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Calculation method of ship collision force on bridge using artificial neural network*

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Abstract: Ship collision on bridge is a dynamic process featured by high nonlinearity and instantaneity. Calculating ship-bridge collision force typically involves either the use of design-specification-stipulated equivalent static load, or the use of finite element method (FEM) which is more time-consuming and requires supercomputing resources. In this paper, we proposed an alternative approach that combines FEM with artificial neural network (ANN). The radial basis function neural network (RBFNN) employed for calculating the impact force in consideration of ship-bridge collision mechanics. With ship velocity and mass as the input vectors and ship collision force as the output vector, the neural networks for different network parameters are trained by the learning samples obtained from finite element simulation results. The error analyses of the learning and testing samples show that the proposed RBFNN is accurate enough to calculate ship-bridge collision force. The input-output relationship obtained by the RBFNN is essentially consistent with the typical empirical formulae. Finally, a special toolbox is developed for calculation efficiency in application using MATLAB software.

Key words: Ship-bridge collision force, Finite element method (FEM), Artificial neural network (ANN), Radial basis function neural network (RBFNN)

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INTRODUCTION

Based on the analyses of bridge accidents, determining lateral design loads resulted from ship collision is greatly important while bridge structures crossing navigable waterways are designed. In addition, calculating ship-bridge collision force can contribute to assess the vulnerability of an existing bridge structure under an accidental impact by ship (Consolazio and Cowan, 2003; Proske and Curbach, 2005). Nevertheless, in a collision, parts of the energy will be consumed in deformation of fenders, displacement of bridge structures and liberation of energy to the surrounding water (Larsen, 1993). Obviously, the determination of ship-bridge collision force is very complex as it depends on the characteristics of the ship and the bridge structure, as well as the circumstances of the collision accident.

Since a pioneer, Minorsky (1959) found a linear relationship between the deformed steel volume and the absorbed impact energy based on an investigation of 26 ship-ship collision cases in 1959, the mechanics principles for ship-bridge collision has been studied and several practical and theoretical calculation methods have been developed (Woisin, 1979; Amdahl and Kavlie, 1992; Pedersen *et al*., 1993). In recent years, application of finite element method (FEM) to calculate ship impact force has been reported. FEM has also been regarded as one of the most effective methods. For instance, Liu and Gu (2002) carried out an advanced research on simulation of the whole process of ship-bridge collision by nonlinear FEM.

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Consolazio and Cowan (2003) successfully developed their ADINA finite element model to compute force-deformation relationships for several hopper barge crushing scenarios. In addition, many researchers (Yan, 2004; Sun, 2005; Chen, 2006) also employed FEM to make a detailed study on the behaviors of ship-bridge collision, respectively. However, the computational demands for conducting high-resolution nonlinear contact impact ship collision analyses using FEM were often translated into the need for supercomputing resources and tens of hours of computing time, so the efficiency of calculation work is reduced greatly. Therefore, Consolazio *et al.*(2005) carried out an advanced research on numerically efficient dynamic analysis of barge collisions on bridge piers by coupling nonlinear barge and pier responses together through a shared collision force and employing numerical procedures for accelerating convergence of the coupled system. Nevertheless, their research was based on the special FB-Pier software.

As used in several application areas (Zhou and Yan, 2002; Zhang, 2004; Fan *et al.*, 2005; Choubey *et al.*, 2006), artificial neural networks (ANNs) may be introduced to calculate the ship-bridge collision force under different conditions. For example, the study by Ma *et al.*(2005) focused on the identification of ship impact force from the dynamic responses using ANN technique.

The paper aims to develop a calculation procedure of ship-bridge collision force in which ANN is combined with FEM to avoid many time-consuming analyses or experiments for different ship velocities and masses. In other words, the computational effort may be saved to some extent. The radial basis function neural networks (RBFNNs) are trained for calculating the ship impact forces by the learning samples obtained from FEM results.

