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Port Mooring Load Prediction based on Neural Networks with the Wavelet Analysis

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Abstract

In order to ensure the safe operation of offshore platform, we need response to the platform motion and forecast mooring force. The prediction method based on numerical calculation and model experiment, has certain limitation. A new principle and method of ship's mooring load measurements based on indirect measurement is presented in order to achieve the short-term and high-precision mooring load prediction, and an algorithm is proposed through which predictions are made by comb the wavelet multi-scale decomposition and reconstruction method with BP neural networks. This paper, by putting a prototype data as learning samples, using the neural network algorithm for forecasting of mooring force, overcomes the traditional B P neural network faults, gets a higher precision. Through comparing the measured data, it demonstrates the feasibility of this method in engineering application.

1. Introduction

As mooring loads are affected not only by environmental factors like winds, streams and waves but also by factors like the hull form of ships, wind age areas and draft sizes. Therefore, being quite random and complex, they are non-stationary time series. In this paper, the theoretical model for the calculation on bollard surface stress under mooring load is built [1, 2]. The bollard surface stress is measured by means of strain electrical measuring method. The simultaneous equations of measurement value and theoretical calculation model are built [3]. And the axial component and a radial component of mooring load are obtained, and the mooring load is composed [4]. Then, in connection with the feature that the short-term mooring load series is quite random and complex, the wavelet multi-scale decomposition method is used to decompose mooring load series into low-frequency approximation decomposition coefficients and layer high-frequency detail decomposition coefficients [5], to rebuild decomposition coefficients of each layer respectively into approximation components and multilayer detail components, and to synthesize prediction results of each layer into desired prediction values. This provides an effective combined prediction method for the short-term mooring load prediction [6].

2. The Combined Prediction Model of Wavelet Decomposition and Neural Networks

According to the wavelet decomposition and reconstruction calculations above, the port transportation port transportation mooring load series can be decomposed layer by layer into different frequency channels. As reconstructed components of each layer are more single in frequency components than the original series and wavelet decomposition has made the series smooth, the reconstructed port transportation port transportation mooring load series is more stationary than the original series. Thus, wavelet decomposition and reconstructed components of each layer can serve as a smooth series to use BP neural networks to make predictions.

A calculation step of the combined prediction model is as follows:

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2.1 The Multi-scale Decomposition of the Port Transportation Port Transportation Mooring Load Series

The right wavelet basis function is chosen and the level N of wavelet decomposition is determined before the original port transportation port transportation mooring load series $v(t)$ (representing the original series collected by the port transportation port transportation mooring load monitoring system) is decomposed into the multi-scale wavelet by layer N. There are $a^N(k)$ and $d^j(k)$ which shows essential change trend in port transportation mooring load s in decomposition coefficients which have undergone multi-scale decompositions.

2.2 The Multi-scale Reconstruction of the Components of Each Layer

The multi-scale reconstruction is carried out of the low-frequency coefficients of layer N of the port transportation port transportation mooring load series and the high-frequency from layer 1 to layer N respectively based on the wavelet basis function chosen by decomposition. The coefficients of each layer are reconstructed to the original scale through the wavelet algorithm, i. e. the port transportation port transportation mooring load components $V^N(t)$ and $W^j(t+1)$ are obtained.

2.3 The Prediction of BP Neural Network Series

$V^N(t)$ and $W^j(t+1)$ are predicted respectively through the use of the BP neural network prediction model. The BP neural network prediction model is a multi-layer feed forward neural network, of which the main features are series forward transfer and error back propagation. The BP neural network used in port transportation port transportation mooring load predictions is a three-layer multiple-input and single- output network structure. The network consists of the input layer, the hidden layer and the output layer. Its topology diagram is shown in Figure4. The network input x_k, which is $V^N(t)$ or $W^j(t)$ after wavelet decomposition and reconstruction, is processed layer by layer from the input layer through the hidden layer until the output layer outputs the component prediction value of each layer $\hat{V}^N(t+1)$ or $\hat{W}^j(t+1)$ $(j=1,2,\cdots N)$. The state of neurons of each layer only affect that of neurons of the next layer. If the output layer cannot get the desired output, transfers to back propagation will occur, adjustments will be made of network weights ω_{ij}, ω_{jk} and thresholds according to prediction errors so that the prediction output of the BP neural network is getting closer and closer to the desired output.

