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MULTI-VIEW GRAPH CONVOLUTIONAL NEURAL NETWORKS FOR ABNORMAL MEASUREMENT DATA IDENTIFICATION IN POWER SYSTEM

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Abstract - This paper introduces a Multi-View Graph Convolutional Network (MVGCN) for anomaly measurement data recognition in power systems. Designed to address challenges in transient anomaly detection, the model enhances feature extraction adaptability and captures complex transient patterns. The architecture integrates graph convolutional operations with multi-view learning, incorporating diverse structural representations of power networks. An attention-based feature aggregation mechanism dynamically fuses multi-view information during graph convolution, prioritizing salient features while suppressing noise. This significantly improves the model's representational capacity and robustness against data irregularities common in grid environments. Evaluations on ENZYMES and PROTEINS datasets—selected for their structural relevance—demonstrate MVGCN's advantages over state-of-the-art baselines. The model more accurately identifies correlations between anomalies and sensor nodes, enabling precise root-cause diagnosis. It also achieves notably higher computational efficiency, substantially reducing training and inference runtime through optimized attention fusion and parallel view processing. These capabilities position MVGCN as a scalable solution for real-time anomaly detection in dynamic smart grids, enhancing grid resilience and operational reliability through rapid, interpretable diagnostics.

Keywords: Multi-view Graph neural networks, Power system, Attention weights, Abnormal data identification.

1. Introduction

As power distribution networks evolve toward greater intelligence and transparency, their structural complexity intensifies. Consequently, anomalous power timing measurements are increasingly prevalent during system operation. Such anomalies may originate from equipment failures, unauthorized consumer consumption, or grid instability [1]. Current research prioritizes developing efficient methodologies for detecting concealed anomalous data within extensive power datasets. These objective addresses limitations inherent in traditional artificial feature extraction algorithms—specifically, their suboptimal fault tolerance and recognition efficiency.

Employing erroneous data in power system state estimation compromises estimation accuracy, potentially leading operators to make erroneous operational decisions. This jeopardizes the economic and safe operation of power systems [1]. Therefore, upon identification, anomalous data must be rectified through compensation techniques. This corrective measure lays a robust data foundation for downstream analyses—including power consumption profiling, system operation optimization, and demand-side management.

Anomaly detection, also referred to as outlier detection, encompasses a diverse range of methods for identifying and recognizing anomalies based on knowledge analysis in the early stage [2]. Moreover, within the current framework of deep learning, there exists an intelligent complex recognition model [3]. Notably, Graph Neural Network (GNN) has garnered significant attention in the field of electric power due to its integration of graph data analysis with network structure. In general, the state of a node is influenced by its neighboring nodes. Specifically, in Graph Neural Networks (GNNs), each node aggregates the features of its neighbors to determine its own feature representation. Depending on the variant of GNN used, different sets of neighboring nodes are

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considered for feature aggregation. For instance, when calculating aggregated features, Graph Convolutional Networks (GCNs) consider only the immediate neighbors of a node [4]-[5]. Conversely, Graph Attention Networks (GANs) incorporate an attention mechanism that assigns varying weights to neighboring nodes during aggregation [6]. GNN can be viewed as a more generalized version of Convolutional Neural Networks (CNNs). Convolutional Neural Networks (CNNs) have limitations in processing data with regular structures, such as 2-D images and 1-D text data. On the other hand, Graph Neural Networks (GNNs) excel in handling non-Euclidean data types like social media networks, 3-D images, telecom networks, and various industry settings [7]-[8]. GNNs iteratively propagate node states using neural networks until reaching equilibrium to provide state representations for each node. Similar to principles from graph theory, an important aspect of GNN involves distinguishing between nodes and edges within the given data. Consequently, the graph is transformed into features suitable for neural network processing. Essentially, each node in GNN aggregates features from its neighboring nodes to derive its own feature representation. In recent years, there has been a proliferation of diverse GNN variants; interested readers can refer to dedicated survey papers on this topic for further details.