CLASSICAL SPECIFICATION METHODS FOR CALCULATING SHIP-BRIDGE COLLISION FORCE

The results obtained from the proposed ANN approach will be compared with the empirical formulae provided by bridge design specifications, so potential improvements in these specifications may be found. Therefore, it is necessary to review some classic specifications briefly at first. Nowadays, bridge design specifications of different countries provide different simplified methods for computing equivalent static loads instead of conducting fully dynamic impact analyses. Generally, the American Association of State Highway and Transportation Officials bridge design specifications (AASHTO, 1994) and the European Standards (1994) are considered as classical and widely used specifications.

AASHTO method

The AASHTO bridge design specifications state that all bridge components in a navigable waterway crossing, located in design water depths not less than 0.6 m, should be designed for ship impact. The minimum design impact load for substructure design should be determined using an empty hopper barge drifting at a velocity equal to the annual mean current for the waterway location. The design barge should be a single 10.7 m×60 m barge, with an empty mass of 180 t, except special design by the owner. Generally, the head-on ship collision impact force on a pier should be taken as:

$$P_s = 1.2\times10^5 V\sqrt{DWT}, \tag{1}$$

where P_s is equivalent static vessel impact force, N; V is vessel impact velocity, m/s; DWT is deadweight tonnage of vessel, t.

Eq.(1) was developed from research conducted by Woisin (1979) in West Germany to generate collision data for protecting the reactors of nuclear-powered ships from collisions with other ships. The ship collision data resulted from collision tests with physical ship models at scales of 1:12.0 and 1:7.5. Woisin's results have been found to be in perfect agreement with those of research conducted by other ship collision investigators worldwide (AASHTO, 1994).

European standard method

The corresponding regulations in 1991-1 Eurocode 1 (ENV, 1994) require that the impact action is represented by two mutually exclusive load arrangements—a frontal force $F\mathrm{d}x$ acting in the longitudinal axis of the pier and a lateral force $F\mathrm{d}y$ acting normal to the longitudinal axis of the pier and a friction force parallel to the longitudinal axis. In addition, hydrodynamic added mass should be taken into account for ship impact forces. For a number of standard ship characteristics and standard design situations, the frontal and lateral dynamic forces may be obtained from Table 1 (ENV, 1994). In harbors the forces given in Table 1 may be reduced by a factor of 0.5.

However, when ship characteristics vary with any standard types, an alternative value for the static equivalent force shall be expressed as

$$P = V\sqrt{KM}, \tag{2}$$

where P is the ship impact force, N; K is equivalent stiffness, N/m (for ship in inland waterways, K=5×10^6 N/m; while for seagoing vessels, K=15×10^6 N/m); M is the mass of the colliding object, kg.

ANN-BASED CALCULATION METHOD

Methodology of the proposed approach

The general methodology proposed in the paper is sketched in Fig.1.

Without loss of generality, the mathematical expression of ship-bridge collision force can be taken as:

$$F = f(x_1, x_2, \cdots, x_n), \tag{3}$$

where F is ship-bridge collision force; x_i is the variable which affects the value of ship-bridge collision force.

As described in the previous sections, it is of great difficulty to obtain the deterministic form of Eq.(3), because the impact load depends on many factors: (1) structural type; (2) shape of the ship's bow; (3) degree of water ballast carried in the forepeak of bow; (4) size and velocity of the ship; (5) geometry of the collision; (6) geometry and strength characteristics of the pier, etc. (AASHTO, 1994). According to the guidance of Eqs.(1) and (2), only mass and velocity of the ship are employed in this paper to determine the ship-bridge collision force. This treatment does not conflict with the main aim to show the effectiveness of the ANN-based method.

It is well known that obtaining some appropriate

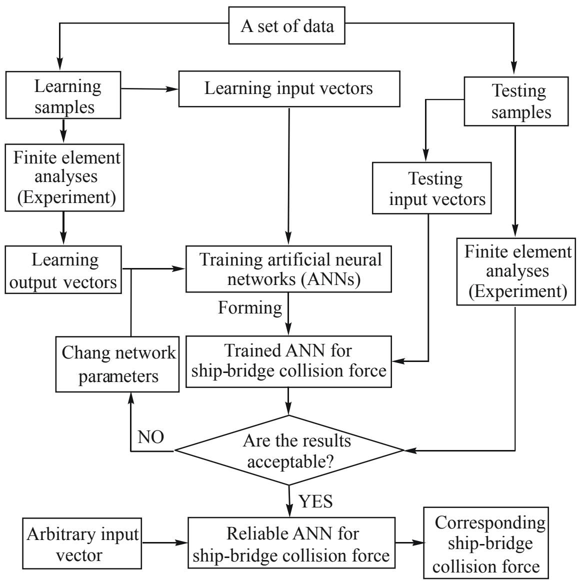

Fig.1 Flow chart of the proposed approach based on artificial neural network (ANN)

