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Smart grid power load type forecasting: research on optimization methods of deep learning models

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Introduction: In the field of power systems, power load type prediction is a crucial task. Different types of loads, such as domestic, industrial, commercial, etc., have different energy consumption patterns. Therefore, accurate prediction of load types can help the power system better plan power supply strategies to improve energy utilization and stability. However, this task faces multiple challenges, including the complex topology of the power system, the diversity of time series data, and the correlation between data. With the rapid development of deep learning methods, researchers are beginning to leverage these powerful techniques to address this challenge. This study aims to explore how to optimize deep learning models to improve the accuracy of load type prediction and provide support for efficient energy management and optimization of smart grids.

Methods: In this study, we propose a deep learning method that combines graph convolutional networks (GCN) and sequence-to-sequence (Seq2Seq) models and introduces an attention mechanism. The methodology involves multiple steps: first, we use the GCN encoder to process the topological structure information of the power system and encode node features into a graph data representation. Next, the Seq2Seq decoder takes the historical time series data as the input sequence and generates a prediction sequence of the load type. We then introduced an attention mechanism, which allows the model to dynamically adjust its attention to input data and better capture the relationship between time series data and graph data.

Results: We conducted extensive experimental validation on four different datasets, including the National Grid Electricity Load Dataset, the Canadian Electricity Load Dataset, the United States Electricity Load Dataset, and the International Electricity Load Dataset. Experimental results show that our method achieves significant improvements in load type prediction tasks. It exhibits higher accuracy and robustness compared to traditional methods and single deep learning models. Our approach demonstrates advantages in improving load type prediction accuracy, providing strong support for the future development of the power system.

Discussion: The results of our study highlight the potential of deep learning techniques, specifically the combination of GCN and Seq2Seq models with attention mechanisms, in addressing the challenges of load type prediction in power systems. By improving prediction accuracy and robustness, our approach can contribute to more efficient energy management and the optimization of smart grids.

KEYWORDS

smart grid, deep learning, optimization of intelligent systems, electric load type prediction, multi-source data, data analysis

1 Introduction

With the continuous development of society and the continuous growth of power demand, the power system is rapidly evolving into a more intelligent, efficient and sustainable form. This is the concept of smart grid. Smart grids are not only the future of the power industry, but also the key to solving energy problems, reducing carbon emissions and achieving sustainable development Han et al. (2022). In smart grids, understanding and predicting changes in electrical load types is critical. Electrical load refers to the power consumption pattern in the power system, which usually includes various types of loads such as household, industrial, commercial and agricultural Li et al. (2022a). Each load type has different characteristics and energy consumption patterns. Therefore, accurate prediction of load types can help power systems better plan power supply strategies, improve energy efficiency, reduce costs, and promote sustainable development.

However, the power load type forecasting task faces many challenges. First, the topology of the power system is usually very complex, including various substations, lines, and transmission towers, which results in complex correlations between power load data. Secondly, the diversity of time series data also increases the difficulty of prediction Xu et al. (2021). Different types of loads exhibit different characteristics over different time periods, which requires models to be able to identify and capture these characteristics. In addition, accurate load type forecasting requires consideration of multiple data sources, such as power system topology, historical time series data, etc. How to effectively integrate these data is also a challenge.

To address these challenges, this study focuses on developing a comprehensive deep learning approach to improve the accuracy and robustness of electric load type forecasting. We will combine graph convolutional networks (GCN) and sequence-to-sequence (Seq2Seq) models to introduce attention mechanisms to better understand and predict different types of power loads. The core idea of this method is to effectively integrate information from different data sources so that the model can better understand the complexity and temporal changes of the power system.

Studying methods and technologies for power load type prediction is of great significance to the development of smart grids and energy management. By improving the accuracy of electricity load type predictions, it can help the power system better adapt to the diversity and complexity of energy sources. This helps achieve high reliability, efficiency and sustainability of the power system, reduces resource waste, lowers carbon emissions, and promotes the integration of renewable energy. In addition, this research also provides new technical support for the intelligence and automation of the power system, laying a solid foundation for building a more intelligent power network and social infrastructure.

In research in the fields of smart grid, power load type forecasting, and deep learning, the following models are mainly used for improvement and research and development.

Convolutional neural networks (CNN) are a model that has achieved great success in the field of computer vision, but it also plays an important role in areas such as electric load type forecasting Bhatt et al. (2021). The main feature of CNN is its use of convolutional layers, which enables it to automatically extract spatial features from input data without manually designing a feature extractor. This feature is particularly useful for power load data processing because power load data often contains rich timing information and volatility that differs between different load types Li et al. (2020). In power load type prediction, the application of CNN is mainly reflected in its excellent feature extraction capabilities. CNN can capture these local features through convolution operations to identify patterns of different load types. In addition, CNN can also build hierarchical feature representation through multi-layer convolution and pooling layers, which helps to understand the information in power load data more deeply. The wide application of CNN lies in the adjustment of its convolution kernel size and number to adapt to features of different scales and complexity. In addition, CNN can also be used in conjunction with other deep learning models and techniques, such as recurrent neural networks (RNN) and attention mechanisms, to better capture temporality and correlation between data.

Recurrent neural network (RNN) is a type of deep learning model suitable for sequence data, which is of great value in power load type forecasting tasks. The unique feature of RNN is that it has internal cyclic connections, which allows the model to process variable-length time series data, which is very important for modeling power load data. In power load type forecasting, RNN can be regarded as a sliding window in time, which can capture the dependence between load data at different time points. This is key to understanding the evolution of load types over time Xiao and Zhou (2020). However, traditional RNN is prone to problems such as gradient disappearance or gradient explosion on long sequence data. For this reason, improved RNN models such as gated recurrent unit (GRU) and long short-term memory network (LSTM) have emerged. GRU controls the flow and memory of information by introducing update gates and reset gates to better process time series data Dhruv and Naskar (2020). These improved RNN models perform well in power load type forecasting, especially when long-term dependencies need to be considered. Choosing an appropriate RNN model depends on the characteristics of the data and the requirements of the task to ensure that it can better capture the information of time series data.

Temporal convolutional network (TCN) is a model that combines CNN and RNN, and it has broad application prospects in power load type forecasting. TCN uses convolutional layers to capture the local and global relationships of time series data, avoiding the gradient problem in traditional RNN. This makes TCN ideal for processing long sequences of data, especially when power load type forecasting needs to consider a wider range of historical information Arumugham et al. (2023). The main feature of TCN is that it has an extended receptive field of variable length, which means that the model can effectively capture features at different time scales. In power load type forecasting, different load types may show different patterns on different time scales, so TCN can help the model better adapt to this diversity Fan et al. (2023). In addition, TCN can be combined with other technologies such as attention mechanisms to further improve model performance.

Gated Recurrent Unit (GRU) is an improved RNN model designed to overcome the problems of traditional RNN. The main feature of GRU is that it has update gates and reset gates inside, which allow the model to better control the flow and memory of information Cheon et al. (2020). In power load type forecasting, GRU can be used to capture long-term dependencies of time series data. One of the advantages of GRU is its simplicity and efficiency. Compared with LSTM, GRU has fewer parameters and therefore trains faster Daniels et al. (2020). This makes GRU ideal for processing large-scale time series data. In power load type forecasting tasks, choosing the GRU model can reduce computational costs while maintaining high performance.

Deep reinforcement learning (DRL) is a powerful model whose main feature is to learn optimal decision-making strategies through interaction with the environment. In the field of smart grid, DRL can be used for load management and optimization to achieve the best balance of energy efficiency and power supply stability Leng et al. (2021). The DRL model can dynamically adjust the power supply strategy according to changing power load conditions, thereby improving energy utilization efficiency. Although DRL models generally require more data and computing resources, they perform well in handling complex decision-making problems. In power load type forecasting, DRL can be combined with other deep learning models to achieve higher-level decision-making and control, contributing to the development of smart grids and optimization of power systems Huang et al. (2019). The choice of DRL model usually depends on the complexity of the task and the problem that needs to be solved.

