learning

1 Introduction

The power system is an intricate network that covers power generation, transmission and distribution. As the nerve center of modern society, the power system has experienced unprecedented high-speed development in recent years. With the rapid progress of science and technology and the continuous growth of energy demand, as well as to meet the construction requirements of smart grids (Chen et al., 2009; Zhang et al., 2009; Dong et al., 2014; Yi et al., 2009; Yu and Luan, 2009), power grids need to not only have a larger capacity and higher efficiency but also need to constitute a more intelligent mode of operation, which leads to a large number of new equipment access requirements. However, this large-scale equipment access also brings a series of challenges for the power grid; whenever a grid accesses new equipment, this may have an impact on the structure, working mode, and stability of the current power grid, and if there is a stability problem in the power grid when accessing new equipment, this may lead to power supply interruptions, equipment damage or even serious accidents, which may have an impact on the stability and operation of society in general (Sanjab et al., 2016; Otuoze et al., 2018; Sun et al., 2018). Therefore, the development of a new grid equipment startup program is crucial, and for actual new equipment access operators, the rationality of the new grid equipment startup program is directly related to personnel safety; thus, new grid equipment startup programs are widely used in various countries as a kind of grid operation ticket for regulation (Li et al., 2010; Mengchao et al., 2010; Harbor et al., 2014; Wang et al., 2014; Ren et al., 2022).

Grid operation tickets are formal documents or recording sheets used in power systems to perform, record, and control grid operations. These operation tickets are usually written guidance or recording tools used when performing various critical operations in power system operation (Zhou and Yang, 2004; Zhou et al., 2004; Liu et al., 2005; Yuan et al., 2022), and their purpose is to ensure that operators perform grid operations, maintenance, switching operations, etc., according to specified procedures and standards to maintain the safe, stable and reliable operation of the grid (Zhu et al., 2003; Wu et al., 2006; Zhu et al., 2022). Initially, the grid operation ticket is manually written by personnel. At this time, the correctness of the grid operation ticket depends on the experience of specific personnel, and the degree of uncertainty is great; however, with the development of science and technology and the continuous construction of power grids and intelligent methods, especially given the rapid development of computer technology, the generation of grid operation tickets has entered the stage of automatic generation. With several years of research on methods of generating grid operation tickets, these methods are divided into rule-based generation (Gong et al., 2006) and neural network-based deep learning generation (Cai and Qi, 2021).

The rule-based generation of grid operation tickets involves generating operation tickets using predefined rules and processes; this method relies more on the accurate specification of grid operations, including the steps, conditions, and limitations of various operations. By developing detailed operating procedures and standardized processes, the process of generating operating tickets can be made more controllable and deterministic. The current rule-based methods for grid operation ticket generation involve expert rules (Tang et al., 2001) and multiple intelligent methods (Zhou et al., 2004). Expert rules are sets of rules and guidelines for generating grid operation tickets based on the experience and knowledge of experts in the domain of power systems (Song, 1999). Hu et al. (Hu et al., 2002) simplified the expert system knowledge base by establishing a generalized cognitive model of power system equipment, which was applied in several substations. Yang et al. (Yang et al., 2004) established an operation based on objects and designed an expert system with a network topology, a knowledge base, and a reasoning mechanism suitable for power system dispatch operations. An intelligent system is usually represented as a computer program that interacts with the outside world through a preset protocol. In a multi-intelligent system, through distributed decision-making, each intelligent body generates corresponding operation tickets according to the part it is responsible for, and they are coordinated in the multi-intelligent system to ensure the consistency and efficiency of the whole grid. Even if one intelligent body fails or is temporarily disabled for some reason, other intelligent bodies can temporarily take over the part that this intelligent body is responsible for to prevent the system from failing and to ensure that the operation tickets can be created. Preventing the system from failing ensures that the generation of operation tickets is not disturbed (Jiang et al., 2005; Li et al., 2016; Yonggang et al., 2016). Guo (Guo et al., 2006) and others built an operation ticket generation system based on the fuzzy cognitive map reasoning model of intelligence. Wei (Wei et al., 2023) and others proposed an optimal fault recovery control (TROFC) scheme for WF acquisition systems based on topology reconstruction. Liu (Liu et al., 2023) and others proposed a prediction method based on Adaboost ensemble convolutional neural network and bidirectional long short-term memory. In addition, there are many rule-based generation methods, such as that of An et al. (2021), who used association rule algorithms to mine historical ticket information and proposed a method to establish a knowledge base of historical tickets. Overall, this rule-based generation method achieves some effectiveness in the region where it is initially constructed, but its cumbersome rule revision process, as well as strong specialization, often necessitates changing the use of the rules when they are migrated elsewhere.

The generation method based on neural network deep learning generation utilizes the historical and online data of the power grid to automatically generate grid operation tickets through the techniques of big data analysis as well as neural network deep learning. CAI et al. (Xinlei et al., 2020) introduced a real-time dispatching business system based on big data applications and artificial intelligence to obtain an automated and intelligent business system. GAO et al. (Gao et al., 2019), by analyzing the power system operation and monitoring processes and incorporating artificial intelligence (AI) technology, illustrated the feasibility of forming dispatch operation tickets based on AI. Ren et al. (Ren et al., 2022) constructed a CNN-BiGRU attention-centered automatic checking model for operation tickets, which effectively improved the verification efficiency. Kumar et al. (Kumar et al., 2019; Kumar et al., 2020) proposed a novel DFOGI for element extraction and a novel HPO for GMPPT based on optimized operation of grid connected partially shaded solar photovoltaic arrays. They employed an enhanced optimal control technique based on adaptive maximization m Kalman filter (AM-MKF) to maximize the power generation of solar photovoltaic panels. Saxena et al. (Saxena et al., 2021) proposed an improved model predictive control method based on a double second-order generalized integrator for the control problem of two-stage three-phase grid connected solar photovoltaic power systems. These demonstrate the feasibility of using neural network deep learning to solve practical problems in power grids. The current generation method based on neural network deep learning is still based only on the original rules for partial modification and does not let the model use historical data or online data to perform end-to-end generation. Therefore, this paper presents a new grid equipment startup program generation method based on the new GATv2 and ERNIE models for end-to-end generation of new grid equipment startup programs through the combination of graph-based deep learning and a text generation model.

