Multi-scale combined prediction model of concrete dam deformation based on VMD-LSTM-ARIMA

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Abstract. The deformation of concrete dam can be regarded as the result of the synergistic action of hydraulic component, temperature component and aging component. According to the different component characteristics of deformation and the correlation of different time scales, a multi-scale combined prediction model for concrete dam deformation based on VMD-LSTM-ARIMA is proposed. Firstly, using the adaptive analysis function of VMD, the trend term and cycle term of dam deformation are decomposed. Secondly, LSTM model is used to effectively predict the cycle term and trend term under different scales, and ARIMA model is used to identify the effective information of the remaining term. Finally, based on a practical project, the effectiveness and superiority of the proposed model are verified by comparing with the conventional combination algorithm. The calculation results show that the combined model fully considers the characteristics of the dam deformation, and can effectively fit and predict the dam deformation.

Keywords: Concrete dam; Deformation prediction; Variational mode decomposition; Long short-term memory network; ARIMA.

1 Introduction

Concrete dams have the advantages of large scale, stable behavior and long service time, and have achieved great practical benefits in flood control, power generation and irrigation [1]. Deformation is a comprehensive reflection of the structural state changes of the dam body and foundation, and is an important symbol to monitor the dam behavior change [2]. According to relevant literature statistics, the common deformation prediction of concrete dams is mainly divided into three types of models: (1) Based on the statistical model of regression, the deformation sequence is divided into water pressure factor, temperature factor and time factor according to the characteristics of effect size [3]. (2) In order to expand the performance of traditional statistical models in the field of nonlinear mapping, various intelligent algorithms, such as neural networks and support vector machines (SVM), are introduced [4-5]. Although such methods can obtain relevant information in the field of nonlinear mapping, they still have shortcomings. (3)

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Various combined prediction models [6-7] proposed to further optimize performance are mainly based on the idea of 'decomposition before prediction'. After the original signal is decomposed into multiple groups of components with different frequencies, various methods are used to analyze and predict on this basis. These methods have been successfully applied in practical engineering, and have achieved great social and economic effects, but there no clear standard for the selection of decomposition scale.

The dam deformation sequence can be regarded as the superposition of a series of factors, among which the water pressure deformation and temperature deformation are mainly caused by the changes of reservoir water level and temperature, and have obvious periodic characteristics. The aging amount mainly reflects the creep and plastic deformation of the concrete and bedrock of the dam body and the compressive deformation of the geological structure of the bedrock, which is reflected as the trend component of the total deformation [8]. Therefore, according to the characteristics of the dam deformation, this paper makes full use of the advantages of the three existing methods, and uses the idea of composite modeling to build models for signals of different frequencies respectively, so as to realize the effective prediction of dam deformation. Firstly, variational mode decomposition (VMD) is proposed to separate the dam deformation time series on multiple scales. By adjusting the correlation adaptive weight factors, the characteristics of different time series can be perfectly adapted to avoid the phenomenon of mode aliasing. Secondly, for the decomposed sequences, long short-term memory neural network (LSTM) is introduced to predict the deformation at different scales [9]. Finally, in order to extract the effective information of the remaining terms, this paper adopts the autoregressive differential moving average model [10] (ARIMA) for residual correction.

In summary, this paper proposes a combined prediction model for dam deformation based on VMD-LSTM-ARIMA, which combines the advantages of VMD, LSTM and ARIMA in dealing with non-stationary nonlinear time series problems at different scales, and applies the combination to dam deformation prediction. Taking the deformation monitoring data of a concrete gravity dam as an example, the combined model is used to predict the dam deformation and is compared with the prediction results of other models to test the prediction effect of the combined model.

2 Research theory of deformation effect size combination model

2.1 Variational mode decomposition of deformation

VMD is a non-recursive and quasi-orthogonal decomposition algorithm based on Wiener filter, which can perform adaptive signal processing [11]. The essence of VMD is to transform the problem of decomposition into a variational optimization problem, and determine the central frequency and bandwidth of each intrinsic mode function (IMF) by searching the optimal solution of the constrained variational model.