However, there are some shortcomings when applying these models to the study of smart grid power load type prediction problems. Although convolutional neural networks (CNN) are good at extracting spatial features, they have limited modeling of time series data and are difficult to capture dynamic changes in load types. Recurrent neural network (RNN) and its improved models (such as GRU and LSTM) can handle time series data, but are susceptible to problems such as gradient disappearance and gradient explosion, which limit their long-term dependency modeling capabilities. Although temporal convolutional network (TCN) overcomes the gradient problem of RNN, it may not be flexible enough to adapt to different scales of temporal data. Deep reinforcement learning (DRL) requires a large amount of data and computing resources, has challenges in complexity, and is not suitable for all power load type prediction scenarios.

In view of this, we propose a GCN-Seq2Seq model that integrates the attention mechanism. This model combines graph convolutional network (GCN) and sequence-to-sequence model (Seq2Seq), and introduces an attention mechanism, which has the following advantages. First, GCN can effectively capture the complex topology of the power system and help the model understand the relationship between different load types. Secondly, the Seq2Seq model is suitable for sequence generation tasks, mapping historical time series data to load type prediction sequences, and better considering timing. Most importantly, the attention mechanism we introduced enables the model to automatically focus on the most important information, improving the accuracy of predictions. Our model has advantages in comprehensively considering the topology, time series data and correlation of the power system, and is expected to improve the performance and efficiency of power load type prediction, which is beneficial to the development of smart grids and the optimization of power systems.

The main contributions of this study are as follows:

- Proposal of new deep learning model. We propose an innovative deep learning model that combines graph convolutional networks (GCN) and sequence-to-sequence models (Seq2Seq), and introduces an attention mechanism. This model can simultaneously consider the topology and timing data of the power system and automatically capture the correlation of load types, thereby improving the accuracy and accuracy of predictions.
- Research on multi-source data fusion. We apply multi-source data fusion to the power load type prediction task, taking into account the topological information and historical time series data of the power system. This data fusion method is expected to improve the robustness and accuracy of load type forecasting and provide more comprehensive information for intelligent management of power systems.
- Promote the sustainable development of smart grids. The results of this study are expected to contribute to the sustainable development of smart grids and efficient management of power systems. Through more accurate load type forecasting, the power system can better adapt to changing demands, improve the reliability and efficiency of power supply, and also provide strong support for the development of sustainable energy integration and smart grids.

In the following sections, we summarize all the model diagrams involved in this study, as well as the data analysis diagrams in Part II. In the third part, we introduce in detail the deep learning model we proposed, that is, the GCN-Seq2Seq model incorporating the attention mechanism, and elaborate on the structure diagram and basic principles of the model. The fourth part is our experiment, which introduces the data sets used in this study, the detailed experimental settings and the analysis of experimental results. The fifth part is the conclusion and summary of the full text. We also describe the shortcomings of this study and the next research direction.

2 Related work

2.1 Intelligent power system

As an innovative field in the power industry, smart power systems cover a series of advanced technologies and concepts, aiming to improve the intelligence, efficiency and sustainability of the power system. The basic concept includes real-time monitoring, control and optimization of power networks to better meet growing power demand. The origins of smart power systems can be traced back to the digital transformation of traditional power systems. With the continuous advancement of information technology, smart power systems have gradually evolved into a complex network that integrates elements such as advanced sensors, communication technology, data analysis, and artificial intelligence to make the power system more flexible and intelligent.

In the field of smart power and energy management, recent research demonstrates the rise of hybrid technology solutions that focus on improving operational efficiency and system resilience against potential risks. A study proposes a reinforcement learning-based energy management system designed to optimize the performance of fuel cell and battery hybrid electric vehicles Reddy et al. (2019). The core of the system is to dynamically adjust the distribution of electric energy, showing the possibility of improving energy efficiency under changing risk conditions. In response to smart grid security issues, especially the threat of denial of service (DoS) attacks, some research has developed a distributed control mechanism. This mechanism combines the system's communication capabilities and control responses to ensure the stability of grid dispatch and operation even in the event of a cyber attack Li et al. (2022b). In addition, for microgrid energy management issues, the latest research introduces a distributed energy management framework to complete dual-mode energy distribution within a predetermined time through event-triggered communication technology. This method can effectively deal with communication delays and ensure the accuracy and reliability of energy distribution Liu et al. (2023). These studies as a whole reflect that the methods used by intelligent systems to improve performance and security are becoming increasingly complex, and interdisciplinary technology integration is a significant trend in current development. From reinforcement learning algorithms to the application of advanced communication protocols, it reflects important steps taken in smart energy distribution and power grid management.

However, smart power systems also face some challenges. Especially in terms of power load type forecasting, challenges mainly include the complex topology of the power system, the diversity of time series data, and the correlation between data. Addressing these challenges is crucial to achieve comprehensive optimization of smart power systems and improve power load type forecast accuracy.

2.2 Deep learning technology

Deep learning technology has achieved remarkable application results in the field of power systems, providing strong support for the intelligence and efficiency of power systems. In terms of power load forecasting, deep learning algorithms can be used to learn and model historical load data to achieve accurate predictions of future power loads. In terms of power system optimization, deep learning technology is used to learn the topology structure and operating status of the power system to achieve real-time optimal dispatch of the power system Ibrahim et al. (2020). In terms of smart grid management, deep learning technology is used to process a large amount of time series data in the power grid, which can realize real-time monitoring, fault detection and intelligent dispatching of the power grid. In terms of power load forecasting, deep learning technology has been successful in many cases. For example, in the power load forecasting of the State Grid, deep learning methods achieve highly accurate load forecasting by learning the complex spatiotemporal relationships of the power system, providing an important basis for reasonable dispatch of the power system O'Dwyer et al. (2019). In terms of power system optimization, deep learning technology has also shown strong capabilities. By training large-scale data from the power system, deep learning models can better understand the modes and trends of system operation, thereby achieving intelligent scheduling and optimization of the system.

Compared with traditional methods, deep learning technology has significant advantages. Deep learning models can learn and capture the complex spatiotemporal relationships in power systems and better adapt to the nonlinear characteristics of the system. Deep learning models can achieve end-to-end learning, learn feature representations directly from raw data, without the need to manually extract features, and improve the generalization ability of the model Zhang et al. (2019). The deep learning model can automatically adjust model parameters to adapt to the characteristics of different power systems, and has stronger adaptability and generalization capabilities.

Although deep learning has achieved remarkable results in power systems, it still faces some challenges. Issues such as power system complexity, data uncertainty, and model interpretability remain the focus of current research. The reason for choosing the deep learning method in this study is its advantages in processing large-scale data, learning complex relationships, and adapting to uncertainty.

2.3 Optimizing deep learning models

In terms of optimization of deep learning models, a variety of methods have emerged in recent years, especially in applications in the field of power systems, including transfer learning, reinforcement learning, hyperparameter optimization, adversarial training, etc. Transfer learning uses the knowledge learned on one task to help learn on another related task. Transfer learning can reduce the dependence on a large amount of annotated data and improve the generalization of the model Hafeez et al. (2020). The introduction of reinforcement learning methods allows the model to optimize its own performance through interaction with the environment, which is particularly suitable for real-time dispatch and control problems in power systems. Optimizing the hyperparameters of deep learning models through search algorithms or adaptive methods can improve the performance and robustness of the model. Introducing adversarial training enables the model to better cope with perturbations and attacks on input data, and improves the robustness of the model.

Optimization schemes based on meta-learning have been applied to deep learning models, especially in the field of power systems. This method has confirmed its effectiveness in improving model performance between different systems through the practice of transfer learning Zhou et al. (2020). At the same time,

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reinforcement learning technology also shows great potential in load forecasting. It can enhance the model's adaptability to complex changes by reproducing different load conditions in a simulated environment. In addition, the introduction of adversarial training is regarded as an important development in the field of power system security. Adversarial samples are added to improve the system's ability to identify network attacks, thereby enhancing the defense mechanism Ye et al. (2020). These research results provide a wealth of ideas and methods for optimizing deep learning models, and provide a reference for our optimization of deep learning models in power load type forecasting.

