Study on stability feature extraction of power system using deep learning

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Abstract. Dynamic security assessment (DSA) of power grids is widely used in dispatching operation systems, and calculation speed is one of its most important performance indicators. In this paper, a stability feature extraction method is proposed, which is useful for quick judgment of stability and assisted decision-making. Firstly, a simulation sample database is constructed based on historical online data and a deep learning model with least absolute shrinkage and selection operator (LASSO) is trained to pick both the high level and low level stability features. While a new operation mode needs to be evaluated, a fast search is implemented to obtain the most similar samples in the database using the chosen high level features; the final result will be determined comprehensively by the familiar samples. If the power grid is in critical condition, a decision-making will be done by using the low level features. The validity of proposed method is verified by the simulation using online data of Northeast Power Grid of China. It is proved that the method meets the requirements for speed and accuracy of online analysis system.

1. Introduction
In order to protect the transmission of electric energy reliability, China Power Grid has carried out many projects such as power transmission from west to east, national networking and UHV transmission, an extra-large-scaled AC / DC hybrid power grid has been accomplished in China[1]. With the expansion of grid-scale, the security and stability characteristics of power grid become more and more varied. In order to enhance the abilities to control the large grid operation, the DSA applications are deployed in all dispatching systems above provincial level [2-5], which is also unknown as online security and stability analysis. A comprehensive security analysis will be made by DSA every 15 minutes, which includes more than 1000 transient stability simulation of predefined faults, and needs extremely large calculation. However, calculation speed is the main performance index, as the analysis result will become meaningless without timeliness. As calculation quantity and speed are contradictory, some kinds of quick judgment technologies need to be proposed which could calculate the stability indicators with small calculation cost and only pick the real dangerous faults to make the simulation, so the computing resource will be saved and early warning time of DSA will be shorten.

With the operation of DSA system, a great amount of historical data has been produced, which both includes the power flow data and stability analysis result. There are many regularities and experiences contained in the historical data, which could be applied in quick judgment of online stability analysis.
to improve the calculation speed and validity. Some analyses of quick judgment have already been made by using historical data and machine learning method [6-11]. In this paper, with the consideration that it is easy to find similar samples in the latest historical online data, the deep learning with LASSO and k-NN method are introduced to extract the stability features and make the quick judgment. It is proved that the method could shorten the calculation time significantly with slight decrease of accuracy, and meets the requirements of online analysis.

The rest of the paper is organized as follows: Section 2 introduces some related concepts, including online small signal stability, deep learning model and LASSO method; Section 3 describes the main ideas and analysis steps of the method; results are illustrated and evaluated in Section 4 using actual data; Section 5 concludes the paper.

2. Related concepts

2.1. Online small signal stability

Transient stability and small signal stability are the most time-consuming analyses in DSA. In this paper, we take online small signal stability for example; the process of transient stability is the same. The frequency and damping ratio of designated oscillation mode are the main indicators of small signal stability. The online small signal stability analysis usually adopts eigenvalues method, which can be divided into three main steps [12]:

1) Linearization of the model. According to the current system operation point, linearize the dynamic models of power elements;
2) Solve eigenvalues and eigenvectors of the state matrix of power system;
3) The coherent generators and oscillation mode analysis. According to the result of eigenvector, we can determine the coherent generators, select the representative generator and analyse the corresponding typical oscillation modes.

At present, the online small signal stability analysis has been put into practical application, but there are still some drawbacks as follows:

- The computation time is too long. Take the online calculation data of real power system as an example, calculation time is usually 1-2 minutes, which is the longest of the online analysis.
- It is possible that the key oscillation mode can’t be found. Because the scale of the modern power system is too large, the dimension of state matrix is always very high, so it is impossible to get all the eigenvalues. In practice, the Rayleigh entropy iterative method is usually used to solve a small amount of eigenvalues between 30 and 200. So, it has the possibility that the eigenvalue of the key oscillation mode can’t be solved.

2.2. Deep learning model

In recent years, deep learning has obtained great development and became the research focus of artificial intelligence (AI) technologies. It is widely applied in image recognition, natural language processing and other fields. Deep learning is good at extracting features or regularities from massive data automatically and reflecting complicated mapping relationship, which meets the requirement of high dimensional, strong non-linear, strong coupling characteristics of power system stability problems.

