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A Multi-Point Joint Prediction Model for High-Arch Dam Deformation Considering Spatial and Temporal Correlation

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Abstract: Deformation monitoring for mass concrete structures such as high-arch dams is crucial to their safe operation. However, structure deformations are influenced by many complex factors, and deformations at different positions tend to have spatiotemporal correlation and variability, increasing the difficulty of deformation monitoring. A novel deep learning-based monitoring model for high-arch dams considering multifactor influences and spatiotemporal data correlations is proposed in this paper. First, the measurement points are clustered to capture the spatial relationship. Successive multivariate mode decomposition is applied to extract the common mode components among the correlated points as spatial influencing factors. Second, the relationship between various factors and deformation components is extracted using factor screening. Finally, a deep learning prediction model is constructed with stacked components to obtain the final prediction. The model is validated based on practical engineering. In nearly one year of high-arch dam deformation prediction, the root mean square error is 0.344 and the R^2 is 0.998, showing that the modules within the framework positively contribute to enhancing prediction performance. The prediction results of different measurement points as well as the comparison results with benchmark models show its superiority and generality, providing an advancing and practical approach for engineering structural health monitoring, particularly for high-arch dams.

Keywords: dam deformation monitoring; deep learning; spatiotemporal cluster; successive multivariate variational mode decomposition; factor screening



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1. Introduction

High-arch dams, like all concrete dams, are subjected to various environmental loads during operation. These external influences can result in the degradation of both the material and structural integrity of high-arch dams. Fortunately, deterioration behavior is a gradual process, which gradually develops from structural local failure to overall instability. Accidents could potentially be prevented through the implementation of scientific and efficient techniques for real-time monitoring of the operational conditions of high-arch dams, promptly detecting any anomalies, and implementing necessary measures [1]. Deformation is a visible indicator of structural alterations in high-arch dams [2], demonstrating the importance of establishing a dependable and precise deformation monitoring model. Such a model holds significant value in comprehending the operational state of high-arch dams and ensuring their safe and enduring function. Moreover, it constitutes a crucial component of advancing intelligent water conservancy initiatives as part of the broader “four pres” framework [3,4].

Monitoring methods for deformation are categorized into mechanics-driven and data-driven approaches based on the modeling process [5]. Mechanics-driven models typically rely on the finite element method, with model parameters possessing clear mechanical significance. However, the deformation mechanisms of high-arch dams involve intricate multifaceted factors, such as high total water thrust, reservoir valley deformation influence, dam overhang action during construction, solar radiation, etc. This poses challenges in establishing a model capable of encompassing these processes, thereby requiring a substantial time investment. Conversely, data-driven models construct a mathematical framework by scrutinizing the causal connections between the measured deformation of high-arch dams and their influencing factors. Furthermore, they are used for future predictions. The big data analysis ability, high prediction accuracy, and extraction ability of these models' complex information have received increasing attention from scholars [6].

Generally, data-driven deformation models can be categorized into statistical, artificial intelligence, and hybrid models. Statistical models employ factorial regression models or deformation time series autoregression to forecast displacement [7,8]. These models are relatively simple and only require specific formulas for prediction. However, they are mainly based on linear assumptions and smooth data, which are insufficient to capture nonlinear deformation characteristics. Advancements in artificial intelligence technology have led to the application of machine learning algorithms in deformation modeling [9–14]. These approaches have significantly enhanced the effectiveness of addressing the nonlinearities inherent in monitoring data. However, as with conventional statistical models, most intelligent models based on machine learning focus only on simulating the static regression relationship between factors and deformation, which only performs well in short-term prediction. Moreover, the dynamic time correlation characteristics of the deformation time series are neglected. Given that environmental factors may exhibit a lag effect on dam deformation, overlooking time dependence can detrimentally impact prediction outcomes. To address these challenges, deep learning algorithms tailored for time series analysis have been increasingly utilized in the dam health monitoring field [15–19]. Their application has facilitated the realization of long-term predictions for deformation series. Attentional mechanisms have also been introduced into deep learning algorithms by focusing on factor features that are more important for long-term deformation in time and factor dimensions [20,21].

The deformation of high-arch dams is a complex manifestation of the structural performance resulting from the combined influence of each section of the dam. However, deformation models are primarily established from a single modeling perspective for individual monitoring points. Moreover, they typically utilize the same input factors for deformation across various measurement points, thereby overlooking the spatial variability of each part of the dam [22]. By neglecting the spatial correlation among multiple deformation points, these models fail to capture the overall deformation behavior of arch dams comprehensively. Therefore, it is crucial to consider the potential correlations between different locations of the dam body in conjunction with the single-point deformation prediction model. To enhance model prediction results, it is essential to incorporate different factor inputs to delineate the spatial variability across different sections of the dam. This approach enables the realization of spatiotemporal synergistic analysis of dam deformation [23]. Inspired by spatiotemporal data modeling, the monitoring model directly incorporates the spatial correlation of deformation data from multiple measurement points. This is achieved by employing a clustering method to group the measurement points, effectively partitioning the dam body's deformation into distinct zones. Subsequently, different spatial influencing factors (SIFs) are assigned as inputs to the measurement points based on the clustering results. This approach accounts for the variability in deformation behavior across different sections of the dam body, thereby improving the model's accuracy and effectiveness.

Deformation values usually have the characteristics of nonlinearity and high volatility. The direct analysis and prediction of a single prediction model may not be consistent between the fluctuating and non-fluctuating phases of the deformation values of the dam.

