

Article

A Hybrid POA-VMD-Attention-BiLSTM Model for Deformation Prediction of Concrete Dams and Buildings

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Abstract

To improve the accuracy of deformation prediction in concrete buildings and large-scale infrastructures such as dams, this study proposes an Attention-BiLSTM model integrated with a parameter-optimized Variational Mode Decomposition (VMD). Specifically, the Pelican Optimization Algorithm (POA) is employed to optimize VMD parameters, enhancing signal decomposition efficiency for structural deformation time series. The optimized VMD is then coupled with a BiLSTM network embedded with an attention mechanism, forming a hybrid prediction framework that captures both temporal dependencies and key feature weights in monitoring data. Using three sets of engineering-measured deformation datasets, the proposed model is validated through comparative analyses with conventional single models (e.g., standalone BiLSTM and VMD-BiLSTM without attention). Results demonstrate that the developed model achieves superior accuracy and stability, significantly outperforming all comparative methods, with the highest R^2 reaching 0.996, while reducing MAE and RMSE by over 60% and 30%, respectively. Quantitative evaluation indicators (e.g., RMSE, MAE, and R^2) confirm that the approach effectively captures both short-term fluctuations and long-term trends of structural deformation. These findings verify its reliability and applicability for intelligent safety monitoring of concrete buildings and infrastructures.

Keywords: building deformation prediction; POA-optimized VMD; attention mechanism; attention-BiLSTM model; structural health monitoring



Academic Editors: Humberto Varum and Salvatore Verre

Received: 28 August 2025

Revised: 17 September 2025

Accepted: 30 September 2025

Published: 14 October 2025

Citation: Zhao, Z.; Fang, C.; Wang, X.; Yang, M.; Zhang, H.; Xu, Z.; Ding, G.; Song, S.; Li, J. A Hybrid POA-VMD-Attention-BiLSTM Model for Deformation Prediction of Concrete Dams and Buildings. *Buildings* **2025**, *15*, 3698. <https://doi.org/10.3390/buildings15203698>

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1. Introduction

China's concrete dam projects rank among the world's top in terms of quantity, height, and scale, making their safe operation of vital importance. Dam safety monitoring, as a key technical means to ensure dam safety, has become a research focus at home and abroad [1–3]. Deformation is a critical indicator for dam safety monitoring. However, due to the large volume of monitoring data and severe noise interference, it is difficult to accurately diagnose the service behavior of dams [4]. Therefore, constructing a high-precision and robust deformation prediction model is of great significance for achieving accurate monitoring of dam safety status and improving engineering safety assurance capabilities.

In recent years, various machine learning methods have been applied to concrete dam deformation prediction to improve model accuracy. Liu et al. used the Random Forest (RF) algorithm to predict concrete dam displacement, demonstrating good performance in short-term deformation prediction tasks [5]. Tao et al. constructed a deformation prediction framework using a Support Vector Regression (SVR) model, achieving certain results in medium-low dimensional data scenarios [6]. Additionally, models such as K-Nearest Neighbors (KNN) and decision trees have been attempted for modeling dam monitoring data [7,8]. Although these traditional machine learning methods have played a role, they struggle to meet the higher requirements for prediction capabilities under complex working conditions.

With the development of deep learning technologies, researchers have begun to introduce neural network models to overcome the limitations of traditional methods in time-series modeling. Wang et al. combined CNN and LSTM neural networks to propose a high-precision prediction model [9,10]. New architectures such as GRU and Transformer have also been introduced to this field [11,12]. LSTM can effectively capture temporal features, making it particularly suitable for time-series prediction tasks like dam deformation. The multi-variable LSTM model constructed by Yu et al. introduced various monitoring indicators, significantly improving prediction accuracy and model stability [13]. Scholars introduced the attention mechanism into the LSTM architecture, enhancing the model's information extraction capability. Scholars proposed a dam displacement prediction method based on an improved LSTM and hybrid optimization algorithm, showing good adaptability and generalization ability [14]. However, these methods still have limitations in handling long-term dependencies or computational efficiency. Recent studies in Buildings have also highlighted the potential of advanced machine learning and hybrid intelligent models for improving the prediction and monitoring of large-scale concrete structures [15]. At the same time, research in Designs has emphasized the durability and mechanical behavior of innovative concrete systems, such as 3D-printed concrete [16] and reinforced concrete members under serviceability limit states [17], further underscoring the importance of integrating intelligent modeling approaches with structural performance evaluation.

The development of signal decomposition techniques in dam deformation prediction has undergone significant optimization: Ensemble Empirical Mode Decomposition (EEMD) improves mode mixing problems by introducing Gaussian white noise [14], Complementary Ensemble Empirical Mode Decomposition (CEEMD) reduces reconstruction errors [15], and Local Mean Decomposition (LMD) enhances the accuracy of instantaneous frequency estimation [16]. However, these methods still have limitations in mathematical theoretical foundations and parameter adaptability. Variational Mode Decomposition (VMD), by modeling signal decomposition as a variational problem, combines strong noise resistance and frequency domain separation capabilities, making it more suitable for processing non-stationary dam monitoring data [17]. Zhang et al.'s composite model based on VMD-LSTM improved prediction accuracy by 23% compared to traditional methods. Wang et al. also confirmed that VMD maintains good performance under complex work-

ing conditions [18]. However, the decomposition effect of VMD depends on parameter selection [19], and existing methods mostly use empirical setting or grid search, suffering from strong subjectivity, weak global search ability, and low optimization efficiency [20]. To address this, researchers have attempted to combine intelligent optimization algorithms with VMD. Traditional optimization methods such as Grey Wolf Optimization (GWO) converge slowly, while the Pelican Optimization Algorithm (POA) [21], with its efficient global search capability, provides a new idea for VMD parameter optimization [22].

Based on this, this paper proposes a VMD-Attention-BiLSTM model combined with the Pelican Optimization Algorithm (POA) [23–25]. The POA optimizes the parameters in VMD, and the optimized VMD is used to decompose the original monitoring data into modal information, thereby reducing noise pollution and preserving the complex features of the monitoring data. On this basis, a bidirectional neural network model with an attention mechanism (Attention-BiLSTM) is selected as the deformation prediction model. Comparisons with other single models show that this method can significantly reduce noise impact and improve prediction accuracy.

2. Methodology

2.1. Pelican Optimization Algorithm (POA)

The POA is a meta-heuristic optimization algorithm based on swarm intelligence, designed to simulate the predatory behavior and social interaction characteristics of pelicans for solving complex optimization problems [26]. This method features few parameters, easy implementation, and strong global search capability, enabling it to find global optimal solutions within a small number of iterations.