3 Methodology

3.1 Overview of our network

For the power load type prediction problem, significant progress has been made in the application of deep learning technology in smart power systems and related work in model optimization. In order to further improve the prediction accuracy, this study adopts an overall model that integrates graph convolution network (GCN) and sequence-to-sequence model (Seq2Seq), and introduces an attention mechanism to solve the problem of smart grid power load type prediction. This model was chosen due to considerations of the complexity and diversity of power systems and the need for accuracy and global information capture. The basic principle of this overall model is to view the power system as a graph structure, where nodes represent specific time points of load data and edges represent topological relationships between nodes. First, through the GCN encoder, the model can effectively capture the topological information of the power system and represent the node features into the encoding of graph data. Next, the Seq2Seq decoder accepts historical time series data as an input sequence and generates a load type prediction sequence. In this process, an attention mechanism is introduced, allowing the model to fuse information based on the importance of different input data and better understand the relationship between time series data and graph data. The advantages of this model are obvious. First, it can comprehensively consider the topology and timing data of the power system while automatically capturing the correlation between different load types, thereby improving the accuracy of prediction. Secondly, the introduction of the attention mechanism enables the model to focus on the most important information for the current prediction, further improving the model performance. Most importantly, the comprehensiveness and global information capturing capabilities of this model are expected to provide a more powerful tool for intelligent management of power systems and forecasting of power load types.

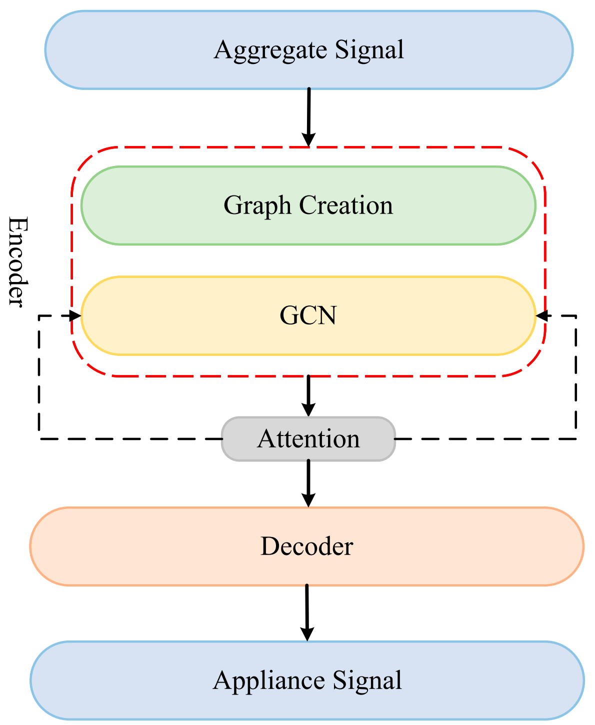

FIGURE 1
Overall flow chart of the model.

Input: Training data: X, Y
Output: Trained GCN-Seq2Seq model
Initialize model parameters Θ randomly;
Initialize learning rate α;
Initialize loss function: $Loss = 0$;
while *not converged* **do**
Sample a batch of training examples $(x_i, y_i) \sim (X, Y)$;
Calculate forward pass through GCN-Seq2Seq model:

$$h_i = GCN(x_i, A)$$
$$\hat{y}_i = Seq2Seq(h_i)$$

Calculate loss:

$$Loss_i = CrossEntropy(\hat{y}_i, y_i)$$
$$Loss = Loss + Loss_i$$

Update model parameters with backpropagation:

$$\Theta = \Theta - \alpha \nabla_\Theta Loss$$

end
Evaluation:
for *each evaluation batch* $(x_e, y_e) \sim (X_{eval}, Y_{eval})$ **do**
Calculate prediction $\hat{y}_e$ using the trained model;
Calculate Recall, Precision, and other evaluation metrics using $\hat{y}_e$ and y_e
end
return *Trained GCN-Seq2Seq model*

Algorithm 1. GCN-Seq2Seq Training.

The structure diagram of the overall model is shown in Figure 1, which shows the relationship between the GCN encoder, Seq2Seq decoder and attention mechanism, forming a comprehensive power load type prediction model.

The running process of the GCN-Seq2Seq model is shown in Algorithm 1.

3.2 Graph convolutional network model

In the model of this study, the graph convolutional network (GCN) is a key component used to process the topological structure information of the power system Hossain and Rahnamay-Naeini (2021). The basic principle of GCN is to capture the relationship between nodes in graph data through effective information transfer Peng et al. (2023), and then encode the features of the nodes Chen et al. (2022). In the overall model, the role of GCN is to treat the power system as a graph structure, in which the nodes of the graph represent load data at different time points, and the edges represent topological relationships between nodes, such

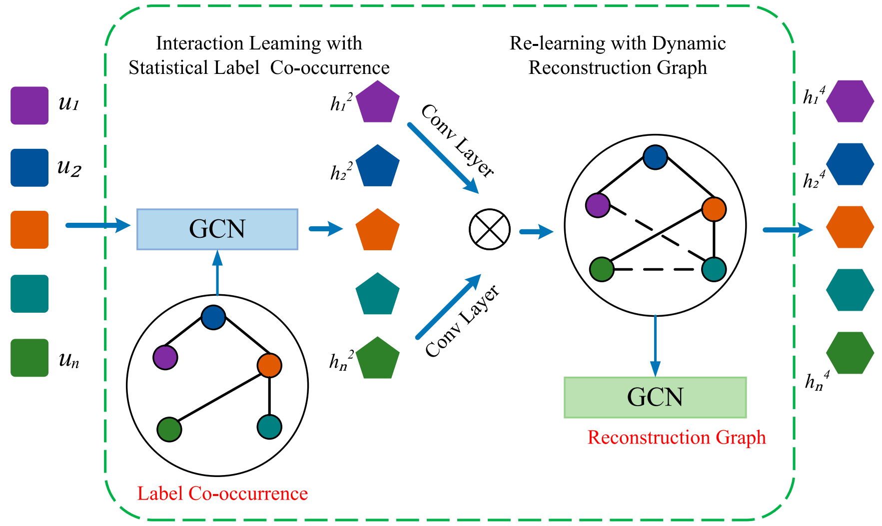

FIGURE 2
Flow chart of the GCN model.

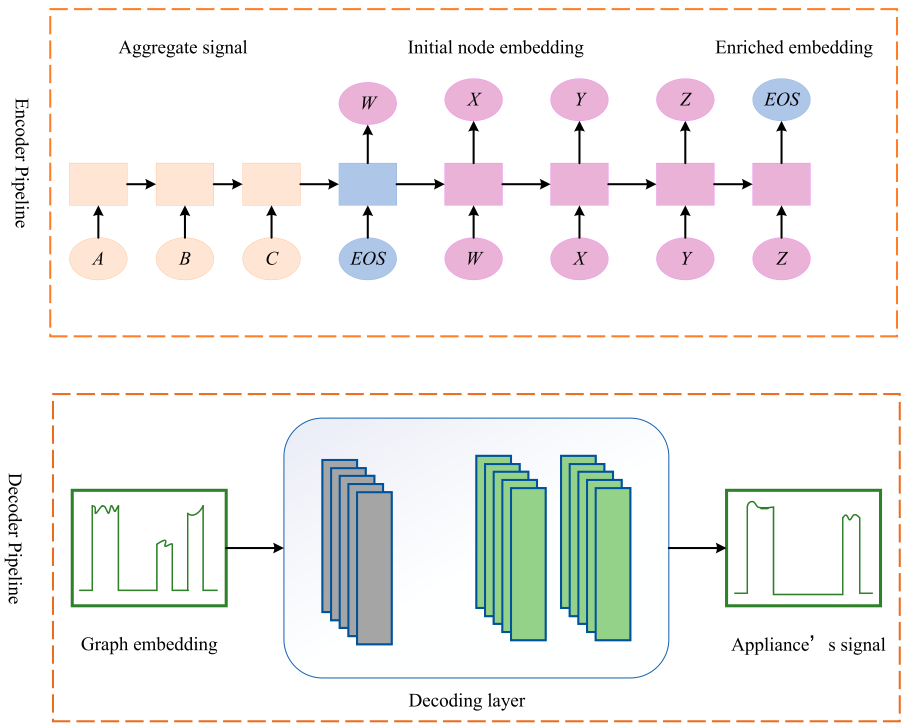

FIGURE 3
Flow chart of the Seq2Seq model.

