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A new method to identify bridge bearing damage based on Radial Basis Function Neural Network

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Abstract. Bridge bearings are important connection elements between bridge superstructures and substructures, whose health states directly affect the performance of the bridges. This paper systematacially presents a new method to identify the bridge bearing damage based on the neural network theory. Firstly, based on the analysis of different damage types, a description of the bearing damage is introduced, and a uniform description for all the damage types is given. Then, the feasibility and sensitivity of identifying the bearing damage with bridge vibration modes are investigated. After that, a Radial Basis Function Neural Network (RBFNN) is built, whose input and output are the beam modal information and the damage information, respectively. Finally, trained by plenty of data samples formed by the numerical method, the network is employed to identify the bearing damage. Results show that the bridge bearing damage can be clearly reflected by the modal information of the bridge beam, which validates the effectiveness of the proposed method.

Keywords: bridge bearing; damage identification; vibration mode; Radial Basis Function Neural Network; finite element model

1. Introduction

The bridge bearing plays an important role in bridge systems by transferring loads between bridge superstructures and substructures, whose health state directly affects the performance of bridge systems. In Chinese railways, bridge structures occupy a large proportion, leading to a great number of bearings. Influenced by the reciprocal actions of wheel loads and the change of the environment, the characteristics of bearings may change, and even damage (such as aging of rubber, cracks, and so on) appears in the bearing systems. If the bearing damage appears in a bridge system, the connection relationship between the bridge beam and the pier changes, and the bridge vibrations may become abnormal. As a result, the service life of the bridge system may be greatly affected. Moreover, when a train running past the bridge with damaged bearings, its running safety and riding comfort may be

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influenced. Thus, the health states of bridge bearings attract much attention recently, and it is meaningful to detect the bearing damage in the bridge engineering. Based on this background, with the purpose of guiding the engineering application, this paper comes up with a new method to identify bearing damage.

By now, many studies have paid their attention to the performance of bridge bearings, and many beneficial suggestions have been proposed. With the increase of lateral forces acting on bridges, Gilstad (1990) investigated the stability of the bearing structures. Considering the nonlinear characteristic, Hamzeh *et al*. (1998) established a 2D finite element model of the rubbing bearing. Adopting this model, the influence factors of bearing stresses and strains were analyzed, and the relationship between the lateral deformation and vertical deformation of the bearing was also obtained. Also taking the bearing's nonlinear behavior into consideration, Mutobe and Cooper (1999) analyzed the nonlinear vibrations of a large bridge with isolation bearings. Olmos and Roesset (2010) investigated the effects of the rubber bearings on the seismic responses of bridges. Yakut and Yura (2002) evaluated the compression and shear properties of the elastomeric bearings at low temperatures, and further discussed the necessity of this experiment from the cost perspective. Gu *et al*. (2010) investigated the aging behaviors of bridge rubber bearings by tests. Filipov *et al*. (2013) calculated the dynamics performance of bridges with nonlinear bearing models subjected to seismic actions. Nevertheless, most of the existing researches focus on the mechanical behaviors of the bearings without damage. Only a few studies do works on the damaged bearings. Kim *et al*. (2006) modeled the damaged bearing as a friction element, and the damage in different degrees was considered as different friction factors. Employing this bearing element, the influences of damaged bearings on the seismic performance of a bridge were analyzed, and the results indicated that the bearing damage had a great effect on the bridge vibrations. After that, the rubber aging and sliding surface abrasion of the bearings were investigated by Itoh *et al*. (2009) and Ala *et al*. (2015) respectively. Although there are many works on bearings, few studies pay attention to the field of bearing damage identification.

Based on the neural network theory, this paper proposes a novel method to identify the bridge bearing damage with the structural modal information. Firstly, the identification methodology is described in detail in Section 2. Then, due to the fact that there are too many kinds of bearing damage, a uniform description for all the damage is defined in Section 3. After that, the feasibility analysis (Section 4) and the sensitivity analysis (Section 5) are conducted to illuminate that the beam modal information is effective and accurate to describe the bearing damage. On this basis, a case study of the bearing damage identification is presented in the last section.

This paper contains several highlights, which are listed below:

- A new bearing damage identification method is proposed systematacially.
- The common characteristics of all the bearing damage types are investigated, and the uniform description for all the damage types is given.
- The sensitivity of the beam vibration mode to the bearing damage is determined.
- The influence of the bridge beam damage on the accuracy of the bearing damage identification is investigated.

2. The bridge bearing damage identification method based on the RBFNN

2.1 Design methodology of a RBFNN

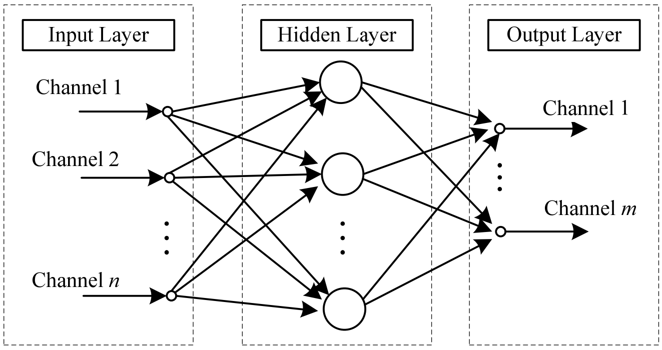


Fig. 1 Structure of the RBFNN

Neural network theory has developed rapidly in recent years, which has been widely applied in the field of damage identifications (Tadesse *et al.* 2004, Lee *et al.* 2005, Bakhary *et al.* 2007, Domaneschi *et al.* 2015). Also, the validity of identifying the structural damage by employing the neural network has been verified in the previous studies. Thus, in this paper, the RBFNN is built based on the neural network theory to identify the bearing damage.

(1) Structure of the RBFNN

The RBFNN is a kind of forward network. Because no feedback exists in the network, the structure of this network is simple. The RBFNN consists of three layers, including the input layer, the hidden layer, and the output layer, as shown in Fig. 1.