Recent advancements in deep learning have demonstrated significant potential for anomaly detection in power systems. Graph Neural Networks (GNNs) were employed in [9] to analyze network structures, where node features are integrated through graph Fourier transforms in feature pooling layers to quantify topological influence. Recurrent Neural Network (RNN) enhancements in [10] first normalize multi-dimensional power data to eliminate dimensional discrepancies, then construct a three-layer 128-node deep recurrent network to compute deviations for anomaly identification. This approach achieved 17.9% and 6.4% higher detection rates, and 17.2% and 8.9% higher recognition rates compared to traditional residual and volumetric mutation methods. To enhance time-series modeling, [11] proposed a CNN-LSTM hybrid architecture with attention mechanisms. The algorithm reconstructs load data within sliding windows and identifies anomalies by comparing reconstruction errors against dynamic thresholds. Further optimizing efficiency, [12] introduced intelligent parameter tuning using Particle Swarm Optimization (PSO) for Bidirectional LSTM (BiLSTM). The PSO-BiLSTM model adaptively predicts load data and rapidly identifies anomalies through error analysis and decision criteria. Bao et al. present a method for detecting data anomalies using computer vision and deep learning techniques. The approach involves transforming original time series measurements into image vectors, which are then fed into a deep neural network to identify various anomalies [13]. Liu et al. [14] suggest an image generation technique to improve the robustness of the graph convolutional neural network model. Wen et al introduced a technique for segmenting time series using GNN and transfer learning [15]. [16] introduces the Dual Autoencoder-Transformer Network (DATN-ND) for anomaly detection. It generates pseudo-anomalous features to amplify the reconstruction error discrepancy between normal and abnormal samples, significantly improving AUC performance on benchmark datasets by decoupling feature representations and enhancing sensitivity to subtle deviations. Cohen et al. propose SPADE (Semantic Pyramid Anomaly Detection), which leverages pre-trained feature pyramids for pixel-level anomaly localization [17]. Zhang et al. develop VadCLIP, a vision-language model that achieves fine-grained anomaly classification via text-visual alignment. By integrating textual prompts with visual embeddings, it attains 88.02% AUC on the UCF-Crime dataset, demonstrating strong zero-shot transferability for cross-modal anomaly interpretation in power system monitoring [18].

They employed diverse datasets with methods such as random mutation and adding random trends to enhance the quality of the analysis results. However, their approach lacks specificity when dealing with anomalous measurements in power systems and faces challenges extracting features from transient anomalies. Hence, this paper proposes an identification method based on multi-view graph convolutional neural networks specifically designed for abnormal measurement data in power systems. The proposed method automates feature extraction while also improving fault tolerance capabilities. It is particularly well-suited for handling large-scale time sequence data found within distribution networks, ultimately leading to enhanced accuracy when detecting anomalies.

2. Multi-view Graph Convolutional Neural Networks Model

2.1 Cause Analysis of Abnormal Data

Due to the increasing number of electricity users, the workload and pressure of the electricity information collection system have also increased, which makes it easy to encounter problems such as abnormal electricity load data for users. Moreover, the internal structure of the electricity information collection system is relatively complex, which increases the probability of abnormal electricity load data. This paper analyses the collection objects and collection methods of the electricity information collection system to explore the causes of abnormal electricity load data.

The electric power information collection system collects electric power information of all power users within the power grid that are supplied by it, among which the collection objects mainly include: various special transformers, industrial and commercial users, and residential users. The collection scope covers the existing distribution transformer monitoring system, central meter reading system, and load management system, etc. The collected content includes event time records, electric energy data, electrical quantities, electric power quality, operating conditions data, etc.

Because of the diversity of collection objects, collection content, and collection methods, there are many reasons for the existence of abnormal data in the electric power information collection system database. Abnormal load data generally refers to the data points that should be input into the electric power information collection system database but are missing or do not match the actual input data, and the existence of abnormal data will destroy the horizontal and vertical similarity and completeness of the daily load curve. The reasons for load data abnormality are as follows:

1) Terminal transmission abnormality: The failure or distortion of the communication module in the remote terminal transmission may affect the integrity of data collection.

2) Instrument fault: There are many types of instrument faults that may cause abnormal data, including: terminal display showing white screen or black screen; battery short circuit, low battery voltage; device suddenly freezing or screen suddenly turning black; fuse melting or burning out; long-term use may cause electronic components aging and unable to work normally; memory fault in the electric energy meter, causing the memory to malfunction and unable to store data normally.

3) Environmental factors causing communication failure: Due to the influence of the installation environment, the transmission signal of the concentrator may be unstable, causing the smart electric energy meter to miss collecting electric power information.

4) Human factors: During the process of supplementary collection, the data filled in by employees may not be standardized or even incorrect, or employees may operate improperly, thus affecting the accuracy of data entry and data collection in the electric power information collection system.