as connection relationships. These nodes and edges constitute the topological information of the power system. The advantage of GCN in power system modeling is mainly reflected in its effective processing of complex topological structures. Compared with traditional methods, GCN can capture the relationship between nodes more comprehensively and achieve a high degree of abstraction and expression of the power system topology. Through an iterative information transfer process, GCN is able to update the characteristics of each node to the weighted average of the characteristics of its neighboring nodes, effectively integrating topological relationships into feature representation. This enables the model to better understand the interactions and correlations between different nodes in the power system, thereby improving the accuracy of load type predictions. Specifically, the ability of GCN lies in encoding the node information of the power system so that the model can better understand the spatiotemporal relationship

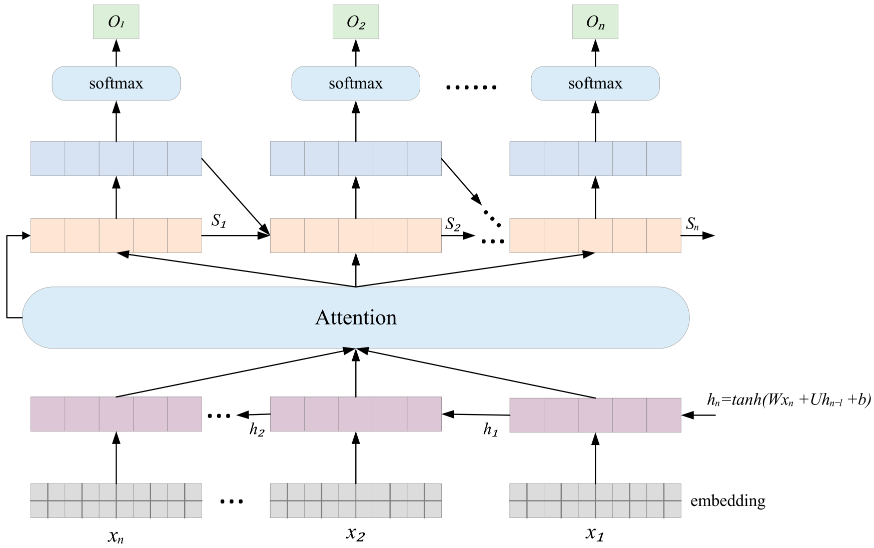

FIGURE 4
Flow chart of the Attention model.

between load data. This specific treatment of topology helps the model more accurately capture the energy consumption patterns of different types of loads, providing a stronger basis for prediction tasks.

The operation process of GCN Model is shown in Figure 2.

The main formula of GCN Model is as follows:

$$H^{(l+1)} = \sigma\left(\widehat{D}^{-\frac{1}{2}}\widehat{A}\widehat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{1}$$

Here, $H^{(l)}$ Represents the node feature matrix for layer l. *sigma* Denotes the activation function, typically using ReLU, etc. *hatA* Indicates the symmetrically normalized adjacency matrix. *hatD* Represents the diagonal matrix of node degrees. $W^{(l)}$ Stands for the weight matrix for layer l.

In this formula, GCN gradually updates the feature representation of nodes through a multi-layer information transfer process, so that each node contains information about its surrounding nodes, thereby taking into account the influence of topological relationships. In the overall model, the role of GCN is to encode the topological structure information of the power system into a more information-rich feature representation, providing important basic information for subsequent load type prediction. Through the use of GCN, the model can better understand the relationship between nodes in the power system and improve the modeling ability of load type prediction problems. This is of great significance for comprehensively considering the complexity and diversity of the power system, thereby improving the accuracy of prediction and the ability to capture global information.

3.3 Sequence-to-sequence model

In our model, the Seq2Seq model (Sequence-to-Sequence model) is a key component for processing time series data and load type forecasting tasks Xiong et al. (2021). The basic principle of the Seq2Seq model is to map the input temporal sequence to the output sequence through an encoder-decoder structure, while retaining and delivering key contextual information Takiddin et al. (2022). The role of the Seq2Seq model in the overall model approach is to take historical time series load data as the input sequence, and then generate the corresponding load type prediction sequence. The key to this process is to encode the rich information of the timing data into a fixed-length vector representation, which is then passed through a decoder to generate a sequence of load types. The encoder of the Seq2Seq model can effectively capture patterns and trends in historical time series data, while the decoder converts this information into load-type predictions Le et al. (2021). The encoder of the Seq2Seq model has excellent capabilities and can effectively capture patterns and trends in historical time series data. By learning representations of historical load data, the encoder is able to extract key temporal features, allowing the model to better understand the information required for load type forecasting tasks. This feature encoding method helps capture the complex relationships between load data, making the model more flexible and accurate when processing time series information. On the other hand, the decoder of the Seq2Seq model is able to effectively utilize the contextual information passed by the encoder when generating load type prediction sequences. By incorporating historical timing correlations into the generation process, the decoder is able to more accurately predict future load types. This end-to-end sequence modeling approach enables the model to perform well in load type prediction tasks, with higher accuracy and robustness compared to traditional methods and single deep learning models.

The operation process of Seq2Seq model is shown in Figure 3.

The main formula of Seq2Seq Model is as follows:

$$h_t = \text{Encoder}\left(x_t, h_{t-1}\right) \tag{2}$$

$$y_t = \text{Decoder}\left(h_t, y_{t-1}\right) \tag{3}$$

Here, h_t represents the hidden state of the encoder, which captures the information in the input sequence x_t and passes it to

TABLE 1 The comparison of different models in different indicators comes from National Grid Electricity Load Dataset, Canadian Electricity Load Dataset, U.S. Electricity Load Dataset and International Electricity Load Dataset.

Model	Datasets															
	National grid electricity load dataset				Canadian electricity load dataset				U.S. Electricity load dataset				International electricity load dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
Wang et al. (2020)	85.37	88.53	85.77	92.21	89.61	91.31	85.47	89.62	96.18	83.14	81.27	87.18	90.46	86.03	84.18	87.40
Mohammadi (2021)	84.43	90.54	88.01	91.33	90.49	84.77	83.87	91.92	86.83	90.44	83.13	86.15	93.26	84.27	91.79	89.77
Alotaibi et al. (2020)	86.27	84.74	82.42	83.91	89.11	87.83	93.21	88.75	96.45	85.19	90.91	89.19	86.95	88.49	88.24	92.31
Alladi et al. (2019)	86.09	91.27	87.89	92.73	88.63	89.49	89.06	84.51	91.60	89.51	85.19	90.82	87.14	91.31	84.89	93.18
Hui et al. (2020)	87.41	89.38	83.71	91.15	87.40	92.31	90.78	93.04	88.87	87.79	85.75	87.34	90.65	85.39	88.21	92.75
Al-Badi et al. (2020)	86.26	91.46	81.13	94.41	96.10	90.63	85.07	91.81	87.90	92.89	85.08	89.92	92.58	87.19	89.76	91.71
Ours	**96.22**	**93.54**	**91.06**	**94.45**	**97.11**	**94.53**	**91.46**	**95.17**	**95.63**	**97.55**	**94.87**	**97.37**	**96.24**	**97.43**	**94.84**	**98.46**

the decoder. y_t represents the output of the decoder, which is the predicted result of the load type. x_t represents the time series data for each time step of the input sequence. h_{t-1} and y_{t-1} represent the encoder hidden state and decoder output of the previous time step, respectively, for context transfer.

The encoder of the Seq2Seq model gradually encodes the historical time series data into hidden states h_t, and passes these hidden states to the decoder, which generates a sequence of load type predictions based on the hidden states. This process allows the model to make accurate load type predictions based on historical data and contextual information. The application of this model in this study plays a key role in helping the model better understand time series data, thereby improving the accuracy of load type prediction and global information capture capabilities.

3.4 Attention mechanism

In our model, the attention mechanism is a key component used to enhance modeling of the relationship between time series data and graph data Li et al. (2022c). The basic principle of this mechanism is to introduce a weight allocation mechanism in the encoder-decoder structure so that the model can focus on the information most relevant to the current prediction when generating load type predictions Massaoudi et al. (2021). In the overall model, the role of the attention mechanism is to enable the model to perform information fusion and selection based on the importance of different input data, thereby improving the accuracy of load type prediction. This mechanism dynamically adjusts the weight of the encoder output through the learned weight, allowing the model to more effectively capture the relationship between time series data and graph data, helping to improve prediction performance Zhang et al. (2020). The advantage of the attention mechanism is that it allows the model to be more flexible and intelligent when processing complex time series data and graph data. By introducing a weight allocation mechanism, the model is able to selectively focus on the part of the historical data that is relevant to the current prediction when predicting the load type at each time point. This dynamic adjustment feature enables the model to better adapt to changes in data distribution at different time points, improving the modeling capabilities of time series and graph data. In addition, the application of attention mechanism helps to improve the model's understanding of the complex topology of the power system, making it more sensitive to capture the correlation between nodes. In models that incorporate attention mechanisms, more targeted attention to key information helps optimize load type prediction performance.