2 Basic theory of the disconnecting switch status monitoring technology based on the internet of things

Several factors need to be considered in a grid start-up program for new equipment. The first is the safety and reliability of the new equipment, which must be considered to ensure that its introduction does not pose any potential risk to the grid system as a whole. Second, compatibility with the existing system must be considered. The new equipment should be able to seamlessly integrate and work with existing equipment without causing unnecessary failures or instability. Then, efficiency and performance optimization must be considered, as the introduction of new equipment should lead to more efficient energy transfer and management, helping to improve the operational efficiency of the entire power system. New grid equipment startup programs can be constructed incorrectly for various reasons, very likely due to failures to access the new equipment after an impact on the power grid and similar factors, which can lead to grid failures and other undesirable outcomes, including accidents. In particular, the reasonableness of the site may be directly related to the safety of the personnel. Therefore, a new grid equipment startup program needs to be extremely accurate; although recommendations for new grid equipment startup programs are given in a series of professional terminology texts, as long as the equipment is established in a rigorous and correct manner, these rules can be expressed in a variety of ways. A complete new grid equipment startup program is divided into five parts: establishing the startup scope, commissioning the project, determining the scheduled startup time, setting startup conditions, and performing startup steps. The start-up scope and scheduled start-up time are often directly known, and the commissioned project is directly determined from the start-up scope; thus, new grid equipment start-up program generation is mainly based on the start-up conditions and start-up steps. Therefore, in general, compared with other types of programs, the new grid equipment startup program has differences in rigor, information asymmetry, and complexity.

(a) Strictness of the differences: A new grid equipment startup program gives the names of the specific equipment involved, and the corresponding operations must be completely consistent with the actual grid equipment; however, for the other statements in the text, one only needs to ensure that the program is reasonable and easy to interpret and that it is in line with the actual use of the power grid as much as possible.
(b) Information asymmetry: The topological information contained in the start-up scope, commissioned items, and scheduled start-up time of the new grid equipment start-up program is not symmetrical with the topological information contained in the start-up conditions and start-up steps.
(c) Complexity difference: The new grid equipment startup programs for different types of equipment, different numbers of pieces of equipment, different topologies of the grid, and other complex factors are also different.

To better generate the initiation scheme, this paper uses the GATv2 model and the ERNIE-GEN model to determine the topological information and the text information, respectively, and adopts a coding strategy based on the device type, a self-attention layer selection strategy based on the complexity of the scheme, and a device information modification strategy to better address the three abovementioned characteristics.

2.1 GATv2 model

The GATv2 model (Brody et al., 2021) is an improved model based on the graph attention network (GAT) model (Veličković et al., 2017), which solves the static attention problem in the original GAT model; i.e., the ordering of the attention weights is independent of the querying nodes, resulting in each node paying attention to the same highest-scoring neighboring node. The GATv2 model improves the expressiveness and robustness of the model by adjusting the linear transformation and the order of attention computation so that each node can focus on different neighboring nodes, thus improving the expressiveness and robustness of the model. The specific structure of the model is as follows:

Encoder: The encoder consists of the decoder portion of a multilayer unidirectional transformer, where each layer of graph convolution uses a self-attention mechanism; i.e., different weights are dynamically assigned based on the similarity and adjacency between the nodes. Thus, the information from the neighboring nodes is fused to encode the input graph structure and extract the semantic features of the nodes.

Decoder: The decoder acts as a multilayer fully connected network that can take the output vector of the encoder as input for different tasks; this network is used in this paper to obtain the node classification task output.

Dynamic Attention: dynamic attention is a major innovation of the GATv2 model, which realizes a dynamic attention mechanism by reversing the order of linear transformation and attention computation so that the ordering of the attention weights is affected by the query nodes, the performance of its attention mechanism compared to the original GAT model is shown in Figure 1. Where the original GAT utilizes the score function e: $R^d \times R^d \to R$ to score the nodes and the equation is shown in Formula 1:

$$e\left(h_i, h_j\right) = LeakyReLU\left(a^T\left[Wh_i \| Wh_j\right]\right) \tag{1}$$

where e (h_i, h_j) denotes the attention weight between node i and node j, a ∈ R2d′ is a learnable vector, LeakyReLU is the activation function, W ∈ R d’×d is a learnable matrix used to vary the node features linearly, and || denotes the vector splicing operation. For node i, after calculating all the neighbor scores, use softmax to normalize the attention weight of the *i*th element to the *j*th element in the sequence and the formula is shown in Formula 2:

$$\alpha_{ij} = \mathrm{softmax}_j\left(e\left(h_i, h_j\right)\right) = \frac{\exp\left(e\left(h_i, h_j\right)\right)}{\sum_{j' \in N_i} \exp\left(e\left(h_i, h_{j'}\right)\right)} \tag{2}$$

The GAT performs aggregation based on these weights to obtain the hidden features of the *i*th node in the GAT and the formula is shown in Formula 3:

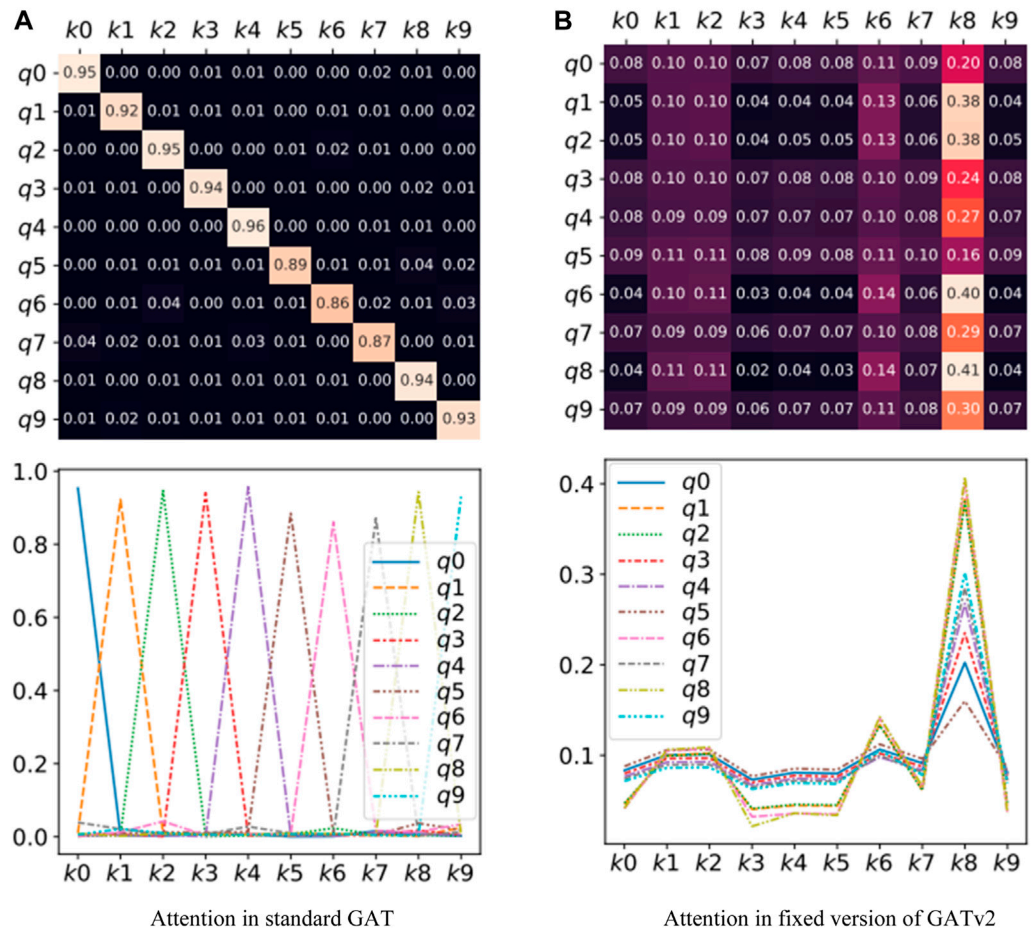


FIGURE 1
Comparison of attention between Gat model and Gatv2 model.

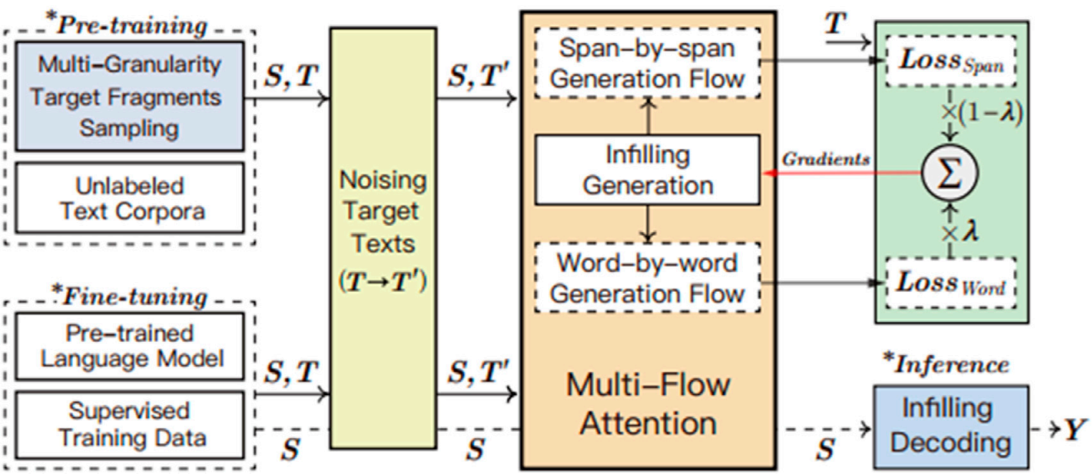


FIGURE 2
Schematic diagram of the ERNIE-GEN framework.

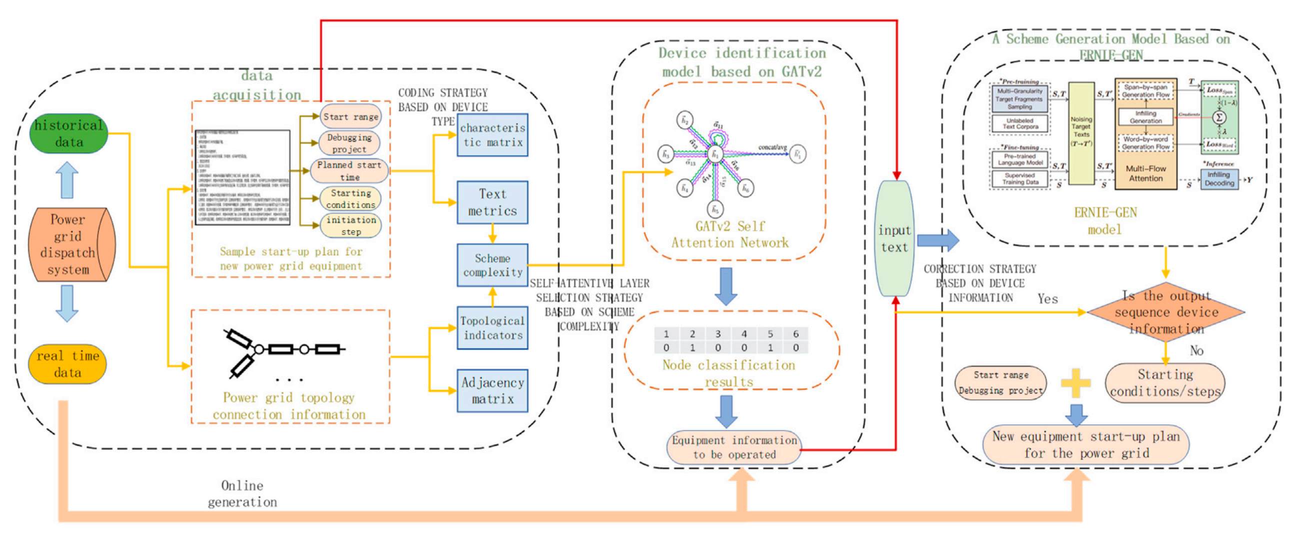


FIGURE 3
Modeling framework of new equipment startup scheme for power grid based on GATv2 and ERNIE models.