Step1 Unilateral spectrum of analytical signal of structural dam deformation time series.

$$\left[\delta(t)+\frac{j}{\pi t}\right]\bullet u_k(t) \tag{1}$$

Where, the number of modal functions is k , the analytic signal is $u_k(t)$.

Step2 Fuses the center frequency predicted by the analytic signal, and moves the spectrum under different scales to the concentrated frequency band, and the result is as follows.

$$\left[\left(\delta(t)+\frac{j}{\pi t}\right)\bullet u_k(t)\right]e^{-j\omega_k t} \tag{2}$$

Step3 Find the L2 norm of the frequency shift signal and estimate the bandwidth. The process can be described as formula (3).

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum\nolimits_k\left\|\left[\left(\delta(t)+\frac{j}{\pi t}\right)\bullet u_k(t)\right]e^{-j\omega_k t}\right\|\right\}$$
$$s.t.\sum_k u_k=f \tag{3}$$

Where, $\{u_k\}$ is kth intrinsic mode function obtained after decomposition, $\{\omega_k\}$ is the center frequency obtained after decomposition

This is to solve the variational constraint problem. In order to transform the constraint problem into a non-constraint problem, Lagrange multiplication operator $\lambda(t)$ and quadratic penalty factor α are introduced. The optimization model is shown as equation (4).

$$L(\{u_k\},\{\omega_k\},\{\lambda\})=\alpha\sum\nolimits_k\left\|\left[\left(\delta(t)+\frac{j}{\pi t}\right)\bullet u_k(t)\right]e^{-j\omega_k t}\right\|_2^2$$
$$+\left\|f(t)-\sum\nolimits_k u_k(t)\right\|_2^2+\left\langle\lambda(t),f(t)-\sum\nolimits_k u_k(t)\right\rangle \tag{4}$$

The "saddle point" obtained by solving equation (4) with multipliers alternating direction algorithm is the optimal solution of the problem. In the process of solving, the appropriate IMF component and center frequency can be determined, and the signals of different frequencies can be separated adaptively.

2.2 LSTM network prediction of deformation

In the field of dam deformation prediction, deformation monitoring data in different time scale are correlated. LSTM, as a backpropagated recurrent neural network, improves the simple nodes of traditional neural networks into the form of storage units in order to learn the correlation between data [12].

2.3 ARIMA model

The principle of ARIMA model is to treat the time series to be predicted as a random series, and use a mathematical model to describe the series approximately. In this paper, the random component composed of the remaind term of the VMD model can be regarded as non-stationary random time series. First, the random components are transformed into stationary time series by differential processing, and then the regression modeling process is carried out. The model can be expressed as formula (10)

$$z_t = \sum_{m=1}^{p} \varphi_m z_{t-m} - \sum_{j=1}^{q} \theta_j a_{t-j} + a_t \tag{5}$$

Where, $\varphi_m \left(m = 1, 2, \cdots, p\right)$ is autoregressive coefficient, $\theta_j \left(j = 1, 2, \cdots, q\right)$ is moving average base, p is the order of the autoregressive part, q is the order of the moving average part; a_t is white noise part.

2.4 Model evaluation index

Average absolute error (MAE), average absolute percentage error (MAPE) and root mean square error (RMSE) are usually used as evaluation indexes in order to objectively evaluate the accuracy of VMD-LSTM-ARIMA combined prediction model for dam deformation. Specifics are shown as formula (11) ~ (13).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{6}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| 1 - \hat{y}_i / y_i \right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2} \tag{8}$$

3 Implementation steps of dam deformation combination model

The process of realizing VMD-LSTM-ARIMA combined prediction model for concrete dam deformation is shown in Figure 1.