2.2 Model Framework

Convolutional neural networks are feedforward neural networks with feature extraction capabilities [14], capable of deeply extracting data features and amplifying the effective parts of the data.

Since the load electricity data used in this paper has high-dimensional, temporal, and similar features, the CNN is used as a time feature extractor in the process of compensating for abnormal data.

In spite of the impressive achievements of graph convolutional networks and their variations in graph modelling tasks, most existing models are designed based on a pre-determined single graph structure. However, this approach may result in differences between the given adjacency matrix and the desired target adjacency matrix for task adaptation, thereby significantly limiting the representational capacity of a single-view graph convolutional network. Hence, this chapter proposes a multi-view graph convolutional neural network model based on attention mechanism.

Consider the following figure data expression,

$$G = \{V, A\} \tag{1}$$

where V represents the set of N nodes in the graph, and A represents the adjacency matrix reflecting the structure of the graph.

Subsequently, an eigenvector of K dimension is computed for each node, and the eigenmatrix representing the graph G can be formulated as follows,

$$X \in \mathbb{R}^{N \times K} \tag{2}$$

For graph convolutional networks, topological information A and original attribute feature X are used to learn new nodes, and the single-layer graph convolutional networks are formalized as

$$Y = g\left(\hat{A}XW\right) \in \mathbb{R}^{N \times L} \tag{3}$$

where $g(\bullet)$ means a activation function. Generally, $\mathrm{ReLU}(\bullet) = \max(0, \bullet)$ can be used. $\hat{A}$ is an adaptive estimation of the degree matrix, W represents learnable parameters in a volume collection.

However, in practical power system scenarios, a single topological view may not adequately capture the entire problem or align with the task objective. Consequently, the graph data $G = \{V, X, A\}$ obtained from a single view is expanded into multi-view graph data encompassing multiple topologies,

$$G^{*} = \{V, X, A_1, A_2, \ldots, A_n\} \tag{4}$$

The multi-view graph convolutional network model framework based on attention mechanism proposed in this paper is shown in Fig. 1 below.

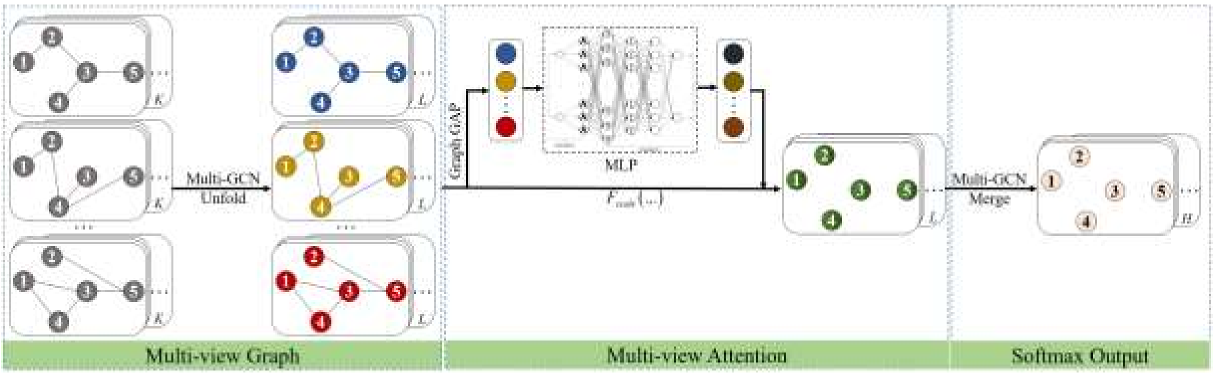

Figure 1: Multi-view graph convolutional network model framework

2.3 Multi-view Graph

As shown in Fig. 1, the multi-view graph (4) with multiple topologies is input to the Multi-GCN Unfold module to learn the representation of all views separately.

$$\hat{X}_i = g_{GCN}\left(X, \hat{A}_i\right) = \mathrm{ReLU}\left(\hat{A}_i X W_i\right) \\ \aleph = \left\{\hat{X}_1, \hat{X}_2, ..., \hat{X}_n\right\} \tag{5}$$

where $\hat{X}_i \in \mathbb{R}^{N\times L}$ represents the representation of the i-th view learned, N represents the number of nodes, and L represents the dimension of the feature vector. $\aleph \in \mathbb{R}^{n\times N\times L}$ represents the collection of all learned views and n means the number of views. For the original graph eigenmatrix of equation (2), it can be expressed as an eigentensor $\aleph \in \mathbb{R}^{n\times N\times L}$.