$$h_i' = \sigma\left(\sum_{j\in N_i} \alpha_{ij} W h_j\right) \tag{3}$$

The dynamic attention of GATv2 solves the problem of the standard GAT problem in which W, a are used sequentially in the scoring function, resulting in a linear layer that collapses into a single layer at the end. By moving an out of the nonlinear result and then running it, in addition, the query-key pair is concatenated first, and then W is used to perform the linear transformation, i.e., at this time, the expression of e (h_i, h_j) is shown in Formula 4:

$$e(h_i, h_j) = a^T LeakyReLU\left(W\left[h_i \| h_j\right]\right) \tag{4}$$

2.2 GATv2 model

ERNIE-GEN is a generative pre-training model proposed by Baidu and the schematic diagram of its framework is shown in Figure 2, ERNIE-GEN model is a generative pre-training model, which is based on Transformer's seq2seq framework, targeting the exposure bias problem in training and the insufficient interaction between encoder and decoder in pre-training that is the exposure bias problem and the equations are shown in Formula 5, 6:

$$Training:\ y_{i+1} \leftarrow MH - Attn(Q = t_i, KV = [S, t \le i]) \tag{5}$$

$$Decoding:\ y_{i+1} \leftarrow MH - Attn(Q = y_i, KV = [S, y \le i]) \tag{6}$$

Where y and t denote the predicted character vector and ground truth character vector, respectively; S is the representation of the encoder side; and the direct influence on the prediction of y_{i+1} is represented as Q, which is used to converge the above representations and is also where the difference between the training and decoding phases has the most direct effect. At the same time, KV differs in training and decoding, but the effect on y_{i+1} is weaker. To solve this problem, ERNIE-GEN introduces several innovative mechanisms to improve the quality and efficiency of natural language generation. The main features of the ERNIE-GEN model are as follows:

Multiflow Attention: Multiple distinct attention flows are added between the encoder and decoder to enhance the codec interaction in such a way that integrated word-by-word and span-by-span generation flows can be applied in parallel with the shared context flow. The multistream computational power's equations are shown in Formula 7–9:

$$X^{(l+1)} \leftarrow MH - Attn\left(Q = X^{(l)}, KV = X^{(l)}, Mc\right) \tag{7}$$

$$A_W^{(l+1)} \leftarrow MH - Attn\left(Q = A_W^{(l)}, KV = \left[X^{(l)}, A_W^{(l)}\right], M_W\right) \tag{8}$$

$$A_S^{(l+1)} \leftarrow MH - Attn\left(Q = A_S^{(l)}, KV = \left[X^{(l)}, A_S^{(l)}\right], M_S\right) \tag{9}$$

where X is the connection between S and T′, X(l) is the layer-l vector sequence of the context stream, and AW(l) and AS(l) are the layer-l vector sequences of the verbatim generation stream and the word-by-word generation stream, respectively.

Infilling Generation Mechanism: By adding a special symbol [ATTN] after each character in the decoder, the model's attention is shifted from the last word to all previous representations to attenuate the dependence on the previous character while unifying the training and decoding conditions.

Noise-Aware Generation Method (NGM): Random noise is added to the input sequence of the decoder during training to train the model to perceive errors and attenuate the impact of errors on subsequent generation by adjusting the attention weights.

Span-by-Span Learning Paradigm: Instead of predicting only one character at each step during training, a semantically complete segment is predicted to improve the coherence and accuracy of generation.

3 Construction of a GATv2 and ERNIE-GEN based model for generating new equipment startup scenarios for the grid

In this paper, we use Python for new grid device bootstrap scheme generation and use the PyCharm platform to realize end-to-