Consequently, a combined model is constructed based on “decomposition–prediction–reconstruction” [24,25]. In general, the combined model mitigates the high volatility observed in the original series, yielding superior prediction performance compared to individual statistical or artificial intelligence models. However, among common decomposition algorithms [26–29], the basis function and decomposition order of the wavelet need to be determined artificially. Empirical mode decomposition lacks mathematical theoretical support and is sensitive to noise and sampling frequency [30]. Adaptive decomposition can be performed for variational mode decomposition (VMD), but the number of modes must be manually formulated [29]. Successive multivariate variational mode decomposition (SMVMD) [31] represents an enhanced iteration of MVMD. It effectively addresses the coupling relationship and correlation between multiple measurement points of deformation of high-arch dams during decomposition without manually determining the number of decomposition modes. Therefore, SMVMD is fitted to decompose the multivariate deformation data of measurement points and their SIFs. Meanwhile, in the combined model, few studies have considered the influence of environmental factors and SIFs on each decomposition mode. Incorporating all factors for each mode component can indeed augment the volume of information. However, the inclusion of numerous factors may lead to challenges such as increased computational complexity, overfitting, and marginal improvements. With so many external factors, feature screening can be used to reduce overfitting and improve training speed. In this paper, the influencing factor was selected by factor filtering as the corresponding influencing factor of each mode among all the factors.

This article presents a novel multi-point joint monitoring framework tailored specifically for addressing the deformation prediction challenges associated with high-arch dams. It contains several modules, such as spatiotemporal clustering, sequence decomposition, factor screening, and deep learning prediction. Its main content is as follows: Firstly, considering the spatiotemporal correlation between the measuring points, clustering method is used to partition them. Subsequently, the SMVMD technique is applied to decompose the data, facilitating the extraction of mode components from the measurement points and enabling the construction of corresponding SIFs. Accordingly, the component factor sets are constructed. The optimal factor set of each mode component is obtained by factor filtering, and its influence relationship on the decomposed mode components is portrayed. Then, the CNN-BiGRU-AM is used to construct the prediction model and stacked to obtain the final results. The ablation test and analysis are employed to explore the prediction performance to verify the effectiveness of the framework combined with practical engineering.

The contributions of this study based on the above description are as follows:

- (1) The SMVMD technique is introduced to realize the same-frequency decomposition of the measurement points within the same area, which reduces the complexity of the multi-point displacement sequence.
- (2) By combining the decomposition technique with mRMR, the relationship between the displacement subsequence and the influencing factors is well established, which then better explains the deformation characteristics of high-arch dams.
- (3) The constructed deformation prediction framework incorporates various modules to improve the prediction accuracy and reduce the complexity of deformation data in different aspects, which can provide specific guidance for the management of water conservancy projects represented by high-arch dams.

The subsequent section introduces the theory adopted, the third part introduces the framework construction and the evaluation indexes adopted in the proposed monitoring framework. The fourth part carries out the performance validation and analysis through an actual case study. The fifth part concludes the whole paper.

2. Methodology

This section focuses on the principles of the algorithms employed in the proposed framework, including clustering, decomposition, feature screening, and a deep learning model.

2.1. Clustering Method for Deformation

The K-means time series clustering approach [32] is employed to categorize multiple measurement points of arch dams into distinct clusters. The fundamental principle behind this approach is to minimize the dissimilarity among samples within the same cluster while maximizing the dissimilarity between clusters, thereby reflecting the spatial correlation among similar measurement points and the spatial variability among dissimilar ones. This clustering process lays the groundwork for selecting appropriate spatial influencing factors (SIFs) in subsequent sections. The Dynamic Time Warping (DTW) distance between measurement points serves as the similarity criterion for K-means clustering. By optimizing a criteria function, specifically the sum of squared errors (SSE), multiple measurement series are allocated into J clusters.

$$SSE = \sum_{j=1}^J \sum_{X_i \in n_j} dtw^2(X_i, c_j) \quad (1)$$

where $c_j = \frac{1}{n_j} \sum_{X_i \in C_j} X_i$ is the mass center of cluster C_j , X_i is the sample point, and n_j is the number of points in cluster C_j .

The implementation process primarily consists of the following steps:

Step 1: Initialize by randomly selecting k time series as clustering centers.

Step 2: Calculate the DTW distance between each time series vector and each clustering center point. Assign each measurement point time series to the cluster center with the closest distance.

Step 3: Update the clustering center by computing the average of all measurement point time series in the cluster, yielding the new clustering center.

Step 4: Repeat steps 2 and 3 until either the clustering center remains unchanged or the maximum number of iterations is reached.

2.2. SMVMD for Multi-Point Deformation Monitoring Data

Deformation is generally affected by various load factors (LFs); the deformation time series has high nonlinearity and volatility. Utilizing the original time series directly may indeed impact the accuracy of the model. Consequently, simultaneous multiscale decomposition of multi-point monitoring data using multivariate mode decomposition reduces the complexity of the monitoring series before forecasting.

SMVMD, as an extension of VMD, inherits the adaptive recursion-based mode extraction method from SVMMD. It offers several advantages, including the elimination of the need to input the number of modes in advance. The multivariate modulation oscillation model in MVMD is also introduced to achieve the multichannel extension of SVMMD. Therefore, the algorithm can take advantage of the mutual information between multiple points to obtain more stable and accurate mode components.