The operation process of Attention Mechanism is shown in Figure 4.

The main formula of Attention Mechanism is as follows:

$$\alpha_{tj} = \frac{\exp\left(e_{tj}\right)}{\sum_{k=1}^{T} \exp\left(e_{tk}\right)} \tag{4}$$

$$c_t = \sum_{j=1}^{T} \alpha_{tj} \cdot h_j \tag{5}$$

$$a_t = \text{Attention}\left(h_t, c_t\right) \tag{6}$$

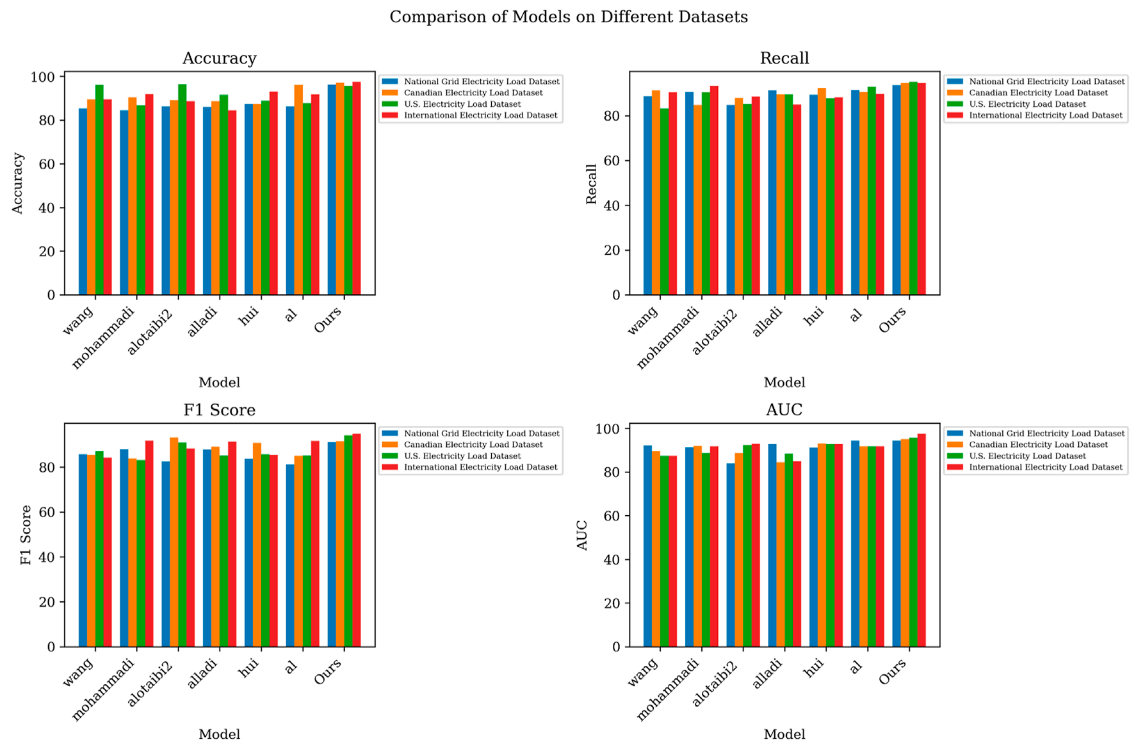

FIGURE 5
Comparison of model performance on different datasets.

Here, Q represents the attention weight of time step Q to time step Q, which is used to measure the importance of different time steps in time series data. Q represents the score for calculating the attention weight, usually obtained using inner product or other methods. Q represents the context vector at time step Q, which is obtained by weighted summation of the encoder output Q according to the attention weights. Q represents the output after applying attention, which is used for load type prediction.

The formulation of the attention mechanism describes how to calculate attention weights, context vectors, and apply attention to improve load type prediction. This mechanism plays a key role in the entire model and helps the model better understand and utilize the correlation between input data.

4 Experiment

4.1 Experimental environment

- Hardware Environment

The hardware environment used in the experiments consists of a high-performance computing server equipped with an AMD Ryzen Threadripper 3990X @ 3.70 GHz CPU and 1TB RAM, along with 6 Nvidia GeForce RTX 3090 24 GB GPUs. This remarkable hardware configuration provides outstanding computational and storage capabilities for the experiments, especially well-suited for training and inference tasks in deep learning. It effectively accelerates the model training process, ensuring efficient experimentation and rapid convergence.

- Software Environment

In this study, we utilized Python and PyTorch to implement our research work. Python, serving as the primary programming language, provided us with a flexible development environment. PyTorch, as the main deep learning framework, offered powerful tools for model construction and training. Leveraging PyTorch's computational capabilities and automatic differentiation functionality, we were able to efficiently develop, optimize, and train our models, thereby achieving better results in the experiments.

4.2 Experimental datasets

This paper mainly uses the following four data sets to study the problem of smart grid power load type prediction.

National Grid Electricity Load Dataset is a very important data set that provides key information for electric load forecasting research. The source of this data set is the State Grid of China, the largest domestic electricity supplier and operator in China. Data is carefully collected and maintained to ensure accuracy and reliability Zhang and Hong (2019). The data set includes multiple years of history, ranging from the past few years up to the most recent electricity load data. This long time span of data allows researchers to analyze seasonal and cyclical changes in electrical loads. The dataset covers different regions within China,

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TABLE 2 The comparison of different models in different indicators comes from National Grid Electricity Load Dataset, Canadian Electricity Load Dataset, U.S. Electricity Load Dataset and International Electricity Load Dataset.

Method	Dataset															
	National grid electricity load dataset				Canadian electricity load dataset				U.S. Electricity load dataset				International electricity load dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time(s)	Parameters (M)	Flops (G)	Inferer Time (ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time(s)	Parameter (M)	Flops (G)	Inference Time (ms)	Training Time(s)
Wang et al. (2020)	367.46	218.53	353.56	356.53	331.13	272.29	349.21	260.46	286.15	238.48	226.97	328.77	272.92	255.75	321.74	321.48
Mohammadi (2021)	317.32	372.23	260.66	395.46	246.31	302.46	365.15	256.97	368.13	268.62	315.85	384.36	312.48	323.29	282.64	437.58
Alotaibi et al. (2020)	233.02	335.08	221.69	391.96	246.57	243.24	238.71	263.57	278.69	301.23	274.23	243.44	328.15	367.46	323.94	403.16
Alladi et al. (2019)	377.90	331.40	221.68	292.55	254.69	341.02	300.53	378.02	311.13	352.42	336.24	388.45	254.93	221.21	284.30	342.21
Hui et al. (2020)	364.86	216.82	351.79	219.93	235.27	205.14	384.18	254.49	284.02	393.12	334.41	218.72	277.72	291.13	286.52	361.66
Al-Badi et al. (2020)	352.07	374.63	221.36	318.28	308.49	214.32	395.20	346.63	224.08	391.79	226.52	300.86	343.67	293.43	388.01	207.65
Ours	**155.22**	**131.23**	**228.77**	**241.43**	**240.17**	**213.87**	**139.59**	**159.33**	**156.57**	**169.47**	**197.89**	**157.64**	**231.01**	**219.01**	**215.05**	**235.17**

