Prediction method of slope construction monitoring indicators based on LMD-SSA-BP

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Abstract. During the construction process of slope engineering, it is greatly affected by the environment and has many safety risks and hidden dangers. By monitoring data and predicting values based on historical monitoring data, dynamic real-time monitoring of ship lock engineering is carried out to determine and adjust future construction processes and safety control measures. This study constructed a computational model (SSA-BP model) for monitoring, forecasting and evaluation of slope engineering during construction period based on machine learning methods. The model is based on the relationship between monitoring data and time, and LMD is introduced for filtering calculation to clarify the trend of monitoring indicators; The sparrow search algorithm was introduced to optimize the model parameters of the BP neural network, making the prediction effect of the model more ideal. After comparative analysis, it was found that LMD has a good filtering effect, and the error evaluation results of the SSA-BP model are better than the BP model and closer to the true values. Research has shown that the prediction effect of LMD-SSA-BP model is closer to the actual engineering monitoring results, and has certain guiding significance and auxiliary decision-making role for future construction.

Keywords: SSA, BP, Slope Engineering, construction monitoring, LMD.

1 Introduction

The prediction of monitoring indicators for slope engineering is an important research link in the current construction and operation process of engineering. There are many safety risks and hazards in slope construction, which are easily affected by the environment. It is necessary to timely and dynamically grasp the monitoring situation of the slope construction process, and combine monitoring data for prediction and analysis. This can timely predict dangerous situations and make emergency measures and process dynamic adjustments.

For engineering monitoring and forecasting, traditional theoretical and numerical simulation methods need to establish mechanical models based on assumed conditions, which may conflict with the on-site conditions of the project; The on-site monitoring method can fully reflect the real-time changes of various monitoring indicators under

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complex construction conditions, but monitoring equipment is prone to damage, often leading to data loss and other situations, and cannot predict the future development of analysis indicators. Artificial neural networks (ANNs) have been widely used in the construction of prediction models in practical engineering due to their excellent self-learning ability and nonlinear mapping ability. Guanglan Wu[1] used BP neural network to predict the deformation of surface buildings during subway shield tunneling construction. Wei Li[2] et al. used BP neural network for deformation monitoring and prediction of foundation pits, and compared and analyzed it with mainstream methods. They found that the BP prediction model had a relatively ideal prediction effect. Yaolin Yi[3] et al. addressed the difficulty of tunnel construction monitoring and used BP neural network for safety monitoring and early warning. However, the BP neural network prediction model still has certain limitations in optimization calculation, leading to excessive prediction errors and affecting the performance of the prediction model. There is also extensive research on the optimization problem of BP neural networks nowadays. Xuhui Chang[4] combined wavelet denoising and PSO algorithm to optimize the BP prediction model for surface monitoring. Huangzhi[5] used GA-BP model to predict and analyze the deformation of foundation pit of subway station. Meng Song[6] used machine learning and optimization algorithms to optimize the structure of oil tankers. Qi Xuliang[7] completed real-time prediction and analysis of FPSO mooring forces through artificial neural networks. Doong[8] used BP neural networks for monitoring coastal abnormal waves to achieve high prediction accuracy. Chen Haili[9] used a deep semi confidence neural network to predict the motion of a floating body. Xu Zhe[10] used the sparrow search method to optimize and adjust the structural finite element model.

This article uses the LMD method to decompose, filter, and synthesize the raw data of slope monitoring indicators for sensor monitoring data, forming monitoring data that can reflect the physical laws of the site; Using SSA and other algorithms to optimize the BP neural network prediction model, improve the model's learning ability, and achieve rapid prediction and trend analysis of monitoring data.

2 Prediction model analysis method

2.1 LMD

The local mean decomposition method decomposes a complex and non-stationary non periodic signal into several physically meaningful instantaneous frequency product function (PF) components and one residual component, and the decomposed vector does not lose the main characteristics of the original signal. For any signal $x(t)$, the decomposition process of LMD is as follows:

(1) Find all local extreme points n_i from $x(t)$, and calculate the average value m_i and envelope estimation a_i of adjacent extreme points:

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

$$a_i = \frac{|n_i - n_{i+1}|}{2} \tag{2}$$

(2) Connect the m_i and a_i of all adjacent extreme points with a line. Then, the sliding average method is used to smooth it and obtain the local envelope estimation function $a_{11}(t)$ and the mean function $m_{11}(t)$.

