7International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 617

TRANSIENT STABILITY ASSESSMENT FOR TRANSMISSION SYSTEMS WITH WIND POWER INTEGRATION BASED ON DEEP RESIDUAL LEARNING

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ABSTRACT

The integration of large scale wind farms has brought new challenges to the transient stability assessment (TSA) problem and difficult measurement of data results in fewer samples. In order to assess the state of the system in the case of small sample data, a deep residual learning (DRL) algorithm that can train deeper neural networks to avoid gradient vanish and gradient explosion is proposed. Firstly, the original input features are constructed by using the data to describe the dynamic characteristics of the power system. Secondly, the DRL trained is applied to the TSA problem. Finally, Compared with the plain convolutional neural networks, the proposed DRL achieves the higher accuracy, moreover, it has the highest unstable F1-score and stable F1-score. Case studies on the modified IEEE New England 39-bus system with wind farms integration exhibit the effectiveness of the proposed algorithm.

Keywords: wind farms, transient stability assessment, simple data, deep residual learning, plain network

1. INTRODUCTION

The large-scale integration of wind farms has made the operation and stability characteristics of the power grid more complicated. It makes the power grid more vulnerable to large damage and major failures. After a large disturbance in the power grid, it is necessary to quickly and accurately judge system state and take appropriate protection measures to prevent large-scale collapse and severe instability of the system. Transient stability assessment (TSA) is one of the important tools in the contingency analysis of power systems [1]. The traditional TSA methods mainly include time domain simulation (TDS) method and energy function method. The speed and accuracy is the key to the security and stability assessment issues. However, the TDS method is complex, time-consuming, hence usually only offline evaluation is possible. Although the direct method is faster than the TDS method, its result is often too conservative.

The operational data collected in the actual grid operation is rich and huge, and the artificial intelligence (AI) method effectively screens out and analyzes the critical data to realize the preliminary judgment of the system stability level and weak links [2]. The AI-based TSA method has a high execution speed and can meet the requirements of online operation [3]. TSA has made great progress from the initial artificial neural network (ANN)-based TSA to the current machine learning-based TSA. ANN has attracted a lot of interests from researchers because of its information distributed storage, information parallel processing, fault tolerance. ANN has been widely used in the critical clearance time prediction, energy margin estimation, maximum rotor angle prediction, or stability classification. However, with the development of ANN, the problems have emerged such as over-fitting, local optimization, and feature extraction difficulty problems. These problems have prompted the formation and development of deep learning network.

Compared with traditional neural networks, deep learning has two advantages: one is it can learn the characteristics of the essential attributes of data, and the other is it can achieve far more precision. Recent work in [4] reported a novel methodology to develop a TSA system based on a temporal self-adaptive scheme, aiming to balance the trade-off between assessment accuracy and response time. Fast transient stability batch assessment using cascaded convolutional neural networks is presented in [5].

Selection and peer-review under responsibility of the scientific committee of the 11th Int. Conf. on Applied Energy (ICAE2019).
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The remainder of this paper is organized as follows: Section 2 introduces the data acquisition. A TSA framework based on deep residual learning (DRL) in detail is proposed in Section 3. The proposed algorithm is implemented in the IEEE New England 39-bus system in Section 4 to test the experimental results. Section 5 gives the conclusion.

2. DATA ACQUISITION

System data is generated in the simulation software of PSD-BPA by considering different load levels, fault location and fault duration. Moreover, when changing the loads, the corresponding changes of generator output to ensure the system power balance and the bus voltage is maintained within a reasonable range of 0.95~1.05p.u. The fault location is located at 0%, 20%, 50%, 80% of the transmission line. The fault type is a three-phase permanent short circuit, and the fault duration is considered to be 0.10s, 0.15s, 0.18s, and 0.20s, respectively. The simulation duration is set to 3s.

This proposed algorithm is in contrast to the algorithms in the existing research literature [6] and is consistent with the original feature data in the literature.

