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Study on the Stress Statistics and its Reliability of the Structure Based on WNN

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Abstract: A large amount of structural distribution data are required in the structure reliability analysis which usually obtained by the simulation or real test. But in fact large machine structure with low fault rate is often unable to get necessary statistic data. And the numerical simulation is very enormous for human and time consumption. Taking the advantages of the real test and simulation, the simulation is done by the Wavelet Neural Network (WNN) and in the real test the arm frame crane is looked as an object. Through the simulation the more samples are obtained to perfect the real test data. Applying to the stress statistical analysis, the results show that the measured stress data as samples to train WNN can further ensure actual prediction. And it is very high efficiency to predict the loading distribution data using the trained WNN. Its results can also meet the requirements of the project. And then the fatigue reliability of structure is computered using the probability distribution and the stress data. The application to the structure shows that the results can reflect the actual conditions.

Key words: Wavelet neural network, stress statistical analysis, reliability

INTRODUCTION

In structural reliability analysis a lot of structure load distribution data are required but it is very difficult to obtain these data. In general the simulation or real test are used to get these data (Liu *et al*., 2003). In this study, combining with the advantages of two methods, the structural stress analysis is developed based on the WNN. WNN is a feed-forward network and it uses the wavelet function and scale function forming neurons (Chen *et al*., 2006). Because WNN combines with a time-frequency localization properties, it has better approximation and error tolerance (Awad, 2010). Nonlinear wavelet is taken as the incentive function, forming the neurons. The measured data are used as samples to train the neural network which can further ensure the authenticity of the prediction.

According to relevant report, the crane accident was caused by the failure of metal structure. So, the reliability for the metal structure will directly influence the service life of the whole machine. And therefore, the reliability prediction for metal structure is essential. It is an effective method using the stress distribution to study the fatigue reliability.

WAVELET NEURAL NETWORK

WNN replace the BP network Sigmoid function using the nonlinear wavelet function or scale function, the signal is transmitted through the selected wavelet linear superposition (Chen *et al*., 2011). The signal s (t) is fitted by the Wavelet base $\Psi_{a,b}(t)$:

$$\hat{s}(t) = \sum_{j=1}^{H} w_j \psi \left| \frac{t - b_j}{a_j} \right| \tag{1}$$

where, $\hat{s}(t)$ is the fitting signal; w_j, b_j, a_j is respectively weight value, wavelet translation factor and scaling factor; H is the wavelet base number. The Morlet mother wavelet (Sharma and Agarwal, 2012) is expressed by:

$$\psi(t) = \cos(1.75t)e^{-\frac{t^2}{2}}$$

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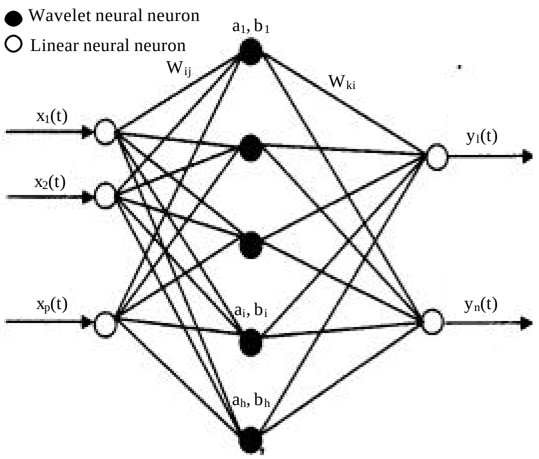

Fig. 1: Self-adaptive wavelet neural network

In practical application, three layer neural network is usually adopted. Suppose the input and output nodes of network respecttively as M and N, a total number of samples as P. Then the output for the pth sample and the nth node is shown below (Sharma and Agarwal, 2012):

$$y_n^p = f\left(\sum_{i=1}^{H} w_{ik}\psi\left(\frac{\sum_{j=1}^{p} w_{ji}p_j - b_i}{a_i}\right) + b_n\right) \tag{2}$$

where, M and H, respectively represents the node number of the input layer and the hidden layer, namely wavelet neuron number, w_{ji} is the weight between the jth unit for the input layer and the ith unit for the hidden layer, w_{ik} is the weight between the ith unit for the hidden layer and the kth unit for the output layer, a_i, b_i is, respectively the scale factor and shift factor for the ith unit of the hidden layer, w_{ji}, w_{ik}, a_i, b_i can be optimized with the error back-propagation method (Hu and Chen, 2009).

In the Fig .1 the input nodes for arm frame structure are the lifting capacity, the working radius and the lifting speed; the output nodes are the mean coefficient and standard deviation coefficient for each measuring point. Provided that the hidden layer nodes are 8, a part of the computation results are used as the input and output value for network training.