The input layer transfers the signal data to the hidden layer. Then, the data are calculated and processed in the hidden layer and the output layer. The hidden layer nodes are formed by the Gaussian Basis Function, as described in Eq. (1) (Hagan 1996)

$$u_j = \exp\left[-\frac{(X-C_j)^{\mathrm{T}}(X-C_j)}{2\sigma_j^2}\right] \quad j=1,2,\ldots,N_{\mathrm{h}} \tag{1}$$

where, u_j is the output of the jth node in the hidden layer; X is the input of the sample; C_j is the central value of the Gaussian Function; σ_j is a constant; N_{h} is the number of the nodes in the hidden layer.

The output layer nodes are usually constituted by simple linear functions, as expressed in Eq. (2)

$$y_i = \sum_{j=1}^{N_{\mathrm{h}}} w_{ij} u_j - \theta \quad i=1,2,\ldots,m \tag{2}$$

where, w_{ij} is the weight value and θ is the threshold value.

(2) Training of the RBFNN

Learning and training of the RBFNN make the neural network more accurate. Usually, about 70% of the total samples are adopted to train the neural network, while the rest 30% of the data are employed to test the network.

The training process can be divided into two stages. In the first stage, the central value of the Gaussian Function C_j and the constant σ_j are determined according to the input data. Then, in the

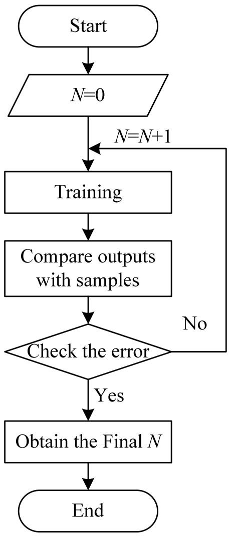


Fig. 2 Determination of the node number in the hidden layer

second stage, the weight value w_{ij} of the output layer are calculated based on the least square method.

Noted that, in the training process, the number of the nodes in the hidden layer is a key parameter, which directly affects the calculated results. In the traditional method, this number is set to be the same value as the number of the input parameters. Obviously, if there are lots of inputs, the numerous hidden layer nodes will slow the computational efficiency, which is unacceptable, so, a modified method is employed in this study, which is displayed in Fig. 2. In this figure, N represents the number of the hidden layer nodes. As known from the figure, the number of the hidden layer nodes changes automatically with the calculation conditions, indicating that the RBFNN established in this paper is highly adaptable.

The design method of the RBFNN is introduced briefly above. It can be known from the methodology that two key issues directly influence the efficiency and the accuracy of the RBFNN, including: a) the input values, and b) the training process. For different work conditions, the selections of the inputs and the training process are different. Hence, in the last section, a case study of identifying bearing damage employing the RBFNN is presented in detail.

2.2 The proposed identification method of bearing damage

Structure damage identification has been a classical research topic for a long time. To the authors' knowledge, few studies focus on the bridge bearing damage identification. Relatively, the damage identifications of bridge beam bodies are not uncommon (Tadesse *et al.* 2004, Lee *et al.* 2005, Bakhary *et al.* 2007, Domaneschi *et al.* 2015). Among the existing studies, the modal information of the beam body is widely employed to identify the damage. The reason is that the modal properties (especially in the low-order modes) are easy to obtain through field tests in the practical engineering (Chena *et al.* 2004, Hea *et al.* 2011, Ubertini *et al.* 2013). Thus, in this paper, the authors proposed a method to identify bridge bearing damage using the beam modal information based on the neural network theory.

The damage identification process can be conducted by the following steps, and the flow diagram of the procedure is displayed in Fig. 3.

(1) Establish the numerical models of bridge systems with bearings;

(2) Employing the model in step (1), carry out plenty of modal analysis under different bearing damage conditions;

(3) Form the data samples of beam modal displacements in accordance with different bearing damage;

(4) Build the RBFNN based on the neural network theory;

(5) Train and test the RBFNN using the data in step (3);

(6) Identify bridge bearing damage employing the trained RBFNN.

To accurately identify bridge bearing damage according to the identification process above, it is worth pointing out that the following key issues should be considered primarily:

(1) Description of the bearing damage. Because there are variety of bearing types and damage types, it is difficult to describe all the damage in all the bearings. Thus, a uniform damage description is needed. This issue is solved in Section 3.

(2) Feasibility of identifying bearing damage using the bridge modal information. This issue is the precondition of the research in this paper, which is discussed in Section 4.