(3) Subtract the smoothed mean signal from $x(t)$ to obtain $h_{11}(t)$:

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

(4) Divide $h_{11}(t)$ by $a_{11}(t)$ to obtain the frequency modulation signal $s_{11}(t)$:

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)} \tag{4}$$

(5) If $a_{12}(t)$=1 is satisfied, then $s_{11}(t)$ is a standard frequency modulation signal; If $a_{12}(t)\neq 1$, then $s_{11}(t)$ repeats the above process as the original data until $s_{1n}(t)$ becomes a standard frequency modulation signal, that is, $a_{1(n+1)}(t)$=1.

(6) Multiply all local envelope estimation functions to obtain the envelope signal:

$$a_{11}(t) = \prod_{q=1}^{n} a_{1q}(t) \tag{5}$$

(7) The first PF component of $x(t)$ is equal to the product of the envelope signal $a_1(t)$ and the pure frequency modulation signal $s_{1n}(t)$:

$$PF_1(t) = a_1(t) s_{1n}(t) \tag{6}$$

(8) Subtract the first component $PF_1(t)$ from $x(t)$ to obtain a new signal $u_1(t)$. Repeat the process with $u_1(t)$ as the new data and repeat it k times until $u_k(t)$ becomes a monotonic function.

$$u_k(t) = u_{k-1}(t) PF_k(t) \tag{7}$$

(9) Finally, $x(t)$ is decomposed into k PF components and the sum of $u_k(t)$, i.e.:

$$x(t) = \sum_{p=1}^{k} PF_p(t) = u_k(t) \tag{8}$$

2.2 BP neural network

For the construction of BP neural network time series prediction model based on historical data, the input layer is composed of historical data, and the time series to be predicted is taken as the output layer. The monitoring data sample is normalized and divided into training set and test set, and the training set data is output in the forward direction and transferred in the reverse direction through error to adjust the weight and threshold, so as to train the neural network model. After the model training, the test set was analyzed for the prediction effect and gradually put into use.

2.3 Sparrow search algorithm

Xue[11] et al. proposed sparrow search algorithm (SSA) according to the bionic principle of sparrow foraging and anti predation. In SSA algorithm, the sparrow population has two identities, the first is the discoverer or joiner, and the second is the Scout. The discoverer directs and leads the participants to search the foraging area and direction; The rest of the sparrows follow and monitor the discoverer to obtain food and other resources, which are called the joiners; Part of the first two groups also have a second identity - scout, which can detect predators and other risk factors and conduct anti predator behavior.

The location of the discoverer is updated as follows:

$$x_{i,j}(t+1)=\begin{cases} x_{i,j}(t)\cdot\exp(\dfrac{-i}{\alpha\cdot T}) & R_2<ST \\ x_{i,j}(t)+Q\cdot L & R_2\geq ST \end{cases} \tag{9}$$

Where t is the current number of iterations, T is the maximum number of iterations, $x_{i,j}(t)$ is the position information value in the first sparrow when the j-dimensional iteration number is t, α is the random number of [0,1], R_2 ($R_2\in$ [0,1]) is the warning value, ST ($ST\in$[0.5,1]) is the safety value, Q is the random number following a normal distribution, L is a 1×d matrix, where each element is 1. When $R_2<ST$, it means that there is no predator around and the discoverer can conduct a large search; when $R_2\geq ST$, the investigator finds the predator and immediately sends an alarm signal and all sparrows quickly fly to other safe areas.

The location of the entrants is updated as follows:

$$x_{i,j}(t+1)=\begin{cases} Q\cdot\exp(\dfrac{x_{worst}(t)-x_{i,j}(t)}{i^2}) & i<\dfrac{N}{2} \\ x_{bestj}(t+1)+\left|x_{i,j}(t)-x_{bestj}(t+1)\right|\cdot A^{+}\cdot L & other \end{cases} \tag{10}$$

Where x_{worst} (t) represents the current global worst position, $A^+ = A\ (AA^{\mathrm{T}})^{-1}$, A represents the 1×d matrix of an internal element randomly assigned 1 or -1, A^{T} is the transpose of A, and $x_{bestj}(t)$ is the best position occupied by the discoverer. When $i>n/2$, the i-only accession indicating poor fitness values is hungry and it needs to fly to other directions to find food.

