Artificial Neural Network Plan for Transmission Tower Structure Safety Assessment

Mi Sun¹,², Jinghai Xie¹,²*, Yu Jiang¹,², Dongyu Su¹,², Shihua Lu¹,² and Jia Guo¹,²

¹State Grid JiBei Electric Power Company Limited Economic Research Institute, Beijing, China
²Beijing Jingyan Electric Power Engineering Design co., LTD, Beijing, China

*Corresponding author e-mail: 116486712@qq.com

Abstract: The security of transmission tower structure is the foundation to ensure the safe operation of power grid. The research of fuzzy qualitative assessment method for the structural health of transmission towers is the basic work of large-scale digital power grid engineering. In this paper, artificial neural network (ANN) is used as a generalized tool for structural health assessment of transmission towers. The feasibility of using artificial neural network to qualitatively evaluate the structural health of transmission towers is verified by numerical simulation data. In order to train the artificial neural network, the displacement, stress and other signals generated by the finite element model are calculated and used as the training input of the artificial neural network. The detailed stress results of the finite element model are calculated as the qualitative evaluation basis of the structural health, and the training output of the artificial neural network is generated. By the same method, the test set is generated, and it is found that the artificial neural network is feasible for the fuzzy qualitative assessment of the structural health of transmission tower, and the misstatement rate is less than 5%.

1 Introduction

Natural disasters such as wind-induced vibration, earthquake, large-area icing and landslide seriously impact safety of power transmission tower structure. For instance, Typhoon Damrey landed on Hainan in 2006, and caused breaking down accidents of more than 30 power transmission towers [1]; in 2014, Typhoon Wilson landed on Guangxi, which caused tripping of multiple lines, brought vast economic losses and seriously affected daily life of people [2]. According to electric power facilities damage investigation in Wenchuan Earthquake [3], the power transmission towers always fell down in earthquake, showing as tower structure collapse, or tower pulling down and transmission line consecutive falling; there are many oversea cases of power transmission tower damage caused by geological process [4]; in early 2008, the once-in-half-a-century snow and ice disaster attacked South China, and power transmission lines suffered serious disaster such as tower falling, collapse and line breaking due to large-area icing [5]; in hilly and mountainous area in China, the impact of landslide on safety performance of power transmission tower is also serious [6-8].

At present, safety performance of power transmission tower structure is mainly inspected by labor line patrol investigation. However, such method has defects such as high labor costs, high hazard, low work efficiency and out-of-work in extreme conditions [9-11]. Arranging sensors to the structure for data
acquisition and health monitoring becomes a safe and reliable method \cite{12-13}. The on-site and nondestructive monitoring method is used to acquire internal information and analyze various characteristics including the structure so as to know structural change caused by damage or degeneration \cite{14}.

However, two problems of sensor application in actual engineering are to be solved urgently: firstly, due to large size and numerous nodes of power transmission tower structure, and multiple towers on line, it is necessary to arrange large amount of sensors, resulting in excessively high cost and against large-area promotion \cite{15}; secondly, it is difficult to extract data which reflect characteristics of structural damage from mass monitoring data, and safety assessment aspect shall be improved \cite{16-18}.

This paper adopts artificial natural network (ANN) as qualitative safety assessment model of the structure, which could organically integrate measured data and simulated data into one model. It uses displacement and stress signals of key structural points on certain power transmission tower calculated by finite element model as ANN training input to train ANN as fuzzy qualitative assessment model for health state of power transmission tower structure.

2 Thinking for qualitative assessment of power transmission structure safety with ANN model

2.1 Overall thinking

The plan is based on the following considerations:
1. The less the sensors on power transmission tower structure are, the better to save costs;
2. For conclusion of safety assessment, it is not necessary to quantitatively and locationally recognize structure damage but it only needs to output overall and qualitative safety conclusion of the structure;

Therefore, ANN is proposed as the normed instrument to realize aforesaid consideration with displacement and stress signal of minor key points on the power transmission tower as ANN input and structure health qualitative conclusion as output.

This paper generates training data with structural finite element model to train generalized regression neural network (GRNN) and improve reliability of assessment model.

2.2 Generation of training data

For neutral network, training data refers to input and output data. The generation method is described in 1.2.1 and 1.2.2.

Pros of training data generated in such method are: 1. Highlighting overall features of structural vibration deformation and avoiding interference of high-order local vibration mode; 2. Lowering dynamic and time-historical analysis to statical analysis, and saving analysis work; this idea is similar to pushover analysis; 3. Making up insufficient measured load data to certain degree.

