Power System Small-signal Stability Assessment Model Based on Residual Graph Convolutional Networks

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Abstract. Small-signal stability (SSA) is important to power system security. A data-driven approach is established for rapid prediction of the power system oscillation characteristics. The key of the approach is the Graph Convolution Networks (GCN) with residual mechanism, which works to aggregate features from high-dimension steady-state operation information and is denoted as ResGCN (RESidual GCN) in the paper. The residual mechanism helps to overcome the network degradation phenomenon. Both the oscillation frequency and damping ratio of multiple modes can be predicted by the proposed model. The performance of the proposed scheme as well as its adaptability to the power system topological changes is verified on the IEEE 39 Bus system.

Keywords: Small-signal Stability; Graph Deep Learning; Graph Convolution Networks (GCN), Residual mechanism.

1. Introduction
With the increase of renewable energy resources and HVDC converters in modern power systems, small-signal stability becomes more and more important for power system secure operation. Online small-signal stability assessment (SSA) is now an essential part in the security defense framework of the power dispatch center, which works to predict the power system oscillation mode and its damping characteristics quickly and accurately.

Traditionally, SSA is solved by mathematical models based on physical principles, which can be divided into two categories. One is the eigen-analysis method based on linearization model [1-2]. Presently, the integration of a large number of converters poses severe challenges to this type of algorithms. Another type of approaches aim to extract the oscillation frequency and damping ratio from the oscillation curves obtained by the time-domain simulation with nonlinear models [3]. The drawback is that the results are subjected to the setting of perturbation types and locations.

In the past decades, data-driven models and artificial intelligence technologies have developed rapidly, and the stability evaluation model based on sample learning has become a new research hotspot. However, most of the relevant researches focus on the transient stability assessment problems. Studies on data-driven models for small-signal stability assessment are rare [4, 5]. Among them, the dynamic characteristics of power system under faults are chosen as the inputs of the model. Ref. [4] adopted the improved XGBoost, whose inputs are manually selected generator characteristics including the
maximum and minimum acceleration of rotors, the maximum, minimum and average acceleration power and the difference between maximum and minimum angle speed. It aims at discriminating the damping level, i.e., unstable, weak and stable. In [5], the transient stability and SSA were combined into a multi-task prediction model. The dynamics containing the voltage amplitude and phase angle at buses under large disturbance are fed in a Convolutional Neural Network (CNN) for transient stability assessment and a Long short-term memory model for system damping evaluation. However, the above method still depends on the transient information after a large disturbance.

More recently, the research attention shifts to data-driven models for SSA with steady-state information, which is even more challenging since the inputs are high-dimensional in a large power grid. Note that the oscillation modes are not only affected by the generators and loads, but also closely related to the network topology. This leaves higher demand for the feature extraction of the model. In [6], Neural Networks with Random Weights is used to reconstruct the input features randomly, before an improved Random Bits Forest predicts the damping. Here the decision tree highly depends on the reconstruction, while it might be damaged due to the randomness of the feature learning based on NNRW.

Graph Deep Learning [7-10] provides a new technical roadmap for high-dimensional feature aggregation considering topological information. Graph Convolutional Network (GCN) and Graph Attention Network have been applied for power system transient stability assessment in [9-10].

In this paper, a SSA model of power system based on the RESidual Graph Convolutional Network (ResGCN) is designed to predict the frequency and damping ratio of multiple oscillation modes in parallel, where feature aggregation is enhanced by GCN and the residual mechanism. The performance of the proposed model and its adaptability to topological changes are verified on the test system.

2. The Principle of ResGCN

2.1. Structure of ResGCN
The overall structure of the ResGCN model is shown in figure 1. We utilize GCN to realize feature aggregation of the steady-state inputs and the residual connection (as orange lines) to overcome network degradation. Then several prediction modules composed by the Multilayer Perceptrons (MLPs) work in parallel to provide both the frequency and damping ratio of specific oscillation modes.

![Figure 1. Diagram of the ResGCN.](image)

2.2. The Principle of GCN
When there are $N$ buses and $L$ transmission lines in the power system, we assume buses as the nodes $V$ and lines as edges $E$. Then system structure can be represented by a graph $G=(V,E)$, which is characterized by a node feature matrix $X$ and an adjacency matrix $A$.

