A Dual-Graph Attention-Based Approach for Identifying Distribution Network Topology

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Overview

The distribution network needs to obtain the correct topology in time during the operation to adjust the control strategy and ensure the safe operation of the distribution network. For the current problems of frequent changes of distribution network topology and difficulties in obtaining topology structure in real time, in this paper , we propose a distribution network topology identification method based on dual graph attention mechanism (TI-DGA), which firstly obtains the attention score by inputting different features and weight matrices in the graph convolution layer, and then uses a pooling mechanism to select top-k node features as the features of the whole graph to achieve the classification purpose.

Contributions:

- we proposed a dual graph attention mechanism method TI-DGA,and the model can be suitable for application to topology feature learning and association feature learning of many different types of data.
- the model framework proposed in this paper is suitable for the application of online and offline patterns of distribution network topology identification.
- compared with other algorithms, the algorithm proposed in this paper has better accuracy on IEEE33 nodes and IEEE57 nodes.

Topology identification framework

Distribution network topology identification includes the following processes:

- Data Acquisition: the section measurement data, node voltage amplitude U, node injected active power P, and the corresponding topology labels are used as the initial samples.
- Data Processing: If the model is trained directly with the original data, it will increase the training difficulty and affect the topology recognition effect, so we normalize the voltage data. Missing data in the test set need to be filled to reduce their impact. In this paper, the kNN algorithm is used to interpolate the missing data.
- Offline Training: The filtered features from the above two steps are used as the input to the model, and the optimization and updating of the model parameters are achieved by iterations of the minimization error function, which consists of the actual and desired outputs of the model.
- Online Application: In this step, the collected measurement data of the current time section of the distribution network is input into the trained learning model, so that the operational topology of the current section of the distribution network can be output in real time.

TI-DGA model

Convolutional layer:

$$Z_U = \sigma(\mathbf{GNN}(U, A))$$

$$Z_P = \sigma(\mathbf{GNN}(P, A + A^2))$$

Attention graph pooling layer:

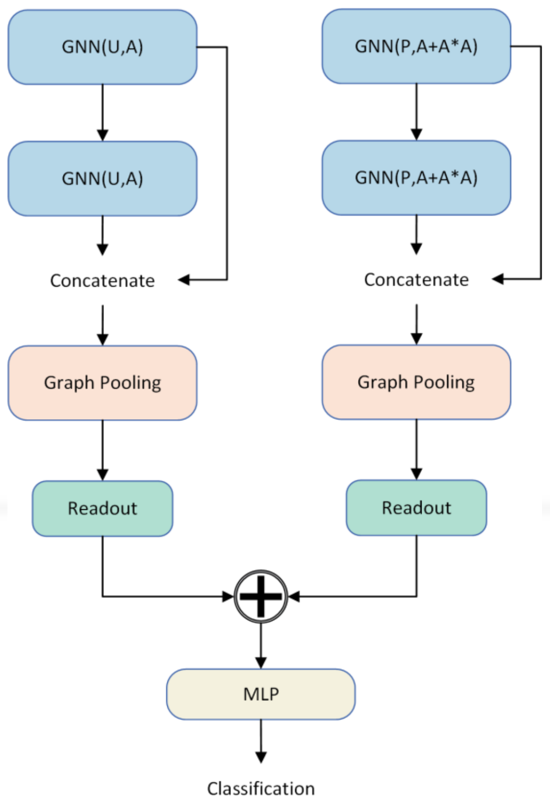
$$Z = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}X\Theta_{att})$$

$$idx = top\_rank_{(Z,[kN])}, Z_{mask} = Z_{idx}$$

Readout layer:

$$s = \frac{1}{N}\sum_{i=1}^{N} x_i \,||\, \max_{i=1} x_i$$

MLP layer: a feedforward fully connected neural network with two hidden layers.



Experiments

TABLE I COMPARISON OF ALGORITHM PERFORMANCE ON IEEE33 NODES

Algorithms	Acc	Pre	Rec
LightGBM	0.864	0.649	0.673
XGBoost	0.932	0.762	0.757
CNN	0.972	0.853	0.894
GCN	0.980	0.874	0.925
SAGPool	0.989	0.893	0.936
TI-DGA	0.994	0.911	0.940

TABLE II COMPARISON OF ALGORITHM PERFORMANCE ON IEEE57 NODES

Algorithms	Acc	Pre	Rec
LightGBM	0.812	0.578	0.603
XGBoost	0.919	0.715	0.692
CNN	0.965	0.825	0.811
GCN	0.975	0.892	0.919
SAGPool	0.983	0.887	0.929
TI-DGA	0.988	0.906	0.931

TABLE III ALGORITHM COMPARISON OF ACC VALUES ON IEEE33 NODES WITH ADDED NOISE

Algorithms	TVE=0.01%	TVE=0.05%	TVE=0.5%	TVE=1%
LightGBM	0.848	0.792	0.724	0.657
XGBoost	0.919	0.874	0.809	0.725
CNN	0.972	0.956	0.899	0.838
GCN	0.976	0.953	0.912	0.846
SAGPool	0.984	0.972	0.935	0.868
TI-DGA	0.992	0.981	0.930	0.872

TABLE III ALGORITHM COMPARISON OF ACC VALUES ON IEEE57 NODES WITH ADDED NOISE

Algorithms	TVE=0.01%	TVE=0.05%	TVE=0.5%	TVE=1%
LightGBM	0.817	0.767	0.681	0.592
XGBoost	0.921	0.892	0.852	0.798
CNN	0.965	0.930	0.873	0.815
GCN	0.977	0.948	0.893	0.834
SAGPool	0.981	0.952	0.917	0.840
TI-DGA	0.984	0.950	0.936	0.857