1) Predicting Displacement Deformation of Bridge Based on CEEMDAN-KELM Model Using GNSS Monitoring Data

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ABSTRACT

Bridges are critical to economic and social development of a country. In order to ensure the safe operation of bridges, it is of great significance to accurately predict displacement of monitoring points from bridge Structural Health System (SHM). In the paper, a CEEMDAN-KELM model [complete ensemble empirical mode decomposition with adoptive noise (CEEMDAN) based kernel extreme learning machine (KELM) ensemble learning strategy] is proposed to improve the accuracy of displacement deformation prediction of bridge. Firstly, the original displacement deformation monitoring time series of bridge is accurately and effectively decomposed into multiple components named intrinsic mode functions (IMFs) and one residual component using CEEMDAN. Then, these components are forecasted by establishing appropriate KELM prediction models, respectively. At last, the prediction results of all components including residual component are summed as the final prediction results. A case study using global navigation satellite system (GNSS) monitoring data is used to illustrate the feasibility and validity of the proposed model. Practical results show that prediction accuracy using CEEMDAN-KELM model is superior to BP neural network model, EMD-ELM model [mode decomposition (EMD) based extreme learning machine (ELM) ensemble learning strategy] and EMD-KELM model in terms of the same monitoring data.

I. INTRODUCTION

Bridges are often among the key transportation infrastructure assets of a country, stimulating regional cooperation and economic and social development. With the continuous development of sensing technology and information science, health monitoring systems are widely used in the safety guarantee of the bridge structure (Yu et al., 2019). As an important monitoring index that reflects the overall stiffness of the structure, displacement deformation is the macro response of the bridge micro complex mechanical mechanism, which contains the internal mechanical evolution information of the structure and affect the safety of bridge structure significantly (Xin et al., 2018). Therefore, accurate prediction of displacement deformation of the bridges is of great scientific significance and application value in finding hidden dangers and ensuring the safety of the bridges.

In recent years, a number of methods have been tried in the problem of displacement forecasting of the bridge, such as linear models, for example, autoregressive moving average model (ARMA) (Cao et al., 2014) and autoregressive integral moving average model (ARIMA) (Cheng et al., 2017); such as nonlinear models, for example, artificial neural networks (ANN) (Yang et al., 2013; Kao et al., 2017) and support vector machine (SVM) (Zhou et al., 2011). Relevant studies have shown that that the monitoring data of large structures has nonlinear and non-stationary characteristics because of the ambiguous service environment. The linear models are only capable of stationary linear time series prediction, which are hard to express in terms of deformation time series with high nonlinear and non-stationary characteristics. The prediction accuracy of the linear models is relatively low.

In particular, ANN has become one of the frequent modeling approaches among these techniques, because of the characteristics of adaptability and they can approximate any continuous nonlinear function with arbitrary precision. However, most ANN-based deformation forecasting methods used gradient-based learning algorithms such as back-propagation neural network (BPNN), which are relatively slow in learning speed and may easily get into local minima points. For SVM model, its key parameters are difficult to be reasonably selected. In recent years, a new learning method for single-hidden-layer feedforward neural network (SLFN) called extreme learning machine (ELM) has been proposed (Huang et al., 2006). ELM can avoid many difficulties faced by gradient-based learning methods such as stopping criteria, learning rate, learning epochs and local minimum. In addition, compared with BPNN, ELM has faster learning speed. However, one drawback of ELM is that the randomly assigned weights can produce a large variation in the prediction accuracy in different trials. In order to solve this problem, Huang et al. (2012) further proposed the kernel ELM (KELM), which requires no randomness in assigning connection weights between input and hidden layers. KELM has been successfully applied in many fields such as exchange rate forecasting (Wei et al., 2018), financial stress prediction (Luo et al., 2018), fault diagnosis (Jiang et al., 2014), and so on.