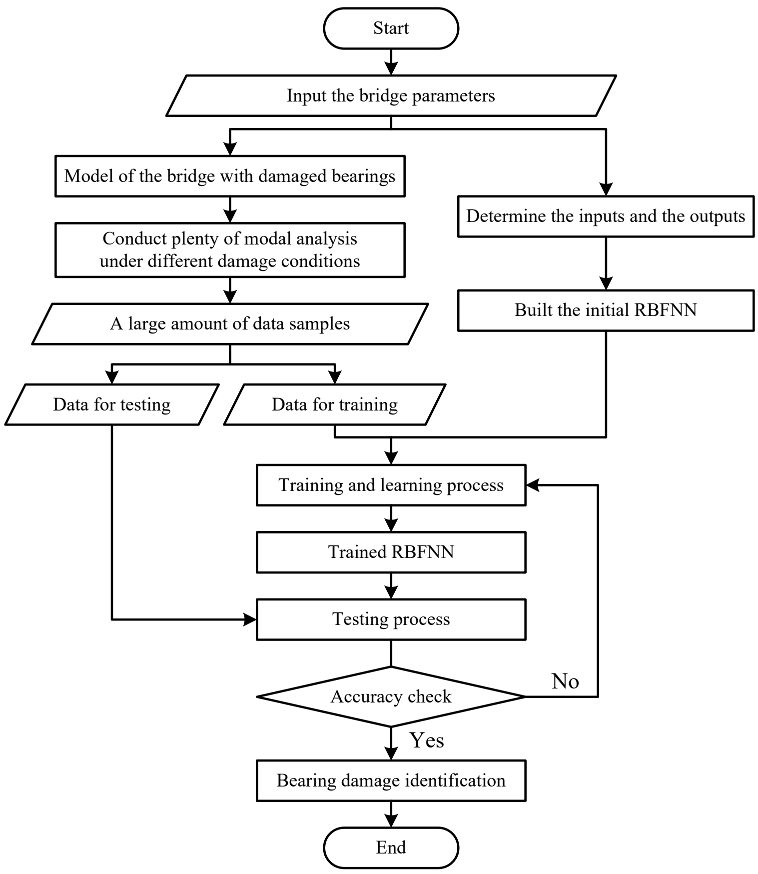


Fig. 3 Bearing damage identification procedure

(3) Sensitivity of identifying bearing damage using the bridge modal information. If the sensibility of the method proposed in this paper is too low, the method cannot be adopted to identify bearing damage. Hence, this issue is worth analyzing, which is shown in Section 5.

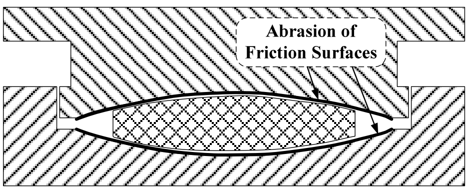
3. Bearing damage explanation

There are many bearing damage types, and different damage types appear in different kinds of bearings. By now, several kinds of bearings are widely adopted in bridge engineering, mainly including the spherical steel bearing (Fig. 4(a)), the basin rubber bearing (Fig. 4(b)), and the laminated rubber bearing (Fig. 4(c)). The common damage for each kind of b

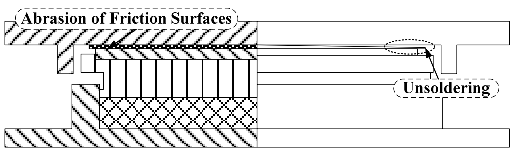
Because of the diversity of bearing damage shown in Table 1 and Fig.4, it is hard to describe all the damage in detail. To find a uniform description for all the damage, their common characteristics should be investigated firstly. Analyzing all the damage types above, the authors divided the bearing damage into two kinds:

Table 1 Common damage for each kind of bearing

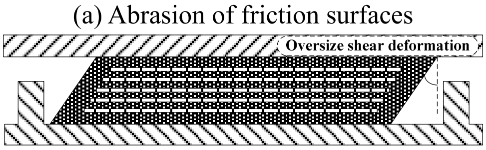
Bearing	Damage
Spherical steel bearing	Abrasion of steel part Steel corrosion Cracks in steel part Plastic deformation of steel part Unsoldering Failure of anchoring part and fixed part
Basin rubber bearing	Rubber aging Crack in rubber part Unsoldering Abrasion of PTFE plate and steel
Laminated rubber bearing	Rubber aging Crack in rubber part Bulge Oversize shear deformation Void between rubber part and support part



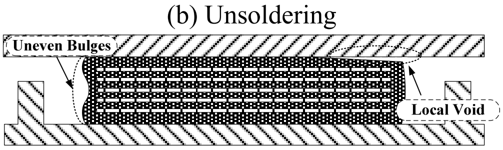
(a) Abrasion of friction surfaces



(b) Unsoldering



(c) Oversize shear deformation



(d) Uneven bulges and local void

Fig. 4 Typical bearing damage

(1) Change of material properties, such as rubber aging. If the material characteristic changes, the elasticity modulus and the shear modulus also change simultaneously. China Academy of Railway Sciences (CARS) investigated many railway bridge bearings serving for almost 20 years, and concluded that the elasticity modulus and the shear modulus of the rubber bearings have increased by 20% and 27%, respectively (Zhuang 2008). These changes directly affect the vertical and horizontal stiffness of the bearing systems.

(2) Degradation of structures, such as plastic deformation and abrasion of steel part. The structure degradations will make the contact relationships between the two contacted parts change, which will directly change the contact forces synchronously. From the dynamics perspective, it is generally known that the contact forces are related to the contact stiffness linearly or non-linearly, i.e., all the changes of the contact forces can be described by the changes of the contact stiffness, no matter the relationships are linear or non-linear.

As known from the above analysis, almost all the bearing damage types change the bearing stiffness. Thus, to describe all the damage under a uniform principle, the bearing damage is considered as the change of bearing stiffness in this paper.

The beam vibrations (in the range of low-frequency) in the orthogonal directions of x, y and z are uncoupled (Clough and Penzien 2003), thus, from the point of bridge vibration, any bearing damage types can also be broken up into the change of bearing stiffness in three directions of x, y and z.

4. Feasibility analysis of bearing damage identification

As the precondition of this study, it is a key issue to investigate whether the change of the beam vibration mode reflects different bearing damage.

Note that, besides the bearing damage, the damage of the bridge beam may also affect the vibration modes, which influences the accuracy of identifying the bearing damage with beam modal information. Thus, two issues are discussed in this section: a) the influence of the bearing damage on the beam vibration modes, and b) the comparison between the influence of bearing damage on the beam vibration modes and that of the bridge beam damage.

4.1 Influence of the bearing damage on beam vibration modes

In order to ascertain the qualitative relationships between different vibration modes and different bearing damage, a simplified beam-bearing model is built, in which the beam is modeled as an Euler-beam and the bearings are described as support springs, as shown in Fig.5. The parameters k_1 and k_2 are the support stiffness at the two beam ends, and l is the length of the beam.