The sparrows responsible for detection generally account for 10% to 20% of the population. The location update formula is as follows:

$$x_{i,j}(t+1)=\begin{cases} x_{bestj}(t)+\beta\left|x_{i,j}(t)-x_{bestj}(t)\right| & f_i>f_g \\ x_{i,j}(t)+K\left[\dfrac{\left|x_{i,j}(t)-x_{worst}(t)\right|}{(f_i-f_w)+e}\right] & f_i=f_g \end{cases} \tag{11}$$

Where $x_{bestj}(t)$ represents the current global best position, β is the step control parameter of normal distributed random number of mean 0, variance of 1, $K(K\in[-1,1])$ represents the sparrow the direction of movement and the step control parameter, f_i represents the current fitness value of the sparrow, f_g and f_w represent the current global optimal and worst value, e is a constant to avoid the denominator of 0. When $f_i > f_g$, the sparrow is at the edge of the population and is vulnerable to predators; when $f_i = f_g$, the sparrow in the middle of the population is aware of the danger and therefore needs to be close to other sparrows to reduce the probability of predation.

2.4 LMD-SSA-BP model

The specific implementation flowchart of LMD-SSA-BP is shown in Figure 1.

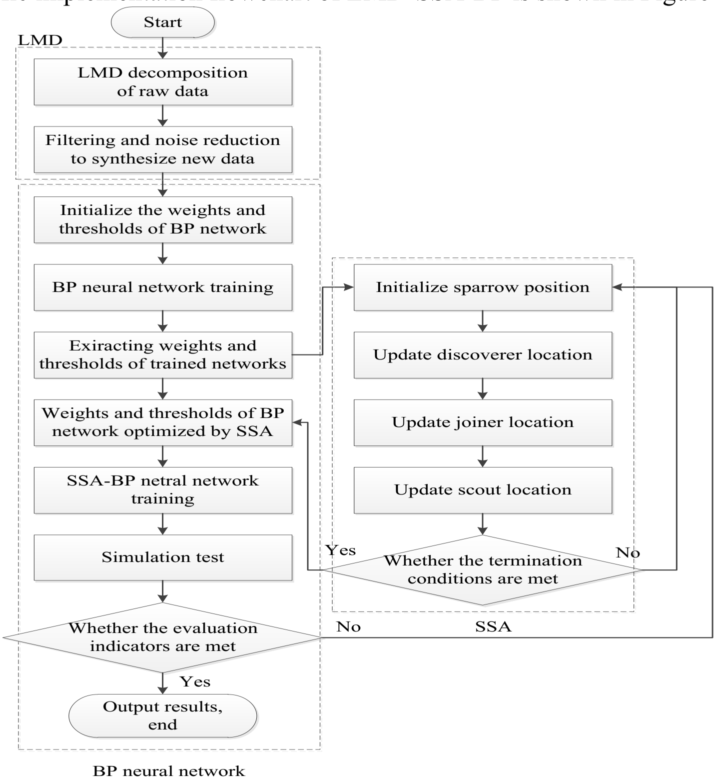

Fig. 1. LMD-SSA-BP flowchart.

The construction process of the LMD-SSA-BP prediction model is as follows:

(1) Establish a database of construction safety monitoring indicators. Based on engineering practice and data research, relevant indicators are selected for real-time monitoring and forecasting according to specifications and other criteria.

(2) Perform abnormal data processing on the sensor monitoring data sequence of monitoring indicators;

(3) Using LMD method to denoise the processed data and obtain a data sequence;

(4) Divide the training and testing sets for predictive model training;

(5) According to the training situation of the BP model, when the error does not meet the standard, the SSA algorithm is used to optimize the BP model.

(6) Extract the weights and thresholds of the BP neural network, and initialize the parameters.

(7) Calculate the fitness values of each sparrow, identify the current optimal and worst fitness values, as well as their corresponding positions.

(8) Select some sparrows with better fitness values as discoverers.