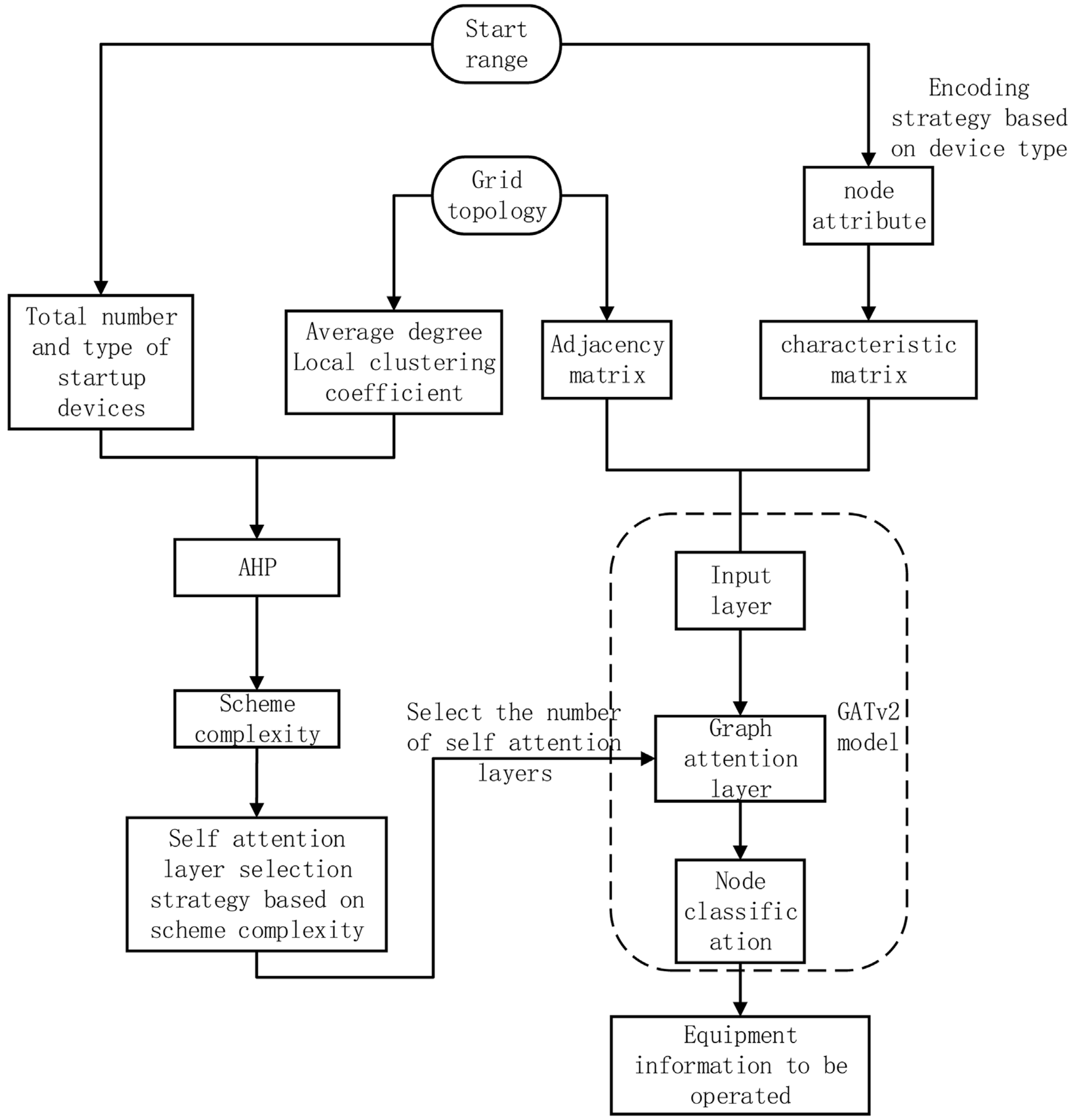


FIGURE 4
Flowchart of GATv2 based device identification model.

end bootstrap scheme generation. According to the above discussion, new grid device initiation schemes have rigor variability, information asymmetry, and complexity variability. In this paper, we propose a fusion topology for a new grid device initiation scheme based on the GATv2 model as well as the ERNIE-GEN model. Additionally, we propose a coding strategy based on device type, a self-attention layer selection strategy based on scheme complexity, and a correction strategy based on device information to address these three characteristics in the generation of new device initiation schemes for power grids.

The model first inputs the startup range into the GATv2 model after applying the device type-based coding strategy, obtains all the information on the devices to be operated based on the self-attention layer selection strategy according to the scheme complexity and then passes this information to the trained ERNIE-GEN text generation model. The ERNIE-GEN text generation model takes the startup range and all the device information obtained from GATv2 as text input and obtains the startup conditions and startup steps based on the device information modification strategy. Finally, the output is directly combined with the known startup scope, scheduled startup time, and commissioned items to obtain the final new grid equipment startup program. The framework structure is shown in Figure 3.

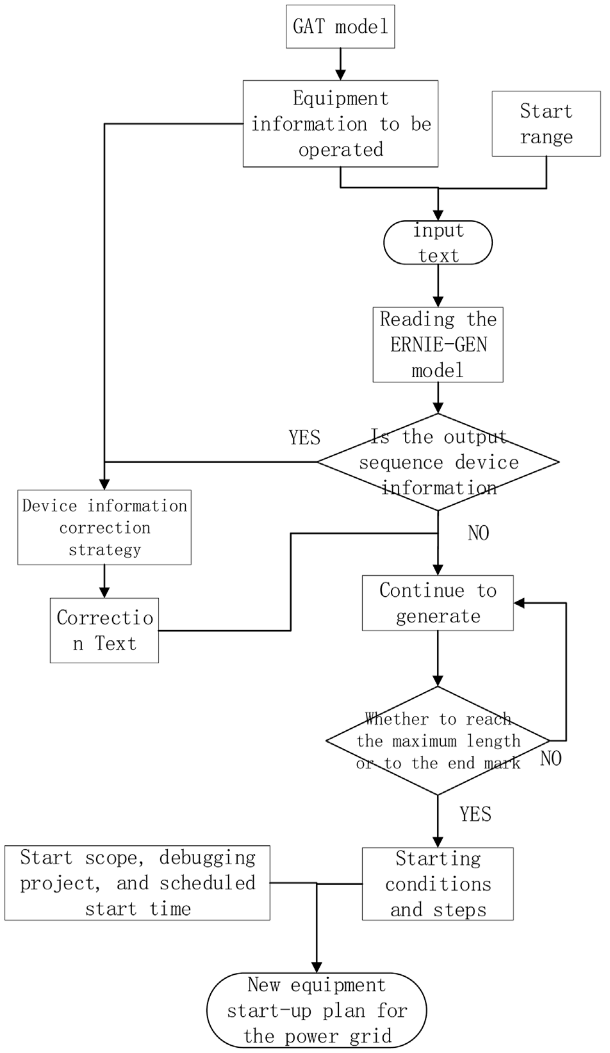


FIGURE 5
Structure of the ERNIE-GEN based scenario generation mode.

3.1 GATv2-based device identification model construction

The GATv2-based device identification model obtains node attributes through the startup range combined with the topology information of the device type-based coding strategy and inputs them as feature matrices. The adjacency matrix obtained based on the grid topology is also fed as input to the GATv2 model, and node classification is used to obtain information about the devices to address the information asymmetry of the grid's new device activation scheme. To address the complexity variability of the startup scheme, the model determines the number of layers of the graph self-attention layer through a selection strategy based on the scheme complexity. The structure of the model is schematically shown in Figure 4.

3.1.1 Coding strategy based on device type

To allow the model to better recognize device types so that it can better handle grid topology information, this paper adopts a coding strategy based on device types. In this paper, all device types are treated as nodes, and devices of the same type are assigned the same encoding as a node attribute instead of directly encoding the name of the device as a node attribute. This approach allows the model to read the device information more efficiently, thus avoiding interference caused by unnecessary information.

3.1.2 Self-attentive layer selection strategy based on scheme complexity

To prevent the overfitting and underfitting of the model due to the complexity variability of the startup scheme, this paper presents a self-attentive hierarchical selection strategy based on the scheme's complexity. By analyzing the characteristics of the new grid equipment startup scheme and incorporating the relevant literature, this paper uses the four indicators of the total number of startup devices, the number of types, the average degree, and the local clustering coefficient based on the hierarchical analysis method to measure the scheme complexity.

Total number of devices to be started: the total number of devices to be activated in the grid's new device startup program;

Number of types: the number of types of equipment to be activated in the grid's new equipment activation program;

Average degree: the average of the degrees of all nodes in the grid topology;

Local clustering coefficient: the ratio of the number of edges that are connected between neighboring nodes of the devices that need to be activated to the maximum possible number of connections. In this paper, we take the maximum value among all the activated devices.

