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Digital prediction model of temperature-induced deflection for cable-stayed bridges based on learning of response-only data

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ABSTRACT

Time-varying behavior of deflection field under effects of non-uniform temperature field is a focus of structural health monitoring for long-span cable-stayed bridges. By using LSTM neural network, it can realize response-only deflection prediction. Through the case study, we can find that: (1) The deflection field shows good linear correlation at each measuring point within main span, while the deflection between main span and side span has obvious nonlinear distribution characteristics; (2) Compared with SVM method, the LSTM model can obtain better prediction results, and it can realize response-only deflection field prediction; (3) Through the improved prediction model, historical deflection data of measured points are introduced to improve prediction accuracy.

1. INTRODUCTION

The installation of health monitoring system for daily operation and maintenance of important structures is the mainstream monitoring method in field of structural health monitoring (SHM). As day-to-day operational maintenance progresses, the data collected by SHM systems is exploding. For massive monitoring data, a variety of machine learning algorithms are used in identification of structural damage and component response prediction (Beltempo 2015, Nguyen 2018). Based on the big data management platform, how to evaluate the structural service state through deep mining method from massive data has become a key research content.

The data collected by SHM system are time-varying response parameters under different environmental loads. When dealing with time series prediction modeling, the previous mainstream machine learning method is support vector machine (SVM) method, which is used in complex nonlinear regression model. However, the calculation error of this regression method cannot meet the accuracy requirements in complex models. Thus a variety of neural network algorithms such as deep learning models and multi-layer neural network structures are used in these kinds of models. Long and short-term (LSTM) neural network can automatically capture complex patterns in time series data and

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provide accurate prediction results, which makes it suitable to build a prediction model in many scenarios (Lara 2020).Through LSTM neural network, the prediction model can be built by combining several modules (Feng 2019).By combining different data optimization processing methods and the advantages of a variety of neural networks, prediction model calculation can be carried out (Liu 2019). The LSTM neural network structure is flexible, and it can be combined with other optimization algorithms, such as Bayesian algorithm, which can further optimize the parameters and improve the accuracy of prediction model (Kulshrestha 2020). This can be used in structural service state evaluation. The structural safety warning can be carried out by combining the output results of neural network with hypothesis testing (Ding 2010).

2. MONITORING SYSTEM OF THE CASE STUDY BRIDGE

This paper is based on the data of a long-span cable-stayed connecting the two sides of Yangtze River. The bridge is 1290 meters long with a main span of 630 meters. The bridge is a three-fold, three-rope structure with an "N" shaped truss structure. The center distance of main truss is 17.1 meters and spaced 15 meters apart. It is 34.2 meters wide and 15.5 meters high.

Fig. 1 shows the layout of deflection measurement points. A total of 11 deflection measurement points are arranged, which are distributed on key sections of each span. Since main span is the main load-bearing part, more deflection measuring points are added at the one-eighth section in this part. Deflection sensors are placed at the bottom of truss, respectively arranged on the upper and lower sides. These deflection measuring points constitute the longitudinal deflection field of the bridge.

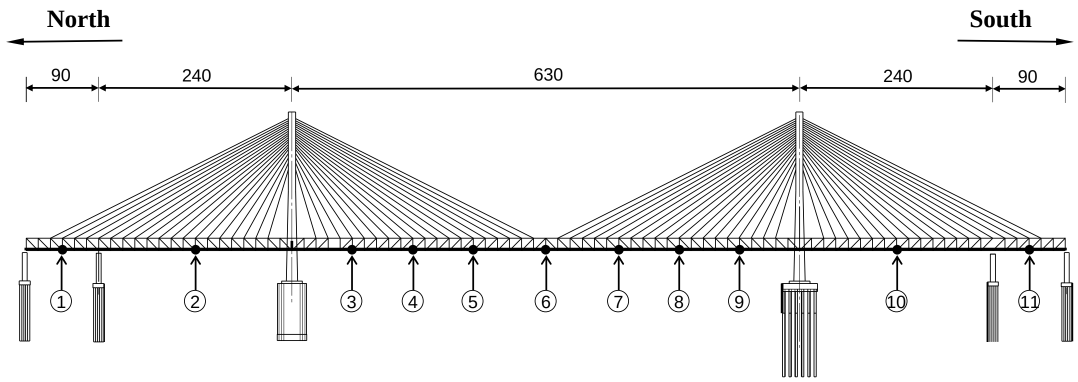
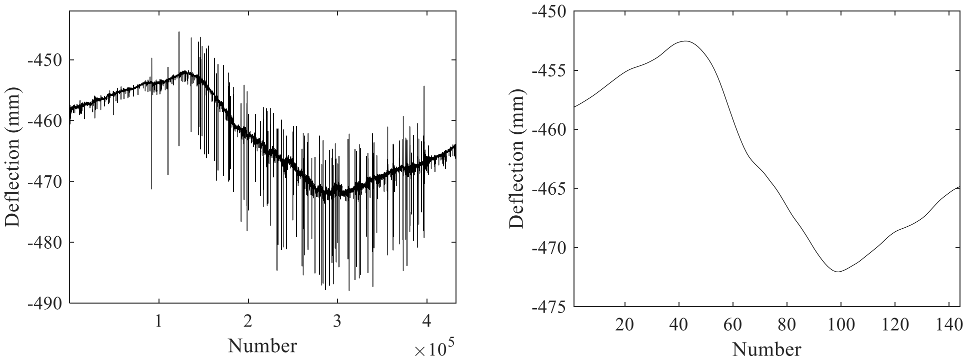