2.1.1. Moving Towards Prey (Exploration Stage)

In this stage, pelicans determine the position of the prey and move within the identified area. By simulating the approaching mechanism of pelican predation strategies, the POA achieves multi-dimensional scanning of the search space and effectively utilizes its exploration capabilities in different regions of the search domain. The position of the prey in the POA is randomly generated in the search space.

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + \text{rand} \cdot (P_j - I \cdot x_{i,j}), & F_p < F_i; \\ x_{i,j} + \text{rand} \cdot (x_{i,j} - P_j), & \text{else}, \end{cases} \quad (1)$$

where $X_{i,j}^{P_1}$ is the position of the j -th dimension of the i -th pelican based on the phase 1 update, I is a random integer of 1 or 2; P_j denotes the prey's position in the j -th dimension, and F_p corresponds to the objective function value. The parameter I is randomly assigned as either 1 or 2 for each individual and each iteration. When the value of I is 2, it induces a larger displacement in the individual, potentially guiding it to explore newer regions within the search space. Therefore, this parameter plays a critical role in influencing the Pelican Optimization Algorithm's (POA) ability to accurately scan the search space.

2.1.2. Spreading Wings over Water Surface (Exploitation Stage)

This stage represents that pelicans have detected the position of fish and complete predation by flying lower (skimming the water surface) to approach fish precisely. The prey's position is identified by pelicans, which then move toward the specified area. By modeling the strategy of pelicans approaching prey, POA can scan the search space and utilize its exploration capabilities in various regions of the search domain. In POA, the prey's position within the search space is randomly generated, enhancing the algorithm's ability for precise searching.

$$x_{i,j}^{P_2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot \text{rand} - 1) \cdot x_{i,j} \quad (2)$$

where $x_{i,j}^{P_2}$ is the position of the j -th dimension of the i -th pelican based on the phase 2 update; R is a random integer of 0 or 2; t is the current iteration number and T is the maximum iteration number. Among them, $(1 - t/T)$ decreases linearly with the iteration process, reducing the global step size to ensure convergence of the algorithm in the later stages.

The following (Figure 1) is a schematic diagram of the Pelican Optimization Algorithm (POA).

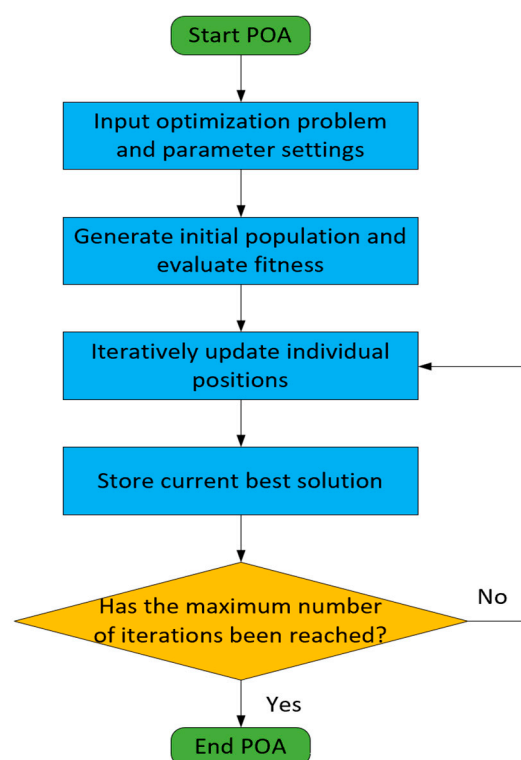


Figure 1. Schematic diagram of the Pelican Optimization Algorithm (POA).

2.2. Variational Mode Decomposition

Variational Mode Decomposition (VMD) is a complex signal processing technique derived from Empirical Mode Decomposition (EMD) [27]. Variational refers to the optimization formulation of the decomposition method. This method decomposes the original signal into multiple finite bandwidth components with different central frequencies according to a preset number of modes, iteratively optimizing each modal component and its central frequency via the alternating direction method of multipliers [28,29]. During the calculation, the system adaptively adjusts the central frequencies of each mode, gradually demodulating nonlinear signal components to the corresponding base frequency bands, ultimately achieving precise separation of modal components with different central frequencies and their corresponding spectral characteristics.

VMD decomposes signals into multiple Intrinsic Mode Functions (IMFs). To obtain the bandwidth and marginal spectrum of IMFs, the Hilbert transform is applied to the modal functions to derive a unidirectional spectrum, which is shifted to the baseband. The bandwidth of IMFs is obtained from the squared norm of the gradient, and the variational problem model is as follows:

$$\begin{cases} \min_{\{u_k\}, \{w_k\}} \left\{ \sum_{k=1}^k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-jw_k t} \right\|_2^2 \right\}; \\ \text{s.t. } \sum_{k=1}^k u_k = f \end{cases} \quad (3)$$

Due to the complexity of solving the variational problem, the Lagrange multiplier method is adopted. The penalty factor α and the Lagrange operator λ are substituted into the model to obtain the extended expression:

$$\begin{aligned} L(\{u_k\}, \{w_k\}, \lambda) = & \alpha \sum_k \left\| \partial(t) \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-jw_k t} \right\|_2^2 + \\ & \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left[\lambda(t), f(t) - \sum_k u_k(t) \right] \end{aligned} \quad (4)$$

To obtain the saddle point of the above formula, the operator alternating azimuth strategy is used to update u_k^{n+1} , ω_k^{n+1} and λ^{n+1} , then the Parseval/Plancherel Fourier isometric transformation is performed, and the final solution is obtained as:

$$\hat{u}_k^{n+1}(\omega) = \left(\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \right) \frac{1}{1 + 2\alpha(\omega - \omega_k)^2} \quad (5)$$

In the formula, ω_k is the center of gravity of the power spectrum of the current modal function.

The calculation formula for the center frequency ω_k is

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}(\omega)|^2 d\omega} \quad (6)$$

2.3. Attention Mechanism

The attention mechanism was proposed inspired by the selective perception of the human visual system [30]. Given the information processing capacity limitations of the human cognitive system, sensory organs preferentially acquire key information through selection while ignoring unimportant information [31]. The attention mechanism in deep learning precisely mimics this biological cognitive characteristic, achieving precise capture of key information in complex environments by establishing a feature saliency evaluation system [32]. At the algorithmic implementation level, this mechanism involves two core elements [33]: selecting the correct information to focus on and allocating appropriate resources to process this information.

This mechanism involves temporarily focusing on multiple inputs, which are weighted by a weighted average, where the weights are determined by a learnable function. By focusing on multiple inputs at different time points, it forms memory, extracts features from input data, and helps the model comprehensively describe traffic dynamics in the input data. The key is that the model has the ability to focus on features based on specific aspects, which helps solve bottlenecks in model processing [34].