Set the dam multi-point deformation time series as $\mathbf{Y}(t) = [y_1(t); y_2(t); \dots; y_d(t)]$, where d is the index of the measurement point, $d = 1, 2, \dots, D$. SMVMD is used to decompose $\mathbf{Y}(t)$ into K multivariate intrinsic mode functions (MIMFs) $\mathbf{u}_k(t)$, $k = 1, 2, \dots, K$, as follows.

$$\begin{cases} \mathbf{Y}(t) = \sum_{k=1}^K \mathbf{u}_k(t) \\ \mathbf{u}_k(t) = [u_{k,1}(t), u_{k,2}(t), \dots, u_{k,c}(t), \dots, u_{k,d}(t)] \\ u_{k,c}(t) = a_{k,c}(t) \cos(\phi_{k,c}(t)) \end{cases} \quad (2)$$

where $\mathbf{u}_{k,c}(t)$ is an amplitude-modulated frequency signal, and $a_{k,c}(t)$ and $\phi_{k,c}(t)$ are the magnitude function and phase function of $\mathbf{u}_{k,c}(t)$, respectively.

SMVMD is a recursive method that separates the MIMF components step by step. Hence, the parameter k is not predefined but rather determined by the recursive conver-

gence criterion. $\mathbf{Y}(t)$ is divided into the k -th MIMF component and the multivariate residual in the recursive process, which is shown below.

$$\begin{cases} \mathbf{Y}(t) = \mathbf{u}_k(t) + \mathbf{Y}_R(t) \\ \mathbf{Y}_R(t) = \sum_{i=1}^{k-1} \mathbf{u}_i(t) + \mathbf{Y}_u(t) \end{cases} \quad (3)$$

where $\mathbf{Y}_u(t)$ is the unprocessed part of the multi-point deformation time series.

The extraction of the k -th MIMF problem is reformulated as a constrained minimization problem, employing several of the same criteria as SVMMD, as follows:

$$\begin{cases} \min_{\{u_k, \omega_k, Y_R\}} \{\alpha J_1 + J_2 + J_3\} \\ J_1 = \sum_{d=1}^D \|\partial_t \left[(\delta(t) + \frac{j}{\pi t}) * u_{k,d}(t) \right] e^{-j\omega_k t}\|_2^2 \\ J_2 = \sum_{d=1}^D \|\hat{\beta}_k(\omega) \hat{y}_{r,d}(\omega)\|_2^2 \\ J_3 = \sum_{d=1}^D \sum_{i=1}^{k-1} \|\hat{\beta}_k(\omega) \hat{y}_{r,d}(\omega)\|_2^2 \\ \text{s.t. } \mathbf{u}_k(t) + \mathbf{Y}_R(t) = \mathbf{Y}(t) \end{cases} \quad (4)$$

where ω_k is the central frequency of each MIMF component; $[\delta(t) + j/(\pi t)] * u_{k,d}(t)$ is the resolved signal for each MIMF component; $e^{-j\omega_k t}$ is the predicted central frequency of each resolved signal; and $\hat{\beta}_k(\omega)$ is the filter.

To solve the constrained optimization problem of the above equation, construct its augmented generalized Lagrange function, which is:

$$\begin{aligned} \mathcal{L}\{\mathbf{u}_k, \omega_k, \mathbf{Y}_R\} = & \alpha J_1 + J_2 + J_3 + \sum_{d=1}^D \|y_d(t) - (u_{k,d}(t) + y_{u,d}(t) + \sum_{i=1}^{k-1} u_{i,d}(t))\|_2^2 \\ & + \sum_{d=1}^D \left\langle \lambda_d(t), y_d(t) - \left(u_{k,d}(t) + y_{u,d}(t) + \sum_{i=1}^{k-1} u_{i,d}(t) \right) \right\rangle \end{aligned} \quad (5)$$

where $\lambda_d(t)$ is the Lagrange multiplier of the d -th measurement point. α is the regularization parameter.

A detailed SMVMD solution procedure for the multi-point series can be found in reference [31]. The saddle points of the above-constrained model are solved using the alternating direction multiplier algorithm (ADMM) to decompose the arch dam multi-point time series $\mathbf{Y}(t)$ into K MIMF components, which are arranged from low to high signal frequencies for further use.

2.3. Deep Learning-Based Deformation Monitoring Model

2.3.1. Model Input Factors

Usually, hydrostatic, temperature, and time effects are chosen to construct a statistical model to explain the displacement of arch dams [33], and the HTT model expression for arch dams is as follows:

$$\begin{aligned} \delta &= \delta_H + \delta_T + \delta_\theta \\ &= a_0 + \sum_{i=1}^4 a_i H^i + \sum_{i=1}^d b_i T_i + c_1 \theta + c_2 \ln \theta \end{aligned} \quad (6)$$

where a_i , b_i , and c_i represent the fitting coefficients; H is the reservoir depth; T_i is the temperature factor, and d is the number of temperature factors. Considering the heat transfer effect within concrete, a hysteresis effect exists between the internal temperature field of concrete and the measured air temperature. The temperature factors are categorized as follows: T_0 , T_1 , T_2 , T_{3-5} , T_{6-15} , and T_{16-30} . Here, T_0 , T_1 , and T_2 represent the measured

air temperature on the day of monitoring, the day before, and two days prior, respectively. Meanwhile, T_{3-5} , T_{6-15} , and T_{16-30} denote the average temperatures over the preceding 3–5 days, 6–15 days, and 16–30 days, respectively. $\theta = t/100$, where t denotes the number of days from the starting date to the monitoring date.