The state of the system is determined by calculating whether the absolute value of the generator rotor angle exceeds 360 degrees over a period of time. If it exceeds 360 degrees, the system is considered as unstable and the class label of "0" is assigned for the simulation case. If it is not exceeded, the system is regarded as stable and the class label of "1" is assigned [6].

3. PROPOSED TSA FRAMEWORK

This paper summarizes the TSA problem as: for y=f(X) and the pattern $\{(y_i,X_i)\}$(i=1,2,...,n). Deep residual learning learns the mapping F from X to y, and quickly identify and train a new pattern of similar patterns $\{(y_i,X_i)\}$. Where y represents the transient stability state of the selected grid, $X = \{x_1, x_2, ..., x_m\}$ represents the feature quantity such as total active load, maximum generator rotor angle at the beginning time of fault and the cutting time of the fault, etc, and *m* is the number of features.

3.1 Network architecture

ANN, Plain and Residual nets are tested in this paper. These networks are shown in Fig 2. ANN will not be described in detail in this section.

Plain Network. The convolutional layers mostly have 1x1 filter and follow two simple design rules: (i) the layers have the same number of filters for the same output feature map size; and (ii) if the feature map size is halved, the number of filters is doubled so as to preserve the time complexity per layer. The network ends with a global average pooling layer and a 4-way fully-connected layer with softmax. The total number of weighted layers are 6 and 11 in Fig 2.

Residual Network. Residual learning was adopted to every few stacked layers. A building block is shown in Fig 1, which was defined as

$$y = F(x,\{W_i\}) + x \tag{1}$$

Where x and y are the input and output vectors of the layers considered. The function $F(x,\{W_i\})$ represents the residual mapping to be learned. For the example in Fig 1 that has two layers. The operation F(x)+x is performed by a shortcut connection and element-wise addition. In this paper, the second nonlinearity is adopted after the addition.

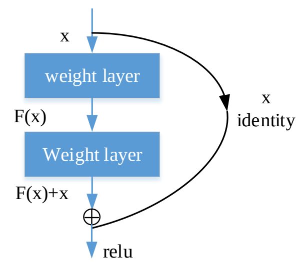

Fig 1 Residual learning: a building block

Compared with the Plain network, the Residual network can train deeper neural networks to avoid gradient vanish and gradient explosion. Residual networks consist of a number of neuron sub-modules connected by a compartment, which we call a residual block. Skip connection is used to directly establish the layer connection, so as to be able to train deeper neural networks and effectively improve the training effect.

3.2 Evaluation of Indices

1) Accuracy of the model: Accuracy is the most commonly used performance metric in a classification task, and is the ratio of the number of correctly categorized samples to the total number of samples. For the sample set D, the classification accuracy is defined as

$$\mathrm{acc}(f;D) = \frac{1}{m}\sum_{i=1}^{m} \mathrm{II}(f(x_i) = y_i) = 1 - E(f;D) \tag{2}$$

2) Stable/unstable F1-score: Although the accuracy is common, it does not meet all the task requirements. For the two-category problem, the sample can be divided into a true positive (TP), a false positive (FP), a true negative (TN), and a false negative (FN) according to the combination of the real category and the learner prediction category. In this case, TP+FP+TN+FN=the total number of samples. Precision and recall are defined as

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$$P = \frac{TP}{TP + FP} \quad (3)$$