2.2.1 Input data

Generation steps are:
1. Apply eigenvalue analysis to finite element model (n degree of freedom), extract vibration mode with larger collision participating mass of m order to comprise vibration mode matrix $\Phi$ with n lines and m rows;
2. Select and load a typical load condition for master load (earthquake), carry out time-procedure analysis to the model and acquire time-procedure $d(t)$ of displacement on each node of the model;
3. Convert displacement time-procedure $d(t)$ to vibration mode coordinate time-procedure $y(t)$ through vibration mode matrix $\Phi$; the conversion method is

$$y(t) = (\Phi^T \Phi)^{-1} \Phi^T d(t)$$

(1)

4. Change load work condition, repeat aforesaid step 2 and 3 several times, and acquire possible maximum value $y_{\text{max}}$ of vibration mode coordinate in each order under typical load through comparison;
5. With possible maximum $y_{\text{max}}$ of vibration mode coordinate of each order as upper limit, generate at random $p$ vibration mode coordinate vectors $y_{ri}$ ($i=1,2,...,p$), and thus retrieve $p$ stochastic nodal
displacement vectors \( d_{R_i}(i=1,2,\ldots,p) \) of the structure; the retrieval method is:

\[
d_{R_i} = \Phi y_{R_i}
\]  

(2)

6. Load nodal displacement \( d_{R_i} \) to the model by nodal enforced displacement method, and calculate displacement and stress of key nodes under such operating conditions as input data. \( p \) stochastic displacement condition may generate \( p \) groups of training input data.

2.2.2 Output data

Generation steps are:

1. In step 6 of aforesaid 1.2.1, calculate and acquire displacement and stress of key nodes and acquire internal force or stress of all rods of the structure;

2. Apply checking computation to bearing capacity and stability of each piece of rod according to specifications based on internal force or stress;

3. Where all rods have passed checking computation of bearing capacity and stability under such operating condition, the output data of the operating condition (or training group) is 1 (healthy); otherwise, the output is 0 (unhealthy).

2.3 GRNN overview

Generalized regression neural network (GRNN) is acquired based on improved radial basis function network (RBF), and has strong nonlinear fitting capacity. When number of samples is small, it has better prediction effect than RBF, and has better processing ability for unstable data. GRNN has four layers of network structure, respectively input layer, model layer, summation layer and output layer. The network structure can be seen in Figure 1.

![GRNN Network Structure](image)

(1) Input layer
Number of nerve cells on the input layer equals to dimension number of input vector in samples, i.e., number of independent variables. Input variables to nerve cells of the input layer successively and pass directly to nerve cells of the next layer (model layer).

(2) Model layer
The number of nerve cells on model layer equals to number of learning samples, and each nerve cell is corresponding to different learning sample. The transfer function of the \( i \) nerve cell can be seen in Formula (3):
\[ p_i = \exp \left[ -\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right] i = 1, 2, \cdots n \]  

(3)

In the formula, \( p_i \) is the transfer function of the \( i \) nerve cell; \( X \) is input variable; \( X_i \) is the learning sample corresponding to the \( i \) nerve cell; \( \sigma \) is the spread value of Gaussian function, i.e., smoothing factor.

(3) Summation layer

Nerve cells of summation layer has two types. One is to carry out arithmetic summation to every nerve cell on the model layer. The transfer function can be seen in Formula (4):

\[ S_D = \sum_{i=1}^{n} p_i \]  

(4)

In the formula, \( S_D \) is arithmetic summation of the summation layer.

The second is to carry out weighted sum of output of every nerve cell on the model layer; the transfer function can be seen in Formula (5):

\[ S_{N_j} = \sum_{i=1}^{n} y_{ij} p_i \quad j = 1, 2, \cdots k \]  

(5)

In the formula: \( S_{N_j} \) is weighted sum of the summation layer; \( y_{ij} \) is the connection weight between nerve cells; \( k \) is number of dimensions of output vector in learning samples.

(4) Output layer

The number of output nerve cells equals to number of dimensions of output vector in learning samples. The output function can be seen in Formula (6):

\[ y_j = \frac{S_{N_j}}{S_D} \quad j = 1, 2, \cdots k \]  

(6)

In the formula, \( y_j \) is output of the output layer.

3. Case Analysis

In order to verify feasibility of aforesaid plan, 1B-ZM3 linear tower structure is selected as the case in numerical experiment.

3.1 Structure overview

The 1B-ZM3 linear iron tower extensively applied to voltage grades below 330 is used as model prototype. The tower is 41.7m high and the nominal height is 36m. The structural sketch can be seen in Figure 2.