The measurement points are subject to the same environmental quantities. Furthermore, there are coupling effects with different associated measurement points, especially the neighboring ones, so the spatial correlation between measurement points can also be used as a basis for modeling; that is, on the basis of selecting the factor proposed in Equation (5) as input factors, the other measurement points associated with the target point (TP) are introduced as the SIFs to be used. m is the number of points associated with the TP. The initial input factor set F_{ini} for multi-point deformation is expressed as follows:

$$F_{ini} = \{H, H^2, H^3, H^4, T_0, T_1, T_2, T_{3-6}, T_{7-15}, T_{16-30}, \theta, \ln\theta, SIF_1, \dots, SIF_m\} \quad (7)$$

2.3.2. Screening of Input Factors

The correlation and redundancy of factors within the model can significantly impact the accuracy of deformation prediction. Max-Relevance and Min-Redundancy (mRMR) is a feature-screening method grounded in mutual information. Its objective is to maximize the correlation while minimizing the redundancy between the model factors and the deformation of the arch dam. By utilizing mRMR, factors are screened and an optimal factor set is selected, thereby enhancing the accuracy of the model's predictions.

x_1 and x_2 are two consecutive random variables. Their probability densities and joint probability densities are $p(x_1)$, $p(x_2)$, and $p(x_1, x_2)$, respectively. The correlation between them can be obtained as:

$$I(x_1, x_2) = \iint p(x_1, x_2) \log \frac{p(x_1, x_2)}{p(x_1)p(x_2)} dx_1 dx_2 \quad (8)$$

Thus, the guidelines for the calculation of maximum relevance and minimum redundancy are obtained:

$$\begin{cases} G(F, y), G = \frac{1}{|F|} \sum_{f_m \in F_{ini}} I(f_m, y) \\ H(F), H = \frac{1}{|F|^2} \sum_{f_m, f_n \in F_{ini}} I(f_m, f_n) \end{cases} \quad (9)$$

where F is the set of factors; $I(f_m, y)$ is the correlation between the factor f_m and the measurement sequence y ; $I(f_m, f_n)$ is the mutual information of the factors f_m and f_n ; G is relevance; and H is redundancy. Finally, the factors in the F_{ini} are ranked by an evaluation function. The more advanced the feature, the stronger the dependency between the feature and the target.

$$\max \Phi(G, H), \Phi = G - H \quad (10)$$

The incremental search algorithm can be implemented to solve the above evaluation function; that is, to add a new q -th factor from the $q - 1$ factors that have been selected to maximize the value of the following equation.

$$\max_{f_n \in X - F_{q-1}} \left[I(f_m, y) - \frac{1}{q} \sum_{f_m \in F_{q-1}} I(f_m, f_n) \right] \quad (11)$$

2.3.3. CNN-BiGRU-AM

Arch dam deformation needs to consider the problems of spatiotemporal data information association and multi-dimensional data feature extraction. Convolution neural networks (CNNs) can extract the complex connection between the LFs and SIFs in the high-dimensional space to form the feature vectors. Bidirectional Gated Recurrent Units (BiGRUs) can capture the long- and short-term information within the time series and use

a rolling strategy to make the prediction. The attention mechanism (AM) assigns different weights to feature components after computational processing to highlight important features and enhance the computational speed of the model. Combined with these three advantages, the CNN-BiGRU-Attention fusion network is constructed as shown in Figure 1. The components are described in detail as follows.

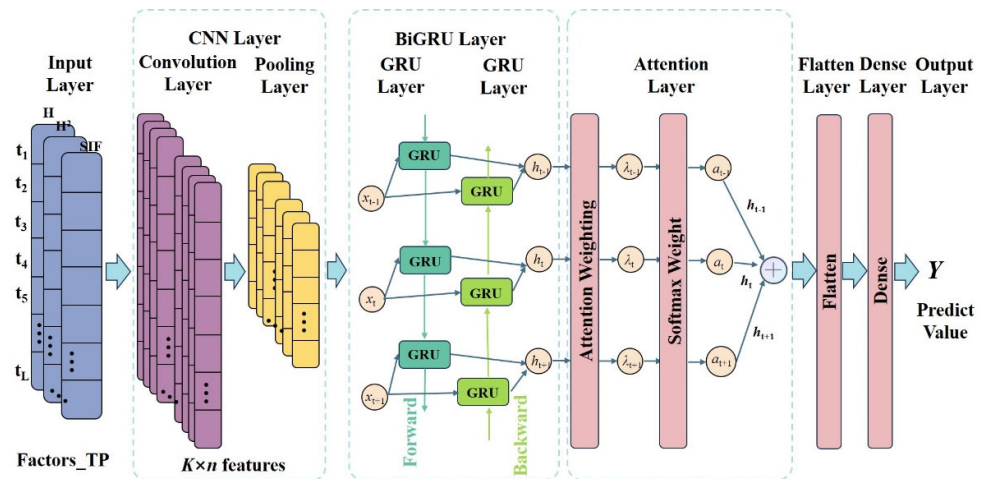


Figure 1. CNN-BiGRU-AM framework.

1. CNN

The CNN model primarily comprises the following layers: the input layer, a convolutional layer, a pooling layer, and a fully connected layer. Using the method of local linking and weight sharing, the data are perceived locally using a sliding window, and complex local features are effectively extracted from the influence factors. Taking the influence factors as the input of the model, a one-dimensional CNN is used to generate feature vectors by scanning the input sets. Finally, the features are processed and passed into the BiGRU network. Regarding parameter settings, the ReLU activation function is employed during the convolution process.

