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SVM-based bridge health condition evaluation forecasting function method and evaluation criteria[1]

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Abstract. A new method for bridge structure health condition evaluation is proposed, i.e. the forecasting function method, and probes into the determination of evaluation criteria. First, Least Square Support Vector Regression (LS-SVR) is used to establish the forecasting function. Then, the confidence interval is used to determine the first evaluation criterion $\epsilon 1$ and the second evaluation criterion $\epsilon 2$ is determined for bridge structure health condition evaluation. Finally, the difference between measured node deflection and predicted node deflection is calculated and compared with both evaluation criteria for purpose of bridge structure health condition evaluation.

Key words. Deflection, forecasting function, least square support vector regression (LS-SVR), evaluation criterion, steel truss bridge.

1. Introduction

In view of the fact that frequent bridge accidents like sudden break-off etc. led to material casualties and property losses, people begin to pay close attention to bridge engineering safety [1]. Many factors may cause bridge collapse, but it is certain that the long-term effect of loads and the material fatigue, corrosion and ageing together with the lack of timely maintenance bring about internal damage accumulation and resistance deterioration of bridge structure, thereby resulting in accidents [2]. Effective means shall be timely employed to monitor and evaluate the health condition of a large number of bridge structures in service and other infrastructures so as to identify the structure damage in a timely manner and give

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early warning on possible disasters so as to avoid tragedies [3]–[5].

China has established health monitoring systems at scores of bridges like Jiangyin Bridge, Humen Bridge, Nanjing Yangtze River Bridge, Runyang Bridge, Sutong Bridge, Wuhu Yangtze River Bridge and Hangzhou Bay Sea-Crossing Bridge since the 1990s, having gathered abundant research findings [6]. Principal indicators for bridge structure health condition evaluation are structural dynamic characteristic indicators like frequency, vibration mode and modal damping [7] etc., which is vulnerable to external environmental noise, and their practical application effectiveness leaves much to be desired.

For the above reasons, this paper employs the latest data mining method, i.e. SVM based on bridge structure deflection to propose a new method for bridge structure health condition evaluation on basis of reference [8], and probes into the method for determining evaluation criteria.

2. Rationale of forecasting function method

2.1. Forecasting function model

Obtain substantive measured data samples of bridge structures in good condition using the bridge structural health monitoring system, and establish the forecasting function relationship between dependent variables and independent variables of bridge structure using such data mining methods as Support Vector Regression Machine

$$\{y\} = \{f(P, x, t,) \cdots\}\,, \tag{1}$$

where $\{y\}$ is a dependent variable, $f(\cdot)$ means a mapping function, P represents the load condition, x stands for the load position, T means the environmental factor, and so on.

2.2. Evaluation criteria $\epsilon 1i$ and $\epsilon 2i$

The determination of evaluation criteria $\epsilon 1i$ and $\epsilon 2i$, ($i = 1, 2, \cdots, n$ referring to the number of measuring point), as the key technique for forecasting function method, is currently considered one of the major and difficult issues that must be addressed during bridge structure health condition evaluation.

2.2.1. Determination of $\epsilon 1i$. The value of $\epsilon 1i$, $i = 1, 2, \cdots, n$ is equivalent to the "normal value" specified in the railway bridge assessment specification. Assign significance level α to the residual error between the predicted value and measured value that obey normal distribution, then $P\alpha = \alpha$ should be of low probability. Determine the value of m through table look-up based on significance level of α and the distribution regularity of residual error, and the confidence interval should be

$$[\hat{y}_i - mS_i\,, \hat{y}_i + mS_i]\,, \quad i = 1, 2, \cdots, L, \cdots n\,, \tag{2}$$

where $\hat{y}_i$ is the predicted value of variable dependent on intact bridge structure and S_i denotes the standard deviation whose value is given by

$$S_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_{ij} - \hat{y}_{ij})^2}\,. \tag{3}$$

wherey_{ij} means the jth measured value of the ith dependent variable, $\hat{y}_{ij}$ is the jth predicted value of the ith dependent variable and N stands for the number of samples. The measured value is considered normal when it falls in confidence in interval (2), otherwise, an anomaly is considered to exist. Thus, it can be seen that the evaluation criterion $\epsilon 1i$ could be determined using the following formula