Inspired by the idea of ‘‘decomposition and ensemble’’ (Yu et al., 2008; Lian et al., 2013), the initial time series can be decomposed into several sub-series. Each sub-series can be predicted separately, and the final predicted result can be obtained by summing the predictive value of each sub-series. Considering the displacement deformation monitoring time series of the bridges is unsystematic and nonlinear, the complete ensemble empirical mode decomposition with adaptive noise (CEENDAN), which is introduced by Torres et al. (2011), is used to decompose displacement deformation series of the bridge. In the paper, a CEEMDAN-KELM model is proposed for bridge displacement prediction. The first step is to decompose the displacement deformation series into several sub-series with CEEMDAN method. The second step is to choose appropriate KELM model for each decomposed sub-series's prediction. Finally, the final predicted value is obtained by summing the each component prediction result. Through the prediction analysis for the GNSS displacement monitoring data from structural health monitoring system of actual bridge, the results show that the model proposed in this paper can achieve high prediction accuracy and validate the feasibility of this model effectively.

II. CEEMDAN METHOD

Empirical mode decomposition (EMD) is an adaptive and efficient time series decomposition method applied to decompose nonlinear and non-stationary signals (Huang et al., 1998). Using EMD, any complex time series can decompose the signal into a small number of intrinsic mode function (IMF) components and a residual component which contains the trend of the original data series.

However, there are also some shortcomings in EMD, and one of the most important problem is the mode mixing, which means either some signals consisting of disparate scales exist in the same IMF or the signals with the same scale exist in different IMFs. To overcome the problem, Wu et al. (2009) presented an ensemble empirical mode decomposition (EEMD) method with the aid of noise-aided analysis. EEMD performs the EMD over an ensemble of the signal plus Gaussian white noise. The addition of white Gaussian noise solves the mode mixing problem by populating the whole time-frequency space to take advantage of the dyadic filter bank behavior of the EMD. However, EEMD also introduces new difficulties. That is, the reconstructed signal includes residual noise and different realizations of signal plus noise may produce different number of modes. For this reason, a novel method which provides an exact reconstruction of the original signal and a better separation of the modes, called CEEMDAN is proposed. The CEEMDAN algorithm can be described as follows:

1. Adding different white Gaussian noise to the original signal $x(t)$, generate $x^i(t) = x(t) + \varepsilon_0 \omega^i(t)$; For every $i = 1, \cdots, I$ decompose each $x^i(t)$ by EMD, until its first mode and compute

$$IMF_1(t) = \frac{1}{I}\sum_{i=1}^{I} IMF_{i1}(t) \quad (1)$$

2. At the first stage ($k = 1$) compute the first residue

$$r_1(t) = x(t) - IMF_1(t) \quad (2)$$

3. Decompose each $r_1(t) + \varepsilon_1 E_1(\omega^i(t))$, until their first EMD mode and define the second CEEMDAN mode

$$IMF_2(t) = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_1(t) + \varepsilon_1 E_1(\omega^i(t))\right) \quad (3)$$

4. For $k = 2, \cdots, K$ calculate the kth residue

$$r_k(t) = r_{k-1}(t) - IMF_k(t) \quad (4)$$

5. Decompose each $r_k(t) + \varepsilon_k E_k(\omega^i(t))$ by EMD and define the $k+1$ CEEMDAN mode as

$$IMF_{k+1}(t) = \frac{1}{I}\sum_{i=1}^{I} E_k\left(r_k(t) + \varepsilon_k E_k(\omega^i(t))\right) \quad (5)$$

Where $E_k(\cdot)$ is the operator that produces the kth mode obtained by the EMD, ω^i is a realization of the zero mean unit variance white noise, ε_k is the noise coefficient that allows to select the SNR at each stage.

6. Go to step 4 for next k .

III. THE PRINCIPLE OF KERNEL EXTREME LEARNING MACHINE

Compared with SVM, KELM is a more recently developed learning technique. It generalizes ELM from explicit activation function to implicit mapping function, which has been proven to have better generalization in many applications. This section gives a brief description of KELM. More details can be found in Huang et al. (2012).