Table 1 Ship characteristics and corresponding dynamic design forces for inland waterways (ENV, 1994)

CEMT* class	Reference type of ship	Length l (m)	Mass M (t)	Force Fdx (kN)	Force Fdy (kN)
I		30~50	200~400	2000	1000
II		50~60	400~650	3000	1500
III	"Gustav König"	60~80	650~1000	4000	2000
IV	Class "Europe"	80~90	1000~1500	5000	2500
Va	Big ship	90~110	1500~3000	8000	3500
Vb	Tow+2 barges	110~180	3000~6000	10000	4000
VIa	Tow+2 barges	110~180	3000~6000	10000	4000
VIb	Tow+4 barges	110~190	6000~12000	14000	5000
VIcc	Tow+6 barges	190~280	10000~18000	17000	8000
VII	Tow+9 barges	300	14000~27000	20000	10000

* CEMT: European Conference of Ministers of Transport classification proposed on June 19, 1992, approved by the Council of European Union on Oct. 29, 1993

learning samples is greatly important as ANN is used. If there were some actual samples of the experimental data, the problem would be solved very well. Since the experimental data about ship-bridge collision are rare and discrete, carrying out an experiment is very difficult and costly. Many researchers have applied FEM technique to solve this type of problem and got some achievements (Liu and Gu 2002; Consolazio and Cowan, 2003; Chen, 2006). As FEM is one of the effective methods for calculating ship-bridge force, the necessary of learning samples for training ANN can be obtained with this method. In this paper, the influencing factors of ship-bridge collision are constant except two variables, which are velocity and mass (or weight) of the ship. A set of input and output data is prepared for developing ANN models. One part of the data is used for training, while the other is for testing the model.

Secondly, the ANN model should be trained after the datasets are pretreated necessarily. Of course, it is important to set the values of network parameters.

Thirdly, the developed ANN model should be tested with other data obtained from the finite element analyses. In comparisons of the results of the proposed ANN approach with those of FEM, the error analyses should be carried out. If the error with respect to this sub-set is not acceptable, the training should be repeated. Indeed, this testing is critical to ensure that the network has successfully learned the correct functional relationship within the whole set of data. In the work, errors occurring at both the learning and testing stages are recorded as root mean squared error (*RMSE*) and correlation coefficient (R^2) defined as:

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i-x_i'\right)^2}, \tag{4}$$

$$R^2=\frac{\sum\limits_{i=1} x_i x_i'-\sum\limits_{i=1} x_i\sum\limits_{i=1} x_i'}{\sqrt{\sum\limits_{i=1}\left(x_i-\sum\limits_{i=1} x_i\right)^2}\sqrt{\sum\limits_{i=1}\left(x_i'-\sum\limits_{i=1} x_i'\right)^2}}, \tag{5}$$

where x_i is the actual value; x_i' is the output value by the trained ANN; N is the number of samples. The Acceptance Criteria for the error is determined with difficult. In fact, it varies with different conditions. The problem needs further research in the future.

ANN model

Since there are a great number of neural network model types for different perspectives on biological neural systems at various levels of abstraction and simulation, the results would vary (Wang, 2006) by using different neural network models. Considering the purpose of calculating ship-bridge collision force, it is necessary to compare some different network models in order to determine a proper one for this paper. In this section, Radial Basis Function (RBF) networks are briefly compared with Backward Propagation (BP) networks as follows.

As stated by Zhang (2004), RBF network is a locally approximating network. Since RBF network could certainly obtain the globally minimum point, the problems of gradient descent methods and locally minima characteristics of BP networks can be avoided by using it. In addition, compared with the slower convergence shortcomings of BP networks, the RBF networks could learn and train rapidly. Generally speaking, the convergence speed of RBFNN is 10^3~10^4 times that of BPNN, so that RBFNN is suitable for real time control (Zhang, 2004). Finally, Gaussian function could provide better ability of dealing with the testing data, as well as increasing the training speed of the RBFNNs. In other words, the generalization ability is further developed.