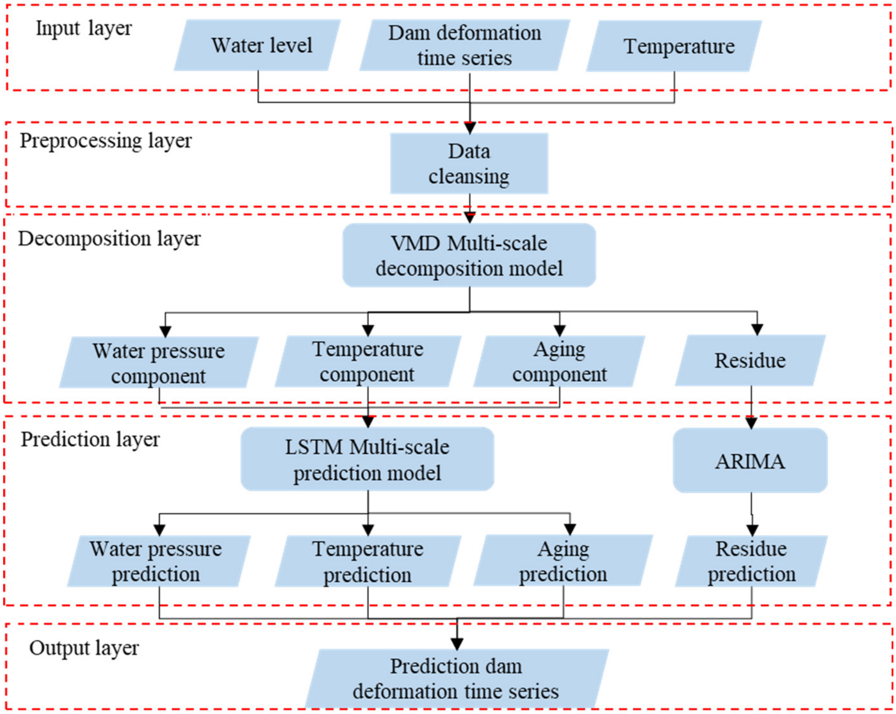


Fig. 1. Flow chart of VMD-LSTM-ARIMA combined prediction model

4 Project example

A concrete gravity dam is divided into 19 sections from the left bank to the right bank, numbered 1#~19#. A monitoring point is set up in each dam section to monitor the horizontal displacement of the dam body. The specific monitoring point arrangement of the gravity dam is shown in Figure 2. In this paper, a total of 163 sets of horizontal deformation data of dam section 7# and monitoring point EX7-1 from November 1, 2011 to April 11, 2012 were selected for analysis. The first 153 sets of measured values were selected as the training set, and the last 10 sets of measured values were selected as the test set. In order to facilitate multi-scale comparison and analysis, the time seris of horizontal deformation, water level and temperature of the 7# dam section during this period is shown in Figure 3.