3.2 Finite element modeling

Create model in MIDAS/Civil. The 3D model can be seen in Figure 3. There are totally 424 nodes and 1071 beam elements. Q235 and Q345 angle iron are adopted, with steel elasticity modulus of \( 2.06 \times 10^5 \) MPa and Poisson’s ratio of 0.3. Totally 23 equal leg angles with different section size, respectively L63\times5, L45\times4, L40\times3, L56\times4, L50\times4, L40\times4, L90\times7, L56\times5, L75\times6, L80\times7, L90\times8 and L110\times7 are set for main materials, diagonal members and auxiliary materials of iron tower to restrict translation degree of freedom of four feet along direction X, Y and Z. Mass of parts shall be taken into account.
3.3 Training set and test set generation of finite element model

Carry out analysis on natural vibration characteristics to the structure, and set modal extraction number is 100 orders, in which parameters of the first ten orders of modal can be seen in Table 1. The first five orders vibration mode of tower model can be seen in Figure 4.

| Modal | Frequency (Hz) | Period (s) | Vibration mode characteristics |
|-------|----------------|------------|-------------------------------|
| 1     | 1.56           | 0.64       | First order Y-direction vibration |
| 2     | 2.00           | 0.50       | First order X-direction vibration |
| 3     | 3.66           | 0.27       | Tower local vibration |
| 4     | 4.64           | 0.22       | Tower local vibration |
| 5     | 4.94           | 0.20       | Tower local vibration |
| 6     | 5.29           | 0.19       | Tower head vibration |
| 7     | 5.69           | 0.18       | Tower head vibration |
| 8     | 5.92           | 0.17       | Tower leg local vibration |
| 9     | 5.97           | 0.17       | First order Z-direction torsion |
| 10    | 6.22           | 0.16       | Tower leg local vibration |

Results of eigenvalue analysis show most vibrations of the structure are parts local vibrations. The frequency of such vibration modes is intensive, and participating mass is small, contributing little to overall vibration. The mode similar to that described in 1.2.1 should be adopted to remove such vibration mode so as to improve computational efficiency.

Based on the criteria of single direction participating mass larger than 1%, 31-order vibration modes are selected to compose vibration matrix $\Phi$. Select 10 pieces of earthquake vibration records including El_Centro, and adjust according to Degree-9 rare occurrence earthquake to estimate upper
value of 31-order matrix coordinate.

In this numerical experiment, extract displacement of two nodes on tower top, four nodes on connecting area (neck) of tower head and body, and normal stress on four nodes at bottom as input data.

Extract bean element stress, and check bearing capacity and stability of parts to judge whether tower is in healthy condition. The result is the output.

In this numerical experiment, totally 100 groups of stochastic enforced displacement conditions are generated, i.e., 100 groups training data is acquired, in which operating conditions with output of 1 (healthy) is accounting for 59%.

3.4 Training overview

The 100 groups of data acquired from finite analysis are applied to GRNN model for training and test. MATLAB software is used to divide 100 groups of set into training set and validation set at random, in which 80 groups are used for training and 20 are used for validation. The optimal spread value is searched within [0.0005, 0.001] by virtue of 5-fold cross-validation method. The optimal spread value of final model is 0.0005. The comparison of actual output result and expected output result of model validation set can be seen in Figure 5.

![Generalized regression neural network test output](image)

**Figure 5 Comparison of Model Validation Results and Actual Results**

The mean absolute percentage error (MAPE) is used to evaluate safety assessment model. The calculation formula can be seen in Formula (7).

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{R'_i - R_i}{R_i} \right|$$  \hspace{1cm} (7)

In the formula, $R'_i$ and $R_i$ are respectively actual output results and expected output results of the model.

Through calculation, MAPE of 20 groups of validation set data is 0, and training effect of the model is favorable.

3.5 Test results

Another 20 groups of input and output are generated as stochastic test set data, and inputted to trained neural network model. Calculation results of formula (7) show MAPE of the data in stochastic
test set is 5%, and the prediction effect of the model is acceptable. Specific test set data and prediction results of displacement and stress can be seen in Table 2.

| Group | Tower top displacement (m) | Tower neck displacement (m) | Tower bottom stress (MPa) | Output |
|-------|---------------------------|-----------------------------|--------------------------|--------|
| Node 1 | X | Y | X | Y | X | Y | X | Y | Node | 1 |
| Node 2 | X | Y | X | Y | X | Y | X | Y | Expected | Model |

4. Conclusion

1. Simulating actual engineering structure of finite element software could provide massive data for establishment of artificial neural network, and analyze according to different requirements.
2. GRNN could be used in safety assessment of power transmission tower structure. GRNN safety assessment model proposed in this paper, by considering factors such as displacement and stress on key nodes of power transmission tower, could accurately predict healthy status of the tower structure with precision of over 95%.