As mentioned above, the nonlinear mapping capabilities of RBF networks are better than those of BP networks, and also the learning speed of RBF networks are faster than those of BP networks. These advantages of RBFNNs are beneficial to solve the calculation problems of ship collision loads on bridge, which are highly nonlinear and complex. In short, using the RBFNNs to calculate ship-bridge force is a very practical and effective way.

Since the RBF networks were firstly proposed by Moody and Darken (1989), they have been used in several fields by some other researchers (Steve *et al*., 1995; Zhou and Yan, 2002; Aguirrea *et al*., 2007).

Generally speaking, the network consists of three layers, i.e., an input layer, a hidden layer and an output layer. The typical structure for an RBF network is shown in Fig.2.

As illustrated in Fig.2, the n dimensional input vectors are $\boldsymbol{X}=(x_1, x_2, \ldots, x_n)^{\mathrm{T}}\in\mathbb{R}^n$, which are passed to the neurons in hidden layer by the connection weights. The hidden layer consists of a set of RBF or

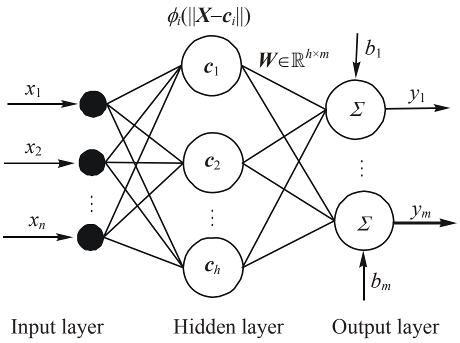

Fig.2 Typical structure of RBF neural networks

pattern units, which are axisymmetric. Functionally, there are three elements in a pattern unit: (1) a center, (2) a distance measure, and (3) an RBF. In Fig.2, a center, $\boldsymbol{c}_i$ is an input vector in training set, which will be stored in the weight vector from the input vector to the hidden layer after training; $\boldsymbol{W}$ is a weight matrix of the output vector; Euclidean norm, $\|\cdot\|$ determines how far an input vector is from a centre; an RBF, $\phi(\cdot)$ is a function of single variable and can use to determine the output of a pattern unit. In fact, there are a number of RBF types, e.g., Gaussian Function as shown in Eq.(6), Reflected Sigmoid Function, and inverse Multiquadric Function. As described in the previous sections, the generalization ability of Gaussian Function is better developed than that of other functions. Therefore, the Gaussian Function is used in this study.

$$\phi_i(\|\boldsymbol{X}-\boldsymbol{c}_i\|)=\exp\left(\frac{-\|\boldsymbol{X}-\boldsymbol{c}_i\|^2}{2\sigma_i^2}\right),\quad i=1,2,\cdots,h, \tag{6}$$

where σ_i is width parameter; the Euclidean distance is expressed as:

$$\|\boldsymbol{X}-\boldsymbol{c}_i\|=\sqrt{\sum_{j=1}^{n}(x_j-c_{ij})^2},\quad j=1,2,\cdots,n;\quad i=1,2,\cdots,h. \tag{7}$$

The response of the output layer neuron may be considered as a map $\boldsymbol{y}$, which is

$$y_k=\sum_{i=1}^{h}w_{ki}\phi_i(\|\boldsymbol{X}-\boldsymbol{c}_i\|)=\sum_{i=1}^{h}w_{ki}\phi_i(\|\boldsymbol{X}-\boldsymbol{c}_i\|)-b_k\quad k=1,2,\cdots,m, \tag{8}$$

where $\boldsymbol{w}_k$ is the weight vector, $\boldsymbol{w}_k\in\boldsymbol{W}$; b_k is the bias term.

The RBF network training algorithm would not be expounded in the paper; details can be referred to (Zhou and Yan, 2002; Aguirrea *et al.*, 2007).