ELM was proposed for the SLFN, where the hidden layer can be any piecewise continuous computational functions including sigmoid, RBF, trigonometric, ridge polynomial and so on. The prediction of ELM is given by

$$f(\mathbf{x}) = \sum_{i=1}^{L} \beta_i h_i(\mathbf{x}) = \mathbf{h}(\mathbf{x})\boldsymbol{\beta} \quad (6)$$

Where $\boldsymbol{\beta} = [\beta_1, \cdots, \beta_L]^T$ is the vector of the output weights connecting the hidden layer and the output layer, L is the number of the hidden nodes, and $\mathbf{h}(\mathbf{x}) = [h_1(\mathbf{x}), \cdots, h_L(\mathbf{x})]$ is the output of the hidden layer with respect to the sample $\mathbf{x}$. According to Bartlett theory (Bartlett et al., 1998), for neural networks with a small training error, the smaller the norms of the weights, the more likely is the generalization performance of the networks. In this spirit, ELM minimizes the training error in tandem with the norm of the output weights:

$$\text{Minimize } \|\mathbf{H}\boldsymbol{\beta} - \mathbf{T}\|^2 \text{ and } \|\boldsymbol{\beta}\| \quad (7)$$

Where $\mathbf{H}$ denotes the output matrix of hidden layer

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}(\mathbf{x}_1) \\ \vdots \\ \mathbf{h}(\mathbf{x}_N) \end{bmatrix} = \begin{bmatrix} h_1(\mathbf{x}_1) \cdots h_L(\mathbf{x}_1) \\ \vdots \\ h_1(\mathbf{x}_N) \cdots h_L(\mathbf{x}_N) \end{bmatrix} \quad (8)$$

and $\mathbf{T}$ denotes the expected output matrix

$$\mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix} \quad (9)$$

The minimal norm least square method was used in the original implementation of ELM:

$$\boldsymbol{\beta} = \mathbf{H}^{+}\mathbf{T} \quad (10)$$

Where $\mathbf{H}^{+}$ is the Moore-Penrose generalized inverse of the matrix $\mathbf{H}$.

It should be noted that when the feature mapping is unknown to users (Huang et al., 2012), a kernel matrix for ELM can be adopted according to the following equation:

$$\Omega_{ELM} = \mathbf{H}\mathbf{H}^T : \Omega_{KELM} = h(\mathbf{x}_i) \cdot h(\mathbf{x}_j) = K(\mathbf{x}_i, \mathbf{x}_j) \quad (11)$$

Where $h(\mathbf{x})$ plays the role of mapping the data from the input space to the hidden-layer feature space $\mathbf{H}$. The orthogonal projection method is adopted to calculate the Moore-Penrose generalized inverse of matrix, namely, $\mathbf{H}^{+} = \mathbf{H}^T(\mathbf{H}\mathbf{H}^T)^{-1}$, and a positive constant C is added to the diagonal of $\mathbf{H}\mathbf{H}^T$. Now the output function of ELM can be presented as follows:

$$f(x) = \begin{bmatrix} K(x, x_1) \\ \vdots \\ K(x, x_N) \end{bmatrix}^T \left(\frac{I}{C} + \Omega_{ELM}\right)^{-1}\mathbf{T} \quad (12)$$

In this specific kernel implementation of ELM, namely KELM, we can specify the corresponding kernel for ELM model, the hidden layer feature mapping need not to be known to users. In this paper, RBF kernel function was adopted. Its formula is as follows:

$$K(x_i, x) = \exp(-\gamma \|x - x_i\|^2) \quad (12)$$

The two main parameters presented in KELM with RBF kernel are penalty parameter C and kernel parameter γ. The first parameter, penalty parameter C, determines the trade-off between the fitting error minimization and model complexity. The second parameter γ of the kernel function, defines the nonlinear mapping from the input space to some high-dimensional feature space.

IV. Proposed Prediction Method Based on CEEMDAN and KELM

A. *CEEMDAN decomposition for the displacement deformation time series of bridge*

The CEEMDAN method is applied to decompose the displacement deformation series $\{X(t), t = 1 \cdots N\}$ adaptively, and several IMF components and a residual component can be obtained. $X(t)$ can be presented as follows:

$$X(t) = \sum_j IMF_i + Residue_j \quad (13)$$

B. *Determination of the structures of forecasting model based KELM*

For a real displacement deformation series of bridge, we assume that the displacement deformation value $X(t)$ at t time can be predicted by the historical displacement value $X(t-1), X(t-2), \cdots, X(t-m)$ at $(t-1, t-2, \cdots, t-m)$ time, and then the forecasting model can be expressed as:

$$X(t) = f[X(t-1), X(t-2), \cdots, X(t-m)] \quad (14)$$

Where $f(\square)$ is a mapping function and m is an embedding dimension. After CEEMDAN decomposition, the original displacement series can be decomposed into several components, and the prediction model can be changed to:

$$IMF_j(t) = f[IMF_j(t-1), \cdots, IMF_j(t-m)] \quad (15)$$

$$Residue_j(t) = f[Residue_j(t-1), \cdots, Residue_j(t-m)] \quad (16)$$

According to the characteristics of each component after decomposition, the corresponding KELM model is established separately for prediction.

C. *Calculation of the final predicted value*

The KELM model is used to forecast each IMF component and residual component, and the prediction results are expressed in terms of $IM\hat{F}_j$ and $Residu\hat{e}_j$. The final displacement deformation predicted value can be obtained by reconstructing all components.

$$\hat{X}(t) = \sum_j IM\hat{F}_j + Residu\hat{e}_j \qquad (17)$$

The flowchart of the proposed method is shown in Figure 1.

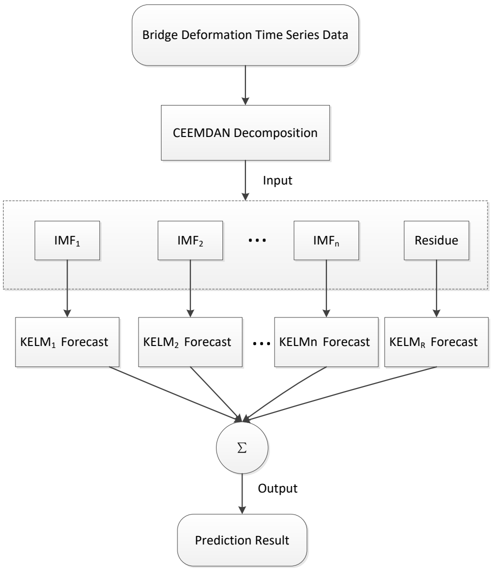


Figure 1. Flowchart of the proposed CEEMDAN-KELM method

D. *Evaluation Index of Prediction Accuracy*

In order to quantitatively evaluate the prediction accuracy of the proposed model, two commonly used evaluation indexes are selected in this paper:

1. Root of Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(X_t - \hat{X}_t)^2} \qquad (18)$$

2. Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|X_t - \hat{X}_t\right| \qquad (19)$$

Where X_t denotes actual displacement deformation of bridge, $\hat{X}_t$ denotes the predicted value of displacement deformation.

V. Case Study

A. *Project Background*

The GeoSHM project supported by the European Space Agency is a system that uses integrated GNSS and Earth Observation technologies for structural health monitoring of large bridges – and in its feasibility study the consortium used the Forth Road Bridge (FRB) in Scotland as its testbed bridge. (Meng *et al*., 2018).

The FRB is the major suspension bridge across the Firth of Forth, linking Edinburgh to the Northern part of Scotland (Figure 2). When opened in 1964, this 2.5km long bridge was the fourth longest suspension bridge in the world and the longest outside the United States of America. The 1,006m long main span of the FRB is suspended from two main cables aerially spun between two 150m high main towers and each side span is 408m long.

Figure 2 the Forth Road Bridge (Scotland, UK).

Figure 3 describes the current status of the GeoSHM sensor system installed on the FRB. Three pairs of Leica GNSS receivers are installed along the main span; one is at the mid span while the other two are at the navigation points. There are two other Leica GNSS receivers located at the top of the North-East and South-West tower legs to monitor deformation of the main tower. In addition, the wind measurement is facilitated by using three WindMaster 3D sonic anemometers placed at the mid span and at the top of the two main towers. Other environmental conditions are determined by the Meteorology station installed at the mid span.