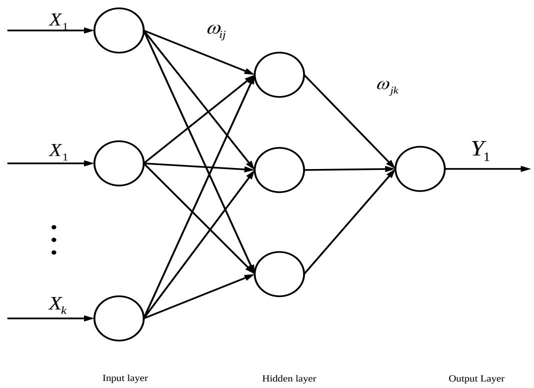

Figure 1. The Topology Diagram of BP Neural Networks

2.4 The Synthesis of Final Prediction Series

The prediction result of $v(t)$ are $\hat{v}(t)$, which is obtained by synthesizing the above mentioned series prediction results $\hat{V}^N(t+1)$ and $\hat{W}^j(t+1)$ through formula (9), *i.e.*, obtain prediction results which correspond to original cable loads.

$$\hat{v}(t+1)=\hat{W}^1(t+1)+\hat{W}^2(t+1)+\text{L}+\hat{W}^N(t+1)+\hat{V}^N(t+1) \quad (1)$$

The combined prediction model combines wavelet decomposition and neural networks. It is constructed in accordance with the above thoughts and calculation steps. Its structural framework is shown in Figure 2.

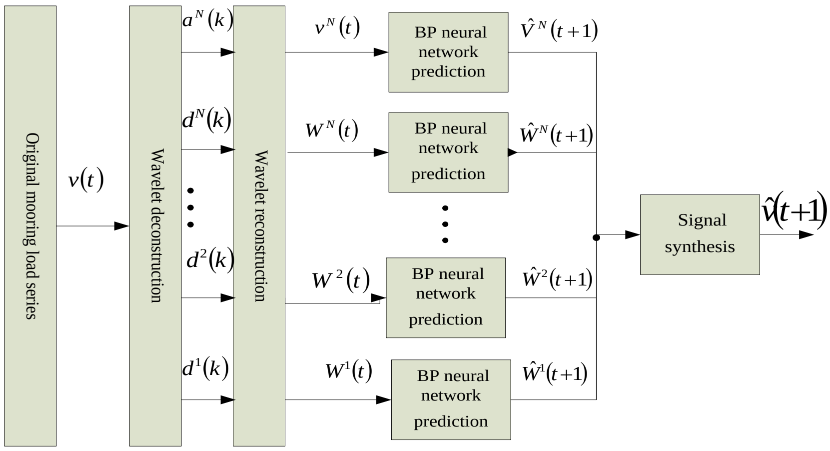

Figure 2. The diagram of the structural framework of the combined prediction model

3. Theoretical Calculation Model of Stress at Measuring Point on Bollard Surface

Theoretical calculation model is built to measuring the port transportation port transportation mooring load which is difficult to be measured directly. So theoretical calculation model can be used to indirect measure the port transportation port transportation mooring load based on the bollard. The bollard body consists of column shell and column inner filler, of which the column shell is generally made of cast steel or cast iron, and the column inner filler is made of concrete or asphalt concrete.

3.1 Calculation of Tensile Stress

Since the axial load line of bollard does not pass through the bollard axis, bollard section will generate deviation due to uneven axial load. To overcome this uneven force which moves the axial load to the axis horizontally, a force couple needs to be added, and its torque is the torque of axial load F_1 to the axis, namely $M_Z = F_1 \times R$, where R is the radius of bollard cross-section. After translation, tensile stress generated by the axial load will distribute on the bollard cross-section evenly (as shown in Figure 3).