APPLICATION OF THE PROPOSED METHOD

According to the procedure as shown in Fig.1, an example will be introduced on how to apply the proposed method to calculate ship-bridge collision force.

Finite element analysis for the fundamental data

The FEM is a powerful tool for simulating the nonlinear structural behaviors. Based on an appropriate failure criterion and finite element model, many studies have proved that the FEM could effectively evaluate the ship-bridge collision forces (Consolazio and Cowan, 2003; Sun, 2005; Chen, 2006). A lot of famous analysis softwares, such as LS_DYNA, DYTRAN and ADINA, have widely been used for simulating ship-bridge collision.

In this study, as illustrated in Fig.1, finite element analysis plays an important role of providing the available fundamental data for the proposed method when the experimental data cannot be obtained. Fortunately, based on Chen (2006)'s research, some appropriate samples can be obtained, so the FEM would not be utilized to calculate ship-bridge collision force in this paper. Table 2 shows the fundamental dataset in terms of ship velocity, ship mass and ship-bridge collision force, which will be used for the following ANN training and testing.

A ship model with a bulbous bow and a rectangular pile-cap were created and meshed automatically by the pre-processor PATRAN. LS_DYNA was employed for the solution. Considering the scope of this paper, the detailed information about FEM can be referred to (Chen, 2006).

ANN design

As described above, the dataset in Table 2 is used to train and validate the RBFNN with different network parameters. Setting ship velocity ($\boldsymbol{V}$) and ship mass (either $\boldsymbol{M}$ or $\boldsymbol{DWT}$) as the input vectors and ship collision force ($\boldsymbol{F}$) as the output one, the first 20 groups of data in Table 2 have been employed to train

Table 2 Fundamental data for training and testing ANN (Chen, 2006)

No.	Actual value				No.	Actual value			
	V (m/s)	*M* (t)	*DWT* (t)	*F* ($\times10^6$ N)		*V* (m/s)	*M* (t)	*DWT* (t)	*F* ($\times10^6$ N)
1	1	4000	3000	7.767	17	7	62000	50000	277.600
2	1	16700	12000	19.981	18	8	4000	3000	38.373
3	1	62000	50000	44.520	19	8	6700	5000	61.809
4	2	4000	3000	13.102	20	8	62000	50000	325.790
5	2	16700	12000	30.341	21	1	6700	5000	17.733
6	2	62000	50000	75.740	22	2	6700	5000	23.403
7	3	4000	3000	16.965	23	3	6700	5000	31.364
8	3	62000	50000	110.770	24	3	16700	12000	43.823
9	4	4000	3000	19.472	25	4	6700	5000	38.442
10	4	62000	50000	168.260	26	4	16700	12000	56.175
11	5	4000	3000	21.525	27	5	6700	5000	44.905
12	5	62000	50000	189.690	28	5	16700	12000	65.841
13	6	4000	3000	25.505	29	6	6700	5000	49.014
14	6	62000	50000	226.390	30	6	16700	12000	85.473
15	7	4000	3000	30.295	31	7	6700	5000	56.768
16	7	16700	12000	102.365	32	8	16700	12000	122.075

V is ship velocity; *M* is ship mass; *DWT* is deadweight tonnage of ship; *F* is ship-bridge collision force, which is the maximum force during ship collision with bridge by the finite element analysis

the ANN models, and the remained 12 groups of data is to validate the developed ANN.

In this study, neural networks have been designed through the function *newrb* in MATLAB, which adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal. The MATLAB function is:

$$net=newrb(\boldsymbol{X},\boldsymbol{Y},GOAL,SPREAD,MN,DF), \quad (9)$$

where $\boldsymbol{X}$ is the input vector; $\boldsymbol{Y}$ is the output vector; *GOAL* is mean squared error goal; *SPREAD* is spread of radial basis functions; *MN* is maximum number of neurons; *DF* is number of neurons to add between displays.

In this research, the value of *GOAL* has been set as 0.001, the value of *MN* is 1000, and the value of *DF* is 1. Since *SPREAD* greatly affects the performance of neural network, three different *SPREAD* values *SPREAD*=(1,2,3) have been discussed to find the best value for a given problem.