Suppose the input data has m features, then the dimensions of each vector x_t ($t = 1, 2, \dots, n$) is m , where the time step is represented by n . The first step is to input the input vector into the first attention layer and obtain the weighted vector through Formula (7). Since Formula (7) contains two learnable weight matrices W_{ax} and V_a , W_{ax} can project the vector x_t into the attention vector space, and V can calculate the weighting value. This process effectively provides differentiated attention to the input vector x_t , thereby reducing

data noise. Subsequently, vector a_t is normalized through the second layer to obtain the fraction of each element in each vector, that is, vector p_t in Formula (8). Finally, the fraction vector p_t follows the Hadamard product of the input vector x_t according to Formula (9), resulting in the output $\tilde{x}_t$.

$$a_t = V_a \cdot \tanh(W_{ax} \cdot x_t + b_a) \quad (7)$$

$$p_t = \text{Softmax}(a_t) \quad (8)$$

$$\tilde{x}_t = p_t \odot x_t \quad (9)$$

2.4. Bidirectional Long Short-Term Memory Model (BiLSTM)

Long Short-Term Memory (LSTM) is developed based on recurrent neural networks (RNN) and is a variant of recurrent neural networks (RNN) [35]. Compared with RNN, LSTM effectively solves the problems of vanishing gradient and gradient explosion existing in RNN through an innovative gated timing mechanism, and improves the modeling ability of long-range timing dependencies. Due to its addition of storage units capable of preserving historical data, it is more convenient to extract various information features. The LSTM network structure adopts a special gate mechanism, and its core design includes three typical gates: the forget gate, the input gate and the output gate. The forget gate, input gate and output gate are, respectively, responsible for filtering historical information, updating the current state and adjusting the feature output. The structure of a neuron is shown in Figure 2.

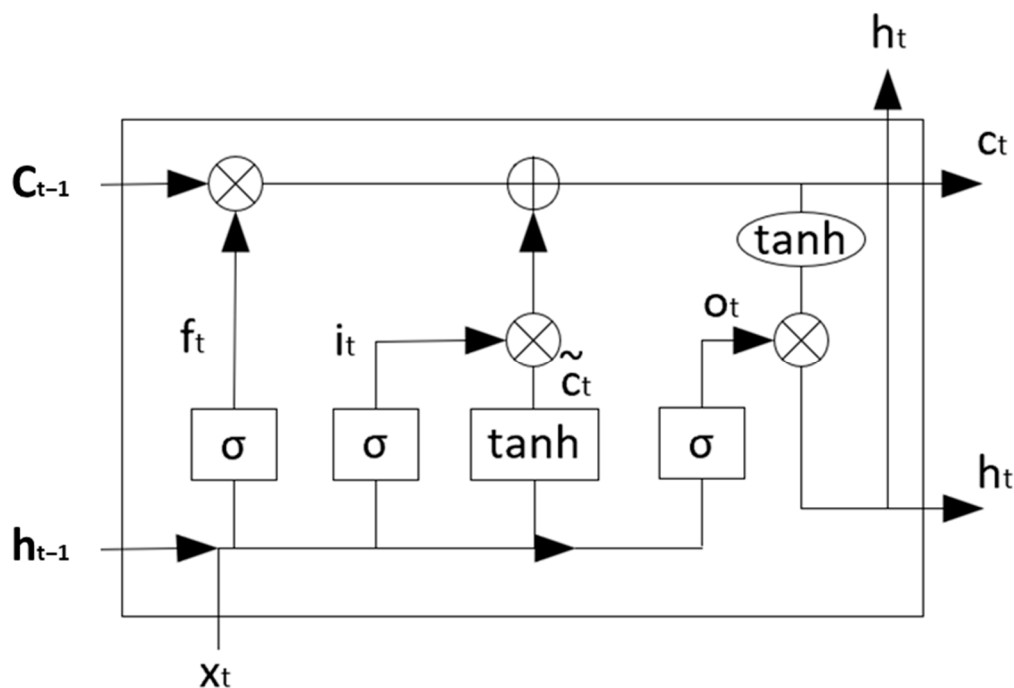


Figure 2. Structure of LSTM unit.

Where f_t is the remaining data information volume of the previous LSTM neuron after passing through the forgetting gate, i_t is the data information input volume of the current LSTM neuron, $\tilde{C}_t$ is the candidate state value of the unit, and C_t is the data information output volume of the LSTM neuron. The mathematical modeling of this network can be achieved through the following key equations:

$$f_t = \sigma(W_{xf} \cdot x_t + W_{hf} \cdot h_{t-1} + b_f) \quad (10)$$

$$i_t = \sigma(W_{xi} \cdot x_t + W_{hi} \cdot h_{t-1} + b_i) \quad (11)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (12)$$

$$\tilde{c}_t = \tanh(W_{xc} \cdot x_t + W_{hc} \odot h_{t-1} + b_c) \quad (13)$$

$$o_t = \sigma(W_{xo} \cdot x_t + W_{ho} \cdot h_{t-1} + b_o) \quad (14)$$

$$h_t = o_t \odot \tanh(c_t) \quad (15)$$

where σ is the sigmoid activation function; $\odot$ is the Hadamard product and x_t is the current input vector. W_{xf} , W_{xi} , W_{xc} and W_{xo} are related to the corresponding weight vectors of the input; h_{t-1} is the state vector of the hidden layer of the previous unit; W_{hf} , W_{hc} , W_{ho} and W_{hi} are, respectively, the hidden layer weights of the state vector; and b_f , b_i , b_c and b_o are the corresponding gates on the bias vector.

BiLSTM is a typical extension of LSTM. Compared with the original LSTM, its search ability has been significantly enhanced. The core structure of BiLSTM consists of two independently running LSTM processing layers [36,37], one handling the forward sequence and the other handling the reverse sequence. Specifically, the forward LSTM layer generates a sequence of forward hidden states, and the reverse LSTM layer generates a sequence of reverse hidden states. The final output of BiLSTM is the connection of these two hidden state sequences. This characteristic makes BiLSTM a robust and effective model for solving the problem of long-term information dependence. Figure 3 illustrates the simplified framework of BiLSTM.

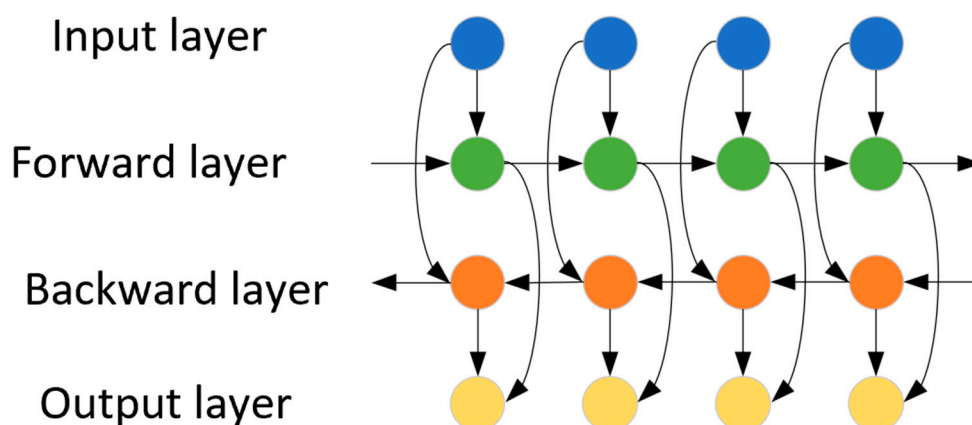


Figure 3. The structure of BiLSTM.