2. BiGRU

The GRU model [34] controls information input and memory and outputs predictions through a gating mechanism while retaining long-term monitoring information. It merges the forgetting and input gates of LSTM into the update gate. The update gate combines the information from the previous time step with the input vector of the current time step in the current hidden state, while the reset gate selectively forgets information in the hidden state from the previous moment.

The BiGRU model comprises two GRUs with opposite propagation directions. Output layer data are determined by both GRUs, rendering the model well suited for addressing multifactorial and complex condition problems. Given that the deformation of arch dams is influenced by both LFs and SIFs, the BiGRU model can effectively leverage the information embedded within the deformation and its associated influencing factors. BiGRU is defined in Equation (12).

$$\begin{cases} \vec{h}_t = GRU(x_t, \vec{h}_{t-1}) \\ \overleftarrow{h}_t = GRU(x_t, \overleftarrow{h}_{t-1}) \\ h_t = w_t \vec{h}_t + v_t \overleftarrow{h}_t + b_t \end{cases} \quad (12)$$

where $GRU(\cdot)$ represents a nonlinear transformation of the time series; x_t is the input factor; $\vec{h}_{t-1}$ and $\overleftarrow{h}_{t-1}$ are the forward and backward hidden layer state output, respectively; w_t and v_t represent the corresponding weights; and b_t represents the hidden layer bias of h_t .

3. AM

AM highlights key features by assigning different weights to the feature vectors, giving enough attention to important features, and ignoring irrelevant information. It is combined with CNN and BiGRU to improve the model's efficiency after the feature extraction and temporal analysis of the input data, respectively. The calculation equation is as follows:

$$\begin{cases} \lambda_t = \text{Tanh}(w^T h_t + b_t) \\ a_t = \text{Softmax}(\lambda_t) \\ v_t = \sum_t h_t a_t \end{cases} \quad (13)$$

where h_t is the BiGRU layer output considered as the input of the AM, λ_t is the attention probability distribution, a_t is the normalized attention layer weights, and v_t is the new feature vector after the transformation of the AM. Finally, the result is mapped by the flatten layer to obtain the prediction result.

3. Framework for the High-Arch Dam Deformation Monitoring Model

3.1. Main Steps of Construction

This section focuses on the construction of the clustering-SMVMD-mRMR-CNN-BiGRU-AM framework for multi-point joint monitoring of arch dam deformation. Figure 2 indicates that the framework mainly consists of four steps: classifying multi-point measurement, displacement influence factor construction, influence factor screening, and deformation prediction.

Step 1: Multi-point data clustering. The target arch dam multi-point deformation data are selected. Then, the points are spatially clustered into subclasses by the k -means method.

Step 2: Displacement influence factor construction. The TP is selected, and the spatially related points within the same class are taken as its SIFs. SMVMD decomposes the multi-point deformation time series data within the same class to obtain MIMF components to reduce the complexity. On this basis, the MIMF components are arranged from low to high frequency and re-grouped into K groups. The k -th group of MIMF components is $\{\text{MIMF}_{k,TP}, \text{MIMF}_{k,1}, \text{MIMF}_{k,2}, \dots, \text{MIMF}_{k,m}\}$, where $\text{MIMF}_{k,TP}$ is the k -th component of the TP. $\text{MIMF}_{k,m}$ is the k -th component of the m -th point spatially related to the TP and considered as a SIF for the $\text{MIMF}_{k,TP}$ component. It and the external LFs form the initial input factors set F_{ini} for $\text{MIMF}_{k,TP}$.

Step 3: Influence factor screening. The optimal factor set F_s matched with each MIMF component of the TP is extracted from the set F_{ini} by mRMR.

Step 4: Deformation prediction. Set the parameters of the CNN-BiGRU-Attention model and construct the prediction model of each component. The input factor of each model is set as $F_s(k)$, and the output is the TP component displacement. The training set is utilized as the learning data to train the deep learning models. After completing the training, the mode deep learning models sequentially obtain the predictions and stack them together to obtain the final prediction.

3.2. Prediction Evaluation

To evaluate the prediction effect of the model, four evaluation indexes, namely, the goodness-of-fit R^2 , mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE), are introduced.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y(t) - \hat{y}(t))^2}{\sum_{i=1}^n (\overline{y(t)} - \hat{y}(t))^2} \quad (14)$$

where n is the number of predictions; $y(t)$ is the measured value; and $\hat{y}(t)$ is the predicted value. The range of R^2 is $[0, 1]$, with values closer to 1, indicating the better fit of the model.