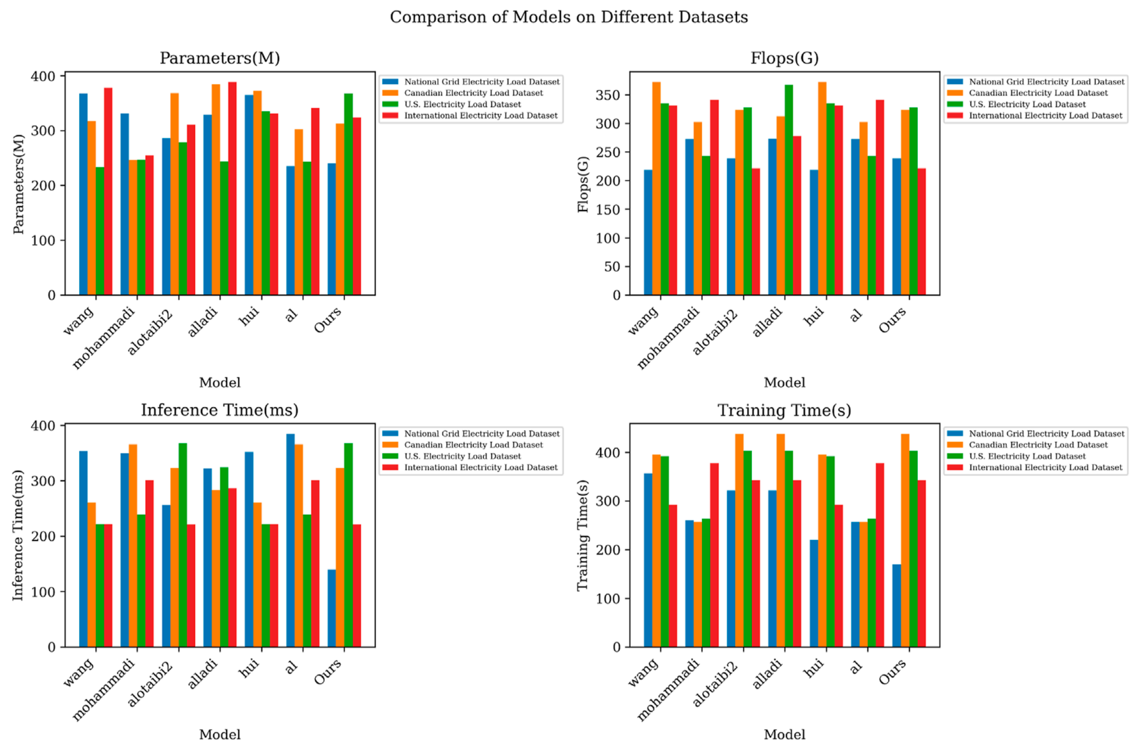

FIGURE 6
Comparison of model performance on different datasets.

including urban and rural areas. This covers China's wide range of geographical and climatic conditions, providing diversity for research. The importance of the National Grid Electricity Load Dataset cannot be underestimated. As data from the State Grid of China, it provides an opportunity to gain in-depth understanding of China's power system operations and load changes. This dataset is critical for power load type forecasting research as it contains rich information that helps researchers understand load patterns in different regions and seasons. In addition, as one of the world's largest electricity consumers, research on China's power system is of great significance to global power management and sustainable development.

Canadian Electricity Load Dataset is an important data resource that provides key information for electricity load forecasting studies. Sources for this data set include the Canadian government and electric utilities across Canada. These agencies are responsible for collecting and maintaining electrical load data to ensure data accuracy and availability. The Canadian Electricity Load Dataset covers multiple years of history, including the past few years up to the latest electrical load data. This long time span of data allows researchers to analyze seasonal and cyclical changes in electricity loads, as well as their evolution over time Iqbal et al. (2021). The dataset covers every province and city in Canada, including places with different climates and electricity needs. Due to Canada's geographical differences and climate diversity, this dataset is diverse and covers electricity load conditions under different conditions. Canadian Electricity Load Dataset is important in the study of electric load type forecasting. First, Canada is a geographically vast country with a variety of climatic and topographic conditions, so this dataset provides information on electricity load characteristics under different meteorological and geographical conditions. Second, this dataset reflects the operation of the Canadian power system, which is critical for power load management and power system optimization. Most importantly, as a developed country, Canada's power system is modern and complex, so the study of power load type forecasting problems has special value.

U.S. Electricity Load Dataset is an important data resource that provides key information for electric load forecasting research. Sources for this data set include the U.S. Energy Information Administration (EIA) and various U.S. power companies Lv et al. (2021). These agencies collect and maintain electrical load data to ensure data accuracy and availability. The U.S. Electricity Load Dataset covers many years of history, ranging from the past few years up to the latest electricity load data. This long time span of data allows researchers to analyze seasonal and cyclical changes in electricity loads, as well as their evolution over time. The dataset covers every state and city in the United States, including places with different climates and electricity needs. As a country with geographical diversity and variable climate, the United States has diverse power load data, covering power load conditions under different conditions. The U.S. Electricity Load Dataset is important in power load type forecasting research, providing information on power load characteristics under different meteorological and geographical conditions, reflecting the dynamics of large-scale power supply and demand.

International Electricity Load Dataset brings together data from the International Energy Agency (IEA) and electricity companies

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TABLE 3 Ablation experiments on the GCN-Seq2Seq module comes from National Grid Electricity Load Dataset, Canadian Electricity Load Dataset, U.S. Electricity Load Dataset and International Electricity Load Dataset.

Model	Datasets															
	National grid electricity load dataset				Canadian electricity load dataset				U.S. Electricity load dataset				International electricity load dataset			
	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC	Accuracy	Recall	F1 score	AUC
RNN	86.65	89.36	85.04	88.27	90.66	89.17	86.61	91.78	95.78	85.53	86.28	86.5	93.26	87.46	91.79	93.49
Resnet50	93.54	92.81	89.93	85.55	90.44	85.62	84.66	94.02	95.12	86.25	89.35	89.89	90.61	86.86	87.03	89.37
Resnet18	89.57	94.27	87.25	87.93	88.83	91.38	90.02	90.14	94.35	93.78	86.15	93.43	91.47	94.61	86.96	88.74
GCN-Seq2Seq	**97.48**	**93.62**	**93.82**	**93.61**	**97.91**	**94.88**	**94.75**	**95.59**	**98.21**	**95.39**	**93.59**	**92.78**	**97.95**	**95.67**	**94.5**	**96.24**

in various countries and regions. The IEA is responsible for coordinating and collecting electricity load data in various countries to ensure the accuracy and availability of data. It covers many years of history, from the past few years up to the latest electrical load data. This long time span of data allows researchers to analyze seasonal and cyclical changes in electricity load, as well as electricity load trends on a global scale Ahmad et al. (2020). The dataset has a global geographical scope, covering multiple countries and regions. This makes it a diverse and comprehensive data resource, including places with different climates, cultures and power system characteristics. International Electricity Load Dataset is important in electric load type forecasting research. First, it reflects the operation of power systems in different countries and regions, providing key information for power load management and optimization on a global scale. Secondly, because it covers multiple countries and regions, this data set helps study cross-border power load forecasting problems and promotes international cooperation and knowledge sharing.

4.3 Experimental setup and details

This study uses the GCN-Seq2Seq model integrated with the attention mechanism to study the problem of smart grid power load type prediction. To ensure accuracy and reproducibility, experimental details need to be carefully designed. The experimental setup and details are as follows:

Step 1: Dataset preparation.

- Data sources: The four data sets come from the State Grid of China, the Canadian government and power companies, the U.S. Energy Information Administration (EIA), and the International Energy Agency (IEA). These datasets are historical power load information collected from different power systems.
- Time span: The data set covers many years of historical data, ranging from a few years to a few decades, to ensure that power load data under a variety of seasons and meteorological conditions are included.
- Geographic scope: These data sets cover different geographical scopes, including various regions in China, different regions in Canada, states and cities in the United States, as well as electricity load data on a global scale.
- Data cleaning and preprocessing: Before using the data, data cleaning and preprocessing are required, including removing missing values, processing outliers, data standardization, etc., to ensure the quality and consistency of the data.
- Data set division: The data set will be divided into a training set, a validation set and a test set. Usually 70% of the data is used for training, 15% is used for validation, and 15% is used for testing. This helps evaluate the performance and generalization ability of the model.

Step 2: Model selection and hyperparameter tuning.