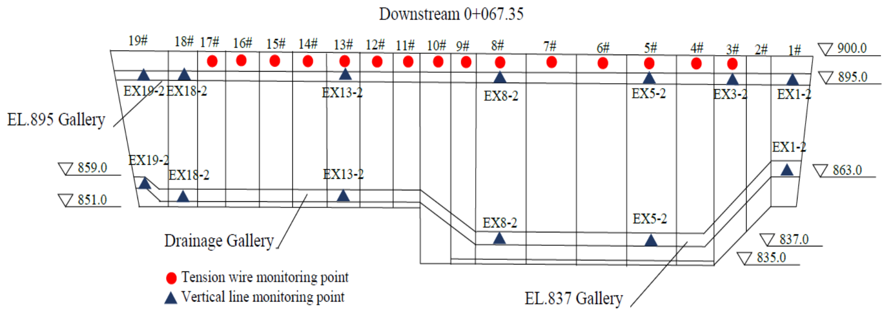


Fig. 2. Concrete dam horizontal displacement monitoring point layout

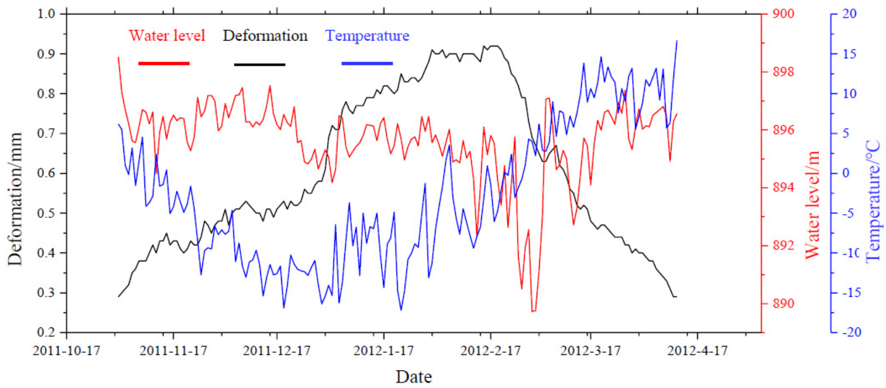


Fig. 3. Time series of point EX7-1 horizontal deformation, reservoir water level and temperature

4.1 Decomposition of monitored sequence

VMD decomposition is performed on the monitoring time series of horizontal deformation at EX7-1. It is adaptive decomposed by VMD into 7 groups of IMF and one remaining term, and the decomposition results are shown in Figure 4. It can be seen from the decomposition results that the frequency characteristics of all components are obvious. The frequency of IMF1~IMF4 component is high, which is similar to the variation law of reservoir water level. The process line of IMF5~IMF7 component is smooth and has obvious periodic characteristics, which is roughly consistent with the law of temperature first decreasing and then increasing in reservoir area. The remaining term Z is a random component, which basically conforms to the normal distribution. The results show that the decomposition effect of VMD in dam deformation monitoring sequence is good, and more obvious multi-scale effect size of dam deformation can be obtained.

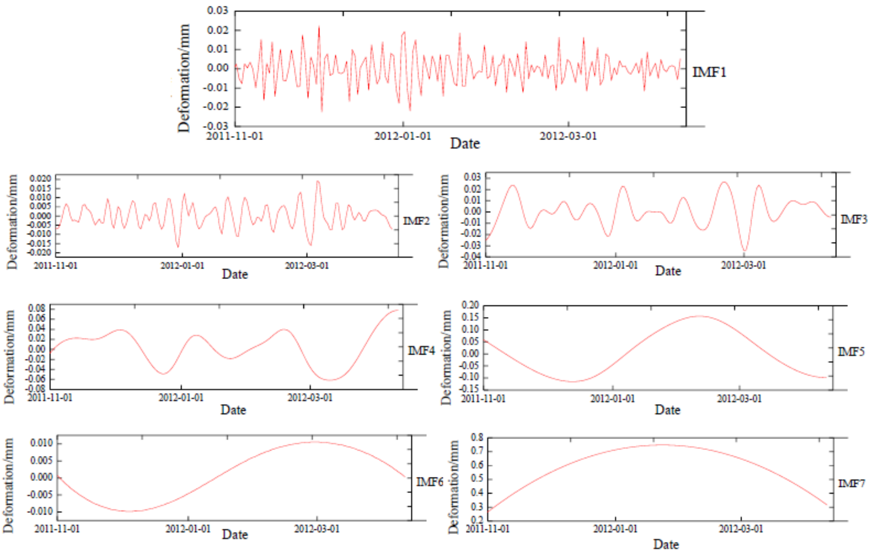


Fig. 4. Results of VMD decomposition of deformation

4.2 Component prediction

The components of each group obtained after VMD decomposition are trained by LSTM algorithm. For the high frequency component, according to the characteristics of the upstream water level, the LSTM parameters are reasonably input. When the window length is 12 and the hidden layer node is 18, the model accuracy is higher. For low-frequency components, the relevant parameters are also substituted into the training. In order to comprehensively compare the prediction accuracy of each algorithm, LSTM, MLR and SVM methods were used to predict the above 7 groups of effect components at different scales, and the results were shown in Figure 5. By comparing the predicted values, it can be found that for the high frequency variable components, SVM and MLR prediction results tend to be linear, while LSTM prediction method can relate the time correlation characteristics of deformation, so it is more accurate. For the low-frequency effect component, the description equation is simple, MLR not only does not need iterative operation and has higher precision, it is a faster and more effective method.