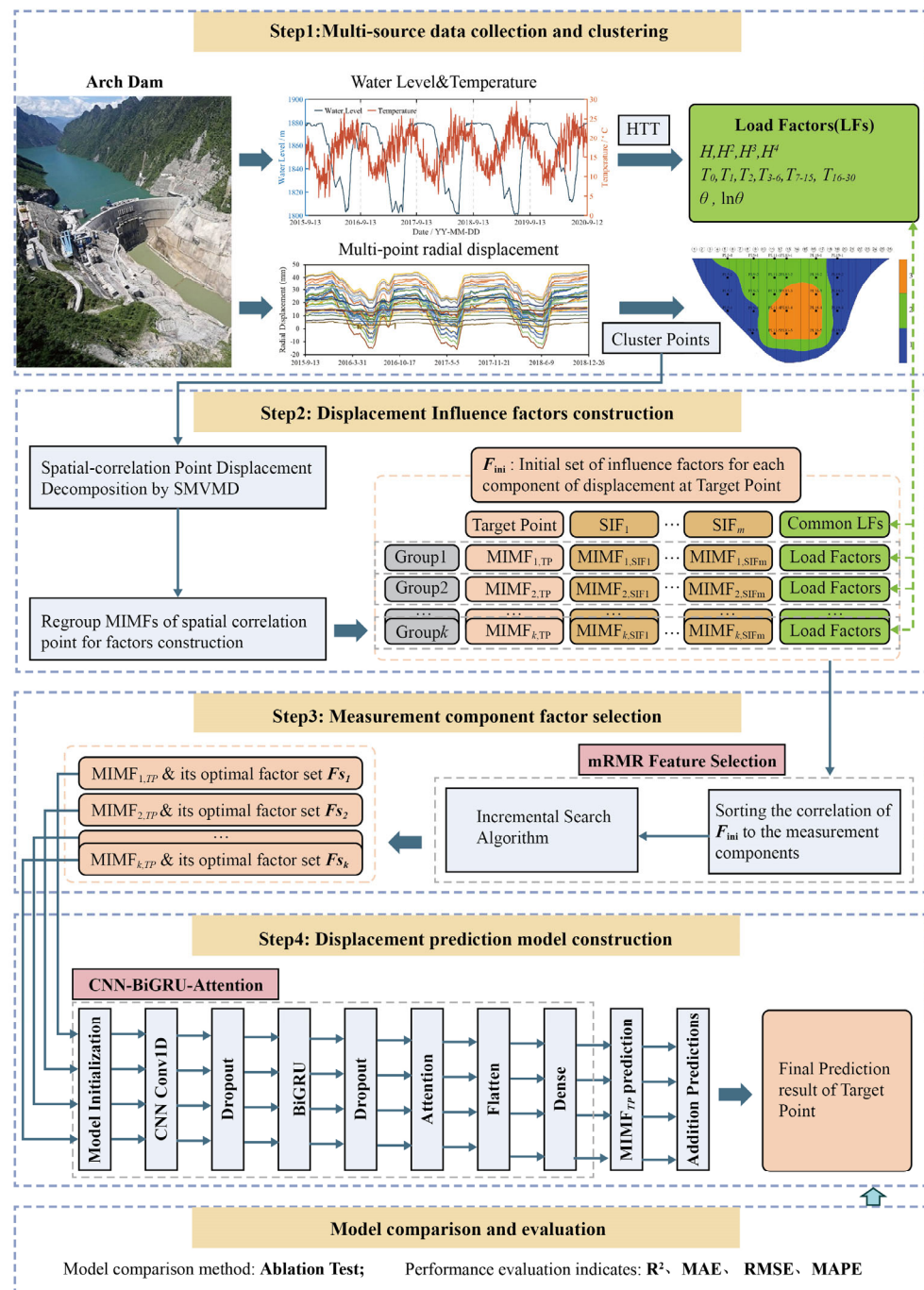


Figure 2. Flowchart of the proposed model.

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{\hat{y}(t) - y(t)}{y(t)} \right| \times 100\% \quad (15)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y(t) - \hat{y}(t))^2} \quad (16)$$

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

It is worth noting that a smaller MAPE, RMSE, and MAE indicate a better effect of the model.

3.3. Computational Complexity Analysis

Based on the above, the proposed computational strategy involves several algorithms in several steps. The computational complexity of each step is discussed to ensure the effectiveness of the proposed strategy. The nomenclature is described in Table 1. The computational complexity of each step is detailed in Table 2.

Table 1. Nomenclature table for Table 2.

Symbol	Description
c	Number of input measurement points
n	Length of the sequence of input points
q	Number of clusters
p	Maximum number of iterations
K	Number of MIMFs
f	Number of influencing factors
w	Number of convolutional kernels
s	Size of the convolutional kernel
m	Number of hidden units of the BiGRU
d	Dimension of the attentional features

Table 2. Computational complexity of the steps in the framework.

Step	Step 1	Step 2	Step 3	Step 4
Computational complexity	$O(pcnq)$	$O(pcnK)$	$O(Kf^3 + Kf^2)$	$O(K(wsn + nm^2 + n^2d))$

4. Case Study

The accuracy of the proposed model was verified by taking the multi-point deformation data of a concrete arch dam as a case study. The chosen arch dam is one of the most representative dams in China and the world. Its construction adopts the world's most advanced arch dam technology, which has high engineering risks. By studying this arch dam, we determined the applicability and effectiveness of our proposed method when facing complex engineering problems.

4.1. Project Review and Data Information

The arch dam is situated along the Yalong River in Sichuan Province, China. The multi-year average streamflow at the dam site is $1220 \text{ m}^3/\text{s}$, and the multi-year average annual runoff is 38.5 billion m^3 . Its foundation surface stands at an elevation of 1580.0 m, while the maximum height of the dam reaches 305.0 m, with a total of 25 dam sections. The normal storage level is 1880 m. The total storage capacity is 7.76 billion m^3 , and the regulatory storage capacity is 4.91 billion m^3 , which is an annual regulatory reservoir. The foundation rock is marble. The dam was constructed with zoned concrete casting, with a concrete elastic modulus of 32~39 GPa and concrete density of $2475 \text{ kg}/\text{m}^3$. Plumb lines were installed in seven dam sections to monitor the horizontal displacement of the dam body. The horizontal displacement data (upstream and downstream direction, downstream is positive) of a total of 29 measurement points on the plumb line of the 5#, 9#, 11#, 13#, 16#, and 19# dam sections were selected for analysis. The selected measurement points are shown in Figure 3a. The analysis period was from 13 September 2015 to 12 September 2020, with five years of valid deformation data. Among them, the first 80% of the measurements were used for model training. The last 20% of the measurements were utilized for model testing.