- Model selection: We will consider using GCN, Seq2Seq, and overall models that introduce attention mechanisms. These

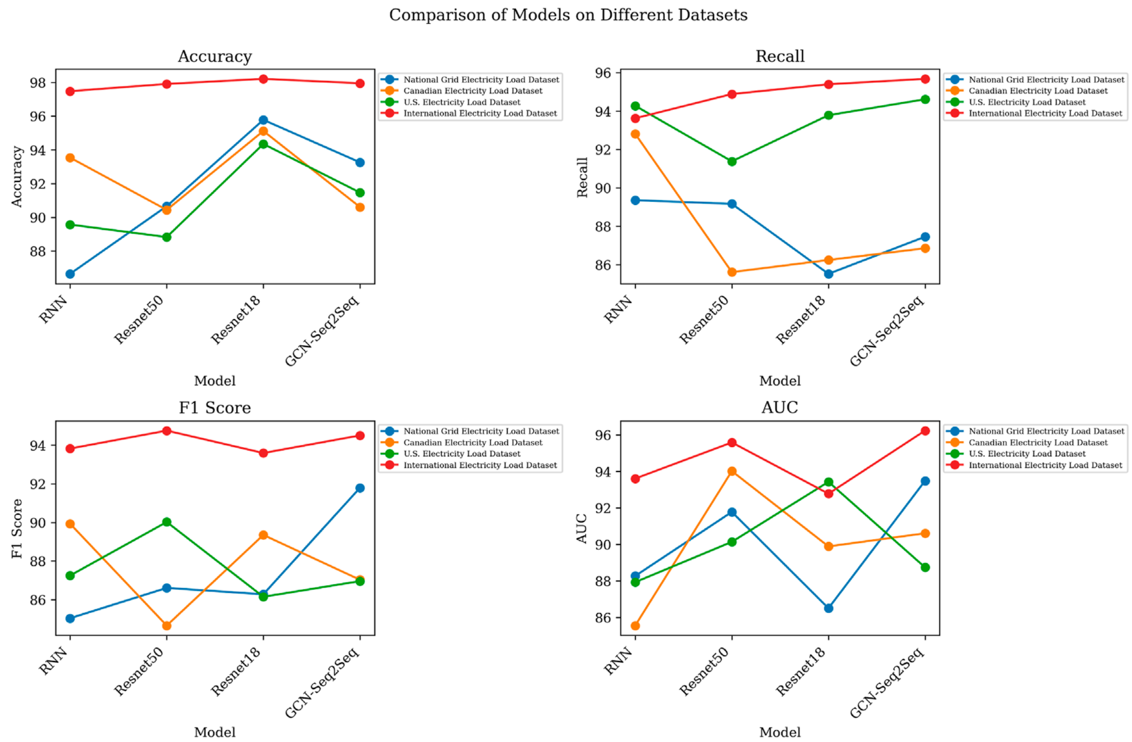

FIGURE 7
Comparison of model performance on different datasets.

models were chosen because of their advantages in processing graph data and time series data.

- Hyperparameter adjustment: In the experiment, we will perform hyperparameter adjustment, including the selection of key parameters such as learning rate, batch size, hidden layer size, and attention weight. We will use cross-validation to evaluate the performance of different hyperparameter settings.

Step 3: Model training process.

- GCN model training: For the GCN model, we will build the graph structure of the power system and use the adjacency matrix for training. GCN will utilize node features and graph structure information for training.
- Seq2Seq model training: For the Seq2Seq model, we will prepare time series data, including historical power load data as the input sequence, and load type as the output sequence. The Seq2Seq model will be trained using an encoder-decoder structure to learn load-type patterns.
- Holistic model training: In the holistic model, we will consider both the graph structure and the time series data of the power system. Attention mechanism will be used to capture the relationship between them. The overall model will be trained taking both data into account.

Step 4: Loss function and evaluation metrics.

- Loss function: We will choose an appropriate loss function to measure the performance of the model, depending on the nature of the problem. For classification tasks, the categorical cross-entropy loss function or the mean square error loss function is usually chosen.
- Evaluation metrics: We will use a series of evaluation metrics to measure the performance of the model, including accuracy, precision, recall, F1 score, etc. These metrics will be used for performance evaluation on the validation and test sets.

Step 5: Experimental Design.

- Ablation experiments: We will conduct ablation experiments to gradually evaluate the impact of each component of the model on overall performance. For example, we will study how the model performs without using the attention mechanism.
- Comparative experiments: We will conduct comparative experiments to compare and analyze our model with other commonly used deep learning models (such as CNN, RNN, TCN, GRU, DRL) to determine the superiority of our model.

Step 6: Results Analysis and Visualization.

- We will conduct a detailed analysis of the experimental results, comparing the performance of different models, the impact of hyperparameter settings, and performance on different data sets. We will use visualization tools to present key results to help gain insight into the model's behavior.

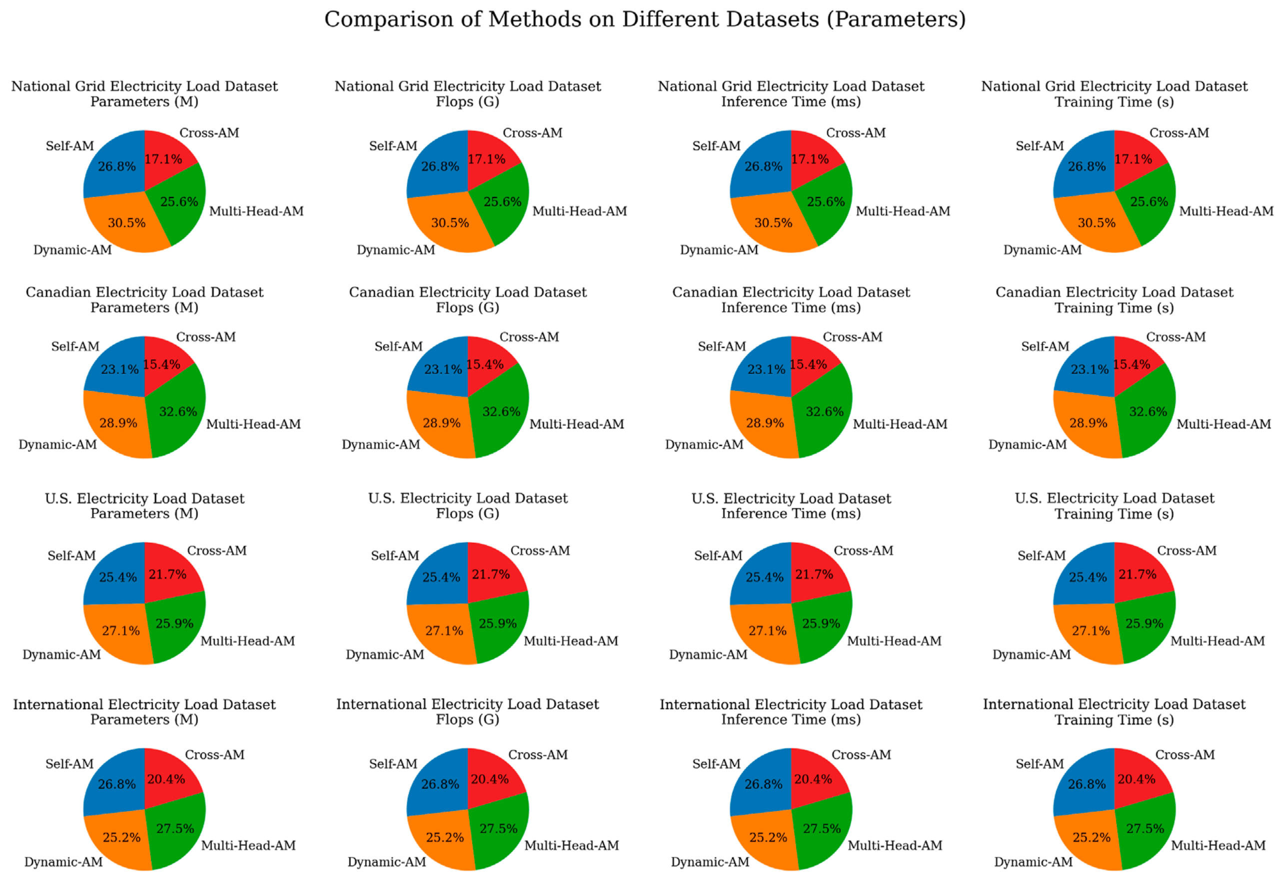

FIGURE 8
Comparison of model performance on different datasets.

4.4 Experimental results and analysis

During the experiment, we collected data including National Grid Electricity Load Dataset, Canadian Electricity Load Dataset, U.S. Electricity Load Dataset, International Electricity Load Dataset. Through experiments, we obtained the following results.