According to the vibration mechanics (Clough and Penzien 2003), the vibration mode function $Y(x)$ of the Euler-beam can be expressed as

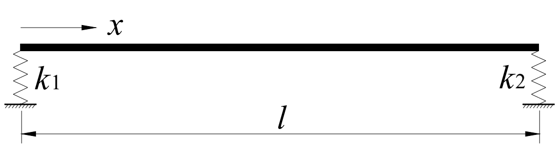


Fig. 5 Spring-supported Euler-beam model

$$Y(x) = A\sin kx + B\cos kx + C\sinh kx + D\cosh kx \tag{3}$$

in which

$$k^4 = \frac{\rho A}{EI}\omega^2 \tag{4}$$

where, x is the coordinate of any point on the beam; A~D are the coefficients; ω is the natural vibration frequency of the beam; ρA is the mass of the beam in per unit length; E and I are the elastic modulus and the section inertia of the beam, respectively. The parameters of the model are listed in Table 2, which are commonly used in Chinese railway bridges.

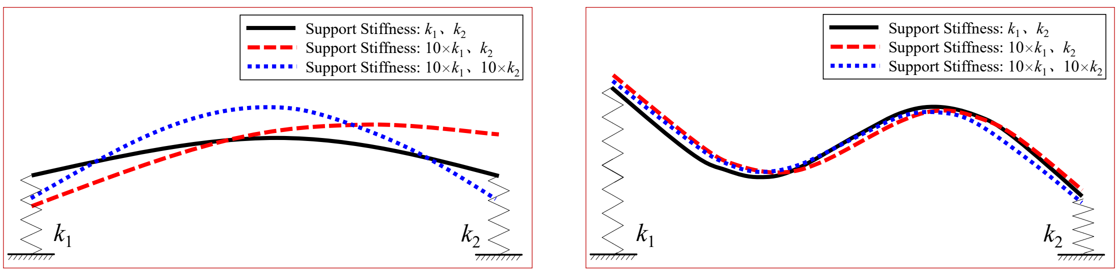
The boundary conditions of the beam could be written as

$$\begin{cases} Y''(0) = 0 \\ Y''(l) = 0 \\ Y(0)\cdot k_1 = EI\cdot Y'''(0) \\ Y(l)\cdot k_2 = EI\cdot Y'''(l) \end{cases} \tag{5}$$

Solving Eqs. (3) and (5) together by numerical methods, the beam vibration modes with different support stiffness are obtained. Fig.6 shows the influences of bearing stiffness on the beam vibration modes. As shown in Fig.6, two notable conclusions can be reached: a) beam vibration modes change obviously with the change of the support stiffness, indicating that the bridge bearing damage distinctly affects the beam vibration modes; and b) the beam modal displacements at the bearing locations are the largest.

Table 2 The parameters of the beam model

Parameters	Value	Units
E	3.6×10^{10}	Pa
I	15	m^4
ρ	2500	kg/m^3
A	12	m^2
k_1	1×10^7	N/m
k_2	1×10^7	N/m
l	30	m



(a) The first-order bending vibration mode (b) The second-order bending vibration mode

Fig. 6 The influences of the bearing stiffness on beam vibration modes

4.2 Influence of the beam damage on the accuracy of bearing damage identification

In order to evaluate the influence of bridge beam damage on the accuracy of the bearing damage identification, a 2D finite element model is established with the parameters in Table 2, as displayed in Fig. 7. In this model, there are 10 beam elements and 2 spring elements. The bearing damage is modeled as the change of the bearing stiffness, while the bridge beam damage is regarded as the change of the elasticity modulus (Tadesse *et al.* 2004, Lee *et al.* 2005, Bakhary *et al.* 2007, Domaneschi *et al.* 2015).

It should be pointed out that the location of the beam damage also affects the beam vibration modes, even if the damage of the beam is at the same level. Thus, the location of the maximum influence of the beam damage on the beam vibration modes is analyzed with the finite element model. The results are shown in Fig. 8. Because the model is symmetric, the same damage value is set to occur at the locations of Element 1, Element 2, Element 3, Element 4, and Element 5, respectively. As shown in Fig. 8, when the damage occurs at the location of the middle element (i.e., Element 5), the influence of the beam damage on the beam vibration mode is the largest, indicating the damage in the middle of the beam has the greatest effect on the vibration mode.

Based on the calculations above, the influence of the damage in the mid-beam on the accuracy of the bearing damage identification is analyzed. Note that, the length of the element (i.e., the extent of the beam damage) greatly affects the accuracy of the bearing damage identification. In the following calculations, the length of the element is set to be 0.006 m, 0.015 m, 0.03 m, 0.06 m, 0.15 m, 0.3 m, 0.6 m, 1.5 m and 3 m, respectively. Also, to make the damage levels of the bearing damage and the beam damage the same as each other, both of the bearing stiffness and the beam elasticity modulus change to be half of the original values.

As known from the theory of vibration mechanics, the essence of the modal displacement is the relative displacement in a certain vibration mode. On this basis, to compare the influence of the bearing damage with that of the beam damage intuitively, a dimensionless parameter is employed, which is defined as