$$\epsilon 1i = mS_i\,, \quad i = 1, 2, \cdots, L, \cdots n\,. \tag{4}$$

2.2.2. Determination of $\epsilon 2i$. According to the allowable values (e.g. allowable deflection and stress) of bridge structure response allowed by relevant bridge design codes and examination specifications, the structure is considered unsafe when the bridge structural health monitoring system detects that the measured value of a certain dependent variable exceeds the allowable value. However, the said allowable values are normally safety thresholds for structural response of designated section (mid-span section). Nevertheless, since the load applied is smaller than designed load during practical operation of bridge structure, bridge structure suffers from a certain degree of damage, and the response values of bridge structure detected by monitoring system normally fail to meet specification-defined safety threshold. As a result, it is impossible for monitoring system to release early warning information in a timely manner. To the end, this paper plans to employ the finite element model that is the closest to the practical structure after model modification, and to appropriately discount the integral stiffness of such finite element model (for example, 90% of stiffness in good condition after discounting indicates a damage degree by 10%).

2.3. Forecasting function method for bridge structure health condition evaluation

Figure 1 shows the process of forecasting function method for bridge structure health condition evaluation.

3. Support vector machine

Support Vector Machine [9] (SVM), as proposed by Vapnik et al. during period from 1992 to 1995, is the latest and most practical part of statistical learning theory and the youngest and fastest growing data mining method. SVM is divided into Support Vector Classification (SVC) and Support Vector Regression (SVR) by application. Since process for establishing forecasting function in this paper is a regression problem, the least squares-support vector regression (LS-SVR) [9] is used

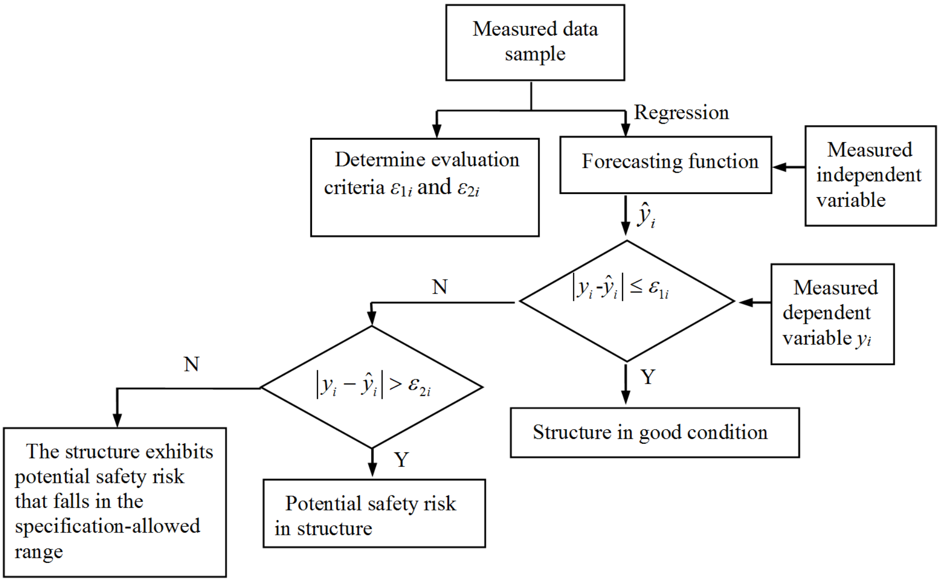

Fig. 1. Flow chart of forecasting function method

to build the forecasting function. As a variant of general support vector regression method, LS-SVR replaces inequality constraint with equality constraint and converts the solving problem of quadratic programming into solving problem of system of linear equations, thereby significantly simplifying the calculation and improving the training rate.

4. Calculation example

In view of the fact that the impact coefficient for long-span railway bridge structure is relatively small ($1 + \mu \le 1.05$ [7]), when a train passes through the bridge, the train load is taken as quasi-static load for field test to monitor the deflection of bridge structure (dependent variable) as well as the substantive data samples of train velocity, axle weight and ambient temperature etc. (independent variables), and to analyze the law that the deflection of bridge structure changes along with the change in such independent variables as train velocity, axle weight and ambient temperature by establishing the forecasting function relationship between dependent variable and independent variable using data mining method based on monitoring data.

A 64 m single line rail simply-supported steel truss bridge is taken as an example to verify the application of forecasting function method for bridge structure health condition evaluation. In order to describe the implementation procedure of this method, a main beam piece of the 64 m single line rail simply-supported steel truss bridge is used as research object (Fig. 2) to simplify the calculation. The dependent variable is the deflection of lower chord nodes 2–8. The independent variables are load condition and load position in this paper. Since this is a simulation bridge structure, all data samples are obtained by adding computed result of finite element model to noise.