While the introduction of multiple views increases storage and parameter requirements by a factor of n compared to classic GCN networks, but the computation of a single view is completely independent and can be accelerated by parallel computation.

2.4 Multi-view Attention

The current research incorporates an attentional mechanism module into the multi-view graph convolution framework in order to improve the resilience of algorithms. As depicted in Fig. 1, the attention mechanism module consists of two crucial elements, the channel for learning attention coefficients and the channel for transmitting features.

The attention coefficient learning channel consists of a Graph Global Average Pooling (Graph GAP) and a Multi-layer Perceptron (MLP). The purpose of this is to obtain the graph-encoded network structure information and node characteristics, and to simplify the redundant nodes in the network structure. The feature pooling operation is to convert the original given graph signal into a simplified graph signal, in which the graph signal after feature pooling still retains the useful information of the original graph signal. GAP is often used in traditional convolutional neural networks to extract global features from Feature maps, as shown in Figure 2, expressed as follows

$$\mathrm{g}_i = g_{GAP}\left(G_i\right) = \frac{1}{\varpi \times \upsilon}\sum_{j=1}^{\varpi}\sum_{t=1}^{\upsilon} G_{i,jt} \tag{6}$$

where $G_i \in \mathbb{R}^{\varpi\times\upsilon}$ is the feature graph of the i-th channel. $\varpi\times\upsilon$ represents the space size of the feature graph G_i, $\mathrm{g}_i \in \mathbb{R}$ can be understood as a statistic, that is, the global feature of the feature graph G_i learned by GAP. As can be seen from eq. (6), the traditional global average pooling strategy only performs a simple arithmetic average operation, which means that each pixel in the feature map contributes the same amount to the final global feature. However, for graph-structured data, different nodes have different meanings and their importance is also different. Therefore, the traditional global average pooling strategy based on arithmetic average operation is not very suitable for graph-structured data. This study proposes a novel global averaging strategy specifically designed for such data.

$$\hat{x}_i = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{\left|\mathcal{N}_{i,j}\right|}\sum_{t=1}^{\mathcal{N}_{i,j}}\left(I + A_i\right)_{jt}\hat{X}_{i,j,t} \tag{7}$$

where $\mathcal{N}_{i,j}$ represents the set of neighbor nodes of the j-th node in the i-th topology view. N indicates the number of nodes in the graph data. $I + A_i$ represents the self-ring adjacency matrix of the i-th view. $\sum_{t=1}^{\mathcal{N}_{i,j}}\left(I + A_i\right)_{jt}\hat{X}_{i,j,t}$ indicates the graph aggregation operation. $\hat{x}_i$ represents the global feature of the i-th view learned by Graph GAP.

After passing through the Graph GAP channel, the representation matrix of each view is aggregated as a global eigenvector,

$$\aleph = \left\{\hat{X}_1, \hat{X}_2, \ldots, \hat{X}_n\right\} \in \mathbb{R}^{n\times N\times L} \to \dot{X} = \left\{\dot{x}_1, \dot{x}_2, \ldots, \dot{x}_n\right\} \in \mathbb{R}^{n\times g} \tag{8}$$

The MLP module is utilized to train the attention coefficient $K = \left\{k_1, k_2, \ldots, k_n\right\} \in \mathbb{R}^{n}$ of each view by incorporating the global features $\dot{X}$ from various perspectives, enabling the assignment of distinct weights to individual views.

Finally, the learned attention coefficient $K \in \mathbb{R}^{n}$ is used to fuse $\aleph \in \mathbb{R}^{n\times N\times L}$ of different views,

$$\bar{X} = F_{scale}\left(\aleph, K\right) = \sum_{i=1}^{n} k_i \hat{X}_i \tag{9}$$

where $\bar{X} \in \mathbb{R}^{N\times L}$ represents the final fusion representation.