Fig1. Bridge deflection monitoring sensor layout (m)

3. DISTRIBUTION CHARACTERISTICS OF DEFLECTION FIELD

The deflection monitoring data is a time-dependent sequence, which includes static deflection induced by ambient temperature and dynamic deflection under various loads. Static deflection is mainly affected by ambient temperature and structural temperature difference. Fig. 2 is the deflection time history curve of typical deflection measuring point 1 in one day. The deflection at middle section of side span has obvious sine wave characteristics, and its variation trend is positively correlated with ambient temperature.



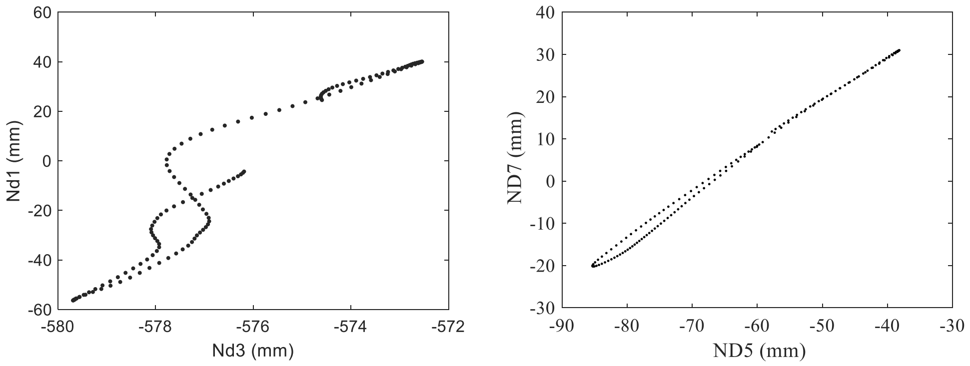
(a) Bridge deflection (b) Temperature-induced deflection

Fig.2 Deflection diurnal curve

The structural static deflection has the following spatial distribution characteristics:

(1) In main span, the deflection data of each measuring point has obvious linear correlation, As shown in Fig. 3 (b).

(2) The deflection data between main span and side span are not linear correlation. As shown in Fig. 3 (a), the scatter plot of deflection data of measuring point 3 and 1 presents "s" shape. The temperature induced deflection between two measuring points has hysteretic characteristics, which may be caused by temperature difference and the mechanical structure characteristics.



(a) Correlation between main span and side span (b) Correlation of deflection in main span

Fig.3 Temperature induced deflection correlation

4. DIGITAL PREDICTION MODEL OF TEMPERATURE-INDUCED DEFLECTION

4. 1 SVM regression model

Support vector machines (SVM) is a common data regression method. It is based on the principle of structural risk minimization and high dimensional space theory. In order to evaluate the regression results, we choose RMSE as the evaluation standard, as shown in Eq. (1). And $y_i$and $\hat{y_i}$ is the collected monitoring data and the calculated prediction data, respectively. The regression effect is shown in Fig.4. There is a great deviation between the predicted results. This does not meet the prediction accuracy requirements in actual application.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i-\hat{y}_i)^2} \qquad \text{Eq. (1)}$$