Power system has a typically hierarchical structure, which is used for building the neural network of deep learning model: we take stations as the basic units and divide the whole system into three levels including district, provincial and regional; establishing the affiliation relationship between the three levels of network through topology analysis; use fully-connected neural network for each sub net and connect them together based on the affiliation to form the deep learning model. The deep learning model is shown in figure 1, which is called grids hierarchical net (GHNet).
2.3. LASSO
LASSO method adds a penalty function of L1-norm of parameters to the cost function of deep learning. It depresses the unimportant coefficients to zero or near zero, and leads to a more refined model. After training the model, the primary parameters will be more prominent, so that the features are extracted out. The cost function of deep learning model with LASSO is shown in formula (1).

\[
J(X) = \frac{1}{N} \sum_{n=1}^{N} \left[ y_n - f_{\text{NN}}(X) \right]^2 + \lambda \|W_1\|_1
\]  

where \(N\) is the number of samples in each batch; \(y\) is the stability index obtained by simulation, like damping ratio of small signal stability; \(f_{\text{NN}}()\) indicates the deep learning model; \(X\) is the input of neural network; \(W_1\) is the first level trainable parameters of neural network; \(\lambda\) is a super parameter used for trade-off between the actual cost and the penalty value of parameter \(W_1\).
In formula (1), the first part reflects accuracy of the model, which indicates the stability characteristics that the model “learned”; the second part reflects the compressibility for unimportant features. We only use L1-norm on the first layer (\(W_1\)), because it is the most direct indicator to pick stability features.

3. Methodology
A kind of fast searching algorithm is implemented in this paper using static state values of power system as its input and damping ratio as its predicting target. Because there are so many static state values that have different influences on the stability, it is impossible to use all of the static state values. Instead, the stability features must be the most influential ones that should be picked out by feature engineering. There are two kinds of feature engineering: model-driven method that uses professional domain knowledge and data-driven method that finds out relationships between data like machine learning. In this paper, the deep learning model with LASSO is proposed for feature engineering, and k-NN is used for quick judgment, the detailed process is as follows:

3.1. Step 1: Establish the historical database
1) Inputs

![Figure 1. GHNet Structure.](image-url)
This step will be done with the operation of the DSA system. The online data is produced every 5 minutes, which both includes the power flow data and stability analysis result. The static state values used as the input of deep learning model are listed in table 1.

| Equipment Type | Static State Value | Symbol | Data Type |
|----------------|--------------------|--------|-----------|
| Generator      | Running State      | S<sub>G</sub> | Integer  |
|                | Active Power       | P<sub>G</sub> | Float    |
|                | Voltage            | V<sub>G</sub> | Float    |
| Station        | Total Active Power of Load | P<sub>L</sub> | Float |
|                | Total Reactive Power of Load | Q<sub>L</sub> | Float |
| DC Line        | Active Power       | P<sub>DC</sub> | Float |

2) Predicting target
We choose the Liaoning - Heilongjiang oscillation mode’s damping ratio as the predicting object. The bigger damping ratio means the more stable power system. If the damping ratio is less than 3%, the Northeast Power Grid of China will be in critical condition. Because the damping ratio is a continuous value, the predicting task can be considered as a regression problem.

3.2. LASSO model training
LASSO algorithm is solved by iteration process:

1) Determine the input as well as the structure of the model, and then determine the dimensions of the parameter matrix W<sub>1</sub>;
2) Define the cost function as formula (1);
3) Use the iterative method to minimize the cost function.

Where λ is a super parameter: a larger λ means emphasis on the penalty term of W<sub>1</sub>, which may lead to a bigger actual error that unable to reflect the stability characteristics of the power grid. Therefore, the selection of λ is the key issue.

In this paper, the model is trained for many times to seek the optimal value of λ. When the penalty term is not considered (λ = 0), the error rate will be the lowest that is defined as the base line. The parameter λ can be equidistant values in exponential coordinate, for example 0.1, 0.01, 0.001, etc.

3.3. Feature selection
According to the characteristics of deep learning model, parameter matrix W<sub>1</sub> represents the weight of each input. The greater value means the more important input. The dimensions of the matrix W<sub>1</sub> are N<sub>1</sub>*N<sub>2</sub>, N<sub>1</sub> and N<sub>2</sub> are the numbers of neuron in layer1 and layer2. Therefore, the algorithm sums the absolute values of each row of the matrix W<sub>1</sub>, and selects the largest number of the results as the stability features.

3.4. Time domain simulation
Calculate the real damping ratio result by small signal stability simulation to verify the method. Then, put the latest power flow data and real damping ratio result into the historical database for next prediction. Algorithm flow chart is shown in figure 2.
4. Examples
The validity of proposed method is verified by simulation using online data of Northeast Power Grid of China. All the power element models above 220kV have been included in the online data. The number of input static state values is 1919, the predicting object is the damping ration of Liaoning - Heilongjiang oscillation mode.