(9) The remaining sparrows serve as followers.

(10) Randomly select a portion of sparrows as watchmen and update their positions through a formula.

(11) Determine if the end condition has been met. If so, proceed to the next step; otherwise, skip to the next step(5).

(12) After adjusting the prediction model, it is embedded into the visual monitoring system for engineering construction safety to achieve early warning and control of the entire process of slope engineering construction.

3 Case analysis

3.1 Engineering introduction

The experimental data selected in this article is the cumulative lateral displacement change data of the slope surface of the Pinglu Canal Youth Hub Project. This set of data includes 1800 data collected by four sets of sensors from March 3, 2023 to May 22, 2023. Firstly, preprocess the 1800 monitoring data, then select 1500 sampling data for prediction, and use the first 1000 sampling data as training data and the remaining data as testing data. The original structural deformation monitoring data is shown in Figure 2.

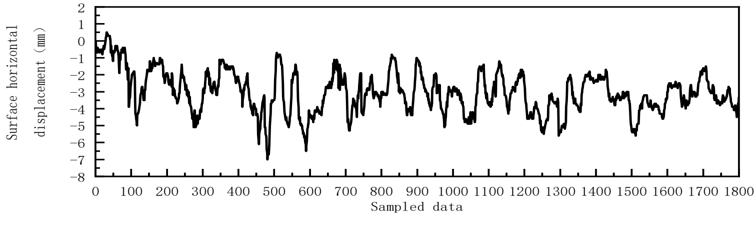

Fig. 2. Sensor monitoring of raw data.

3.2 LMD filtering analysis

In order to improve the accuracy of data analysis and prediction, the LMD method is first used to preprocess the original data. LMD denoising is the process of decomposing the PF components containing high-frequency noise layer by layer from the original signal using the LMD model, thereby eliminating the influence of these noise components and treating the remaining part of the signal as the denoised signal. In order to verify the effectiveness of the LMD empirical mode decomposition denoising method, the data was subjected to LMD decomposition and denoising processing on the basis of the original data. After LMD decomposition, a total of 9 components with different frequencies, PF1~PF8 and $u(t)$, can be obtained. Each layer of PF component presents different component characteristics. The decomposed signals are sorted in order of their frequency, and the higher the frequency, the lower the frequency of the higher level components. Among them, LMD stops due to the obvious monotonicity of $u(t)$. Draw the above components separately in different coordinate systems, as shown in Figure 3.

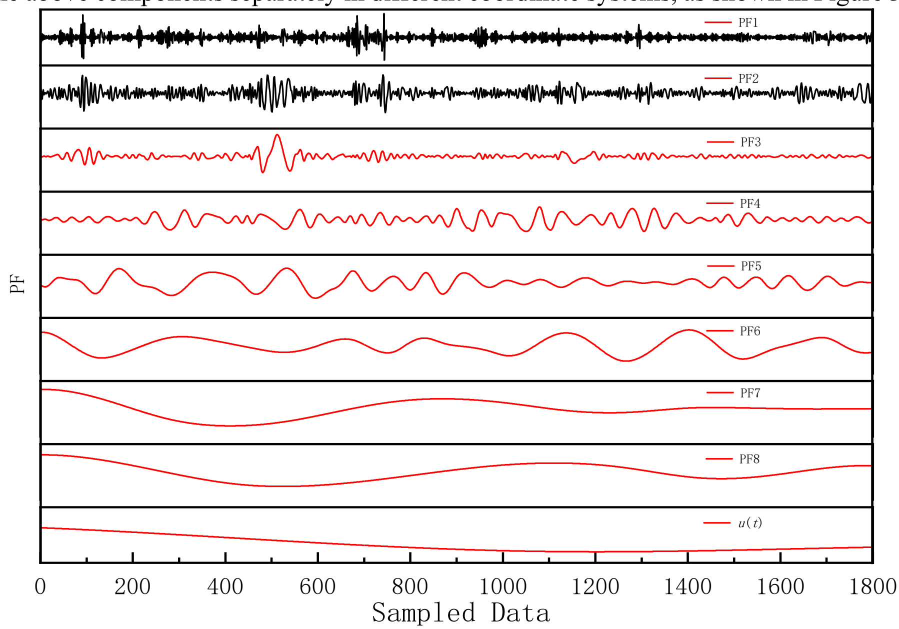

Fig. 3. PF component and residual component.