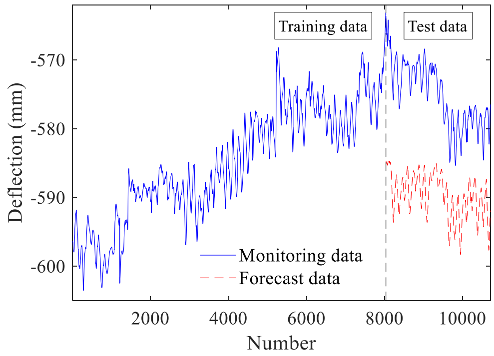
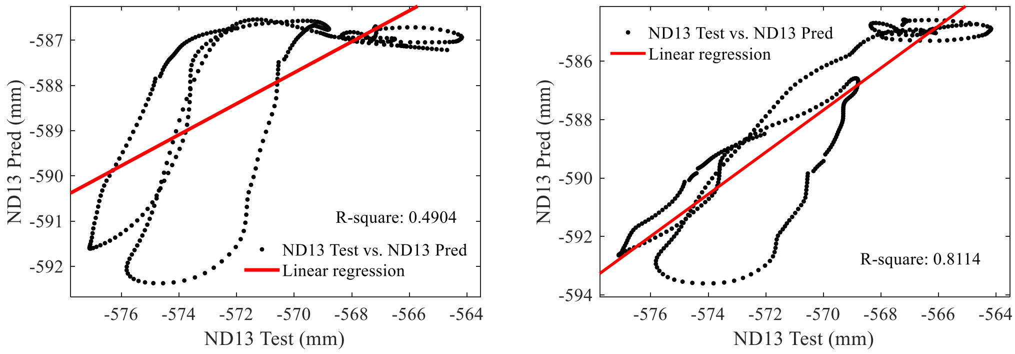


Fig 4. SVM single-point to single-point prediction model

4.2 LSTM models

LSTM neural network is a special recurrent neural network (RNN) designed to sholve the long-term dependency problem of RNN. In order to compare the calculated results between different models, same data set under various working conditions were used to test the LSTM prediction model. Fig 5 shows the prediction results of LSTM neural network are obviously better than SVM algorithm.



(a) SVM regression model (b) LSTM prediction model

Fig 5. Comparison of SVM and LSTM calculation results

Since the results of nonlinear regression model of temperature-induced deflection field between main and side span is obviously not good, more deflection data of key sections are introduced as input to observe whether the model accuracy can be improved.

Therefore, the following part uses deflection data of whole bridge to make regression under various conditions: (1) use multi-point deflection data of main span to predict side span deflection; (2) use main span and side span data to predict side span deflection; (3) predict main span deflection by multiple measuring points within main span; (4) use main span and side span data to predict deflection of key section in main span.

4.3 Improved prediction method of LSTM model

Based on basic LSTM neural network structure, the improved prediction method not only uses temperature-induced deflection data of multiple measuring points at current time as input and output sets, but also adds historical time period data of multi-point deflection in input set of prediction model. Through the experiment, the data scale of introduced input set is selected as 1hour.

Compared to SVM regression model, the RMSE value of LSTM model can be reduced by 16% - 36%. LSTM models shows a greater performance in the prediction for deflection field. But in Case 3, when the input and output data sets are both from the main span deflection, the two models did not perform well. The fitting effect of the LSTM model in case4 has been significantly improved, especially the improved prediction method of LSTM model.

Table 1 Comparison of model results

Working conditions		SVM	LSTM	Improved LSTM	LSTM/ SVM	Improved LSTM/LSTM	Improved LSTM/SVM
Single-point to single-point		15.02	12.55	8.89	16.5%	29.2%	40.8%
Multi-point to single-point	Case 1	1.09	0.68	0.53	37.6%	22.8%	51.8%
	Case 2	1.20	0.94	0.67	21.3%	28.6%	43.8%
	Case 3	5.28	3.71	0.83	29.6%	77.6%	84.3%
	Case 4	0.73	0.46	0.34	36.6%	25.5%	52.8%

* 1.The data are RMSE values of various models under different working conditions.
* 2. LSTM/SVM= (R1-R2)/R1; Improved LSTM/LSTM= (R2-R3)/R2; Improved LSTM/SVM= (R1-R3)/R1
R1, R2, R3 respectively represents the RMSE of SVM, LSTM and improved LSTM model.

5. CONCLUSIONS

(1) Through the study of distribution characteristics of deflection field all over the bridge, it can be found there is obvious linear correlation between the measuring points within main span. While there are obvious nonlinear distribution characteristics between the measuring points of main span and the side span.

(2) SVM algorithm is used to predict the temperature-induced deflection field, in which the accuracy of single point to single point regression model is low. Based on the basic LSTM neural network structure, an improved prediction method is proposed by introducing historical deflection data of measuring points to be predicted, which can greatly improve the prediction accuracy. The improved LSTM neural network prediction model can be applied to the temperature induced static deflection prediction of the whole bridge under various conditions.

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