When the bollard gives rise to axial tension caused by the axial load, linear strain of various vertical line segments will be same, so the tensile strain ε' caused by the axial load at each measuring point is same. According to the Hooke Theorem, axial load is as follows:

$$F_1 = \varepsilon'(E_1A_1 + E_2A_2) \quad (2)$$

Where: A_1 is the cross-sectional area of column shell; A_2 is the cross-sectional area of column inner filler; E_2 is the elastic modulus of column inner filler.

Then, the tensile stress caused by the axial force is: $\sigma' = E_1\varepsilon'$; according to formula (1), ε' can be expressed as $\sigma' = E_1F_1/(E_1A_1 + E_2A_2)$.

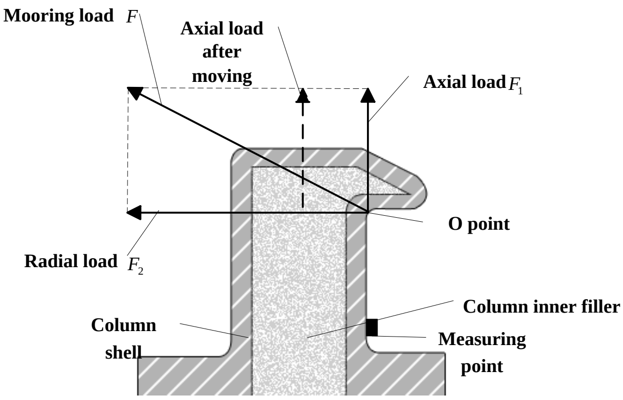

Figure 3. Bollard Structure and Force Analysis

3.2 Calculation of Bending Stress

Radial load F_2 causes bending deflection of bollard, and only generates action of bending moment to neutral axis z on bollard cross-section. Since the bending rigidity of bollard is great, which generates small bending deflection, the additional bending moment caused by axial load is small, which can be negligible. Therefore, cross-sectional bending moment M on bollard is the sum of cross-sectional bending moment M_1 on column shell and cross-sectional bending moment M_2 on column inner filler, namely:

$$M = M_1 + M_2 = E_1I_{z_1}/\rho + E_2I_{z_2}/\rho \tag{3}$$

Where: I_{z_1} is the inertia moment of neutral axis z of column shell cross-section, $I_{z_1} = \pi\left((2R)^4 - (2r)^4\right)/64$; I_{z_2} is the inertia moment of neutral axis z of column inner filler cross-section, $I_{z_2} = \pi(2r)^4/64$; r is the radius of column inner filler cross-section; ρ is radius of curvature of neutral layer.

$1/\rho = M/\left(E_1I_{z_1} + E_2I_{z_2}\right)$ can be got according to formula (2); then, bending moment of column shell cross-section $M_1 = E_1I_{z_1}/\rho = E_1I_{z_1}M/\left(E_1I_{z_1} + E_2I_{z_2}\right)$, where M is the sum of bending moment generated by radial load F_2 and bending moment generated by translation of axial load, namely $M = F_1R + F_2l$; l is the distance between the point of load and the measuring point cross-section of bollard cable.

Then, the bending stress at the measuring point is $\sigma'' = M_1y/I_{z_1}$, where y is the distance between the measuring point and neutral axis.

In order to determine the distance between each measuring point and the neutral axis, arc length s_{A_1B} and s_{A_2B} from measuring point A1 and A2 to point B which is the intersection of the projection of cable load direction on bollard cross section and the cross section before measurement(ship may move back and forth in the case of mooring, resulting in minor change of the contact point of cable and bollard; however, such change is slow and the system is subject to measurement and design in a short time. Field surveyors can quickly measure the arc length again and modify the parameters in the measurement system when finding that the contact point changes significantly in the case of measurement. In the future, displacement sensors can be chosen to fuse to the system established in this text for real-time detection of the contact point of the cable and bollard if the development of cable load monitoring system is subject to the measurement for a long time), so the included angle between the line of measuring point and center of circle of the cross section and neutral axis z is $\alpha = s_{A_1B}/R - \pi/2$ and $\beta = s_{A_2B}/R - \pi/2$ (see Figure 4), and then, distance between the measuring point and the neutral axis is $y_{A_1} = R\sin\alpha$ and $y_{A_2} = R\sin\beta$.