$$R = \frac{TP}{TP + FN} \quad (4)$$

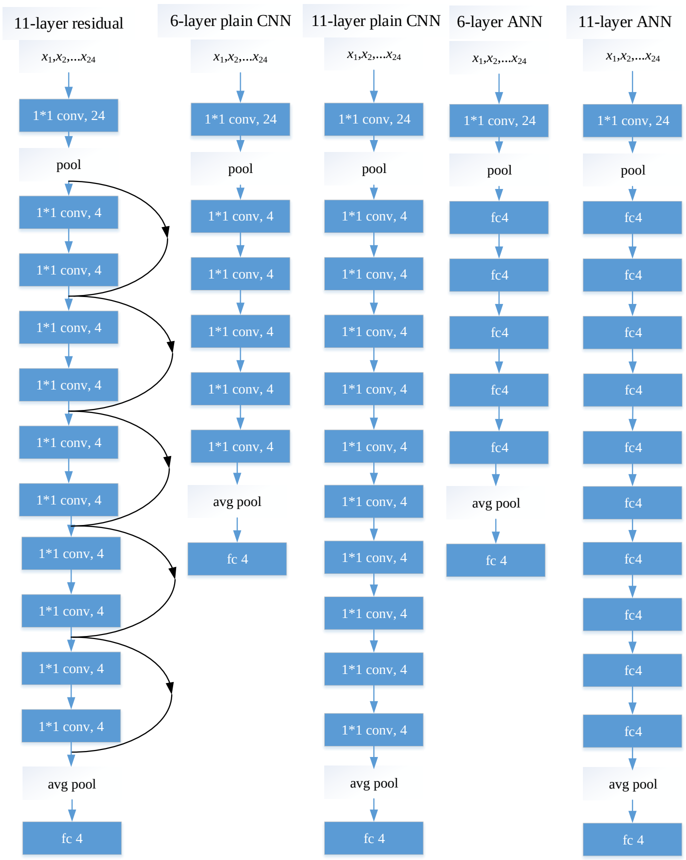

Fig 2 Example network architectures for TSA

Precision is the ratio that is correctly predicted to be positive and positive for all predictions. Recall rate is the proportion that is correctly predicted to be positive and positive for all.

F1-score is a measure of the classification problem. It is the harmonic mean of the precision rate and the recall rate, with a maximum of 1 and a minimum of 0. The large the F1-score, the better the effect. The definition of F1-score is

$$F1 = \frac{2 \times P \times R}{P + R} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (5)$$

When F1-score is small, TP increases relatively, while F1-score decreases relatively, that is, both P and R increase relatively.

4. EXPERIMENTAL RESULTS

4.1 Test System and training details

The New England 39-bus test power system is modified to train and evaluate the performance of the proposed algorithm, which is shown in Figure 2. The test system involves 39 buses, 10 generation units including 5 traditional generators and 5 wind farms, 19 loads, and 46 transmission lines. For the optimization of the proposed network, we adopt an Adaptive Moment Estimation (Adam) optimizer with 10^{-3} learning rate. The experiments are performed on a workstation with I7-7700k CPU and a GeForce GTX 1080Ti GPU. The PyTorch framework provided by FaceBook is selected for establishing the proposed residual neural network.

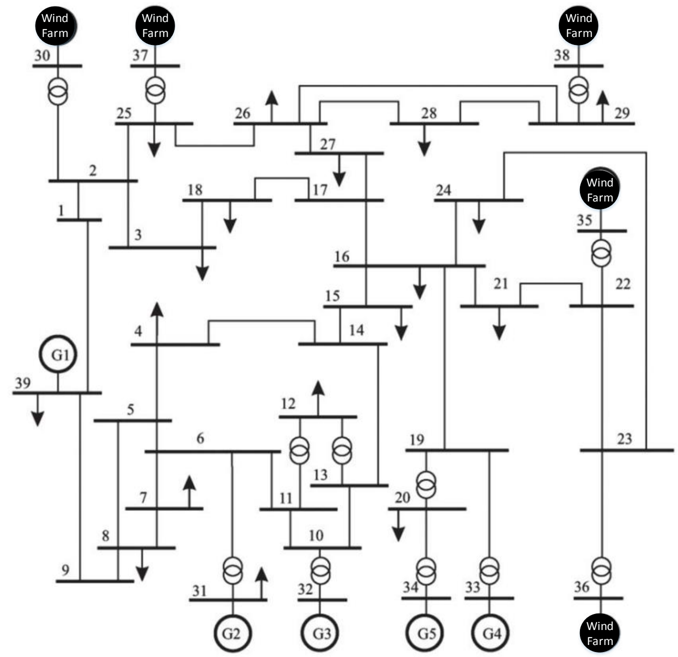

Fig 3 the modified New England 39-bus system

4.2 Specific analysis of the proposed algorithm

In this paper, the small sample data is used to verify the effectiveness of the proposed algorithm. The total data is 2158, including 1378 stable data and 780 unstable data. The training data and testing data are divided according to the following table I. Among them, in order to reduce the impact of training sample category imbalance on model training, we divide the stable and stable data according to the ratio of 1:1 when dividing the data set. The confusion matrix of the proposed algorithm is presented in Table II.