4.1. Model training
Choose seven different parameter λ for model learning respectively: 0, 0.1, 0.01, 0.001, 0.0001 and 0.00001. The results are shown in table 2.

| λ       | Error rate | Compression ratio |
|---------|------------|-------------------|
| 0 (reference) | 0.17% | 1.18% |
| 0.00001 | 0.23% | 16.62% |
| 0.0001  | 1.15% | 62.17% |
| 0.001   | 8.06% | 79.42% |
| 0.01    | 35.62% | 85.14% |
| 0.1     | 47.85% | 61.83% |

The error rate while λ=0.1 or λ=0.01 is obviously too large, indicating that the model cannot reflect the stability characteristics of the power grid, so it needs to be ignored. The rest results show that the error rate increases with the increase of λ, while the compression ratio of \( W_1 \) also increases as expected. We choose the LASSO model with \( \lambda=0.0001 \) as the best model.

4.2. Feature selection
We use the sum of the absolute value of parameter matrix \( W_1 \) to extract the low level features, and the results are shown in table 3. We use back propagation algorithm (BP) to calculate the sensitivities of the low level features with the online data at 10:00 on November 25, 5 of the largest positive and negative sensitivities are also shown in table 3. For convenience of comparison, we only pick out generator’s active power features.
Table 3. Low level features.

| Variable name | Weight of the feature | Sensitivity |
|---------------|-----------------------|-------------|
| HLJ.JX.#1     | 10.81                 | -0.001343   |
| HLJ.JXER.#1   | 19.23                 | -0.000767   |
| HLJ.JXER.#2   | 20.58                 | -0.000667   |
| HLJ.JX.#2     | 15.90                 | -0.000639   |
| HLJ.QTH.#1    | 8.23                  | -0.000473   |
| LN.YSH.2#     | 9.83                  | 0.000627    |
| LN.QH.1#      | 12.98                 | 0.000435    |
| LN.YK.1#      | 8.86                  | 0.000403    |
| LN.GJZ.2#     | 9.17                  | 0.000402    |
| LN.DD.1#      | 10.53                 | 0.000330    |

As the results shown in table 3, the sensitivities of generator’s active power in Liaoning are positive, and the sensitivities in Heilongjiang are negative. The results meet the characteristics of Northeast Power Grid, as the electricity power is mainly transmitted from Heilongjiang to Liaoning.

32 high level features can be calculated by deep learning model, because the number of neurons in the last hidden layer is 32.

4.3. Quick judgment

Take the online data at 10:00 on November 25 for example, 5 most similar samples are found by using high level features shown in table 4. The average of the 5 most similar samples is 0.207084, while the simulation result is 0.207118. The error rate is 0.016%, which is extremely low.

Table 4. The most similar samples.

| No | Date time       | Distance | Damping ratio |
|----|-----------------|----------|---------------|
| 0  | 2018_11_25T00_00 | 0        | 0.207084      |
| 1  | 2018_11_25T09_45 | 7.068e-5 | 0.206563      |
| 2  | 2018_11_25T09_30 | 7.537e-5 | 0.206329      |
| 3  | 2018_11_25T10_20 | 7.653e-5 | 0.207589      |
| 4  | 2018_11_15T12_15 | 9.026e-5 | 0.207754      |
| 5  | 2018_11_15T20_35 | 9.227e-5 | 0.207353      |

Another interesting situation is that: some similar samples are not the closest ones in time, like 4 and 5 in table 4. It is due to the high dimensionality and high non-linearity of stability problem of power system.

4.4. Decision-making

We changed the operation mode of the online data at 10:00 on November 25 by using the low level features in table 3: reduce the active power of each generator with negative sensitivity by 10MW, and increase by 10MW otherwise. Our aim was to increase the damping ratio to make the power system more stable. The simulation result of damping ratio of new operation mode is 0.210108, which is increased as expected.

5. Conclusion

A deep learning model with LASSO is proposed to extract the high level and low level features based on historical database, which is very appropriate for online stability analysis. Simulation and experimental results verify the correctness and effectiveness of the proposed method. It is also necessary to make further improvements, such as:

1) Try more features that make influence on the stability of power system;
2) Rapid and valid method of determining the adjustment quantities;
3) Study on rapid and automatic methods for searching the optimal value of super parameter $\lambda$. 
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