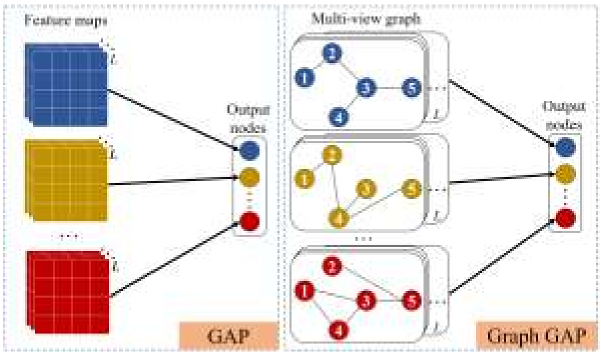

Figure 2: Graph Global Average Pooling

2.5 Softmax Output

As shown in Fig. 1, the initial feature matrix (2) learns the representation of multiple views (5) through the Multi-GCN module, and a more comprehensive fusion phonology (9) is learned by considering the importance of different views through the attention mechanism and the multi-view fusion module. The fusion $\bar{X} \in \mathbb{R}^{N\times L}$ input is classified into a multi-layer forward network to obtain the final prediction category, expressed as

$$X^{*} = \sum_{i=1}^{n} g_{GCN}\left(\bar{X}, A_i\right) = \text{softmax}\left(\sum_{i=1}^{n} \hat{A}_i \bar{X} W_i\right) \tag{10}$$

where $X^{*} \in \mathbb{R}^{N\times H}$ represents the final category distribution.

The Softmax activation function is designed as:

$$\text{softmax}\left(\sum_{i=1}^{n} X_{ij}^{*}\right) = \frac{e^{X_{ij}^{*}}}{\sum_{j=1}^{H} e^{X_{ij}^{*}}} \tag{11}$$

where H indicates the number of categories.

3. Abnormal Measurement Data Identification Algorithm

Current anomaly detection algorithms for power systems are broadly categorized into three paradigms: data-oriented, network-oriented, and hybrid approaches. While anomalous consumption data consistently manifests as lower reported energy readings in smart meters, the specific characteristics vary depending on the underlying cause. Traditional identification methods predominantly rely on manual feature engineering to discern distinct anomaly types. For instance, abrupt consumption drops are engineered as features to detect current shunts, while null or missing measurements signify potential electronic meter failures. However, these approaches exhibit significant limitations: they are heavily dependent on domain expertise, incur high development costs, and require continuous feature engineering to adapt to evolving anomaly patterns. To address these constraints, this paper proposes a Multi-View Graph Convolutional Neural Network (MV-GCN) based method for automated identification of anomalous measurement data in power systems. This framework enables adaptive detection of novel anomalous consumption behaviors within smart meter data without explicit feature engineering. The overall architecture of the proposed method is depicted in Fig. 3.

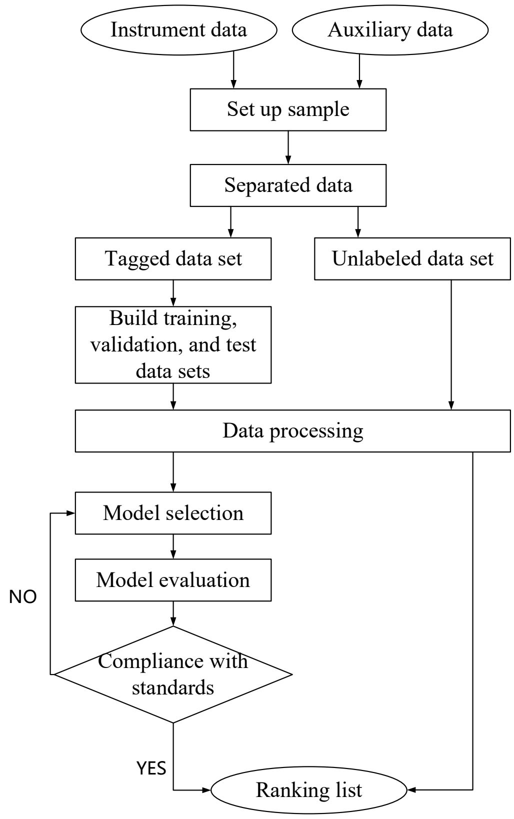

Figure 3: Abnormal measurement data identification process framework

The cross-entropy loss function has been selected as the model's loss function,

$$\zeta = -\sum_{k \in V_L} \sum_{j=1}^{H} \xi_{kj} \ln X_{kj}^{*} \tag{12}$$

where V_L represents a marked collection of nodes. $\xi \in \mathbb{R}^{|V_L| \times H}$ represents the marker indication matrix.