From Figure 3, it can be seen that after LMD decomposition, the data is decomposed into 10 layers of relatively stable components, and each layer of data presents different characteristics. The first two layers show more obvious high-frequency characteristics and weak periodicity, and the higher the component, the lower the frequency. Among them, PF1 has the highest vibration frequency and the greatest fluctuation. After LMD decomposition, the data is effectively decomposed into high-frequency and low-frequency components, and then the high-frequency noise components in the signal are effectively removed. This study decomposes deformation monitoring data into 10 layers using LMD, and determines useful signals and noise signals by comparing the correlation coefficients between each layer's sub components and the original signal. Through calculation and analysis, it can be seen that PF3~PF8 and u (t) represent trends, with weak frequency and volatility, and high correlation with the original monitoring data. The above 7 components are superimposed and reconstructed as the filtered signal, as shown in Figure 3.

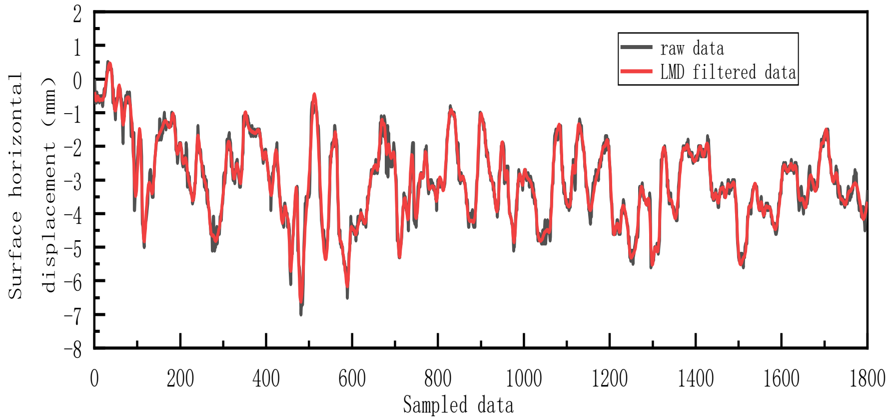

Fig. 4. Comparative analysis between LMD filtering processed data and raw data.

The LMD filtering result is shown in Figure 4, and it can be seen that selecting the last 7 layers of components as the LMD filtering result makes the overall data smoother and more stable, and the overall trend remains unchanged compared to the original data. The results show that the LMD filtering method effectively reduces the non-stationary nature of monitoring data, adaptively separates useful signals and noise signals in the data, and provides a good data foundation for subsequent data prediction. This method fully explores some implicit information such as data volatility, weak periodicity, and changing trends, which is more conducive to the training and simulation prediction of later prediction models.

3.3 SSA-BP model

The prediction effect of surface horizontal displacement of the slope during the construction period of the project was compared and analyzed using BP model, SSA-BP model, and ISSA-BP model with reverse learning and Cauchy variation. After the SSA algorithm extracts weights and thresholds for optimization calculation, the model prediction can be observed through two values: mean square error and MAPE. At this point, observing the fitting curves before and after optimizing the prediction model (Figure 5), it can be seen that the SSA algorithm can make the BP model's prediction curve converge to the monitoring data curve, indicating that the optimization effect of the SSA algorithm on weights and thresholds is more significant and has higher accuracy.

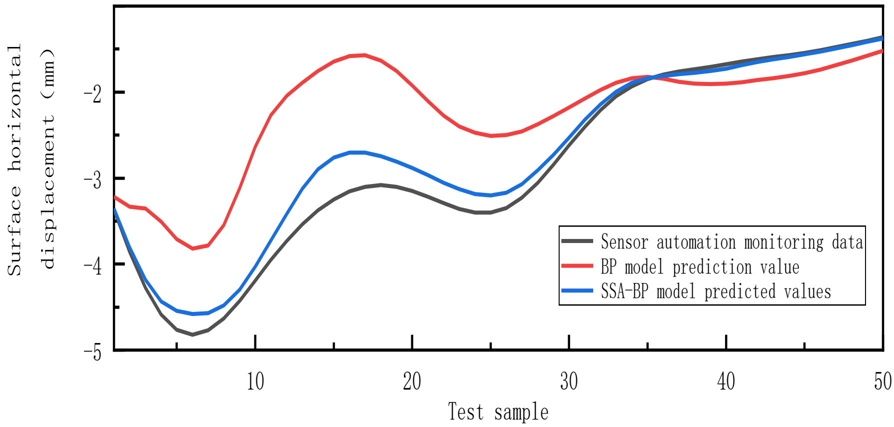

Fig. 5. Comparison chart between surface horizontal displacement monitoring values and predicted values of various models.