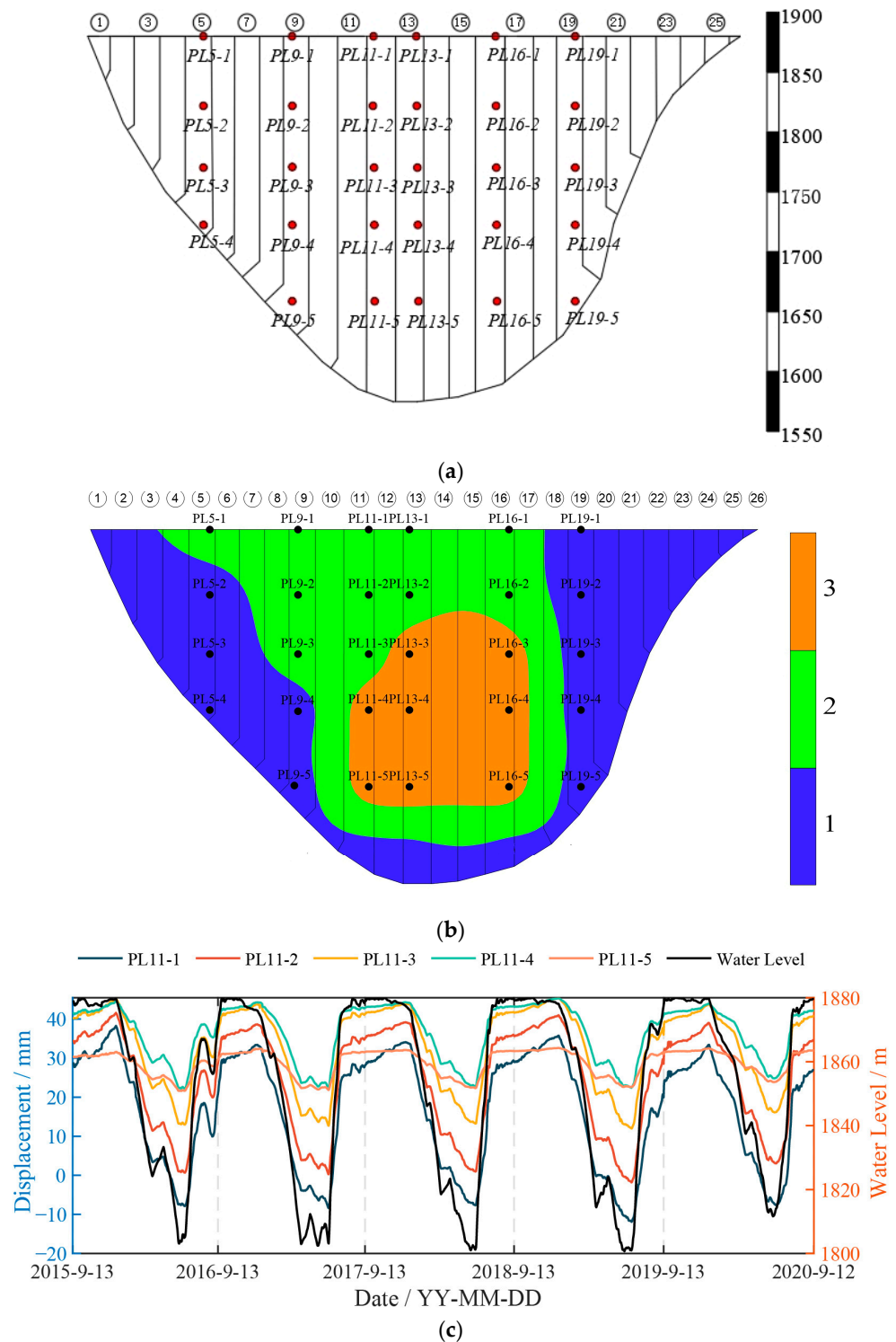


Figure 3. Partitioning of deformation points for the case study. (a) Arrangement of selected measurement points; (b) deformation point partitions; (c) deformation comparison of PL11 in two clustering areas.

4.2. Design of Ablation Tests

For convenience, the proposed framework was marked as M0, and the full structure of the framework was named clustering + SMVMD + mRMR + CNN + BiGRU + AM. To test the effectiveness of M0 and the gain effect of its modules on the performance of the framework, the ablation test method was adopted for comparative analysis. The test was designed with 10 benchmark models, marked M1 to M10, each of which was compared

against the baseline model, denoted as M0. Detailed construction information for each model is shown in Table 3.

Table 3. Details of the model in the ablation test.