The propagation principle of a GCN layer is expressed by Eq. (1):

$$
\tilde{H}^l = f(H^l, A) = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^l W^l + b^l)
$$

where $\tilde{A} = A + I_N$ with $I_N$ as the identity matrix. $\tilde{D}$ is the degree matrix of nodes with $\tilde{d}_{i,i} = \sum_j \tilde{a}_{i,j}$. $H^l$, $\tilde{H}^l$ represent the input and output node feature matrix of the $l$th GCN layer. $W^l$ is a learnable
parameter matrix, while $b$ is the bias matrix. $\sigma$ denotes the activation function, such as the ReLU function.

2.3. Residual Mechanism
To alleviate the network degradation, the main idea of the residual mechanism is to concatenate the inputs and the outputs of the GCN layer, such that the input information can be preserved to the next layer [11]. Specifically, the residual mechanism is expressed by Eq. (2):

$$H^{t+1} = \tilde{H} \parallel H^t$$

where $H^{t+1}$ represents nodes feature matrix after the residual mechanism, and $\parallel$ means the concatenation operation. In this paper, three GCN layers are constructed to form the feature aggregation module of ResGCN-SSA with the first two layers of GCN contain the residual mechanism.

3. Small-signal Stability Assessment Model Based on ResGCN of Power System

3.1. The Proposed SSA Framework
The training and evaluation process of ResGCN-SSA is shown in figure 2, including data preparation, offline training and online application.

![Figure 2. Diagram of the SSA framework.](image)

1) Data preparation: In this stage, we generate the inputs and the labels for the training samples.
2) Off-line training: Training samples are fed into the model and all the model parameters are adjusted iteratively by back-propagation of error to achieve the best performance.
3) Online application: During online application, real-time operation state of the power system is obtained from SCADA and the corresponding input quantities are fed into the trained model. According to the predicted damping ratio, power system operators can carry out necessary control measures to ensure the security of the power system.

3.2. Graphical Inputs
1) Node feature matrix:
The node feature matrix $X \in \mathbb{R}^{N \times d}$ is derived from the arrangement of the voltage amplitude and phase at buses, the active and reactive power of generators, the active and reactive power of loads.
2) Adjacency matrix:

The adjacency matrix $A$ is relevant to the node admittance matrix, whose element $a_{(i,j)}$ is as follows:

$$a_{(i,j)} = \begin{cases} 
\frac{|y_{(i,j)}|}{y_{(i,j)}^{\max}} & y_{(i,j)} \in A, i \neq j \\
0 & y_{(i,j)} \in A, i = j 
\end{cases}$$

where $|y_{(i,j)}|$, $y_{(i,j)}^{\max}$ denote the elements and the maximum element in the admittance matrix.

3.3. Generation of Labels

The frequency $f$ and damping ratio $\zeta$ of each oscillation mode are selected as the labels. Their definitions are listed in Eqs. (4)-(6):

$$\lambda = \sigma \pm j\omega$$

$$f = \frac{\omega}{2\pi}$$

$$\zeta = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}}$$

where $\lambda$ represents the eigenvalue to determine the small-signal stability.

4. Application on the IEEE 39 Bus System

4.1. Data Preparation

The operation states with all transmission lines on service are denoted as the "Base" cases, while the "N-1" cases are generated by randomly switching off transmission line to test the topology learning of ResGCN. Besides, the loads are changed within 75% to 120% of the basic load level, while randomly adjust the generators for feasible power flow. we finally get 5,250 cases, which are divided into a training set (70%) and a test set (30%). The simulations are conducted on PSD-BPA for the labels. By comparisons of groups of parameters on the test set, the three-layer GCN in figure 1 is the best to fulfill the small-signal stability assessment.

4.2. Evaluation Metric

The average arctangent absolute error percentage (MAAPE)\[12\] is selected to measure the performance of the model. Eq. (7) measures the relative error between the two targets:

$$\text{MAAPE}_y = \frac{1}{M \times B} \sum_{k=1}^{M} \sum_{i=1}^{B} \arctan\left( \frac{y^k_i - \hat{y}^k_i}{\hat{y}^k_i} \right), y = f, \zeta$$

where $y^k_i$ refers to the labeled frequency or damping ratio of the $k^{th}$ mode of the $i^{th}$ sample, while $\hat{y}^k_i$ refers to the predicted one. $M$, $B$ is the number of the modes and samples.