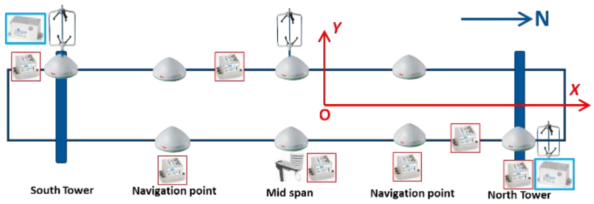


Figure 3 GeoSHM sensor system on the FRB

B. *Displacement deformation dataset from GeoSHM*

The displacement deformation data of GeoSHM system are measured by GNSS and transferred to the main GeoSHM server located at the University of Nottingham for processing and storage. The sampling rate of GNSS receiver is set to 10Hz. According to Ogundipe et al. (2014), the influence of high frequency error is usually eliminated by calculating average deformation in time interval. For this reason, the displacement deformation data of GNSS after 10 minutes average are used to predict and analyse. Here, the 2-day lateral (along the y axis) displacement deformation data at the mid span are considered, as shown in Figure 4.

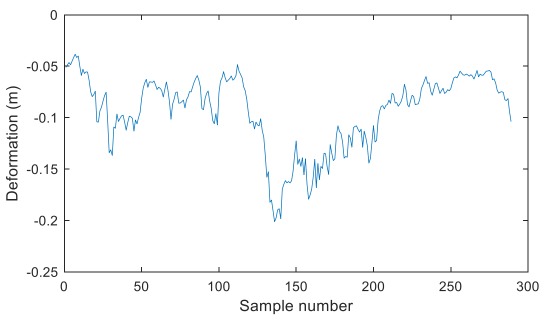


Figure 4 Deformation time series

C. *Forecasting results and performance evaluation*

The original time series is firstly decomposed into several IMFs and one residue using CEEMDAN method. The amplitude of adding noise is set to 0.2, the number of ensemble is 50. The decomposition results with CEEMDAN can be seen in Figure 5.

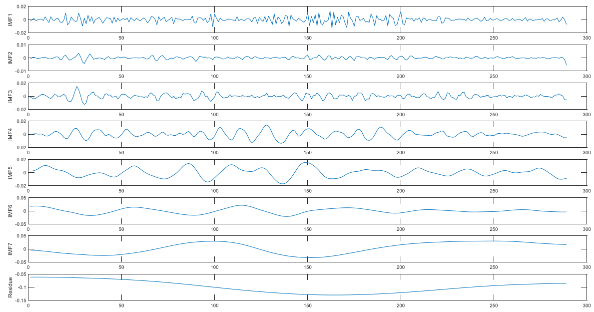
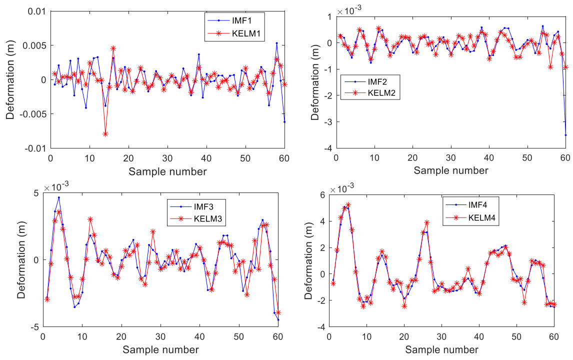


Figure 5 CEEMDAN decomposition

According to the characteristics of the variation of different components, different model parameters need to be set when using the KELM model for forecasting. It can be seen from equation (13) that when different embedding dimensions are used, that is, when the number of model inputs is different, the number of samples constructed for the deformation series is also different. To this end, this paper unified the deformation of the last 10 hours as the forecast object for the construction of the sample set.

The embedding dimension corresponding to IMF1 is set to 6; the embedding dimension corresponding to IMF2, IMF3, and IMF4 is set to 5; the embedding dimension corresponding to IMF5, IMF6, IMF7 and residue is set to 4. The KELM parameters corresponding to each component are determined by grid search strategy (Zhao et al., 2017). The forecasting results for IMFs and residue are shown in Figure 6.