Table I Training data and testing data

	Stable data	Unstable data
training data	600	600
testing data	778	180

Table II Confusion matrix

		Prediction results	
		unstable	stable
Actual results	unstable	157	23
	stable	81	697

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4.3 Comparison of Different Classifiers

For validity verification, eight types of algorithms including KNN, SVM (different kernel functions are used), ANN and CNN are used to compare the proposed TSA model. The ANN algorithm and the CNN algorithm use 6-layer and 11-layer respectively (excluding the lass full connection (fc) layer—for classification). The reason for adopting 6-layer and 11-layer is that the proposed algorithm includes 5 res blocks, which are replaced by 1 convolution layer/full connected layers, or 2 convolution layers/fully connected layers. Thereby, Plain CNN6/ANN6 and Plain CNN11/ANN11 are obtained. Table III presents the performance indices of the proposed algorithm and other comparison algorithms.

Table III shows that CNN with res blocks has the highest accuracy based on the small sample data. It can also be obtained from Table III that in the experiment CNN with Res blocks has the biggest unstable F1 and stable F1. That means the proposed algorithm achieves the highest accuracy and F1-score, which are asymptotically more efficient than other algorithms.

Table III contrast of TSA of different models

	Classification accuracy	Unstable F1-score	Stable F1-score
KNN(K=3)	84.24%	66.96%	89.65%
SVM(Linear kernel)	80.48%	60.63%	87.02%
SVM(RBF kernel）	19.00%	31.69%	0.51%
SVM(sigmoid kernel)	81.21%	——	89.63%
ANN 5	81.63%	64.23%	87.64%
ANN 10	84.55%	68.38%	89.78%
Plain CNN 5	78.39%	61.02%	85.05%
Plain CNN 10	81.84%	64.63%	87.78%
Proposed(CNN with Res blocks)	**89.14%**	**75.12%**	**93.06%**

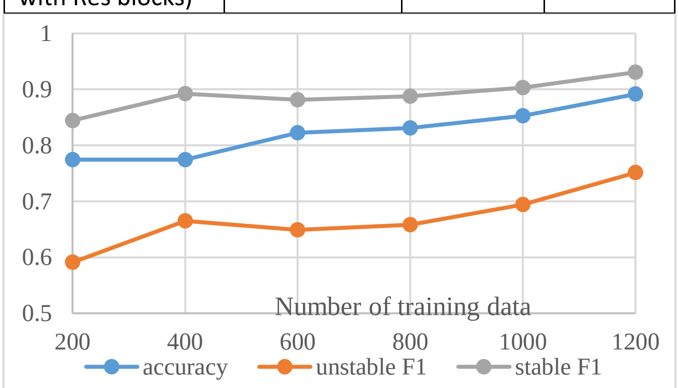

Fig 4 Accuracy, unstable F1 and stable F1 on different data

4.4 Comparison of effects under different data volumes

The comparison results based on small sample data are presented in Fig 4. It shows that the proposed algorithm can achieve high accuracy, unstable F1 and stable F1. If the amount of data for training is large, these indices will be higher.

5. CONCLUSION

TSA framework with sample data based on the DRL is presented in this paper. Eight types of algorithms including KNN, SVM (different kernel functions are used), ANN and CNN are used to compare the proposed TSA model. Example result shows the DRL algorithm with five building blocks has exhibited satisfactory performance. It is suitable for TSA based on an insufficient amount of data or a small amount of data. In conclusion, the results demonstrate that the highest accuracy, unstable F1-score and stable F1-score, which guarantee the performance of the TSA framework.

ACKNOWLEDGEMENT

This work is supported by the State Grid Corporation of China Science and Technology Project.

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