RESULTS AND DISCUSSION

According to the above design, six different RBFNNs have been trained and tested to show the effectiveness of the ANN-based method for calculating ship-bridge collision force.

Figs.3 and 4 show the correlation of ANN outputs and FEM results, which are close, especially when *SPREAD* is 1 or 2. When *SPREAD* is 1 in Fig.4, the results (*RMSE*=2.3397 and R^2=0.9996) show good agreement with the FEM results (or the experimental results). As a result, the proposed RBFNN is thought to be effective for mapping relation of *V-M-F* or *V-DWT-F*, particularly as *SPREAD* equals 1 or 2. In other words, *F* can be deduced from the RBFNN approach.

By determining the best network parameters for ANN, the velocity-force (*V-F*) relationship and mass-force (*M-F* or *DWT-F*) relationship are further discussed in the following. With *M* or *DWT* changed, the velocity-force relationship is shown in Fig.5 and Fig.6.

Figs.5 and 6 show that an approximately linear-relationship can be found between the ship velocity and the ship-bridge collision force, either in terms of *M* or *DWT*. On the one hand, the relationship is in good agreement with Eqs.(1) and (2). On the other hand, it is confirmed that the ANN-based method for ship-bridge collision force is reliable.

Similarly, the mass-force (*M-F* or *DWT-F*) relationships are discussed with different values of ship velocity (*V*). The results are shown in Figs.7 and 8.

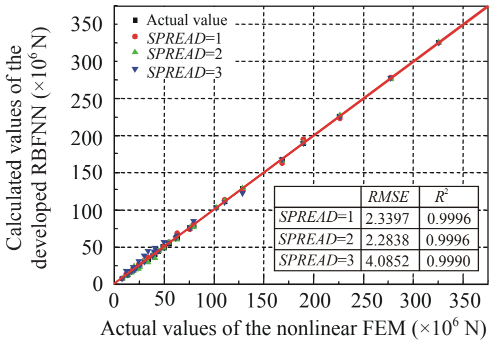

Fig.3 Simulation comparisons in neural network with mapping relation of *V-M-F*

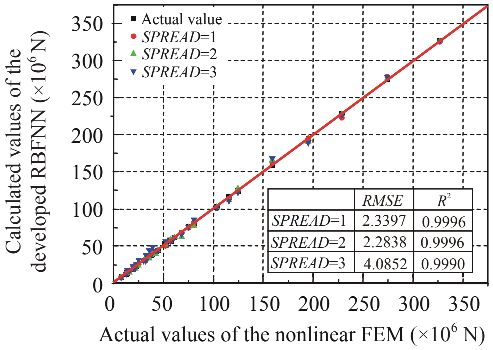

Fig.4 Simulation comparisons in neural network with mapping relation of *V-DWT-F*

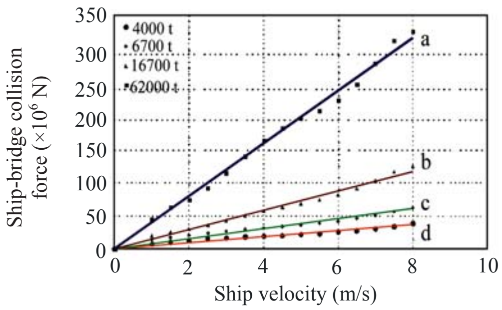

Fig.5 Relation curve of *F-V* with different *M*. a: y=39.512x, R^2=0.9936; b: y=14.528x, R^2=0.9861; c: y=7.5252x, R^2=0.9484; d: y=4.5831x, R^2=0.9389

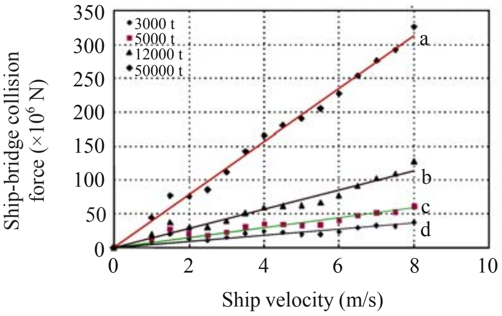

Fig.6 Relation curve of *F-V* with different *DWT*. a: y=39.248x, R^2=0.9923; b: y=14.236x, R^2=0.9554; c: y=7.3909x, R^2=0.8655; d: y=4.5706x, R^2=0.7664