An algorithmic description of the proposed abnormal measurement data identification algorithm is listed below:

Algorithm 1: MVGCN Abnormal Measurement Data Identification

1: Algorithm Inputs: Raw graph data $G = \{V, A\}$, single-layer graph convolutional network $Y = g\left(\hat{A}XW\right)$, multi-GCN model g_{GCN}, multi-view attention g_{GAP}, feature decoder F_{scale},

2: Algorithm Outputs: Abnormal measurement date identification, using equation (10),

3: Begin:

4: $G^{*} = \{V, X, A_1, A_2, ..., A_n\} \leftarrow G = \{V, A\}$, using equation (3),

5: $\hat{X}_i \leftarrow X$, using equation (5),

6: $\aleph = \left\{\hat{X}_1, \hat{X}_2, ..., \hat{X}_n\right\} \rightarrow \dot{X} = \{\dot{x}_1, \dot{x}_2, ..., \dot{x}_n\}$, using equations (6)-(8),

7: Compute the feature decoder of each input using the eq. (9),

8: **Output** X^{*},

9: End

4. Experimental Verification

In order to verify the validity of the power system anomaly measurement data identification method based on graph convolutional network constructed in this paper, the following test platform is built: desktop computer Intel Xeon (R) CPUE5-1650V4 processor and GTX3080TiGPU, with 128GB memory and 64-bit Linux operating system. The algorithm design is implemented by using Python in Pycharm. Involved in this experimental data set, respectively, including the figure data set and electric power testing data set, the benchmark figure database for download two public figure data sets, ENZYMES [8] (contain 600 chart, six categories) and PROTEINS [9] (contain 1113 chart, two categories). The power detection dataset is derived from a household electricity consumption situation in Paris, a total of 1,440 days, 2,044,567 data values, including date, voltage, current and other 10 attributes [19]-[20]. At the same time, the evaluation system on the basis of the test data set and its true value on use precision (Prec) and accuracy (Acc) and recall rate (Rec) and F1 - score (F1) to assess the performance of our method and the baseline model, evaluation model as follows,

$$\begin{aligned} F1 &= \frac{2 \times \text{Prec} \times \text{Rec}}{\text{Prec+Rec}} \\ \text{Prec} &= \frac{\text{TP}}{\text{TP+FP}} \\ \text{Rec} &= \frac{\text{TP}}{\text{TP+FN}} \\ \text{Acc} &= \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \end{aligned} \tag{13}$$

where the predicted positive sample with positive label is recorded as TP, the predicted positive sample with negative label is recorded as FP, the predicted negative sample with positive label is recorded as FN, and the predicted negative sample with negative label is recorded as TN. Note that our data set is unbalanced, which justifies the choice of these metrics, which are appropriate for unbalanced data. To detect exceptions, we set the threshold using the maximum exception score on the validation dataset. At the time of testing, any time step with an exception score that exceeds the threshold will be considered an exception.

In order to verify the feasibility of the algorithm, five popular anomaly measurement data recognition methods were selected for comparative testing, including KNN [6], FB [7], AE [9], DAGMM [12], LSTM-VAE [13]. Whole experiment of figure convolution neural network model from two aspects of the recognition performance is analyzed, the first is the benchmark of using public figure data on the performance of the MVGCN model is analyzed, the experiment conducted 6 times, random use of 70% of the data set as a training set, 20% for validation set and 10% for the test set. Fig. 4 and 5 show the t-SNE results of sensors embedded in the training model of ENZYMES and PROTEINS in the dataset. Different colors represent different types of clusters. It can be seen that two types of sensor data (in the dotted circle box) are forming local clusters, which is consistent with the measurement types of the two types of PROTEINS data. Tab.1 shows the precision and F1-score of the algorithm in this paper compared with other classes on the datagram dataset of ENZYMES and PROTEINS.

The results in Fig. 6 and 7 show that the GDN was better than the baseline on both data sets, with high accuracy on both ENZYMES and PROTEINS, 0.9899 and 0.9822, respectively. In most cases, the classification performance of MVGCN model is better than that of graph neural network models without layered pooling. Therefore, the increase of hierarchical pooling operation process not only helps to better aggregate node features, but also reduces redundant node information, thus simplifying the structure of the graph. The comparison of running time of different data sets of the model is shown in Fig. 8. According to the changes shown in the figure, the running time of KNN is much higher than other class models. Because MVGCN uses hierarchical feature pooling operation, its running time is significantly reduced, which is similar to that of LSTM-VEM.