2.5. Model Construction Process

Combined with the above methods, a dam deformation prediction model based on POA-VMD-Attention-Bi LSTM was constructed, which improved the accuracy of the dam deformation prediction model. The specific modeling process is as follows:

Step 1: Import the original deformed data and extract the time series for subsequent analysis.

Step 2: Use POA to optimize the hyperparameters of VMD, including the number of decomposition times and the maximum number of iterations, and conduct modeling and analysis using the best combination of hyperparameters. The original signal is decomposed into several intrinsic modal functions (IMF) with limited bandwidth to extract multi-scale features.

Step 3: Apply Savitzky–Golay filtering to smooth each IMF component to reduce local fluctuations and noise interference.

Step 4: Reconstruct the smoothed IMF components to obtain the smoothed reconstruction result of the overall signal.

Step 5: Normalize the reconstructed signal and construct the time series samples using the sliding window method.

Step 6: Construct a prediction model that combines the Bidirectional Long Short-Term Memory Network (BiLSTM) with the Attention mechanism (Attention), and input the training set data for model training.

Step 7: Make predictions for the test set, calculate evaluation metrics to quantify the prediction accuracy of the model, and verify the accuracy of the proposed model by comparing it with other models.

Figure 4 is the flowchart of the model construction.

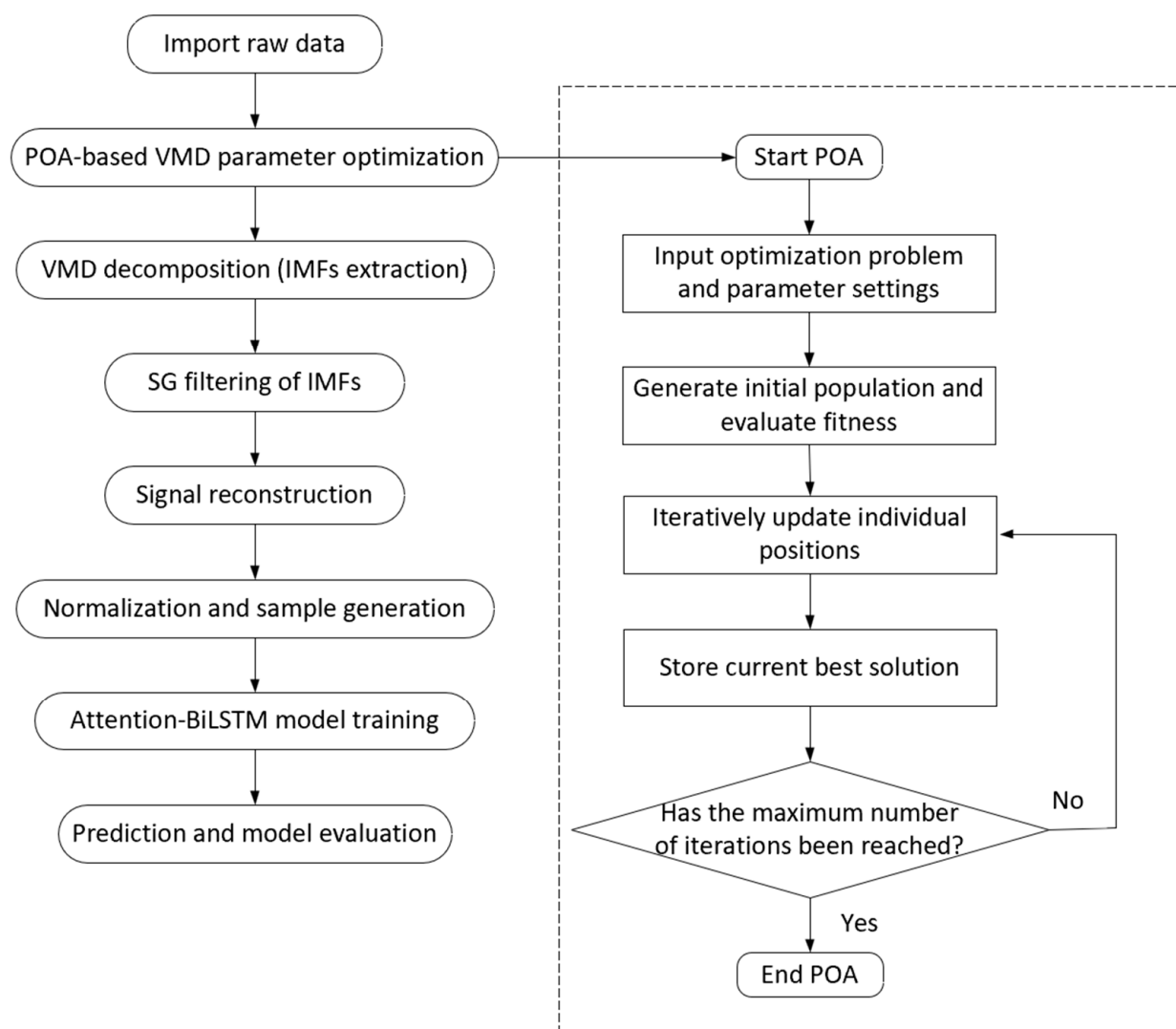


Figure 4. Flowchart of model construction.

3. Engineering Examples

3.1. Project Overview

An engineering example is selected from a certain concrete arch dam in southwest China. The dam height is 305 m, the maximum elevation of the dam is 1885.0 m, and the minimum reference elevation is 1580.0 m. The thickness-to-height ratio is 0.207. The dam body is poured in 25 sections. The horizontal radial displacement of the dam is detected in 7 parts through vertical lines. The precise distribution of deformation measurement points is shown in Figure 5. The red dots are different monitoring points for the dam.