When we look at the results in Table 1, we can clearly see that our model performs significantly better than other models on different datasets. Specifically, on the National Grid Electricity Load Dataset, our model achieves 96.22% accuracy, 93.54% recall, 91.06% F1 score, and 94.45% AUC, which performance metrics significantly exceed other models, such as wang, mohammadi, alotaibi2, alladi and hui. On the Canadian Electricity Load Dataset, U.S. Electricity Load Dataset and International Electricity Load Dataset, our model also achieves the highest level of performance indicators, indicating its strong generalization ability on different data sets. Digging further into Figure 5, we can see that after visualizing the results from Table 1, the comparison of model performance becomes clearer. In this visualization, our model sits at the top of each dataset by a clear margin, outperforming other models. This visualization presents the superior performance of our model on different datasets, further confirming the excellent performance of our method in power load type forecasting tasks. It should be emphasized that on the International Electricity Load Dataset, our model performed particularly well, reaching an AUC of 98.46%, which is much higher than other models. This shows that the introduction of the attention mechanism has important advantages for processing international-scale power load data and can more accurately capture the complex patterns of load types.

By analyzing the data in Table 2, we can clearly see the performance of our model on different data sets. First, we note that our model has a much lower number of model parameters than other models on each dataset. For example, on the National Grid Electricity Load Dataset, our model parameters are only 155.22M, while the number of parameters of other models exceeds 230M, which indicates that our model has a more lightweight design. Furthermore, our model has the lowest Flops and inference time on all datasets, further demonstrating its efficiency. This is critical due to resource constraints and response time requirements in real-world applications. After visualizing these performance indicators, as shown in Figure 6, we can see that our model achieves the best performance on each data set, which further confirms its superior effect in power load type forecasting tasks. It is worth noting that despite having fewer model parameters, our model performs particularly well on the International Electricity Load Dataset,

TABLE 4 Ablation experiments on the Cross Transformer module using different datasets.

Method	Dataset															
	National grid electricity load dataset				Canadian electricity load dataset				U.S. Electricity load dataset				International electricity load dataset			
	Parameters (M)	Flops (G)	Inference time (ms)	Training time (s)	Parameters (M)	Flops (G)	Inferer time (ms)	Training time (s)	Parameters (M)	Flops (G)	Inference time (ms)	Training time (s)	Parameter (M)	Flops (G)	Inference time (ms)	Training time (s)
Self-AM	336.01	251.09	237.01	310.23	347.66	341.35	247.57	391.58	355.73	293.54	298.49	385.64	273.67	245.87	354.32	380.89
Dynamic-AM	383.13	314.22	252.49	291.59	327.17	357.61	365.72	350.76	361.81	265.79	242.14	283.27	373.96	293.19	226.47	386.15
Multi-Head-AM	320.99	353.55	241.41	318.34	343.52	331.01	230.23	365.21	325.45	306.16	229.15	284.00	351.07	285.38	378.83	395.05
Cross-AM	214.96	166.91	202.23	236.12	156.41	178.81	189.85	108.81	118.44	116.06	224.99	187.49	218.82	212.00	232.96	189.94

further verifying its generalization ability on different data sets. This shows that our model not only performs well in performance but also has a lightweight design that is applicable to various power load data sets.

By analyzing the data in Table 3, we can gain an in-depth understanding of the performance of the GCN-Seq2Seq module on different data sets and its impact on the overall performance of the model. First, we focus on the key performance indicators of the model on four different data sets, including accuracy (Accuracy), recall rate (Recall), F1 score (F1 Score) and AUC value (Area Under the Curve). On the National Grid Electricity Load Dataset, the GCN-Seq2Seq module achieved excellent performance, with an accuracy of 97.48%, a recall of 93.62%, an F1 score of 93.82%, and an AUC value of 93.61, significantly better than other models (RNN, Resnet50 and Resnet18). This shows that the GCN-Seq2Seq module has excellent classification performance in the power load type prediction task. On other data sets, the GCN-Seq2Seq module also performed well and maintained a high level of performance. Especially on the Canadian Electricity Load Dataset and International Electricity Load Dataset, the model's accuracy exceeded 97.9%, the recall rate exceeded 94.75%, the F1 score exceeded 94.5%, and the AUC values exceeded 95.59% and 96.24%. This further verifies the generalization ability and stability of the GCN-Seq2Seq module. After visualizing these performance indicators, as shown in Figure 7, we can clearly observe the excellent performance of the GCN-Seq2Seq module on different data sets, as well as its advantages over other models. The introduction of this surface attention mechanism module significantly improves the model's performance in power load type prediction tasks.

By analyzing the data in Table 4, we can gain an in-depth understanding of the performance of the Cross Transformer module on different data sets and its impact on the overall performance of the model. This table provides key performance indicators on four different data sets, including model parameters (Parameters), number of floating point operations (Flops), inference time (Inference Time) and training time (Training Time). First, let's focus on the performance of the Cross Transformer module on the National Grid Electricity Load Dataset. This module has a parameter volume of 214.96M, a floating point operation count of 166.91G, an inference time of 202.23 ms, and a training time of 236.12s. These metrics show the module's performance level when processing this data set. Then, we observe the performance of the Cross Transformer module on the other three datasets. On the Canadian Electricity Load Dataset, U.S. Electricity Load Dataset and International Electricity Load Dataset, the module has performance indicators of 156.41M, 178.81G, 189.85 ms and 108.81s respectively, and corresponding results of 118.44M, 116.06G, 224.99 ms and 187.49s numerical value. These data show the performance changes of the Cross Transformer module on different data sets. By visualizing these performance metrics, we can more clearly observe the performance of the Cross Transformer module on different data sets. As shown in Figure 8, the module performs poorly on the National Grid Electricity Load Dataset but has better performance on the other three datasets. This shows that the Cross Transformer module has certain flexibility and adaptability when dealing with different data distributions and tasks.

5 Conclusion and discussion

In this study, we focus on solving the problem of power load type prediction in smart grids to help the power system better understand and manage load changes. We propose an innovative deep learning model that combines graph convolutional network (GCN), sequence-to-sequence (Seq2Seq) model and attention mechanism to comprehensively consider the complex topology and time series data of the power system to achieve more accurate Load type forecasting. Specifically, we first use the GCN encoder to process the topological structure information of the power system and represent the node features into encoding of graph data. Next, the Seq2Seq decoder takes the historical time series data as the input sequence and generates a prediction sequence of the load type. In this process, an attention mechanism is introduced, allowing the model to fuse information based on the importance of different input data. Finally, the outputs of the GCN encoder and Seq2Seq decoder are integrated to achieve more accurate load type prediction. Through extensive experimental verification, we demonstrate the excellent performance of this model in load type forecasting tasks, significantly improving the accuracy of load type prediction in power systems.

Despite its remarkable results, this study suffers from two major flaws. First, the performance of our model in handling extreme situations needs to be further improved, such as sudden power load fluctuations, which require more robust processing capabilities. Secondly, our study still needs to be verified in more actual power systems to further confirm its generalization ability and robustness. Future research directions will consider improving the robustness of the model and extending the scope of experimental validation to more comprehensively evaluate its performance. It is also expected to explore more smart grid application areas, such as automated operation and maintenance of power systems and smart energy interaction, to further promote the development and application of smart grids.

This research provides an innovative method to solve the problem of power load type prediction and has important practical significance. By combining graph neural networks, sequence generation models, and attention mechanisms, we achieve more accurate predictions of power system load types, helping smart grids achieve more efficient energy management and optimization. This is of great significance to the high reliability, efficiency and sustainability of the power system, and also makes a positive contribution to the development of smart grids and sustainable energy integration.

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

HS: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Writing–original draft. YR: Investigation, Methodology, Project administration, Resources, Writing–original draft. SW: Conceptualization, Formal Analysis, Methodology, Project administration, Resources, Software, Writing–original draft, Writing–review and editing. BZ: Investigation, Methodology, Project administration, Resources, Writing–review and editing. RY: Investigation, Project administration, Supervision, Visualization, Writing–review and editing.

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Conflict of interest

Authors YR, SW, BZ, and RY were employed by China Electric Power Research Institute Co., Ltd.

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.

Publisher’s note

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