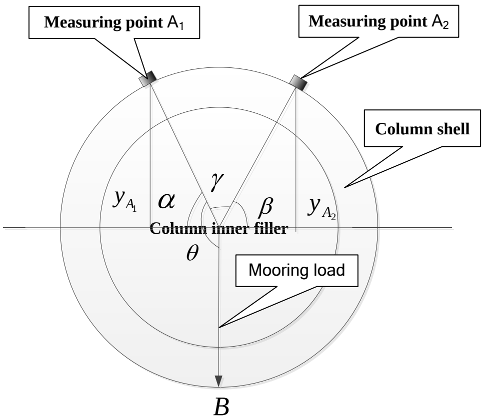

Figure 4. The Distance between Each Measuring Point and the Neutral Axis

Therefore, the bending stress at measuring point can be expressed as $\sigma_i'' = E_1(F_2 l + F_1 R) y_i / \left(E_1 I_{z_1} + E_2 I_{z_2}\right)$, where σ_i'' is the bending stress at measuring point i, and y_i is the distance between measuring point i and the neutral axis.

4. The Component Prediction and Result Synthesis of Port Transportation Mooring Loads of Each Layer

The multi-input and single-output neural network structure is used to predict port transportation port transportation mooring load components of each layer respectively. In this, 5 neurons are used in the input layer, *i.e.*, the data of five sampling points are inputted, 6 neurons are used in the hidden layer, and 1 neuron is used in the output layer. The initial weight of the network is given by the random function. After wavelet decomposition and reconstruction is used, the first 100 data of the components of each layer train each neural network respectively.

Through the established BP neural network prediction module, the last 20 component data of d^1, d^2, d^3 and a^3 are predicted and compared with actual values respectively, which, as can be seen from Figure 4, has achieved quite good results in the component prediction of each layer.

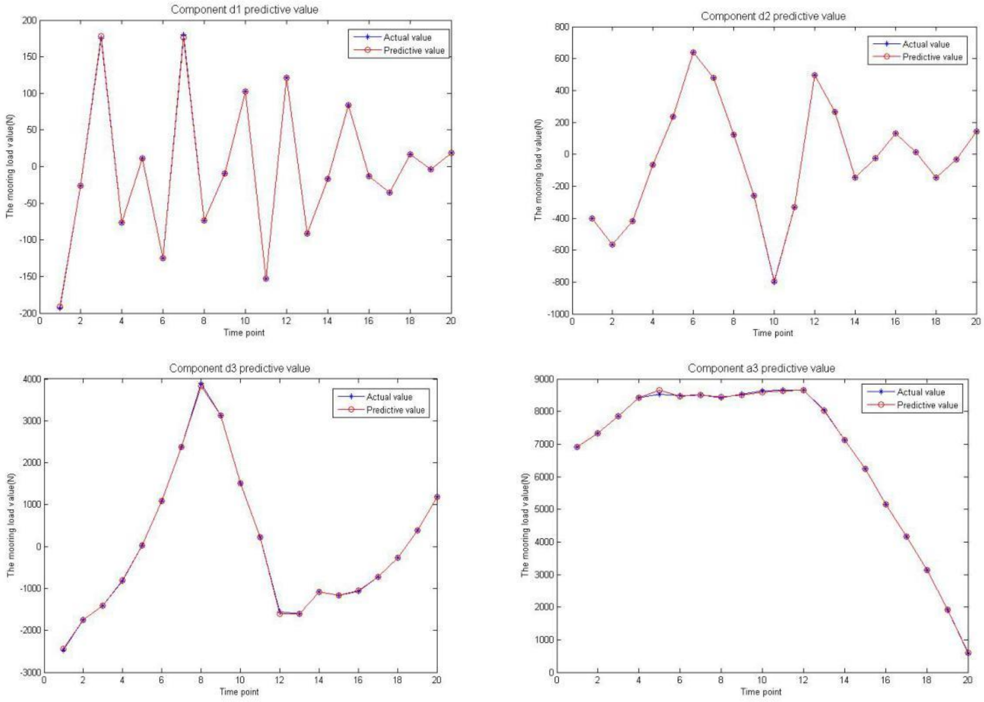

Figure 5. The Prediction Results of the Components of Each Layer

After the component prediction of each layer is completed, the prediction results are synthesized based on the following formula:

$$\hat{v}\ (t+1)=\hat{d}^1+\hat{d}^2+\hat{d}^3+\hat{a}^3 \qquad (4)$$

into the prediction series of the original port transportation port transportation mooring load as in Figure 5..