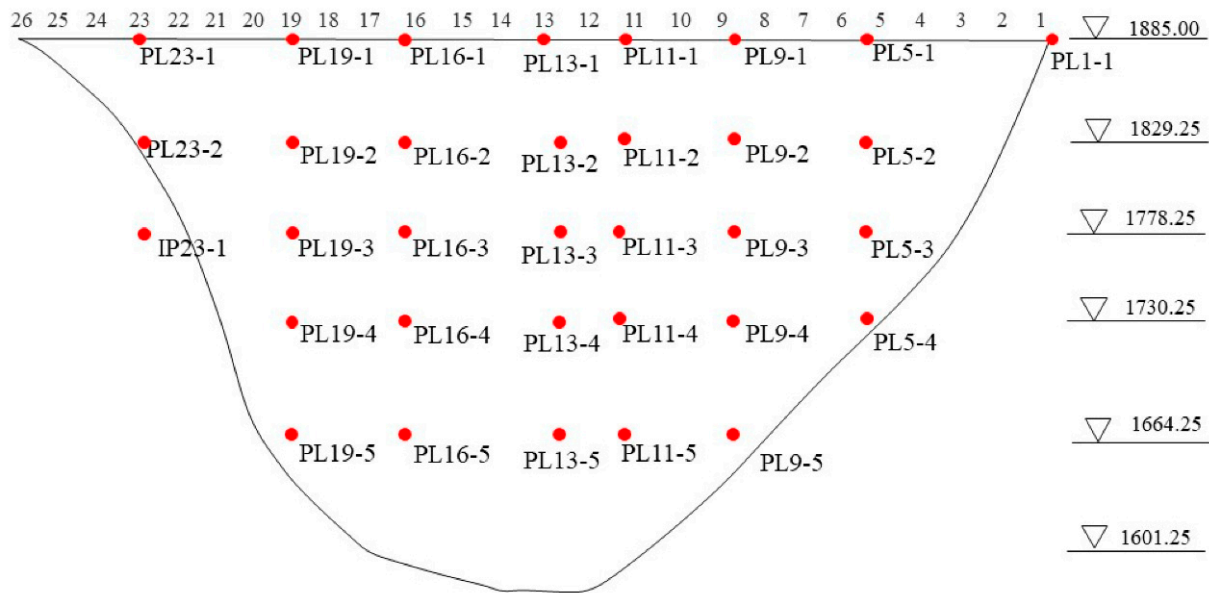


Figure 5. Distribution of measurement points on the concrete dam.

3.2. POA-VMD

The hyperparameters of VMD are optimized using the POA, including the number of decompositions and the maximum number of iterations, to achieve the best VMD modal component that can retain useful information the most.

In this study, to ensure the reproducibility and convergence of the hyperparameter optimization for Variational Mode Decomposition (VMD), the Pelican Optimization Algorithm (POA) was employed for parameter tuning. The main hyperparameters were configured as follows: a population size $N = 30$ was chosen to balance search space coverage and computational efficiency; the inertia/adjustment factor was set within the range $[0.4, 0.9]$ to dynamically balance exploration and exploitation; the maximum number of iterations was set to 200, with early termination triggered when the convergence threshold of the objective function fell below 10^{-6} , thereby ensuring computational convergence and stability.

A composite objective function based on reconstruction fidelity and modal independence was selected to simultaneously achieve noise suppression and preservation of original information. It is defined as:

$$J = \alpha \cdot (1 - \text{Corr}(x, \hat{x})) + \beta \cdot \sum_{i \neq j} |\text{Corr}(\text{IMF}_i, \text{IMF}_j)| \quad (16)$$

where x denotes the original signal, $\hat{x}$ represents the reconstructed signal from VMD, and $\text{Corr}(\cdot)$ indicates the correlation coefficient. The coefficients α and β are weighting factors (in this study, $\alpha = 0.6, \beta = 0.4$). The rationale for this objective function is twofold: the first term ensures high correlation between the reconstructed and original signals, thereby preventing information loss; the second term minimizes the correlation among IMF components to enhance the independence of the decomposed modes, which facilitates the separation of noise from useful signals. POA optimization seeks the optimal decomposition level and penalty factor for VMD by minimizing J , ultimately yielding a decomposition configuration that balances noise suppression and feature preservation.

To validate the effectiveness of the POA in optimizing VMD parameters, a comparative analysis was conducted with PSO and GA algorithms. Table 1 presents the optimal parameter combinations identified by different optimization algorithms along with their corresponding objective function values.

Table 1. Performance comparison of different optimization algorithms.

Optimization Algorithm	Optimal Mode Number K	Optimal Penalty Factor α	Min Objective Function Value	RMSE	MAE	R ²
POA	5	2000	0.156	0.293	0.202	0.992
PSO	6	1800	0.198	0.701	0.518	0.966
GA	7	3000	0.210	0.728	0.545	0.954

As evidenced in Table 1, the POA achieved the smallest objective function value of 0.156, indicating that the VMD optimized by POA yields the most effective outcome. This advantage is directly reflected in the performance of the final prediction model. The proposed POA-VMD-Attention-BiLSTM model attained the lowest RMSE of 0.293 and MAE of 0.202, along with an R² value closest to 1 (0.992), demonstrating significantly higher prediction accuracy compared to the alternative models.

Taking monitoring point PL5-3 as an example, the parameters of VMD were optimized using the Pelican Optimization Algorithm (POA), resulting in an optimal penalty factor of 2000 and a decomposition mode number of 5. The original time-series data was subsequently decomposed based on these optimized parameters. The parameters of the Savitzky–Golay filter are set to a window length of 11 and a polynomial order of 3. This combination has been experimentally proven to effectively suppress the residual high-frequency noise in the VMD reconstructed signal while best preserving its original trend and periodic modal characteristics. After smoothing processing, 5 IMF modal components are obtained. The component waveform diagrams of the deformation corresponding to the measurement point PL5-3 at different scales are obtained, as shown in Figure 6. From the decomposition results, IMF1–IMF2 mainly reflects low-frequency slowly varying components, reflecting the long-term evolutionary trends and the cumulative effects of external loads; IMF3 shows certain periodic fluctuations, which are somewhat related to seasonal temperature or water level changes; while IMF4–IMF5 have smaller amplitudes and present high-frequency disturbances, being more akin to random noise or the effects of short-term environmental factors.

3.3. Model Prediction

There are a total of 33 measurement points in the dam body. In this section, the dam deformation data of the three measurement points, PL5-3, PL16-2, and PL19-2, of the dam are taken as examples to verify the effect of the model proposed in this paper. PL5-3 is close to the dam shoulder rock mass, and PL16-2 and PL19-2 are close to the arch crown beam. The deformation data from this measurement point is representative. This study evaluates the effectiveness of the proposed model through a comparative analysis with several benchmark models: a VMD-BiLSTM model integrated with an attention mechanism, a standalone BiLSTM model without VMD processing, a POA-VMD-BiLSTM model without an attention mechanism, and a baseline BiLSTM model. This comparison aims to quantitatively validate the individual contribution of each module to the overall predictive performance. Modeling and analysis were conducted based on the monitoring data from 1 July 2013 to November 1, 2016. By comparing the validation effects of different time series proportions (70/30, 75/25, 80/20, and 85/15), the data is divided into training and testing sets using an 80:20 proportion. The performance indicators under different proportions are shown in Table 2. The model has undergone multiple experiments, and the main hyperparameters are shown in Table 3.