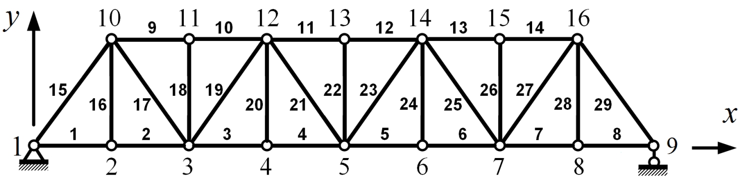

Fig. 2. Finite element model

4.1. Finite element model

The plane rod element is used to build the plane finite element calculation model for a piece of main truss. There are in total 16 nodes (Fig. 2, larger normal letters), and the rod piece between each two nodes is taken as a unit. A total of 29 rod units (Fig. 2, smaller boldface letters) are determined, the unit elasticity modulus $E = 210\,\mathrm{GPa}$, the sectional dimension is as bridge drawing. Constrain the vertical and longitudinal line displacement simulation fixed hinge support along the bridge at node 1, and constrain the vertical line displacement simulation movable hinged support at node 9.

Load condition: single locomotive, dual locomotives, triple locomotives, single train (1 locomotive connected to 8 carriages, this arrangement makes it possible to cover the bridge and keep such a state for a certain period of time), dual trains (2 locomotives connected to 8 carriages). The locomotives are of Dongfeng-IV with an axle weight of 23 t as shown in Fig. 3, the carriage is of model C62 with an axle weight of 20.15 t as shown in Fig. 4 [10]. The effect of vehicle-bridge coupled vibration is not taken into account, the deflection at each lower chord node (nodes 2–8) is calculated by simplifying train load to a series of static loads moving on the bridge.

4.2. Establishment of deflection forecasting function for each lower chord node

Five load conditions are taken into consideration. The train moves from left to right with a loading step of 4 m, the calculation start when the first front wheel of the train gets in contact with the bridge (the position of the first wheel set is 0) until the last rear wheel set gets off the bridge (the position of the first wheel set: bridge length + train length). Independent variables of forecasting function: quantity of carriages x_1 (0 or 8), quantity of locomotives x_2 (1, 2 or 3), position of the first wheel set of train x_3 (value range from 0 to bridge length + train length), locomotive axle weight and carriage axle weight are not taken as independent variables since they are constants, the dependent variable is the deflection of seven lower chord nodes. Each node is provided with 178 training data samples. In order to check the generalization of forecasting function, the load step for test sample calculation is 5 m (different from the step chosen for training sample, i.e. 4 m) so as to ensure most data in test sample are not included in training sample (142 in total). Use LS-SVR and training set for the regression of deflection forecasting function for each node (7 forecasting functions in total).

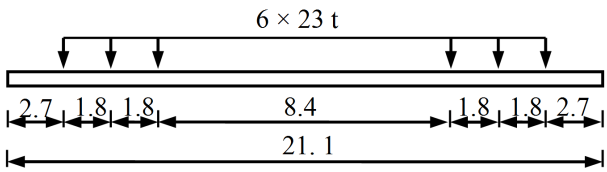

Fig. 3. Schematic diagram of axle weight and wheel base of Dongfeng-IV locomotive (dimensions in m)

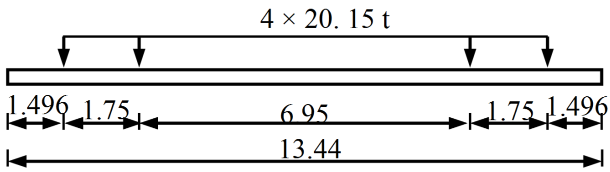

Fig. 4. Schematic diagram of axle weight and wheel base of carriage C62 (dimensions in m)

Substitute the independent variable $\{x_{i1}, x_{i2}, x_{i3}\}$, $(i = 1, 2, \cdots, 142)$ in test set sample into the deflection forecasting function for above 7 lower chord nodes, respectively, to work out the corresponding predicted value of deflection. Fig. 5 and Fig. 6 are the comparison charts between the predicted value of deflection of the five nodes and the deflection value calculated using finite element model. The condition is almost consistent at other nodes. Computational formula for residual error is determined from the formula

$$\text{error} = y_{\text{calculated}} - y_{\text{predicted}}\,, \tag{5}$$

where $y_{\text{calculated}}$ means the deflection calculated by finite element method and $y_{\text{predicted}}$ represents the deflection calculated from the forecasting function.