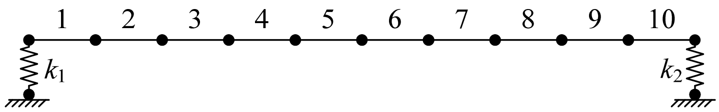


Fig. 7 Finite element model of the bridge

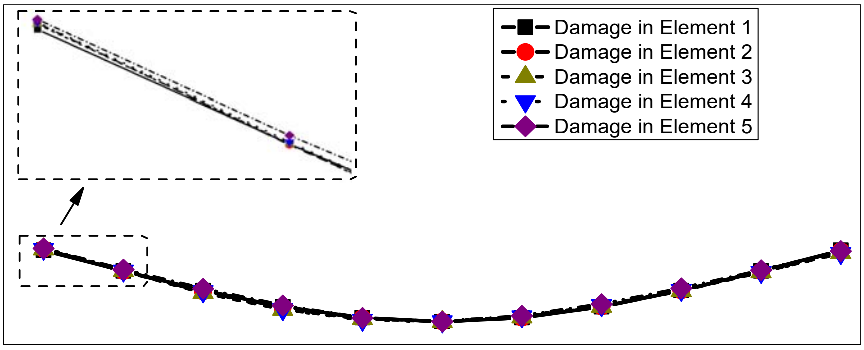


Fig. 8 Influence of the beam damage location on the beam vibration mode

$$\varepsilon = \frac{E - E_0}{E_0} \times 100\% \tag{6}$$

in which

$$E = \frac{D_{\max}}{D_{\min}},\ E_0 = \frac{D_{0\max}}{D_{0\min}} \tag{7}$$

where, ε is the dimensionless parameter for comparison; E and E_0 represent the modal displacement ratio under the damaged condition and the undamaged condition, respectively; $D_{\max}$ and $D_{\min}$ are the maximum and minimum modal displacements in the damaged condition, respectively; while $D_{0\max}$ and $D_{0\min}$ are the maximum and minimum modal displacements in the undamaged condition, respectively.

The comparison between the influence of the bearing damage on the beam vibration mode and that of the bridge beam damage is given in Fig. 9. As seen from this figure, when the extent of the beam damage increases, the effect of the beam damage on the vibration mode becomes large. When the length of the beam damage reaches around 0.04 m, the influence of the beam damage on the vibration mode is the same as that of the bearing damage. That is to say, if the length of the beam damage is less than 0.04 m, the influence of the beam damage is smaller than that of the bearing damage. The shorter the beam damage is, the smaller the influence of the beam damage on the accuracy of bearing damage identification is.

In conclusion, if the beam damage is very small, the influence of that on the bearing damage identification can be ignored. As the length of the beam damage increases, the effect of the beam damage on the accuracy of the bearing damage identification increases, and the accuracy of the bearing damage identification becomes low.

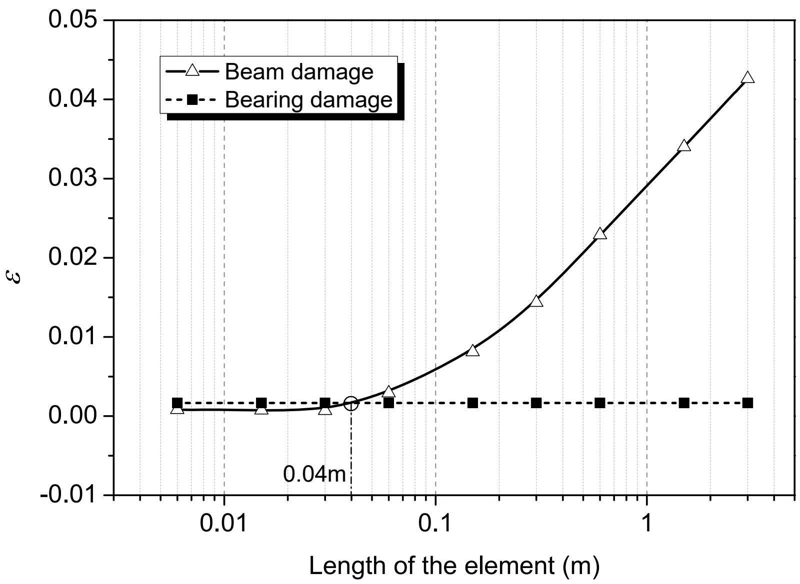


Fig. 9 Comparison between the influence of the bearing damage on the beam vibration mode and that of the bridge beam damage

5. Sensitivity analysis of bearing damage identification employing modal information

From the above analysis, it can be known that the bearing damage can be identified by the beam modal information. Further, in order to figure out the sensibility of the beam modal information to the bearing damage, a sensitivity analysis is conducted in this section adopting the mechanical model in Fig. 5.

In order to obtain this sensibility, several tiny increments are added to the original support stiffness respectively to calculate the effects of the small changes of the support stiffness on the vibration modes of the beam. Compared with the original support stiffness of 1×10^7 N/m, the tiny increments are set to be 1×10^1 N/m, 1×10^2 N/m, 1×10^3 N/m, 1×10^4 N/m, 1×10^5 N/m, 1×10^6 N/m, and 1×10^6 N/m, respectively. Fig. 10 shows the relationships between the normalized modal displacements of the beam-end and the increments of the support stiffness.

It can be seen from the figure that, as the increment value increases, the normalized modal displacement decreases. The figure can be divided into three parts, describing part I, part II, and part III, which are separated by the two points of 6000 N/m (0.6‰ of the original stiffness value) and 1×10^5 N/m (1% of the original stiffness value). In part I, the normalized modal displacement of the beam-end remains unchanged. Relatively, the displacement changes slowly in part II, but rapidly in part III. The figure indicates that, only when the changing value of the bearing stiffness is larger than 6000 N/m, the bearing damage can be reflected by the beam vibration modes. However, when the increment value changes from 6000 N/m to 1×10^5 N/m, the effect of the bearing damage on the beam modal information is relatively small, so the damage information is not easy to identify in these situations. Relatively when the increment value reaches 1% of the original stiffness value (i.e., 1×10^5 N/m for this beam model), the normalized modal displacement changes sharply with the change of the bearing stiffness.

From the investigation in this section, it can be concluded that, when the change of the bearing stiffness reaches 0.6‰ of the original stiffness value, the damage information can be reflected by the beam vibration mode. Further, if the changing in the bearing stiffness reaches 1% of the original stiffness value, the bearing damage can be much easier to identify through by the beam modal information.