4.3. Comparison of Model Precision and Its Adaptability to Topology

The proposed model are compared with two baseline models, where MLP is a shallow network and CNN is a deeper one. The results of different models are demonstrated in figure 3. MAAPE- $f$ and MAAPE- $\zeta$ represent the predictive errors of the frequency and damping ratio.
The model proposed in this paper has better performance, whose MAAPE-$\zeta$ and MAAPE-$f$ are 0.64% and 6.04% respectively. The CNN performs worse under "N-1" cases since it fails to capture the local changes of the operation topology. The high-dimensional inputs, however, lead to more difficulty in shallow learning based on MLP, whose MAAPE-$\zeta$ and MAAPE-$f$ increase to 2.78% and 13.48%.

4.4. The Effectiveness of the Residual Mechanism

This subsection discusses the role of the residual mechanism in model performance. The test results concerning ResGCN and GCN are shown in figure 4.

![Figure 4. Comparison of GCN and ResGCN.](image)

Here the MAAPE-$\zeta$ of the samples predicted by ResGCN moves towards 0. Pay attention to "abnormal samples" with large MAAPE-$\zeta$ higher than 15%. There are far more abnormal samples based on GCN than ResGCN, which means the residual mechanism can enhance the ability of the model to distinguish the topologies. As a result, the accuracy of ResGCN on MAAPE-$\zeta$ is 1.74% higher than that of GCN.

5. Conclusion

In this paper, a ResGCN-based small-signal stability assessment model is proposed and verified on IEEE 39 Bus system. The conclusions are listed below:

1) Based on stacked GCN, the steady-state information of different nodes and their high-order neighbors can be fully and effectively aggregated. As a result, the adaptability of the model to topology changes becomes stronger. The experiments show that our method outperforms CNN and MLP under "N-1" cases.

2) The residual mechanism is designed for better performance. Compared with the conventional GCN model, the improved ResGCN can effectively improve the accuracy by reducing the risks of over-smoothing.
In the future, we would like to seek solutions to improve the predictor(MLPs) for online application in larger-scale power systems.

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References
[1] Campagnolo J M, et al. An efficient and robust eigenvalue method for small-signal stability assessment in parallel computers[J]. IEEE Transactions on Power Systems, 1995, 10(1): 506-511.
[2] Du Z , et al. Calculation of electromechanical oscillation modes in large power systems using Jacobi-Davidson method[J]. IET Proceedings - Generation Transmission and Distribution, 2005, 152(6):913-918.
[3] Zhao S, et al. Forward and Backward Extended Prony (FBEP) Method for Power System Small-Signal Stability Analysis[J]. IEEE Transactions on Power Systems, 2017:1-1.
[4] Hu W, et al. Online evaluation method for low frequency oscillation stability in a power system based on improved XGboost[J]. Energies, 2018, 11: 3238.
[5] Azman S K, et al. A unified online deep learning prediction model for small signal and transient stability[J]. IEEE Transactions on Power Systems, 2020, 35(6): 4598-4598.
[6] Liu S, et al. A data-driven approach for online inter-area oscillatory stability assessment of power systems based on random bits forest considering feature redundancy[J]. Energies, 2021, 14(6): 1641.
[7] Bruna J, et al. Spectral networks and deep locally connected networks on graphs[J]. arXiv preprint arXiv, 2014, 1312.6203.
[8] Kipf T N, et al. Semi-supervised classification with graph convolutional networks[J]. arXiv preprint arXiv, 2016, 1609.02907.
[9] Huang J, et al. Recurrent graph convolutional network-based multi-task transient stability assessment framework in power system[J]. IEEE Access, 2020, 8: 93283-93296.
[10] Huang J, et al. A topology adaptive high-speed transient stability assessment scheme based on multi-graph attention network with residual structure[J]. International Journal of Electrical Power & Energy Systems, 2021, 130(1): 106948.
[11] Li Q, et al. Deeper insights into graph convolutional networks for semi-supervised learning[C]//Thirty-Second AAAI conference on artificial intelligence. 2018.
[12] Kim S, et al. A new metric of absolute percentage error for intermittent demand forecasts[J]. International Journal of Forecasting, 2016, 32(3): 669-679.