As shown in Figs. 5 and 6, the predicted deflection fits well with theoretical calculated deflection of the 5 lower chord nodes. The forecasting function for node deflection established with LS-SVR is reliable and well generalized, all residual errors being within the range of ± 0.2 mm and symmetrically distributed about zero line. The substantial consistency with normal distribution means that the predicted deflection has no abnormal value.

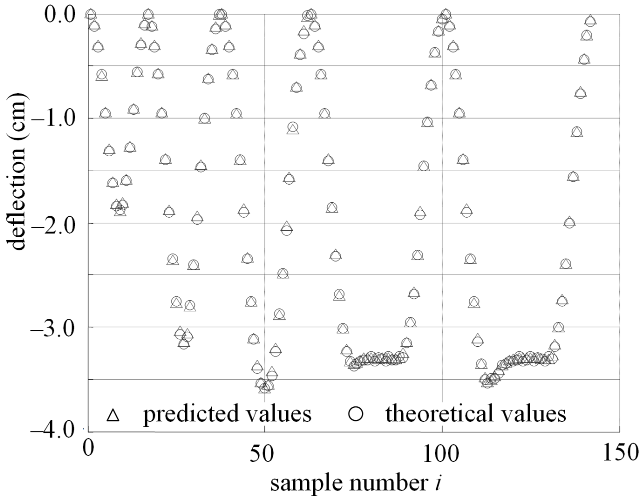

Fig. 5. Chart of comparison between predicted values and theoretically calculated values of lower chord nodes

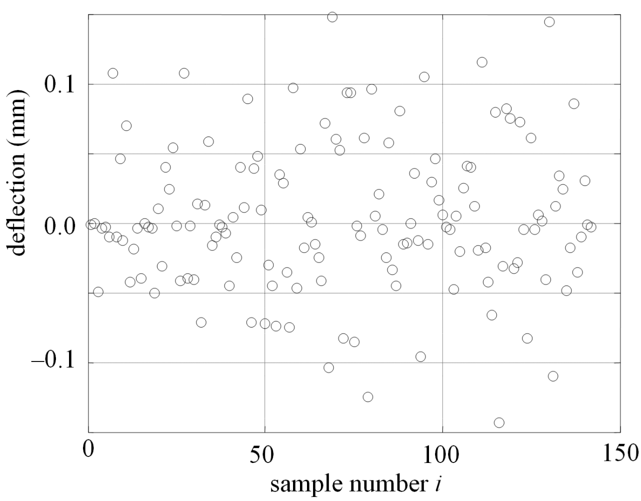

Fig. 6. Residual plot of predicted values and theoretically calculated values of lower chord nodes

4.3. Determination of evaluation criteria conclusions

The criteria ε_{1k} and ε_{2k} (k being the number of the node, $2 \leq k \leq 8$) for evaluation of the bridge with the forecasting function of each node are determined by the method described in Section 1.2.

4.3.1. Determination of the first evaluation criterion ε_{1k}. Since the data sample contains no measured data in this paper, the measured deflection is to be simulated by adding Gaussian random number to the deflection in calculated data sample

$$y_{i\text{measured}} = y_{i\text{calculated}} \cdot (1 + \varepsilon R_i)\,, \tag{6}$$

where i is the data sample number ($1 \le i \le 142$), $y_{i\text{measured}}$ denotes the ith simulated measured deflection, $y_{i\text{calculated}}$ represents the ith theoretically calculated deflection, R_i stands for the ith normal distribution random number with the mean equal to 0 and variance equal to 1 and ε is the level of noise.

The noise level ε in this paper is 3%, in other words $\varepsilon = 0.03$. Substitute now the simulated measured data sample with a noise level of 3% into formulae (3) and (4), and assume that the significance level $\alpha = 0.05$. Then $m = 1.96$ according to table look-up.

Table 1 shows the evaluation criterion ε_{1k} for each lower chord node.

Table 1. Evaluation criterion ε_{1k} in mm for each lower chord node

Node number k	2	3	4	5	6	7	8
ε_{1k}	0.8	1.2	1.4	1.6	1.4	1.2	0.8

According to the analysis of ε_{1k} of each node, the mid-span node 5 has the largest value of ε_{1k}, which decreases gradually towards both ends, while the end nodes 2 and 8 have the smallest values of ε_{1k}.