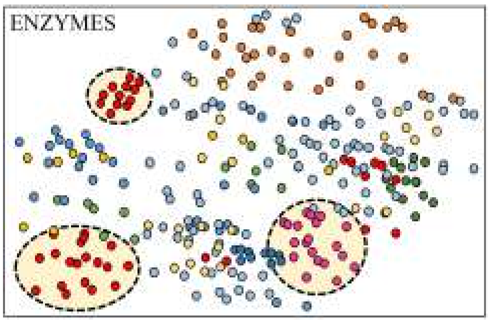

Figure 4: t-SNE results of a training model on ENZYMES data set

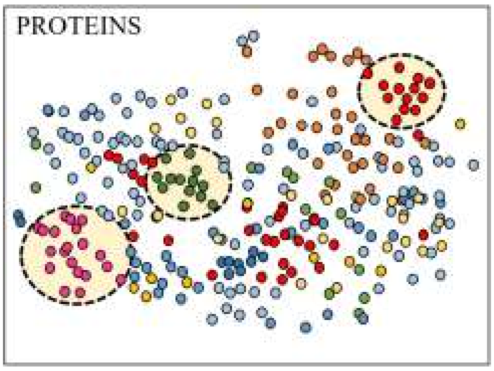

Figure 5: t-SNE results of a training model on PROTEINS data set

Table 1 Abnormal test data identify classification precision and F1-score results

Method	ENZYMES		PROTEINS	
	Prec	F1	Prec	F1
KNN	9.83	0.14	9.57	0.14
FB	25.37	0.33	24.64	0.32
AE	73.44	0.66	46.34	0.45
DAGMM	42.16	0.52	69.21	0.44
LSTM-VAE	95.23	0.74	88.88	0.35
MVGCN	98.76	0.86	97.83	0.68

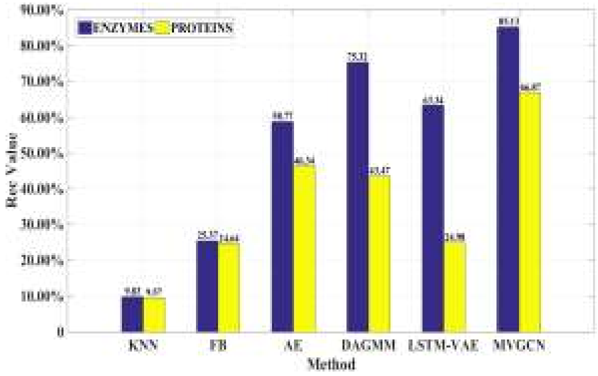

Figure 6: Abnormal test data identify classification recall rate results of each model

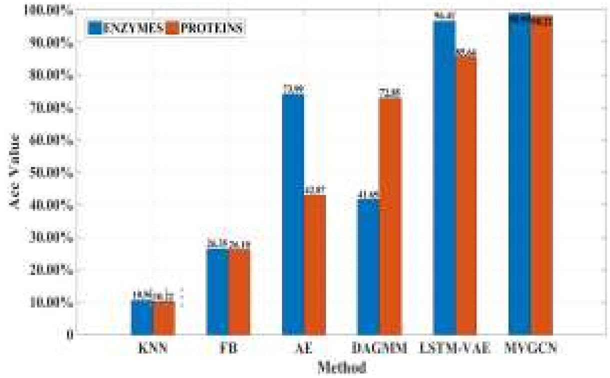

Figure 7: Abnormal test data identify classification accuracy results of each model

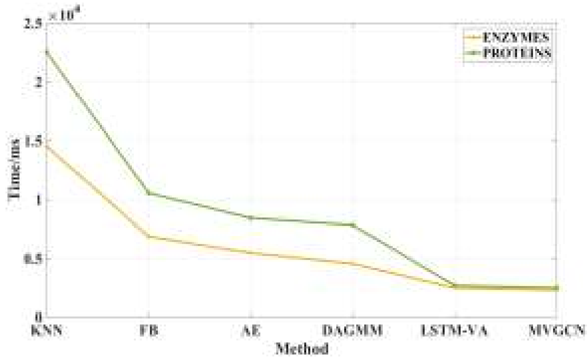

Figure 8: The running time of each model in different data sets

In order to study the feasibility and irreplaceability of each module in the proposed algorithm, this paper observed how the performance of the model would change by gradually excluding modules. Firstly, in the experiment, the graph structure based on the prior information is replaced with a static single complete graph to ensure that each node is connected to other nodes, so as to explain the necessity of the graph structure learning module. Secondly, for statistical sensor feature geometry using embedded vectors, we weaken the MLP model in Equation (6) for further investigation.