MEASUREMENT AND PREDICTION OF THE STRUCTURAL STRESS DISTRIBUTION PARAMETERS

Analysis of measured structural stress distribution parameters: According to the stress characteristic and the actual operation, the crane working cycle is firstly to

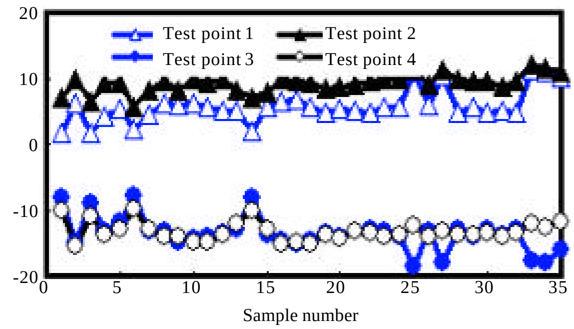

Fig. 2: Stress mean curves of each test point

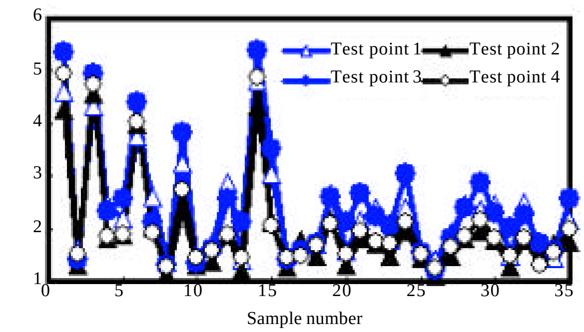

Fig. 3: Stress standard deviation curves of each test point

adjust the instrument to zero and then to test the lifting movement, no-load decline, capture bulk material and heavy lifting to the minimum load amplitude, unloading operation and finally the circulation ends.

Measuring points are the joint section of fixed leg and the girder root. In general, the stress amplitude distributions of the structure obey to the normal distribution. According to the experimental results from Fig. 2 and 3, the stress mean fluctuation for the lifting capacity, lifting speed, amplitude is small during the entire cycle, the standard deviation is also the smaller. The stress process is the smooth ergodic process and its amplitude distributions submitting to the normal distribution. In actual test there are some errors which can be ignored because it is very small.

Predicting algorithm of the wavelet network training samples: According to the K-L (Karhunen-Loeve) transformation principle, the network training sample pretreatment is realized. Suppose a observed vector $X = (x_1, x_2,\ldots, x_n)$ which is composed of the coordinate representation for n arbitrary independent base vectors (Alzori *et al.*, 2009). If $t_1, t_2,\ldots, t_n$ is n base vectors and matrices $T = (t_1, t_2,\ldots, t_n)$, then X can be expressed as:

$$X = YT = \sum_{i=1}^{n} y_i t_i \tag{3}$$

where, Y is the new feature vector required to transform. If the m items (m<n) is to approximate, then:

$$\hat{X} = \sum_{i=1}^{m} y_i t_i + \sum_{i=m+1}^{n} b_i t_i$$

To make the mean square value of the error Δx the minimum, it should satisfy the orthogonality condition: $t_i^T t_i = 1$ and b meets $b_i = E(y_i) = E(X)\, t_i^T$. So, the formula can be gained below:

$$E(\|\Delta X\|^2) == \sum_{i=m+1}^{n} t_i^T C_{ovx} t_i = \sum_{i=m+1}^{n} \lambda_i \tag{4}$$

where, C_{ovx} is the covariance matrix for X, λ as $_i$ ith characteristic value for C_{ovx}.

Therefore, the mean square error of ΔX is minimum. Namely the smaller the sum of λ_i for m+1 item, the mean square error is smaller. In the practical use, λ_i need to be normalized getting the new eigenvalue:

$$\lambda_i^* = \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} (i = 1, 2, \cdots, n)$$

Queueing λ_i* and then a valve value δ is set. if i>L, Δ_i*<δ. Without losing the main features, the sample vectors reduce from n dimension to L dimension. Thereby the sample pretreatment is completed.

After network learning and training end, the weight matrix W_1, W_2 and deviation matrix B_1, B_2 for each network neuron can determine the character of the network.

Set P as input variables matrix, ONE is a matrix 1 for the 1 row and N columns, N is the number of columns for the matrix $W_1 \times P$, then $z = W_1 \cdot P + B_1 \cdot ONE$, $A_1 = f(z)$:

$$A_n = W_n \cdot A_{n-1} + B_n \cdot ONE_{n-1} \tag{5}$$

where, f (z) is the wavelet function.

The stress mean μ and the stress sample variance σ from m+1 th to nth can directly be gotten by the network predicting.

EXAMPLE ANALYSIS

The crane is used for the real test, all sizes of the crane arm structure are fixed. In more general, 6, 11, 20, 25 and 31 serial samples are randomly select as the test sample, the other samples are chosen as training samples