For the hierarchical analysis method, this paper adopts the expert scoring method to determine the relative importance of two factors and constructs its judgment matrix A, which is shown in Formula 10.

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \tag{10}$$

Where, a_{ij} denotes the importance of factor i relative to factor j, $a_{ii} = 1$, $a_{ij} = 1/a_{ji}$, after obtaining the judgment matrix.

Formula 11 is applied using the maximum eigenvalue and eigenvector to solve for the weight vector and the consistency index:

$$AW = \lambda_{\max} W \tag{11}$$

where A is the judgment matrix, W is the eigenvector, and λ_{max} is the maximum eigenvalue. Each component of W represents the weight of a factor, and these values need to be normalized. λ_{max} represents the degree of consistency of the judgment matrix; if $\lambda_{max} = n$, then the judgment matrix is completely consistent. If $\lambda_{max} > n$, there is some inconsistency in the judgment matrix; therefore, the formula for verifying the consistency of the judgment matrix is as shown in Eqs 12, 13:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{12}$$

$$CR = \frac{CI}{RI} \tag{13}$$

where CI is the consistency index, CR is the consistency ratio and RI is the random consistency index, which is obtained based on the

TABLE 1 Data distribution table for new device startup plan.

	Type of line protection	Terminal box replacement type	CT replacement type	Line start type (shock)
quantities	30	100	100	40
Text length	547–937	547–1531	599–1642	430–472
Maximum length of a single sentence	91	117	115	72
Maximum number of device types	3	4	4	2

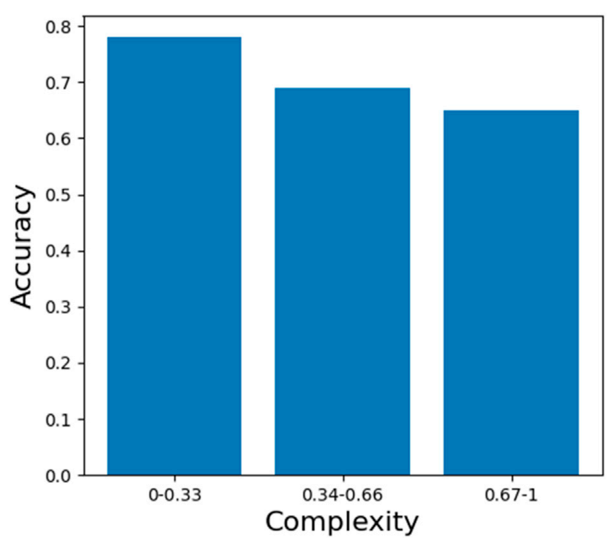


FIGURE 6
Structure of the ERNIE-GEN based scenario generation mode.

average of the random matrix. If CR < 0.1, it means that the consistency of the judgment matrix is acceptable; otherwise, the judgment matrix needs to be modified. Finally, its complexity scplex is calculated using the formula shown in Eq. 14:

$$scplex = W_1{*}num + W_2{*}type + W_3{*}avdg + W_4{*}cluster \quad (14)$$

where num is the total number of startup devices, type is the number of types, avdg is the average degree, cluster is the local clustering coefficient, and W_1, W_2, W_3, and W_4 are the respective coefficients. Finally, the complexity is divided into three types, simple, more complex and complex, and the number of layers of self-attention increases according to the increase in complexity.

3.2 Construction of ERNIE-GEN based scenario generation models

The ERNIE-GEN-based (Xiao et al., 2020) scenario generates the model by inputting the input text as well as the corresponding output text into the model, which is trained. The text is fine-tuned through preprocessing, encoding and decoding, and text generation; based on whether the loss function converges, it is determined whether to make parameter updates.

TABLE 2 Correspondence between program complexity and number of self-attention layers.

	Program complexity		
	0–0.33	0.34–0.66	0.67–1
Number of layers of self-attention	1	2	3

When the model training is complete, the program generation model will receive the information about the equipment to be operated, which is generated by the GATv2-based equipment recognition model combined with the startup scope as the input text, and the equipment information is combined with the correction strategy to generate the startup conditions and startup steps in the startup program. The generated startup conditions and steps, together with the known startup scope, commissioned items, and scheduled startup time, directly form the startup plan for the new equipment in the grid. The structure of the model is schematically shown in Figure 5.

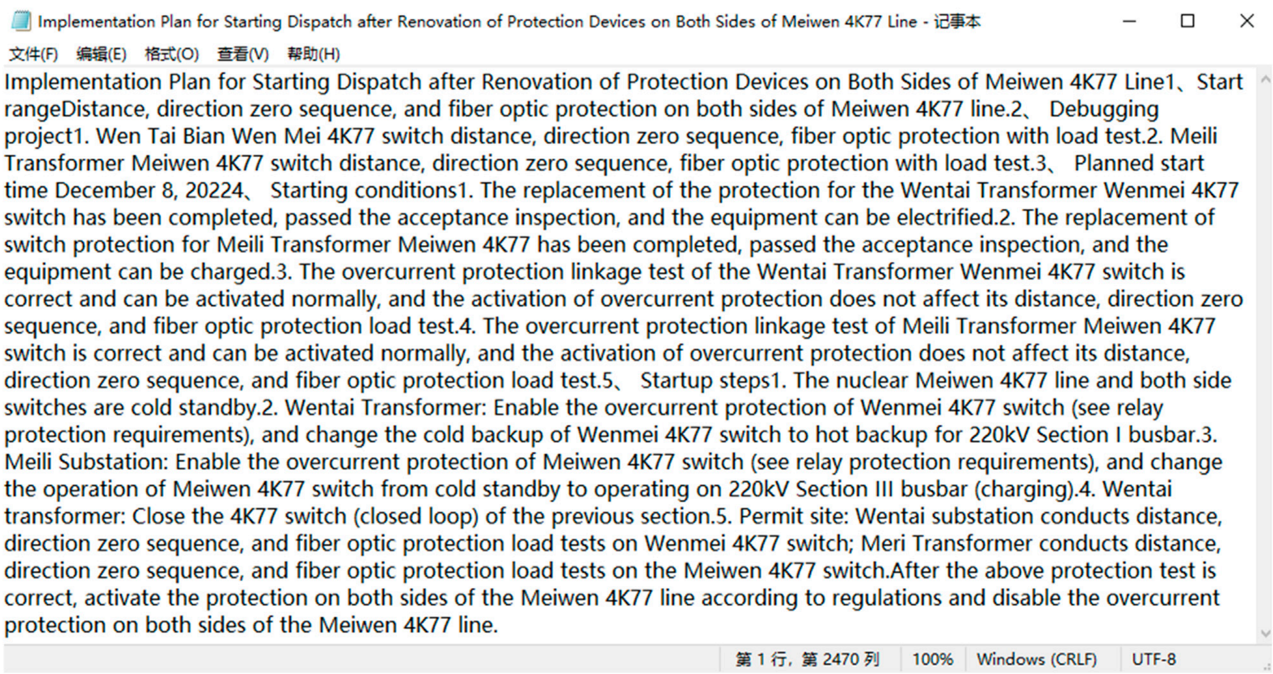
3.2.1 Correction strategy based on device information