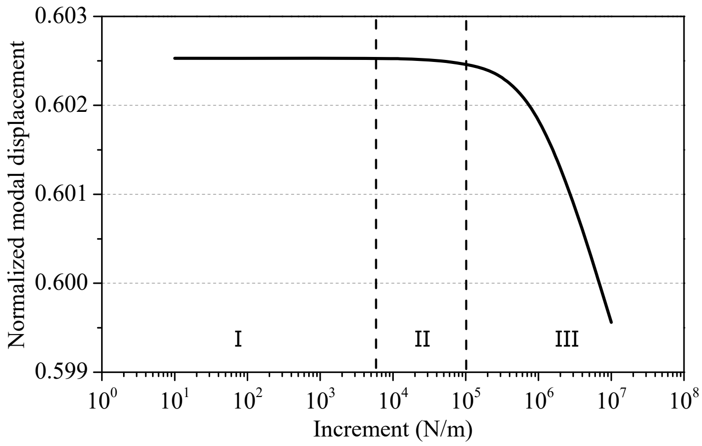


Fig. 10 Relationship between the normalized modal displacements of the beam-end and the changing in the support stiffness

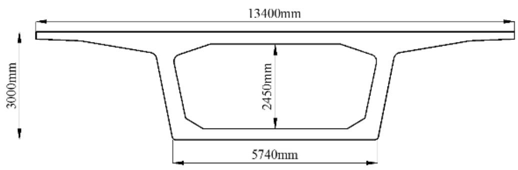
6. Case study and discussions

Based on the method proposed in Section 2, the RBFNN is employed to identify the bridge bearing damage through an engineering case study in this section.

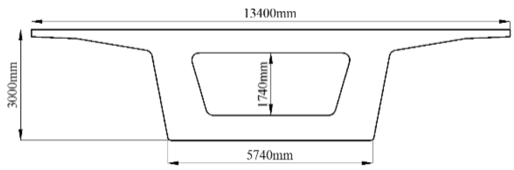
6.1 Case description

The 32 m-long simply supported girder bridge is chosen as the research object in this work, which is widely employed in Chinese high-speed railway. The structure of the bridge is given in Fig. 11, and the bearing arrangement is displayed in Fig. 12.

(a) 32m-long simply supported girder bridge



(b) Mid-span of the beam



(c) Beam-end of the beam

Fig. 11 Structure of the bridge

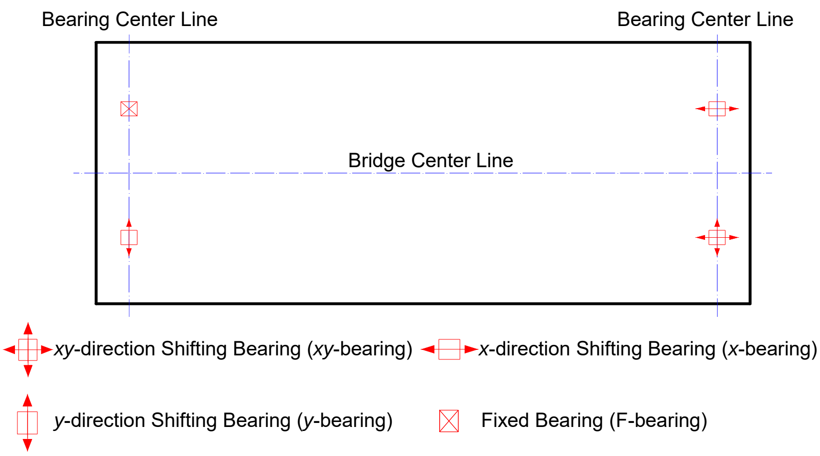


Fig. 12 Arrangement of the bearings

Table 3 Damage conditions

Number	Damage bearing	Damage description
No.1	F-bearing	The lateral stiffness increases by 2 times
No.2	x-bearing	The vertical stiffness increases by 3 times
	y-bearing	The longitudinal stiffness reduces to 1/5 of the original value

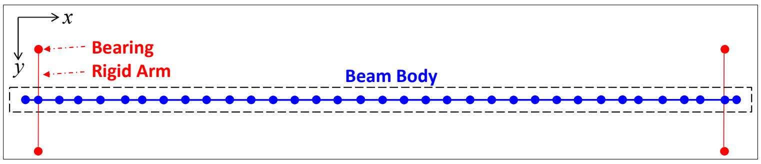
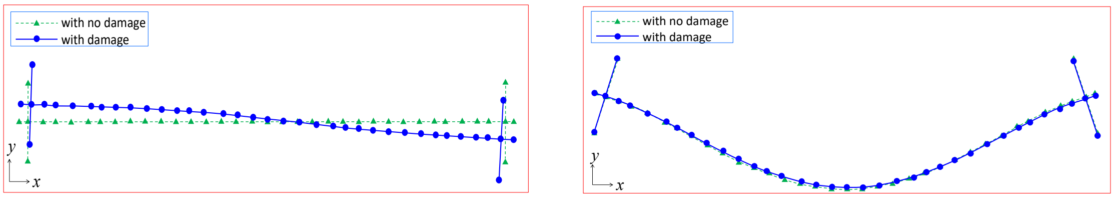


Fig. 13 The finite element model of the bridge with bearings (top view)



(a) First-order vertical vibration mode (b) First-order lateral vibration mode

Fig. 14 Effects of the x direction stiffness changes of fixed bearing on different beam vibration modes (top view)

To verify the effectiveness of the proposed method in this paper, two damage conditions are set, which are listed in Table 3. In the No.1 damage condition, only one bearing is damaged, while in the No.2 damage condition, the damage appears in two different bearings. In the following parts, based on the identification methodology proposed in this paper, the RBFNN is established to identify these damage information.

6.2 Preparation for the RBFNN

As known from the design method of the RBFNN, several analysis should be performed in advance to determine the inputs, the outputs, and the data samples for training. To do these calculations, a 3D finite element model of the bridge with bearings is built, as shown in Fig. 13. In the finite element model, the bridge beam is modeled by the spatial beam element and the bearings are regarded as springs. The bearing nodes are connected to the beam with four rigid arms (beams with big stiffness and small mass).

(1) Determine the inputs

It can be known from Section 4 that the changes of beam vibration modes can describe the bearing damage, and the modal displacements at the bearing locations are the largest. Thus, the modal displacements at the four bearing locations can be selected as the input values.