The accuracy of the prediction results of the above 7 groups of components was calculated, and the results were shown in Table 1. As can be seen, for high-frequency components, all indexes of LSTM algorithm are lower than MLR and SVM. Moreover, it can be seen from the trend of the prediction chart that the prediction trend of the LSTM algorithm is closer to the measured situation, while other algorithms are in the shape of horizontal lines and cannot clearly identify the trend. In summary, LSTM is a more accurate and effective prediction algorithm for high-frequency components. For the low-frequency component, the accuracy indexes of MLR are much lower than other algorithms, indicating that this MLR algorithm can accurately and quickly predict periodic time series.

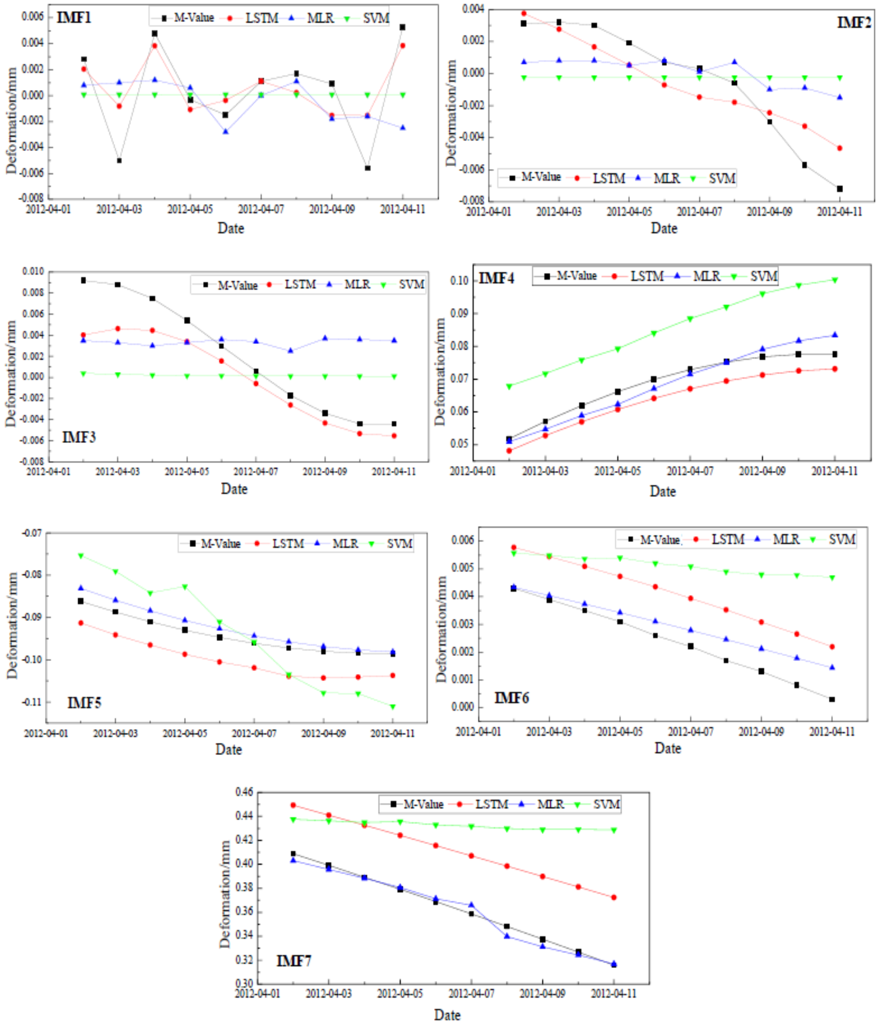


Fig. 5. EX7-1 Deformation component prediction results

Table 1. Prediction accuracy index of each scale component

Index	IMF1			IMF2			IMF3		
	LSTM	MLR	SVM	LSTM	MLR	SVM	LSTM	MLR	SVM
MAE/mm	0.0015	0.0032	0.0028	0.0013	0.0024	0.0029	0.0019	0.0042	0.0042
MAPE	0.8804	1.2870	1.0064	0.6084	0.8471	1.0626	0.5561	1.5426	0.9628
RMSE/mm	0.0021	0.0039	0.0032	0.0013	0.0029	0.0036	0.0024	0.0052	0.0052

table 1(continue)