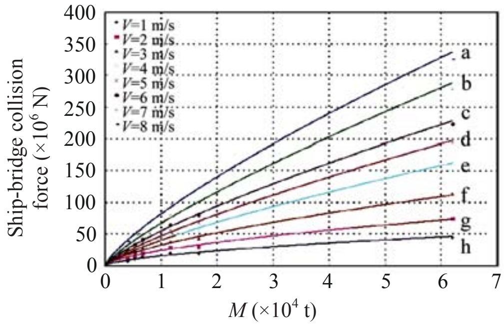

Fig.7 Relation curve of *F-M* with different *V*

a: y=0.0667$x^{0.7728}$, R^2=0.9974; b: y=0.0433$x^{0.7977}$, R^2=0.9970; c: y=0.0422$x^{0.7788}$, R^2=0.9972; d: y= 0.0347$x^{0.7837}$, R^2=0.9971; e: y=0.0376$x^{0.7584}$, R^2=0.9965; f: y=0.0686$x^{0.6705}$, R^2=0.9936; g: y=0.0931$x^{0.6051}$, R^2=0.9862; h: y=0.0689$x^{0.5908}$, R^2=0.9575

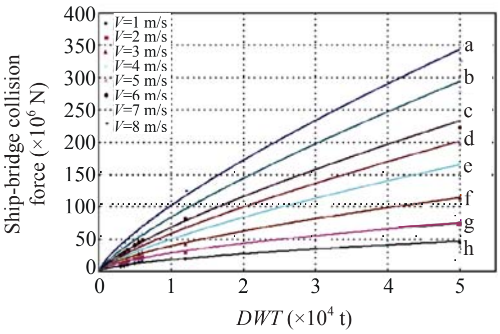

Fig.8 Relation curve of *F-DWT* with different *V*

a: y=0.0978$x^{0.7544}$, R^2=0.9948; b: y=0.0642$x^{0.7790}$, R^2=0.9946; c: y=0.0616$x^{0.7613}$, R^2=0.9954; d: y= 0.0504$x^{0.7665}$, R^2=0.9963; e: y=0.0535$x^{0.7427}$, R^2=0.9971; f: y=0.0926$x^{0.6578}$, R^2=0.9961; g: y=0.1203$x^{0.5949}$, R^2=0.9907; h: y=0.0868$x^{0.5819}$, R^2=0.9655

Figs.7 and 8 show a nonlinear relationship between ship-bridge collision force F and ship mass (M or DWT), whose tendency is basically in consistence with the power function. Therefore, the power function $Y=AX^B$ is chosen to fit the above relationships, and the results are shown in Figs.7 and 8. As a result, the relationships of F, V and M (or DWT) can be obtained as the follows:

$$F = 1.21\times10^{-2} V \cdot M^{0.72}, \tag{10}$$

$$F = 1.75\times10^{-2} V \cdot DWT^{0.70}. \tag{11}$$

It should be noted that the equivalent force in Eqs.(10) and (11) is different with the maximum force shown in Table 2. According to the European Standard 1991-1Eurocode 1 (EVN, 1994), the equivalent force can be obtained with the maximum force multiplied by a reduction factor of 0.85. Fig.9 shows the comparisons between the results by Eq.(10) or Eq.(11)

and the results by FEM, which were shown in Table 2. Although the values of *RSME* are not perfect, the results could be accepted for practical engineering. It shows that the proposed method is appropriate to calculate the ship-bridge collision force.