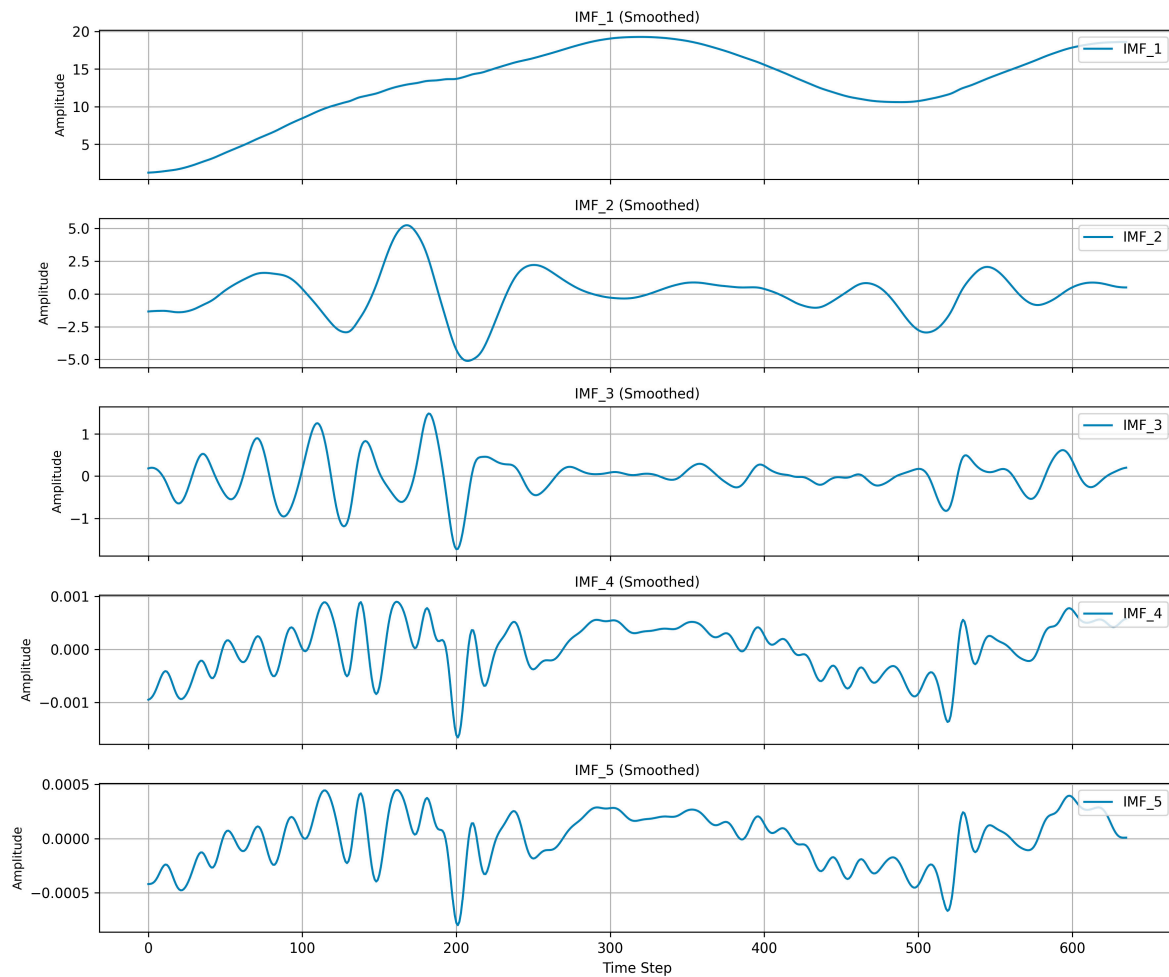


Figure 6. Waveform diagrams of each component of PL5-3 after POA-VMD.

Table 2. Performance Metrics under Different Proportions.

Proportion	70/30	75/25	80/20	85/15
MAE	0.241	0.219	0.202	0.220
RMSE	0.313	0.307	0.293	0.315
R ²	0.963	0.977	0.991	0.968

Table 3. Configuration of Main Hyperparameters for Model Training.

Hyperparameter	Learning Rate	Batch Size	Epochs	Dropout Rate
Value	0.001	16	200	0.3

The deformation variation curves of the dam at the three measurement points PL5-3, PL16-2 and PL19-2 are shown in Figure 7.

It can be observed from the figure that, in terms of the overall trend, all three curves show obvious periodic fluctuation characteristics, reflecting that the deformation of the dam exhibits periodic fluctuations over time.

Among them, PL16-2 has the largest amplitude of deformation, with a peak value close to 30 mm, and fluctuates violently, indicating that this location is relatively sensitive to external environmental factors. In contrast, the variation at PL5-3 and PL19-2 points is relatively small, the fluctuation is relatively stable, and the peak and off-peak ranges are concentrated between 10 and 20 mm. Furthermore, the deformation curves of the three monitoring points have a high degree of consistency on the time axis, indicating that their

deformation processes have good synergy and temporal consistency, which conforms to the typical overall force and response characteristics of the dam body.

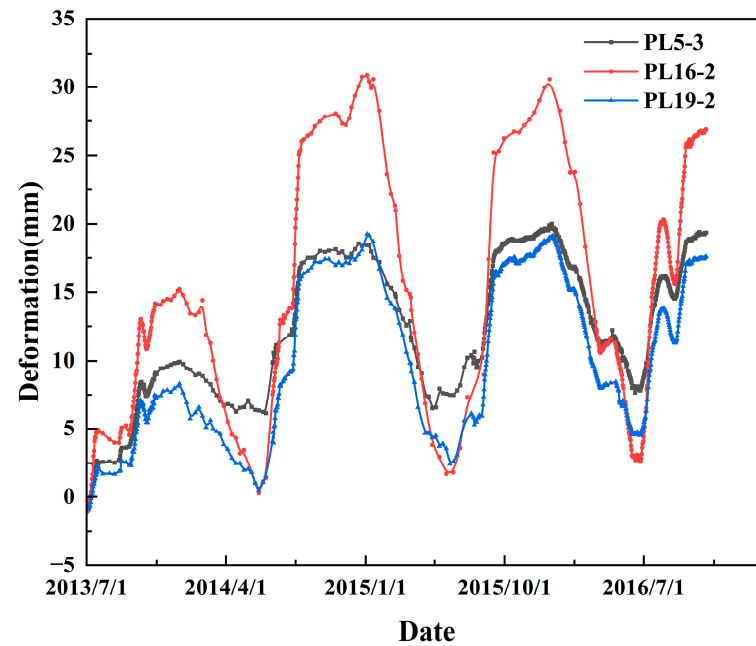
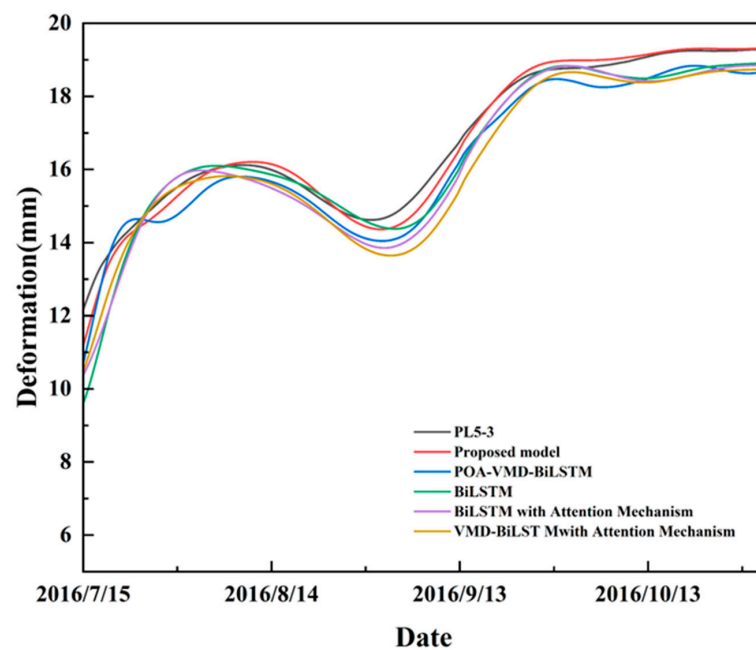