IMF4			IMF5			IMF6			IMF7		
LSTM	MLR	SVM	LSTM	MLR	SVM	LSTM	MLR	SVM	LSTM	MLR	SVM
0.0049	0.0028	0.0172	0.0052	0.0018	0.0082	0.0014	0.0006	0.0029	0.0459	0.0049	0.0683
0.0643	0.0375	0.2249	0.0617	0.0188	0.0863	1.4229	0.6359	2.8511	0.1350	0.0119	0.1823
0.0052	0.0032	0.0161	0.0054	0.0020	0.0087	0.0016	0.0008	0.0028	0.0472	0.0046	0.0723

4.3 Residual term prediction

For the random component Z composed of residual term, this paper builds ARIMA to model and predict it. In the actual modeling process, with the help of correlation graph test method and information criteria, this paper considers the relatively good convergence of BIC criteria, and finally determines ARIMA (2,1,0). The final dam deformation prediction result can be obtained by reconstructing the sequence of the IMF component prediction results obtained by the above algorithms. The fitting and prediction results of the combined model of monitoring point EX7-1deformation are shown in Figure 6.

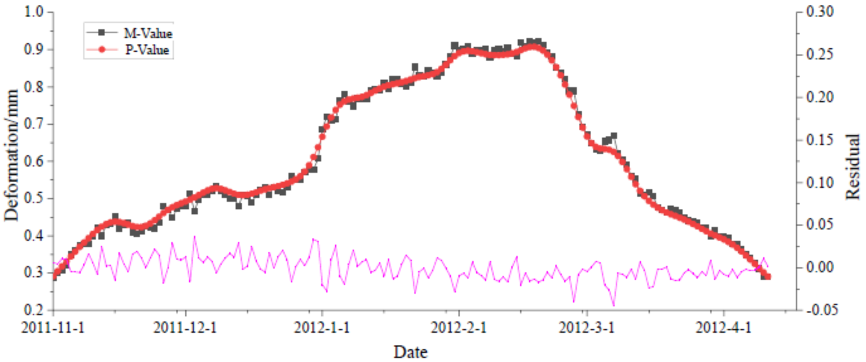


Fig. 6. Deformation of multi-scale combined model fitting and prediction results

4.4 Model comparison and precision analysis

In order to reflect the superiority of VMD for signal multi-scale adaptive processing, VMD is compared with traditional decomposition methods EMD and EEMD. As can be seen from Figure 7(a), VMD can decompose according to the characteristics of the signal itself, and the prediction results of this method (VLA) are obviously superior in accuracy compared with ELA and EELA. It can be seen that the multi-scale combined prediction model based on VLA can fully consider the component characteristics of deformation and the correlation of different time scales, and has good prediction accuracy.

On the other hand, in order to verify the advantages of VLA multi-scale combination algorithm, its prediction results were compared with the following common combination algorithms:

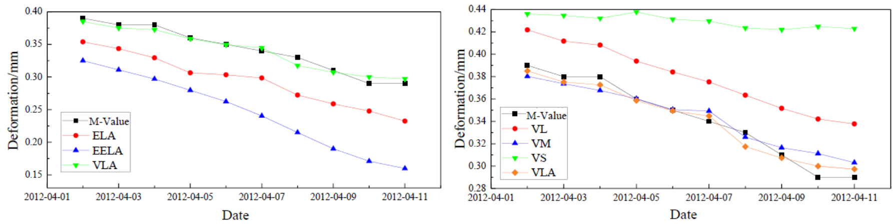
(1) VMD-LSTM(VL), only LSTM algorithm was used to predict each IMF component;

(2) VMD-MLR(VM), only MLR prediction is used for each IMF component;

(3) VMD-SVM(VS), only SVM regression prediction was used for each IMF component;

(4) VMD-LSTM-ARIMA(VLA), LSTM algorithm was used to predict each IMF component, and ARIMA was used to extract relevant information in the remaining items, and finally reconstructed into predicted values.