Nevertheless, every node has three displacements in directions of x, y, and z. Because the beam vibrations are uncoupled in these three orthogonal directions, the bearing damage in one direction has no influence on the displacements in the other two directions. Thus, to reduce the number of the input values, modal analysis is performed to investigate the influences of the bearing damage in different directions on the modal displacements of the beam. Fig. 14 shows the effects of the stiffness change of the F-bearing in x direction on the beam modal displacement.

As to the longitudinal (i.e., x direction) stiffness change of the F-bearing, the beam body rotates an angle in the first-order vertical vibration mode (VVM), as seen in Fig. 14(a), leading to the longitudinal displacements of the four bearing nodes. Conversely, the change of the longitudinal stiffness has almost no effect on the lateral vibration mode (LVM), as displayed in Fig. 14(b). Thus, the longitudinal displacements of the four bearing points in the first-order VVM can be used to identify the bearing damage in x direction. Similarly, the lateral (i.e., y direction) displacements at the four bearing locations in the first-order LVM can be used to identify the bearing damage in y direction, and the bearing damage in vertical direction can be identified by the vertical displacements of the bearing points in the first-order VVM.

In conclusion, 12 displacements are needed to identify the bearing damage in all directions, including the longitudinal and vertical displacements at the 4 bearing locations in the first-order VVM and the lateral displacements of the 4 bearing points in the first-order LVM. Moreover, to make the displacement values more intuitive, these 12 values are normalized (divide the

Table 4 Inputs of the RBFNN

Channel	Input parameter
1	Normalized displacement of the F-bearing in x direction in the 1st VVM
2	Normalized displacement of the x-bearing in x direction in the 1st VVM
3	Normalized displacement of the y-bearing in x direction in the 1st VVM
4	Normalized displacement of the xy-bearing in x direction in the 1st VVM
5	Normalized displacement of the F-bearing in y direction in the 1st LVM
6	Normalized displacement of the x-bearing in y direction in the 1st LVM
7	Normalized displacement of the y-bearing in y direction in the 1st LVM
8	Normalized displacement of the xy-bearing in y direction in the 1st LVM
9	Normalized displacement of the F-bearing in z direction in the 1st VVM
10	Normalized displacement of the x-bearing in z direction in the 1st VVM
11	Normalized displacement of the y-bearing in z direction in the 1st VVM
12	Normalized displacement of the xy-bearing in z direction in the 1st VVM

Table 5 The output parameters of the RBFNN

Channel	Output information
1	Damage in x-direction of the F-bearing
2	Damage in y-direction of the F-bearing
3	Damage in z-direction of the F-bearing
4	Damage in y-direction of the x-bearing
5	Damage in z-direction of the x-bearing
6	Damage in x-direction of the y-bearing
7	Damage in z-direction of the y-bearing
8	Damage in z-direction of the xy-bearing

displacements by the maximum displacement in the same direction). Finally, 12 dimensionless values are obtained, which are the determined input parameters of the RBFNN, as listed in Table 4.

(2) Determine the outputs

For a simply supported girder bridge, the bearing damage can appear in total 8 locations and directions, including x, y, z directions of the F-bearing, y and z directions of the x-bearing, x and z directions of the y-bearing, and z-direction of the xy-bearing. Therefore, the neural network has 8 output parameters of the neural network, which are listed in Table 5.

(3) Determine the data samples for training

Large numbers of data samples are needed to train the RNFBB. To obtain these samples, adopting the aforementioned 3D finite element model, numerous modal calculations are conducted under different combinations of different bearing damage. In this work, total 1200 data samples are formed by the different bearing stiffness and the corresponding normalized-displacements at the bearing locations. These samples are used to train and test the RBFNN.

6.3 The designed RBFNN for bearing damage identification

The input layer and the output layer are determined in the previous section. Based on the design method of the RBFNN in Section 2.1, adopting the Gaussian Function as the basis function, the initial RBFNN is established. To make the neural network accurate, the training and testing process are carried out in this section.

800 data samples are employed to train the RBFNN, the errors in the training procedure for all the samples are displayed in Fig. 15. As seen from the figure, the error values fluctuate around 0, indicating that the result of the training process is acceptable.

After the training process, the rest 400 samples are adopted to test the RBFNN. Further, a linear fit process is also carried out, and the results are given in Fig. 16. As shown in the figure, the correlation coefficient is larger than 0.99, indicating that the results of testing process and linear fit process are in good agreement with each other.

Note that, in the designed RBFNN, the output value 0 means no damage occurs in the corresponding bearing, while the value 1 represents the corresponding bearing damages. From Fig. 16, it also can be seen that the test results for ‘damage’ are in the range of 0.94 to 1.11. The fluctuations of the results for ‘damage’ are all less than ±0.2, and this value is determined to be the threshold level in the following bearing identification.

Based on the training process and the testing process, the RBFNN established in this paper can be employed to identify the bearing damage accurately.