Figure 7. The deformation variation curves of the dam at the measurement points PL5-3, PL16-2 and PL19-2.

In conclusion, the periodicity, difference and synergy of the deformation data of the three measurement points provide a reliable basis for the construction and generalization performance evaluation of the subsequent prediction model.

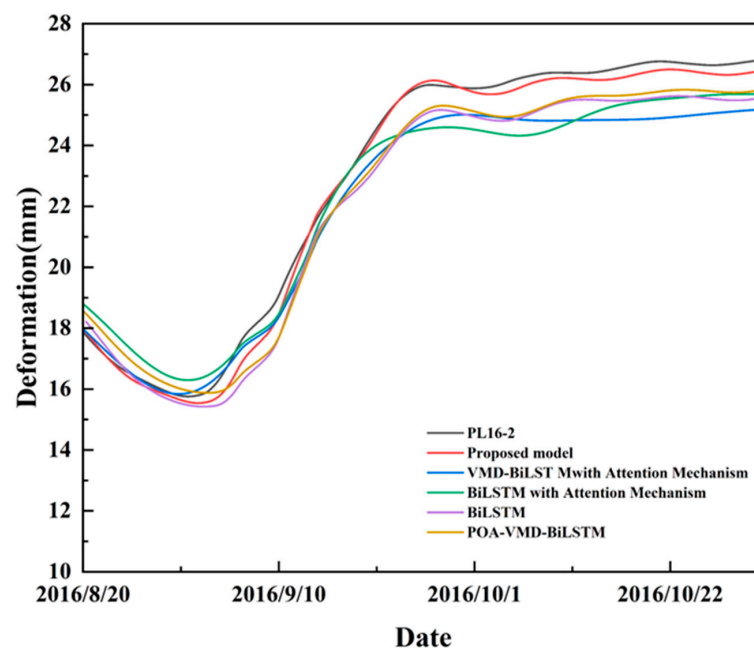
3.4. Results and Discussion

The prediction results of each measurement point of different models are shown in Figure 8.

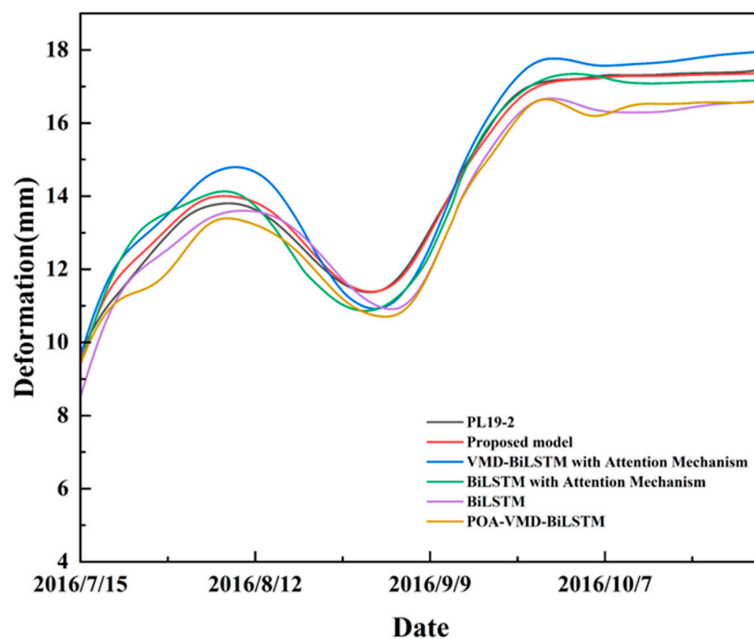


(a) PL5-3

Figure 8. Cont.



(b) PL16-2



(c) PL19-2

Figure 8. Deformation prediction results in the test set.

Figure 8 shows the deformation prediction of three measurement points over time. All the models can follow the general trend of the actual deformation of the dam. However, the other models deviate from the real deformation curve and the prediction accuracy is insufficient. In contrast, the proposed model is closer to the actual value, has a smaller deviation from the real deformation curve, and can better predict the deformation of the dam. This means that it has better generalization and accuracy in capturing complex trends.

The results show that the proposed model, through POA-VMD, combines the bidirectional long short-term memory model with the attention mechanism, significantly enhancing the model's ability to accurately capture and predict deformations. Specifically, the Pelican Optimization Algorithm (POA) effectively improves the selection efficiency of parameters for Variational Mode Decomposition (VMD), making the signal decomposition

process more adaptive and stable, thereby enhancing the extraction ability of key modal features in the original deformation sequence. The optimized various modal components are more physically interpretable, which is conducive to extracting the deep temporal structure in the subsequent modeling stage.

On this basis, the bidirectional Long Short-Term Memory Network (BiLSTM) combined with the Attention Mechanism further improves the model's response ability to the characteristics of key time series. BiLSTM comprehensively captures the forward and backward dependencies in the time series by using a bidirectional structure, while the attention mechanism dynamically allocates the weights of different time steps, improving the expression and prediction accuracy of the model in complex deformation patterns.

In conclusion, the model proposed in this study has significant advantages in capturing nonlinear and multi-scale temporal characteristics, can predict the evolution process of dam deformation more accurately, shows good generalization ability and robustness, and has high engineering application value.