5. The Error Analysis of Prediction Results

The average relative error, the absolute maximum relative error and the root mean square error are used as error indicators to evaluate prediction results. The indicator is calculated as follows:

The average relative error:

$$RME=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{v}(t)-v(t)}{v(t)}\right| \qquad (5)$$

Absolute maximum relative error:

$$MRME=\max\left|\frac{\hat{v}(t)-v(t)}{v(t)}\right| \qquad (6)$$

Root mean square error:

$$RMSE=\sqrt{\frac{1}{N}\sum_{t=1}^{N}[v(t)-\hat{v}(t)]^2} \qquad (7)$$

And the BP neural network and the wavelet neural network model are selected to predict original port transportation port transportation mooring load series. The prediction results are analyzed and compared with the combined prediction model proposed in this paper. The comparison results are shown in Figure6. As can be seen through error analysis, the combined prediction average error proposed in this paper are down by 75.8% and 32% respectively compared with the BP neural network prediction method and the wavelet neural network prediction method, and other evaluation indicators are all better than the two methods mentioned above.

Experiment results show that the combined algorithm has achieved the short-term high-accuracy port transportation port transportation mooring load prediction, that it has quite great subdivision and self-learning abilities, that it is more suitable for port transportation port transportation mooring load predictions than the BP neural network and the wavelet neural network, and that it can meet the engineering needs of accuracy.

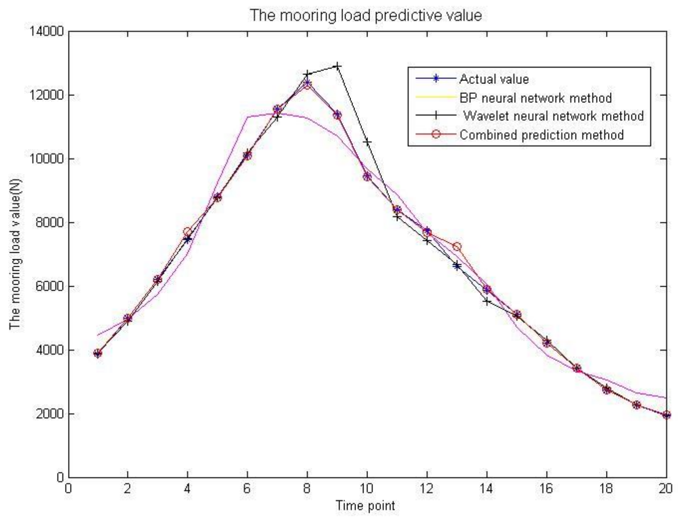

Figure 6. The Comparison Chart of Prediction Results

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Table 1. The Error Analysis Table of Each Prediction Method

Evaluation index Prediction method	RME	MRM E	RMSE
Combined prediction method in this paper	1.87%	0.09	151.1
Wavelet neural network method	2.75%	0.13	438.6
BP neural network method	7.72%	0.28	517.6

6. Conclusion

Due to the combined effects of quite a number of factors, mooring load measurement method which is based on theoretical calculation model of stress at measuring point on bollard surface is built to collect mooring load series. The series is characterized by the fact that it is quite random and complex. In connection with this feature, a prediction method is proposed by which wavelet analysis and BP neural network are combined to build models. Experimental results show that the prediction accuracy of this method is higher than the wavelet neural network method and the traditional neural network method, that it can meet engineering needs, and that it can be applied to short-term mooring load warning systems in harbors.

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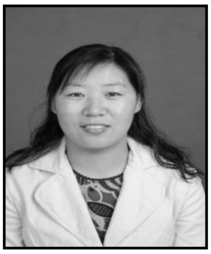

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