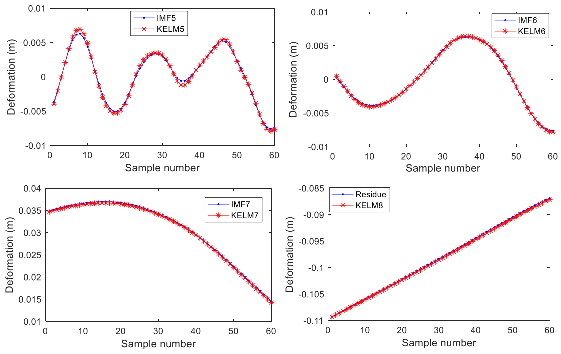
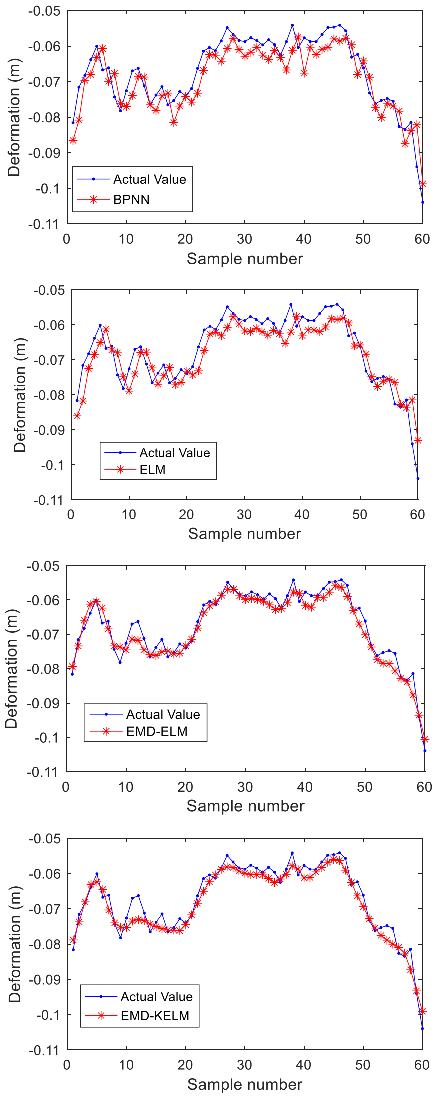


Figure 6 Comparison of predicted value and actual value of each component

As shown in figure 6, the predicted value and actual value for each component are very close for every calculation. Because this is a corresponding KELM model for the deformation characteristics of each component.

The final predicted value is obtained by adding the predictive values of IMFs and one residual. In order to compare with the model of this paper, BPNN model, ELM model, EMD-ELM model and ELM-KELM model are established for forecasting analysis. The final prediction results of various models are shown in Figure 7.



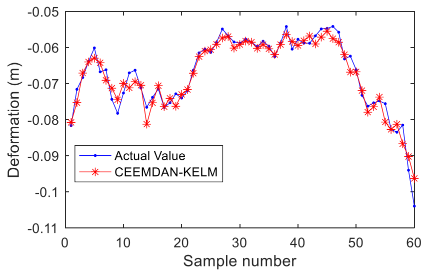


Figure 6 Comparison of final predicted result and actual value of five models

The statistical results of the accuracy indexs of various models are shown in Table 1.

Table 1 Comparison of five models for forecasting precision index

Model	RMSE(m)	MAE(m)
BPNN	0.0048	0.0040
ELM	0.0046	0.0038
EMD-ELM	0.0029	0.0024
EMD-KELM	0.0027	0.0023
CEEMDAN-KELM	0.0024	0.0019

As can be seen from Table 1, the forecasting performance of the three ensemble model, EMD-ELM, EMD-KELM and CEEMDAN-KELM, is better than those of the single BPNN model and ELM model. Especially, we can see that CEEMDAN-KELM model has better forecasting result than the other four models in terms of getting the smallest RMSE and MAE.

VI. Conclusion

This paper makes full use of the adaptive decomposition characteristics of CEEMDAN and the excellent generalization ability of KELM, and proposes a bridge deformation combined prediction model based on CEEMDAN and KELM. Based on actual GNSS deformation monitoring data from the GeoSHM system, it can be found that the proposed CEEMDAN-KELM model has the better forecasting performance. This study provides a new solution for bridge deformation prediction.

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