The equipment information in the new equipment startup program of the power grid is rigorous, but when generating text based on the equipment information, it is possible that the generation process is not completely rigorous. Therefore, this paper presents a correction strategy based on device information. When the sequence of the generated text output is the device information, it will be directly selected from the information on the devices to be activated, after which the text will be corrected.

4 Case validation

4.1 Case data and simulation

In this paper, according to the actual grid history of a local new grid equipment startup program that is to be verified by offline calculations, the startup program-specific data include the line protection type; terminal box replacement type; CT replacement type; and line startup type (impact), of which there are four. These data are shown in Table 1.


Implementation Plan for Starting Dispatch after Renovation of Protection Devices on Both Sides of Meiwen 4K77 Line - 记事本

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Implementation Plan for Starting Dispatch after Renovation of Protection Devices on Both Sides of Meiwen 4K77 Line1、Start rangeDistance, direction zero sequence, and fiber optic protection on both sides of Meiwen 4K77 line.2、 Debugging project1. Wen Tai Bian Wen Mei 4K77 switch distance, direction zero sequence, fiber optic protection with load test.2. Meili Transformer Meiwen 4K77 switch distance, direction zero sequence, fiber optic protection with load test.3、 Planned start time December 8, 20224、 Starting conditions1. The replacement of the protection for the Wentai Transformer Wenmei 4K77 switch has been completed, passed the acceptance inspection, and the equipment can be electrified.2. The replacement of switch protection for Meili Transformer Meiwen 4K77 has been completed, passed the acceptance inspection, and the equipment can be charged.3. The overcurrent protection linkage test of the Wentai Transformer Wenmei 4K77 switch is correct and can be activated normally, and the activation of overcurrent protection does not affect its distance, direction zero sequence, and fiber optic protection load test.4. The overcurrent protection linkage test of Meili Transformer Meiwen 4K77 switch is correct and can be activated normally, and the activation of overcurrent protection does not affect its distance, direction zero sequence, and fiber optic protection load test.5、 Startup steps1. The nuclear Meiwen 4K77 line and both side switches are cold standby.2. Wentai Transformer: Enable the overcurrent protection of Wenmei 4K77 switch (see relay protection requirements), and change the cold backup of Wenmei 4K77 switch to hot backup for 220kV Section I busbar.3. Meili Substation: Enable the overcurrent protection of Meiwen 4K77 switch (see relay protection requirements), and change the operation of Meiwen 4K77 switch from cold standby to operating on 220kV Section III busbar (charging).4. Wentai transformer: Close the 4K77 switch (closed loop) of the previous section.5. Permit site: Wentai substation conducts distance, direction zero sequence, and fiber optic protection load tests on Wenmei 4K77 switch; Meri Transformer conducts distance, direction zero sequence, and fiber optic protection load tests on the Meiwen 4K77 switch.After the above protection test is correct, activate the protection on both sides of the Meiwen 4K77 line according to regulations and disable the overcurrent protection on both sides of the Meiwen 4K77 line.

第 1 行，第 2470 列 100% Windows (CRLF) UTF-8

FIGURE 7
The generated result diagram of the protection startup scheme on both sides of the Meiwen 4K77 line.

According to each specific startup scenario, the startup range is constructed according to the method in Section 3 based on the device identification model of GATv2 after verifying that it corresponds to the grid topology, and the correspondence between the scenario complexity and the self-attention layer is shown in Table 2.

The samples under each scenario complexity are partitioned at a ratio of 8:2, and the accuracy of the final model obtained for each scenario complexity case is shown in Figure 6.

The information of the equipment to be operated and the range of activation in the activation scheme are taken as input texts, and the activation conditions and steps are taken as the corresponding output texts, and they are corresponded to each other to generate the model training and reading according to the scheme of ERNIE-GEN in Section 3. Since the non-equipment words in the text of the grid new equipment startup program only need to be correct and fluent, there is no strict requirement as in the case of equipment. If the direct use of text similarity detection is difficult to detect whether the semantics of non-equipment vocabulary change, so the generated text is uploaded to the traditional five-proof inspection system for inspection as the accuracy, and finally obtained the accuracy of ERNIE-GEN's program generation model is 0.876,545. One of the new device startup schemes obtained is shown in Figure 7.

4.2 Verification of ablation experiments

To better demonstrate the advantages of the model in addition to the new device startup scheme generation method, this paper focuses on ablation experiments on three strategies, namely, the device type-based coding strategy, the scheme complexity-based self-attention layer selection strategy, and the device information-based correction strategy. For the sake of narrative convenience, the device type-based coding strategy module is denoted as A, the scheme complexity-based self-attention layer selection strategy is denoted as B, and the device information-based correction strategy is denoted as C. Among them, the GATv2-based device recognition model is evaluated using the accuracy rate as the index, and the average accuracy rate of the three different complexity levels is taken as the most useful index; the ERNIE-GEN-based scheme generation model is evaluated using the device name accuracy rate as the accuracy rate. The results are shown in Figure 8.