Finally, the attention mechanism is removed and all neighbors are aggregated using equal weights instead.

The experimental results are shown in Tab.2 and Fig. 9-11. As you can see from the table, replacing the learned graph structure with a full graph will degrade the performance of both data sets. The effect on PROTEINS data set was more obvious. Therefore, the graph structure learner improves the learning performance of large-scale data sets. If the embedding vector of sensor features is disabled in the attention mechanism, the above two types of data sets perform worse than the original model framework designed in this paper, which means that the embedding feature of the framework can improve the learning process of the weight coefficient of the attention mechanism. At the same time, the removal of attention mechanism has the greatest impact on abnormal data recognition performance compared with the removal of other modules. This may be due to the fact that different sensors in a power system behave differently at different times, and equal weights represent equal treatment of all neighbors of each sensor, causing noise and misleading the model. The increase in the running time shown in Fig. 11 indicates that the graph structure learning algorithm in each module of the GCN model significantly affects the running time, while the attention concentration combined with the data in Fig. 10 mainly affects the accuracy of algorithm recognition. It is not difficult to find that the Multi-view Graph algorithm can improve the computation speed through parallel computation although the number of graphs is increased. The increase of Graph GAP process not only helps to better aggregate node features, but also reduces redundant node information, thus simplifying the structure of the graph so that the running time changes very little.

Table 2 Abnormal test data identify classification precision and F1-score results

Method	ENZYMES		PROTEINS	
	Prec	F1	Prec	F1
MVGCN	97.99	0.81	95.63	0.57
-Multi-view Graph	95.88	0.75	92.21	0.49
-MLP	92.55	0.71	90.86	0.44
-AM	70.59	0.67	61.33	0.41

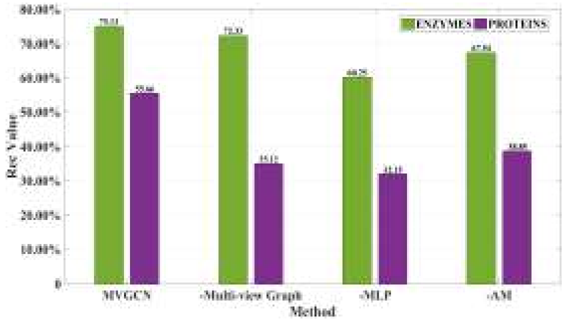

Figure 9: Abnormal test data identify classification recall rate results when each module is missing

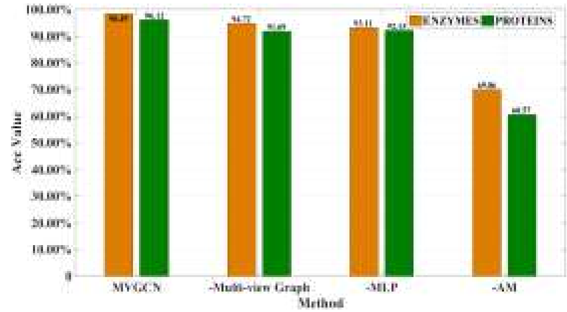

Figure 10: Abnormal test data identify classification accuracy results when each module is missing

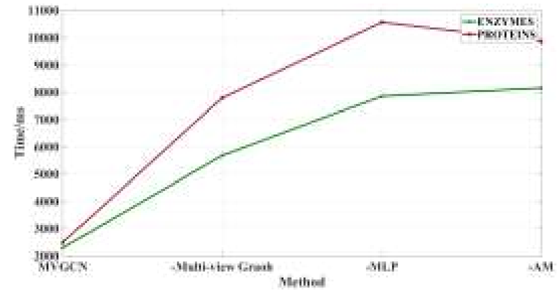

Figure 11: The running time of GCN model in different data sets when each module is missing

5. Conclusions

In the face of the problem of feature extraction of transient anomaly data in power system, this paper proposes a method of power system anomaly measurement data recognition based on graph convolutional network, which learns the relationship graph between sensors and uses embedded vectors to characterize the mode deviation between sensors. Experiments show that the MVGDN model is superior to other algorithms in terms of accuracy. By comparing the evaluation values such as running time, recall rate and F1, it can be proved that the graph convolutional network can effectively identify abnormal data, cluster and summarize, and shorten the operation cycle of the processing core.

In the future research, we will focus on updating the learning weights and change factors of the graph structure to reduce the computational memory usage of the algorithm, so as to further improve the practicability of the method in power system.

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