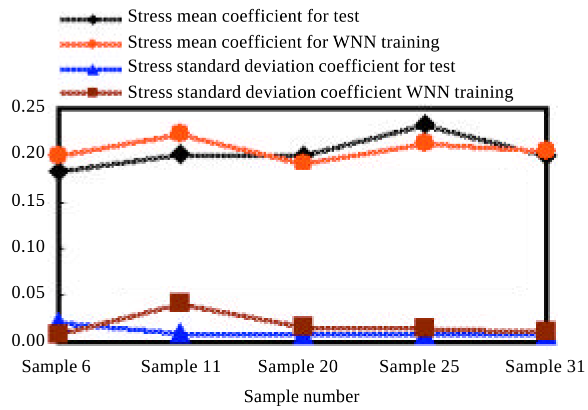

Fig. 4: Comparison of WNN training results and test samples for test 1

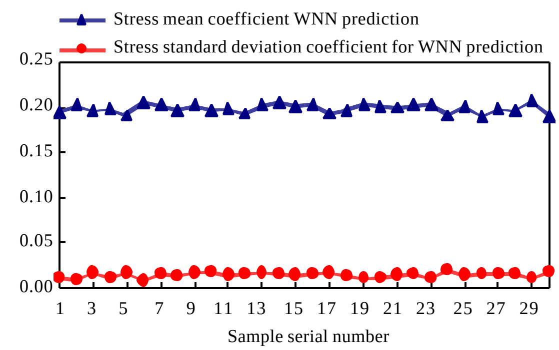

Fig. 5: Results of WNN predicting 30 samples for test 1

which learning rate is 0.01 and the accuracy of convergence is 0.001. Take for an example of test 1, the comparison of neural network training results and testing samples for test 1 is shown in Fig. 4.

From Fig. 4, the maximum prediction error of the stress mean coefficient and the standard deviation coefficient for the test 1 is, respectively 10.4 and 317%. Similarly the maximum prediction error for the test 2 is respectively 10.8 and 44%; the maximum prediction error for test 3 is respectively 12.7 and 360%; the maximum prediction error for test 4 is respectively 10.1 and 300%. So, the predicting results of stress mean coefficient is quite acceptable. The error of the standard deviation coefficient is too big since the value itself is too small. but it will not affect the distribution estimation of the overall parameter, so the error value is not important. It can play a advantageous role to engineering analysis.

In this study 65 samples are selected. Because the test has 35 samples, the neural network prediction will use 30 samples. The prediction results as an example of test 1 is smooth and the smaller error (about 4.069%) which are shown in Fig.5.

STRUTURAL FATIGUE RELIABILITY ANALYSIS

The structure fatigue reliability is analyzed on the basis of the measured and simulated stress data and P-S-N curve.

The limit state function of structural fatigue strength is expressed by (Gong, 2007; Gong *et al*., 2002):

$$Z(t) = \sigma_{-1}^{m} - \frac{1}{N_0}\sum_{i=1}^{N(t)} \sigma_i^m \quad (6)$$

where, N_0 is the fatigue life of the structure (usually 2×10^6 cycle times for crane), $\sigma^m{}_i$ is the stress for the each cycle, $\sigma^m{}_{-1}$ is the fatigue limit strength of the structure.

The fatigue reliability of the structure is express by:

$$R(t) = P\{Z(t) > 0\} = \Phi(\beta_{Z(t)}) \quad (7)$$

Where:

$$\beta_{Z(t)} = \frac{E[Z(t)]}{\sqrt{D[Z(t)]}}$$

is defined as the reliability index function.

For fatigue analysis, usually m = 3, the mean and variance of $\sigma^3{}_{-1}$ can be expressed as below:

$$E[Z(t)] = E\left[\sigma_{-1}^{m}\right] - E\left[\frac{1}{N_0}\sum_{i=1}^{N(t)} \sigma_i^m\right] \quad (8)$$

$$D[Z(t)] = D[\sigma_{-1}^{m}] + D[\frac{1}{N_0}\sum_{i=1}^{N(t)} \sigma_i^m] \quad (9)$$

The distribution parameters μ and s of the maxmam stress point 3 for the structure is respectively -47.0 and 16.22 Mpa. Using Q235 material, the distribution parameters for the structural fatigue limit is, respectively $\mu\sigma_{-1}$ = 183.3 Mpa and $\mu\sigma_{-1}$ = 8.89 Mpa. Through the Eq. 8~9, the reliability index function $\beta_{Z(t)}$ = 6.73, so the structural reliability can be obtained as 0.98.

In actual engineering, it is so less for the structural reliability near to 1. In this study, the volume of grab bucket is relatively small. Therefore lifting capacity is much lower than the rated lifting capacity and the stress of the structure is too small compared with its allowable value. And so high reliability occur. The application to crane structure also shows that the result can reflect the actual conditions.

CONCLUSION

- The advantages of the measurement and simulation have been combined to gain the necessary structural load distribution data. WNN is used for simulation. Through network calculation and comparison, the optimal number of samples for network are determined. And the simulation of the structural stress process was realized by the measured data
- The structural stress process were discussed from the aspects of the measuring point arrangement and the stress parameters distribution. With application to the crane structure, the coefficient of the stress mean and standard deviation for each point can be gained. The results show the simulation data can be acceptable for engineering analysis. And it can also satisfy the engineering requirement
- The relation of the resistance force and fatigue limit of structure are built according to the probability distribution. The structural fatigue damage process was the normal distribution according to the statistics analysis. So the structural fatigue reliability can be described by the reliability coefficient. The application to the crane structure show that the results accord with the actual working condition

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