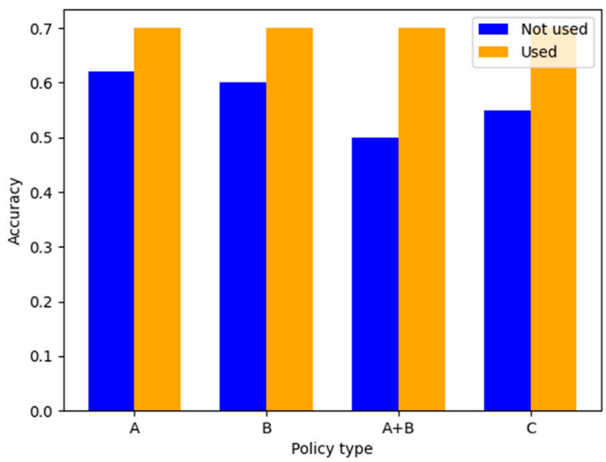

FIGURE 8
Comparison chart of ablation experiment results.

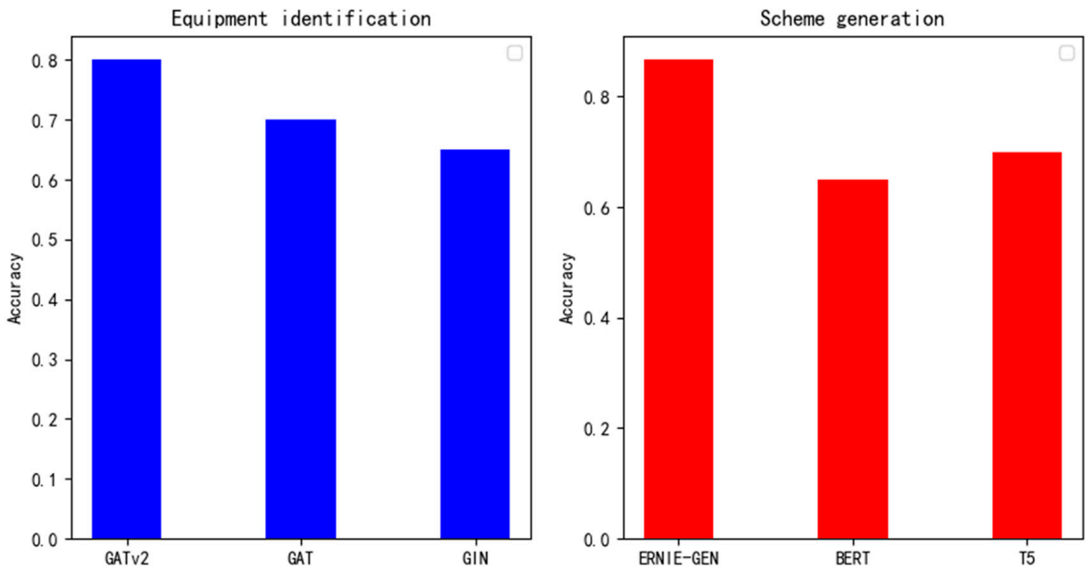

FIGURE 9
Comparison of results from different models.

By analyzing the comparative graphs of the ablation experiment results, we can see that all three strategies achieve better results under the corresponding models. Combining the three characteristics of the new grid equipment startup scheme—strictness variability, information asymmetry, and complexity variability—we can see that the three strategies achieve better performance on the GATv2 model as well as on the ERNIE-GEN model and generate a strict and reasonable new equipment startup scheme.

4.3 Comparison with other models

To further demonstrate the advantages of this model in addition to new grid equipment startup program generation, this paper uses the GAT and GIN models for comparison. Because the GIN model does not have a self-attention layer, only the GAT and GATv2 models are compared using this strategy; similarly, the BERT and T5 models are used to compare the startup scheme generation models, and the results obtained for both are shown in Figure 9.

From the model result comparison diagram, we can easily see that in terms of the device identification model and the generation model, among the models compared in this paper, the proposed model achieved the highest accuracy. Combined with the extremely high accuracy requirements for generating a new grid equipment startup scheme, the fusion topology of the new grid equipment startup scheme in this paper ensures the accuracy of the scheme.

5 Conclusion

With the rapid progress of science and technology, the continuous growth of energy demand, the rapid construction of power grids, and high-speed development, a large number of new equipment requires access to power grids. The rationality of a new grid equipment startup program is related to the safety of the grid as well as the safety of personnel; thus, many countries use new grid equipment programs as grid operation tickets for evaluation.

At present, power grid equipment startup program generation methods are divided into rule-based generation methods and neural network-based deep learning generation methods. Rule-based methods have a certain degree of effectiveness in the regions where they were established, but in general, the rules often need to be revised during migration to other regions. Current generation methods based on neural network deep learning generation, in general, have not been able to avoid this limitation either. Therefore, in this paper, from a practical point of view, we fully consider the difference in rigor, information asymmetry, and difference in complexity of new equipment startup programs for power grids; use the GATv2 model and the ERNIE-GEN model to address the topology and the text, respectively; and fully utilize a coding strategy based on the type of equipment, a self-attention layer selection strategy based on the complexity of the program, and a revision strategy based on the information of the equipment to address the above three characteristics. The model is also verified to be able to efficiently and accurately generate new equipment startup schemes for power grids through actual power grids, ablation experiments are used to verify the efficiency of the three strategies, and model comparison experiments are used to verify the accuracy of the proposed model. The results show that the method proposed in this paper can efficiently and accurately generate new grid equipment startup schemes. This approach provides a new idea for the development of new grid equipment startup schemes through deep learning.

Since the method of this paper uses an offline dataset for training that does not cover all types of new equipment startup scenarios for power grids, When the example model in this article starts scheduling for new types of equipment, such as 220 KV equipment in a certain location, the generated startup plan has a certain deviation from the actual startup party, its training needs to be enhanced for use in real power grids to better utilize the requirements of real power grids for new equipment startup scenario generation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

TM: Writing–original draft. XL: Writing–original draft. XW: Writing–original draft. LW: Writing–original draft, Writing–review and editing. WT: Writing–original draft, Writing–review and editing. LS: Writing–original draft, Writing–review and editing. XG: Writing–original draft, Writing–review and editing.

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Conflict of interest

Authors TM, XL, and XiW were employed by State Grid Shanxi Electric Power Company.

Authors LS and XG were employed by Beijing Kedong Electric Power Control System.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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