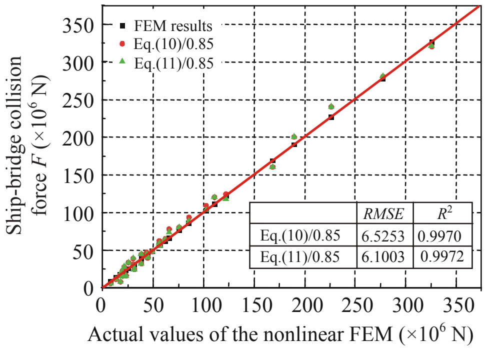

Fig.9 Comparisons between the results by Eq.(10) or Eq.(11) and the results by FEM

In addition, the comparison between Eq.(11) and AASHTO formula has been performed to investigate the relationship of them. The results are shown in Fig.10. When *DWT* is about 15160 t, the result calculated by Eq.(11) is equal in the AASHTO. If *DWT* is less than 15160 t, the value to that in the AASHTO is greater than that with Eq.(11). However, when *DWT* is more than 15160 t, the value by AASHTO is less than that of Eq.(11). In the same way, the comparison between Eq.(10) and European Standard has also been implemented. The results are shown in Fig.11. The similar conclusion can be obtained despite in different critical equal points, that is, *M* is about 37000 t. Meanwhile, the conclusion can contribute to improving the design specification of ship-bridge collision force in the future.

Developed toolbox using MATLAB

In order to realize the intelligent calculation for ship collision force on MATLAB platform, the special toolbox has been developed, which could improve the efficiency of the calculation work of ship impact load. The main interface of special toolbox is shown in Fig.12.

This software comprises five functional modules: (1) the module of RBFNN toolbox, (2) the module of simplified formula toolbox, (3) The module of AASHTO toolbox, (4) The module of Chinese Norms toolbox, and (5) the reserved interface for future expansion.

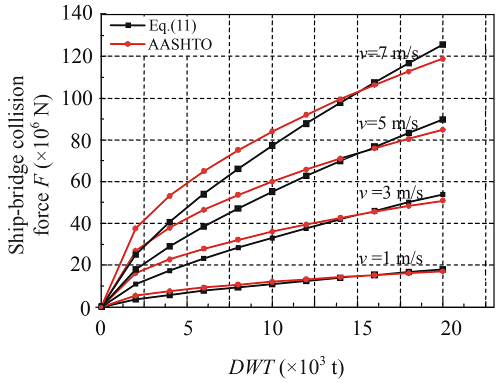

Fig.10 Comparison between Eq.(11) and AASHTO with different V

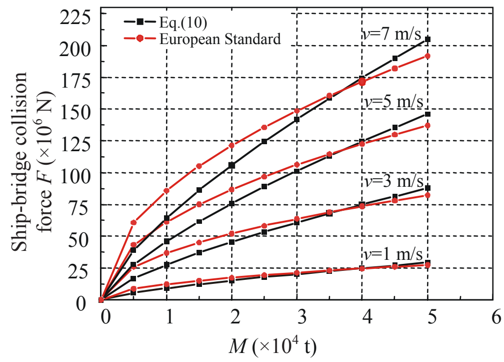

Fig.11 Comparison between Eq.(10) and European Standard with different V

Fig.12 The main interface of the toolbox for calculating ship-bridge collision force

In order to develop a powerful and easy-to-use software for calculating ship-bridge collision force in the future, the software has the following advantages: (1) modularization; (2) expandability; (3) accessibility; (4) adaptability; (5) portability.

CONCLUSION

This research aims at developing an ANN-based approach for calculating ship-bridge collision force. Therefore, the basis methodology of the proposed approach was advanced with a practical example, and the following conclusions can be drawn:

(1) Based on the results of finite element analyses, the ANN were trained and validated. The results of ANN and FEM were very close to each other. It shows that ANN method for ship-bridge collision force is appropriate based on its nonlinear mapping ability. It should be noted that due to the limited number of the learning samples, however, the generalization of neural network also is limited to some degree.

(2) Calculation time of FEM is about tens of hours and every different ship velocity or mass has to be calculated one by one. In contrast, training time for ANN is about 10 min. After the training of ANN, any different values of ship velocity and mass can be calculated efficiently within an acceptable error.

(3) According to the results from the ANN simulation, the relationship between ship velocity and ship-bridge collision force is approximately linear, which is in accordance with the statements in the AASHTO and the European Standard. However, the relationship between the ship mass and the ship-bridge collision force is different from those in the AASHTO and the European Standard. Finally, the simple equations have been suggested with the necessary mathematical treatment and compared with the formula in the AASHTO and the European Standard.

(4) Finally, the intelligent calculation program for ship-bridge collision force has been developed to save many computational efforts for engineers in practice.

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