4.3.2. Determination of the first evaluation criterion ε_{2k}. According to the Fundamental Code for Design on Railway Bridge and Culvert [11], the allowable value of the mid-span deflection of simply-supported steel truss bridge is equal to 1/900 of the span. Since the span of steel truss bridge in this study is 64 m, the allowable mid-span deflection $f = 64/900 = 0.0711\,\text{m} = 71.1\,\text{mm}$.

The second evaluation criterion ε_{2qk} for each lower chord point under any condition is calculated, when elasticity modulus of all units in finite element model (Fig. 2) is reduced by 10%. Table 2 shows the values of ε_{2qk} for each lower chord point under various load conditions.

$$de(\%) = \frac{E \cdot A_{\text{Without damage}} - E \cdot A_{\text{With damage}}}{EA_{\text{With damage}}} \cdot 100\% = \\ = \frac{A_{\text{Without damage}} - A_{\text{With damage}}}{A_{\text{With damage}}} \cdot 100\%\,, \tag{7}$$

where E means the elasticity modulus of material, $A_{\text{Without damage}}$ is the sectional area determined when the rod piece is free of damage and $A_{With\ damage}$ represents the sectional area determined when the rod piece is damaged. Table 2 shows the evaluation criterion ε_{2qk} for each lower chord node under various load conditions.

Table 2. Evaluation criterion ε_{2qk} in mm
for each lower chord node under various load conditions

Load condition	node 2	node 3	node 4	node 5	node 6	node 7	node 8
Single locomotive	0.8	1.3	1.9	1.9	1.9	1.3	0.8
Dual locomotives	1.5	2.5	3.4	3.5	3.4	2.5	1.4
Triple locomotives	1.7	2.9	3.9	4.0	3.9	2.9	1.6
Single train	1.5	2.6	3.7	3.7	3.7	2.7	1.6
Dual trains	1.6	2.8	3.9	4.0	3.8	2.8	1.6

4.4. Health condition evaluation

Assuming there are two states of damage:

1. The unit 3 in finite element model as shown in Fig. 2 (indicated by smaller boldface letter) is damaged by 20%, while unit 5 is damaged by 30%.

2. The unit 5 is damaged by 50%, while the unit 11 is damaged by 40%.

Check the effectiveness of health condition evaluation performed by the above forecasting function method.

Simulated calculation of the difference between the maximum deflection of each node and maximum deflection in damage-free state is performed by the finite element method for the two above states of damage and under various load conditions as shown in Table 3.

Table 3. Difference between maximum deflection (in mm) in the two above states of damage and maximum deflection in damage-free state (DS means the damage state)

Load condition	DS	node 2	node 3	node 4	node 5	node 6	node 7	node 8
1 locomotive	1	0.2	0.4	0.7	0.8	0.9	0.5	0.2
	2	0.4	1.0	1.6	***2.4***	***2.5***	***1.5***	0.6
2 locomotives	1	0.5	1.0	**1.4**	1.5	**1.5**	1.1	0.5
	2	1.0	2.2	3.2	***4.4***	***4.3***	***3.0***	***1.4***
3 locomotives	1	0.5	1.1	**1.6**	**1.8**	**1.8**	**1.3**	0.6
	2	1.2	2.5	3.7	***4.9***	***4.9***	***3.3***	***1.7***
Single train	1	0.5	1.0	**1.6**	**1.6**	**1.7**	**1.2**	0.6
	2	1.1	2.3	3.5	***4.6***	***4.6***	***3.1***	***1.6***
Dual trains	1	0.5	1.1	**1.6**	**1.8**	**1.8**	**1.2**	0.5
	2	1.2	2.5	3.6	***4.9***	***4.9***	***3.2***	***1.5***

As indicated by boldface numbers in Table 3, the maximum deflection difference is greater than ε_{1k} at some nodes in damage state 1, when the program gives an alarm signal indicating structural safety risk in a specification-allowed normal service condition. As indicated by italic boldface numbers, the maximum deflection difference is greater than ε_{2k} at some nodes (which are normally near the units with significant damage) in damage state 2, when the program gives critical alarm indicating serious structural safety risk.

5. Conclusion

This paper proposes a deflection-based forecasting function method for bridge structure health condition evaluation. This method is composed of two major sections: First, establish correct forecasting function, second, determine two evaluation criteria. Demonstration is performed with a simply-supported steel truss bridge on railway as example. According to the result, forecasting function method could efficiently and accurately evaluate the health condition of simply-supported steel truss bridge structure on railway. In case of large bridge structures, it is advisable to establish as many forecasting functions for node or section as possible when building forecasting function for health condition evaluation, omission may happen if forecasting function fails to be established adequately.

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