5. Acknowledgments

This subject relies on the State Grid "Technical Research on Tower Health Monitoring and Safety Assessment under the Digital Grid Ecology" (B3018F20000K) project.

About the author: Sun Mi (1988-), female, born in Changde, Hunan Province, Engineer, is engaged in structure design of power transmission line.

References

[1] Tang Siqing, Zhang Mi, Li Jianshe, et al. Review of Blackout in Hainan on September 26th--Causes and Recommendations [J]. Automation of Electric Power Systems, 2006, 30(1):1-7.
[2] Xiao Fei. Analysis on Impact of Typhoon “Rammasun” on Power Grid in Coastal Areas of Guangxi [J]. Hongshui River, 2015(2):79-81.
[3] Zhang Dachang, Zhao Wenbo, Liu Mingyuan. Analysis on Seismic Disaster Damage Cases and Their Causes of Electric Power Equipment in 5·12 Wenchuan Earthquake [J]. Journal of Nanjing University of Technology (Natural Science Edition), 2003, 31(1):44-48.
[4] Su Qiaolei. Study on Active Seismic Control Optimization of Transmission Tower Structure [D]. Xi’an: Xi’an University of Architecture and Technology, 2012.
[5] Xiong Tiehua, Liang Shuguo, Wu Haiyang. Failure Modes Analysis of a Broken Down Transmission Tower Under Ice Loads [J]. Chinese Journal of Computational Mechanics, 2011, 28(03):468-472+478.
[6] Wu Zhibin. Landslide Control Method of 149# Tower Footing on 500kV Gansu-Sichuan Line I, II [J]. Electronic Production, 2014, 07:207-208.
[7] Yan Fuzhang, Yuan Zhaoxiang, Sheng Dakai, et al. Geo-Hazard and Prevention for Ertan-Zigong 500 kV Transmission Lines [J]. Electric Power Construction, 2010, 31(5):26-29.
[8] Li Wei. Study on Vulnerability Evaluation Model of Overhead Transmission Lines to Landslides [D]. Chongqing: Chongqing University, 2014.
[9] Li Jiaxun. Exploration on the Implementation of "New Infrastructure" in the Field of New-type Urbanization Development [J]. Construction Economy, 2020, 41(10):5-8.
[10] Yang Chen. Advances and Prospects for Optimal Sensor Placement of Structural Health Monitoring [J]. Journal of Vibration and Shock, 2020, 39(17):82-93.
[11] Li Dehai, Li Dandan. Overview of Vision-based Transmission Line Automatic Monitoring Technology [J]. Heilongjiang Electric Power, 2019, 41(06):559-564.
[12] Peng Xiangyang, Qian Jinju, Wu Gongping, Mai Xiaoming, Wei Lai, Rao Zhangquan. Full Automatic Inspection System and Its Demonstration Application Based on Robot for Overhead Transmission Lines [J]. High Voltage Engineering, 2017, 43(08):2582-2591.
[13] Qian Jinju, Peng Xiangyang, Mai Xiaoming, Yi Lin, Rao Zhangquan. Automatic Online/Offline Device of Inspection Robot for Overhead Transmission Lines [J]. Guangdong Electric Power,
2017, 30(05):101-107.
[14] Housner G W, Bergman L A, Caughey T K. et al. Structural Control: Past, Present and Future[J]. Journal of Engineering Mechanics, 1997, 123(9):897-971.
[15] Zhao Xiuqi. Study of Optimal Sensor Placement for Civil Engineering Structure Based on Modern Intelligent Algorithm [D]. Liaoning University of Technology, 2016.
[16] Li Hui, Bao Yuequan, Li Shunlong, et al. Data Science and Engineering for Structural Health Monitoring [J]. Engineering Mechanics, 2015 32(8):1-7.
[17] Li Aiqun, Ding Youliang, Wang Hao, et al. Analysis and Assessment of Bridge Health Monitoring Mass Data - Progress in Research/Revelopment of "Structural Health Monitoring" [J]. Scientia Sinica Technologica, 2012, 42(8):972-984.
[18] Zhu Hongping, Yu Jing, Zhang Junbing. A Summary Review and Advantages of Vibration-based Damage Identification Methods in Structural Health Monitoring [J]. Engineering Mechanics, 2011, 28(2):1-12.