To quantitatively compare the performance of the above-mentioned models, three statistical indicators were used: Root Mean square error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R^2). It should be noted that the units of MAE and RMSE remain consistent with the measured physical quantity (mm), thereby providing an intuitive understanding of the prediction error magnitude in physical terms. The MAE characterizes the overall mean deviation and is suitable for assessing the general level of error, while the RMSE is more sensitive to larger deviations, effectively highlighting the impact of outlier errors. In contrast, R^2 is a dimensionless metric, with values closer to 1 indicating a higher goodness of fit. Generally, model performance is considered superior when MAE and RMSE values are closer to 0 and R^2 is closer to 1. Their calculation formulas are as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (17)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|^2} \quad (18)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (19)$$

where $\hat{y}_i$ and y_i are the predicted and actual values of the i -th sample, $\bar{y}$ is the average value of the sample as a whole, and n is the length of the sample.

The results of the three evaluation indicators of each model are shown in Table 4.

Table 4. The evaluation index results of each model PL5-3, PL16-2 and PL19-2.

Model		Proposed Model	VMD-BiLSTM with Attention Mechanism	BiLSTM with Attention Mechanism	POA-VMD-BiLSTM	BiLSTM
PL5-3	MAE	0.202	0.622	0.562	0.569	0.495
	RMSE	0.293	0.768	0.693	0.682	0.667
	R^2	0.991	0.910	0.923	0.941	0.899
PL16-2	MAE	0.218	0.812	0.831	0.826	0.816
	RMSE	0.272	0.883	0.945	0.879	0.982
	R^2	0.996	0.950	0.943	0.958	0.940
PL19-2	MAE	0.170	0.489	0.446	0.717	0.635
	RMSE	0.253	0.557	0.488	0.775	0.732
	R^2	0.994	0.958	0.933	0.913	0.921

The results of the prediction set show that all models exhibit acceptable prediction performance. The MAE and RMSE at the three measurement points of the model proposed in this study are smaller than those of the other models, and R^2 is also closer to 1 compared with the other models. All of this demonstrates the superiority and accuracy of the predictive ability of the proposed model.

For the PL5-3 measurement point, the MAE value of the proposed model is 0.202 and the RMSE value is 0.293, both of which are smaller than the MAE values and RMSE values of the other models. Its R^2 is even closer to 1 compared with the other models, which is 0.991. PL16-2 has achieved an impressive R^2 value of 0.996. Among the three measurement points, the MAE value and RMSE value of the model proposed by PL19-2 were the smallest, which were 0.170 and 0.253, respectively, and its R^2 value was 0.994. The results were significantly better than those of the other models.

Quantitative analysis based on comparative results demonstrates that each module contributes significantly to model performance. Notably, the POA module provides the most substantial improvement, increasing R^2 by 8.87% and reducing MAE by 76.3% at measuring point PL19-2. The VMD module effectively reduces RMSE by 33.3% at the same point, while the attention mechanism contributes to a 73.6% reduction in MAE at measuring point PL16-2. The results indicate that the POA module plays a dominant role, whereas the VMD and attention mechanisms enhance performance substantially through feature decomposition and noise reduction, respectively. The synergistic integration of these three components achieves optimal predictive performance.

4. Summary

This study proposes a new hybrid model to address the limitations of traditional dam deformation prediction methods in dealing with long-term series data, further enhancing the prediction ability. The parameters of Variational Mode Decomposition (VMD) are optimized by using the Pelican Optimization algorithm (POA), and bidirectional long Short-Term Memory (BiLSTM) is combined with the attention mechanism to predict the deformation of the dam. In practical engineering applications, the accuracy and stability of the prediction of this model are significantly better than those of other models. Compared with other benchmark models, the proposed approach achieves an average improvement of 0.05 in R^2 while reducing MAE and RMSE by over 60% and 30%, respectively. At its best, the model attains an R^2 of 0.996 with an MAE as low as 0.170, underscoring its superior predictive capability.

Despite the satisfactory performance achieved, the computational efficiency of the proposed framework, primarily attributed to the iterative nature of the POA-VMD optimization, presents a potential constraint for scenarios demanding real-time forecasting. Future work will prioritize developing a lightweight model variant and exploring transfer learning strategies to enhance deployment efficiency. Furthermore, while the current architecture demonstrated robustness, systematically automating the selection of hyperparameters (e.g., via Bayesian optimization) could further improve its adaptability and user-friendliness for broader engineering applications. Extending the model to integrate multi-source monitoring data (e.g., stress and seepage) also represents a promising direction for developing a more comprehensive structural health evaluation system.

Against the backdrop of the continuous deepening of intelligent management of infrastructure in our country and the increasing demands for the accuracy, reliability and timeliness of dam safety monitoring data in the field of water conservancy projects, the emergence of this model provides us with a new exploration direction. It not only performs outstandingly in terms of prediction accuracy and stability but also integrates deep learning technology, featuring scalability and generalizability. It is expected to lay a solid

foundation for enhancing the national dam safety monitoring standards. Based on this, it is suggested that the outlier prevention methods based on artificial intelligence be incorporated into official regulations, a multi-agency data coordination mechanism be established, and model-driven prediction and real-time outlier detection be applied in policy-making to promote evidence-based decision-making in dam risk management.

This model and related strategies not only improve the accuracy of fault error detection in dam monitoring data but also provide theoretical and practical guidance for the future infrastructure risk governance system. Subsequently, its application within the framework of national security and disaster reduction can be further explored.

Author Contributions: Methodology, Z.Z., C.F., M.Y. and S.S.; software, C.F., M.Y. and S.S.; formal analysis, X.W. and J.L.; investigation, H.Z., Z.X. and G.D.; resources, H.Z., Z.X. and G.D.; writing—review and editing, Z.Z., C.F., M.Y. and S.S.; supervision, G.D.; project administration, H.Z. and Z.X.; validation, G.D., G.D. and J.L.; writing—original draft preparation, Z.Z.; data curation, X.W.; funding acquisition, M.Y., H.Z. and Z.X. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research and Development Program of China (2024YFC3214903), the Jiangsu Province Natural Science Fund (BK20241743), the Hunan Water Conservancy Technology Project (XSKJ2024064-50), the Central Public-Interest Scientific Institution Basal Research Fund, NHRI (Y424013), the Water Resources Science and Technology Program of Hunan Province (Grant number XSKJ2022068-07), the Plan Project of Water conservancy Science and Technology of Zhejiang Province (Project no. RC2183 and RC2457), Hohai University, and the Central Universities' Basic Research Operating Expenses Project (No. B230201011).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

Conflicts of Interest: Author Huaijun Zhang and Zhengfei Xu were employed by the company Lianyungang Water Conservancy Project Construction Management Center. Guoqiang Ding was employed by the company Ningbo Daxie container terminal co., ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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