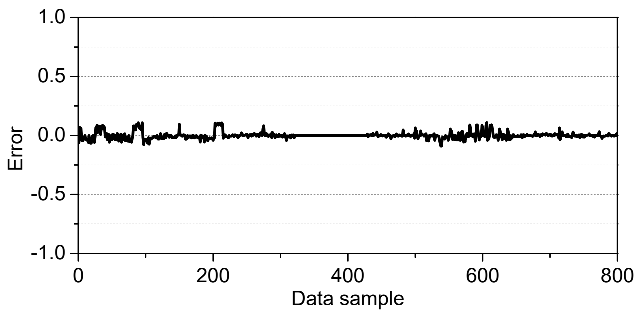


Fig. 15 The errors in the training procedure

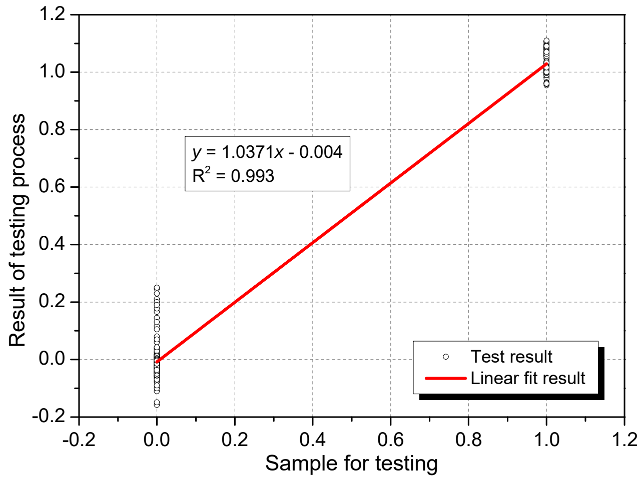


Fig. 16 The result of the testing process

6.4 Results and discussions

Adopting the trained RBFNN, the identification of the damage in Section 6.1 is conducted in this section, and the results are also discussed.

Modal analysis of the bridge with damaged bearings is carried out, and the normalized displacements of the bearing nodes are listed in Tables 6-7. On this basis, the input parameters of the RBFNN is determined according to Table 4, which are listed in Table 8.

Put the input parameters into the RBFNN, the output results are shown in Fig. 17.

It can be seen from Fig. 17(a) that the damage information of the second output channel is 1.06, while the values in the other channels are all less than 0.35. Because the threshold level of damage identification is determined to be ±0.2 (as seen from Fig. 9), the damage is identified to appear in the *y*-direction of the F-bearing (i.e., the channel 2). Comparing the identification result with the No.1 damage condition, it can be known that the identification under this work condition is correct.

Table 6 Normalized displacements of the bearing nodes under No.1 damage condition

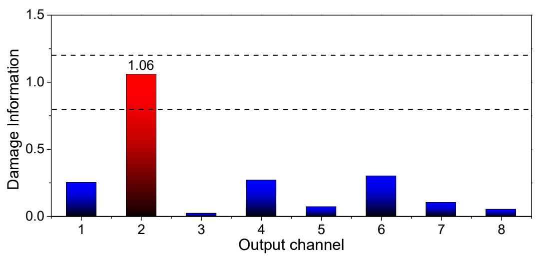
Normalized displacement	F-bearing	*x*-bearing	*y*-bearing	*xy*-bearing
Displacements in *x* direction in the 1st VVM	1	-0.989	1	-0.989
Displacements in *y* direction in the 1st LVM	1	0.995	1	0.995
Displacements in *z* direction in the 1st VVM	1	1	1	1

Table 7 Normalized displacements of the bearing nodes under No.2 damage condition

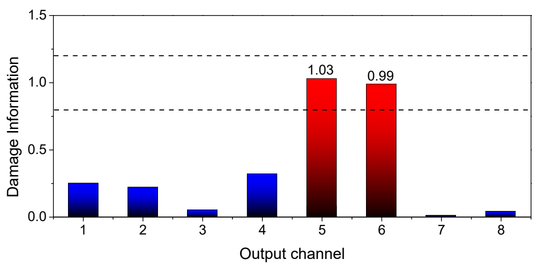
Normalized displacement	F-bearing	*x*-bearing	*y*-bearing	*xy*-bearing
Displacements in *x* direction in the 1st VVM	0.993	0.993	1	0.985
Displacements in *y* direction in the 1st LVM	1	1	1	1
Displacements in *z* direction in the 1st VVM	0.864	0.068	1	0.847

Table 8 Inputs of the RBFNN

Channel	No.1 damage condition	No.2 damage condition
1	1	0.993
2	-0.989	0.993
3	1	1
4	-0.989	0.985
5	1	1
6	0.995	1
7	1	1
8	0.995	1
9	1	0.864
10	1	0.068
11	1	1
12	1	0.847



(a) Identification result in No.1 damage condition



(b) Identification result in No.2 damage condition

Fig. 17 Bearing damage identification results

Similarly, as shown in Fig. 17(b), the damage appears in the 5th and the 6th output channels, indicating the damage occurs in the *x*-bearing and the *y*-bearing, which is also consistent with the No.2 damage condition.

From the above results, it can be concluded that the RBFNN is effective to identify the bearing damage. Moreover, the identification results for the bearings without damage are all less than 0.35, which are much less than the identification values of the damaged bearings. This also reveals the identification method proposed in this paper has high accuracy.

Although the RBFNN is effective to identify bearing damage, this method still has some limitations, which are listed below. Further studies are needed to make the identification method proposed in this paper more accurate, more stable and more robust.

• If the bridge beam also damages, the accuracy of the bearing damage identification is affected.

• The environment should be stable, because the beam vibration modes are affected by some environmental factors, such as the temperature.

• If the bearing stiffness changes very small, it is difficult to identify this damage based on the method proposed in this paper.

7. Conclusions

This paper has proposed a new method to identify the bridge bearing damage with the beam modal information based on the RBFNN. Primarily, a uniform description for all the bearing damage has been defined. On this basis, the feasibility and sensitivity of identifying the bearing damage by bridge vibration modes have been investigated. After that, based on the neural network theory, a RBFNN has been established and trained to identify the bearing damage, in which, the beam vibration modes and the damage information have been chosen as the inputs and the outputs, respectively. From the study in this paper, the following conclusions can be reached.

• The bridge bearing damage can be reflected by different beam vibration modes, indicating that it is feasible to identify the bearing damage adopting the beam modal information.

• Only when the change of the bearing stiffness reaches 0.6‰ of the original stiffness value, the damage can be reflected by the beam vibration mode. Further, if the change reaches 1% of the original value, the bearing damage can be easily identified.

• The RBFNN is effective to identify the bearing damage. The damage identification method proposed in this paper is also suggested to be employed in the other structure damage identifications.

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