The comparison of prediction results of the above models is shown in Figure 7(b). It can be seen that VLA algorithm and VM algorithm are better than VL and VS in the final prediction results of measured values. This is because LSTM can identify the correlation between time series and better reflect the working characteristics of actual deformation. The information in the residual value can be extracted effectively, and the prediction accuracy is the highest.



(a) VMD-EMD-EEMD (b) VL-VM-VS-VLA

Fig. 7. Comparison of different prediction methods

5 Conclusion

Aiming at non-stationary and nonlinear dam deformation data, a combined prediction model based on VMD-LSTM-ARIMA(VLA) is proposed by combining variational mode decomposition, long short-term memory neural network and autoregressive differential moving average model. Through the analysis of project example, the prediction results of this model are compared with the conventional methods, and the following conclusions are obtained:

(1) The VMD decomposition of the original monitoring sequence of dam deformation can effectively avoid the mode aliasing phenomenon, and at the same time, multiple groups of dam deformation components with different characteristics can be adaptive, which is conducive to multi-scale exploration of dam deformation rules.

(2) The model adopts different modeling and prediction methods for the high-frequency periodic component and the low-frequency trend component of the dam deformation component, which is conducive to fully exploring the dam deformation information and has the characteristics of both accuracy and convenience. The example shows that the VLA combination model has certain advantages in dam deformation prediction and can provide reference for the corresponding work.

References

1. Wu Zhongru. Theory and Application of Safety Monitoring of Hydraulic Structures [M]. Beijing: Higher Education Press, 2003.
2. Hu Yuhan, Bao Tengfei, Zhu Zheng, Gong Jian. Deformation prediction model of arch dam based on IBC-FCM-RVM algorithm [J]. Journal of Wuhan University (Engineering and Technology Edition),2020,53(12):1055-1064.
3. Zhou Lanting, Xu Changhua, Yuan Zhimei, Lu Tao. Dam deformation prediction based on CEEMDAN-PSR-KELM [J]. Yellow River of China,2019,41(06):138-141+145.
4. Su H, Li X, Yang B, et al. Wavelet support vector machine-based prediction model of dam deformation[J]. Mechanical Systems and Signal Processing, 2018, 110: 412-427.
5. An Hongbo, Zhou Bin, Lu Xianjian, Liu Haifeng. Dam deformation monitoring data prediction based on EEMD-GA-BP model [J]. Journal of Yangtze River Research Institute,2019,36(09):58-63.
6. Kang Chuanli, Chen Yang, Zhang Linwei, Shi Manxing, Gu Junfeng. Application of wavelet and chaotic neural networks in dam deformation prediction [J]. Yellow River, 2019, 42(03):101-104+116.
7. Zhang Hao, Xu Sifa. Multi-scale dam deformation prediction based on empirical mode decomposition and genetic support vector machine [J]. Chinese Journal of Rock Mechanics and Engineering,2011,30(S2):3681-3688.
8. Tang Wang, Ma Shangchang, Li Cheng. LSTM ground temperature prediction method based on sliding window [J]. Journal of Chengdu University of Technology (Natural Science Edition),2021,48(03):377-384.
9. Hu Anyu, Bao Tengfei, Yang Chenlei, Zhang Jingying. Combined prediction model of dam deformation based on LSTM-Arima and its application [J]. Journal of Yangtze River Scientific Research Institute, 2019,37(10):64-68+75.
10. Tang Wang, Ma Shangchang, Li Cheng. LSTM ground temperature prediction method based on sliding window [J]. Journal of Chengdu University of Technology (Natural Science Edition),2021,48(03):377-384.
11. Dragomiretskiy K, Zosso D. Variational mode decomposition[J]. IEEE transactions on signal processing, 2014, 62: 531-544.
12. Petersen N C, Rodrigues F, Pereira F C. Multi-output bus travel time prediction with convolutional LSTM neural network[J]. Expert Systems with Applications, 2019,120:426-435.