The overall analysis of the model for predicting surface horizontal displacement can be quantitatively analyzed through Table 1. Firstly, the MAPE of the SSA-BP model is significantly reduced compared to the BP model, indicating that the overall prediction error of the optimized SSA algorithm is relatively low; The MAE of the SSA-BP model is also significantly smaller than that of the BP model, indicating that its error is also smaller; Comparing RMSE, it can be concluded that the SSA-BP model is less susceptible to interference from abnormal data. Overall, the SSA-BP model performs well in the overall evaluation indicators.

Table 1. Comparison table of overall evaluation indicators for the model.

Model	RMSE	MAE	MAPE
BP	740	922	19.04 %
SSA-BP	63.33	35.21	3.79%

Comparing the prediction errors of surface horizontal displacement values under various prediction models, it can be seen from Figure 6 that the predicted values of the SSA-BP model are closer to the monitoring values. Compared with the BP model, the prediction errors of settlement in each period have been significantly reduced, while the accuracy improvement of the SSA-BP model is relatively small. Moreover, the SSA-BP model has increased the number of samples with relative errors below 5% compared to the BP model to 88% of the original. In summary, the SSA algorithm solves the problem of the BP model being prone to local minima and affecting prediction accuracy, achieving monitoring value prediction of monitoring indicators and long-term trend analysis in the future.

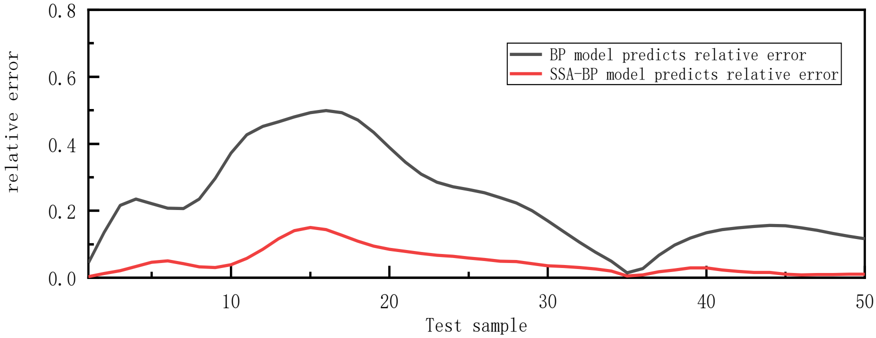

Fig. 6. Comparison chart of relative prediction errors for each test sample.

4 Conclusion

The construction process of typical hazardous engineering projects has randomness and complexity, but monitoring indicators still undergo data changes according to certain rules under the influence of main control factors, and secondary factors fluctuate to a certain extent in the form of noise on the change trend, with distinct trends. The LMD filtering method effectively reduces the non-stationary nature of monitoring data, adaptively separates useful signals and noise signals in the data, and provides a good data foundation for subsequent data prediction. This method fully explores some implicit information such as data volatility, weak periodicity, and changing trends, which is more conducive to the training and simulation prediction of later prediction models.

Predicting and evaluating future security status based on filtered data, using neural network methods to predict and evaluate monitoring data. Using a BP neural network prediction model and combining historical monitoring data to predict future development trends. Through analysis, it can be concluded that the weights and thresholds of the BP model are important factors affecting errors, while the SSA algorithm is essentially a means of adjusting the parameters of the BP prediction model. Therefore, it can reduce various error indicators of the BP neural network. In other words, the SSA algorithm can adjust weights and thresholds, and the prediction model has strong adaptability without obvious overfitting, improving global exploration performance and achieving better prediction results.

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