Model Mark	Model Framework	LFs	SIFs
M0	clustering + SMVMD + mRMR + CNN + BiGRU + AM	✓	✓
M1	SMVMD + mRMR + CNN + BiGRU + AM	✓	✓
M2	SVMD + mRMR + CNN + BiGRU + AM	✓	×
M3	clustering + mRMR + CNN + BiGRU + AM	✓	✓
M4	Clustering + MEMD + mRMR + CNN + BiGRU + AM	✓	✓
M5	clustering + SMVMD + CNN + BiGRU + AM	×	✓
M6	SVMD + CNN + BiGRU + AM	×	×
M7	clustering + SMVMD + CNN + BiGRU + AM	✓	✓
M8	clustering + SMVMD + mRMR + GRU	✓	✓
M9	CNN + BiGRU + AM	✓	×
M10	SVR	✓	✓

Note: ✓ represents the factors are considered in the model, × represents the factors are not considered in the model.

Of the above models, M1 does not spatially partition the deformation points. It takes into account the spatial influence exerted by all measurement points on the target measurement points to demonstrate the effectiveness of the deformation spatiotemporal clustering module. M2 does not input SIFs and aims to demonstrate the effect of spatial correlation on the deformation. M3 and M4 aim to demonstrate that the SMVMD module can extract potential features in multiple points and improve performance. M5, without inputting load factors, is designed to demonstrate the impact of environmental parameters on the deformation. M6 aims to compare the prediction accuracy between the autoregressive and the factorial regression models. M7 eliminates the factor-screening module and explores the impact of mRMR on prediction accuracy. M8 is used to compare the prediction accuracy of different models by replacing advanced deep learning algorithms with simple machine learning algorithms. M9 is used as a deep learning benchmark model to test the effectiveness of modules such as spatiotemporal clustering, multivariate decomposition, factor screening, and SIF inputting. M10 is used as the most basic machine learning model to compare with M0, highlighting the superiority of the performance of the proposed framework.

4.3. Partitioning of Deformation Points

The 29 horizontal deformation points of the high-arch dam were first analyzed by spatial clustering. The K-means clustering method generally uses the elbow method to determine the optimal number of clusters. According to the elbow method, the optimal number of clusters was determined as 3. Figure 3b shows the deformation measurement point partitioning results obtained by the K-means optimal number of clusters. Figure 3c shows the deformation changes in PL11 in the cross-section of the crown cantilever, highlighting different change laws in two clustering areas. The points of PL11 in zone 2 are in the water level change zone above the dead water level, and their measured values are affected by the water level change and ambient temperature, as well as the dam overhanging effect, which leads to a larger magnitude of displacement change. The points in zone 3 are in the lower part of the dam body below the dead water level, and they deform downstream under the influence of the continuous water pressure, and the corresponding deformation amplitude is smaller than that of the points in zone 2.

4.4. Multi-Point Joint Prediction Modeling

Based on the results in the previous subsection, a multi-point joint deformation monitoring model is established for the measurement points in zone 3. The measured data in zone 3 and the corresponding environmental quantities are illustrated in Figure 4. The

model performance is analyzed and verified by taking the PL13-3 in zone 3 as an example. Figure 4c reveals that the relationship of the measured data of PL13-3 with environmental quantities is highly nonlinear, showing complexity and the need for a decomposition method to reduce its nonlinearity and fluctuation. PL13-3 is marked as the TP, and the same zone points PL11-4, PL11-5, PL13-4, PL13-5, PL16-3, PL16-4, and PL16-5 are the spatially associated points, marked as SIF1~SIF7. SMVMD decomposes TP and SIF1~SIF7. The maximum and minimum bandwidths α of the extracted modes were set as 1000 and 1, respectively. The time step of the dual ascending modes is 0, and the convergence and termination tolerances of the ADMM are 10^{-7} and 10^{-5} , and β , as the change rate of α , is 1.414. Figure 5 reveals that $MIMF_{1,c}$ reflects the overall fluctuation trend of the original deformation sequence and accounts for a larger proportion. In contrast, $MIMF_{2,c} \sim MIMF_{4,c}$ accounts for a smaller proportion and has a higher frequency than $MIMF_{4,c}$.

The corresponding input factor sets are selected for the components with different features to construct the component prediction models. MRMR performs factor screening, and the best factors set $F_s(k)$ for each component are extracted. The maximum acceptable number of factors (1~19) for each component was firstly set by pre-setting. Then, the corresponding factor number results were filtered sequentially by the mRMR method, and the prediction accuracy of the model was obtained by inputting the corresponding factor number results into the prediction model. By comparing the prediction accuracies obtained by inputting different optimal factor numbers for each component, the minimum RMSE envelope is determined. Figure 6 shows the correlation between different amounts of factors in the input and the RMSE of the model, and the number of factors corresponding to different MIMF components is different. The deformation error varies when entering a different number of factors or the same number of different factors. Thus, $F_s(k)$ for each MIMF is determined. Table 4 displays the optimal factor sets for each MIMF component identified through the mRMR screening process, and the factors are sorted by the degree of importance. It is found that each MIMF component is affected by the SIFs, and the degree of influence is larger than that of the environmental factor, demonstrating a spatial correlation between each point during the normal operation of the dam. In addition to the SIFs, $MIMF_{1,TP}$ and $MIMF_{2,TP}$ are also affected by the hydrostatic factor and the aging factor, and $MIMF_{2,TP}$ and $MIMF_{3,TP}$ are affected by the temperature factor.

Table 4. Best factor sets for each MIMF component.

Name of Component	Number of Factors	Selected Factors (in Order of Importance)
$MIMF_{1,TP}$	11	$MIMF_{1,SIF3}, MIMF_{1,SIF4}, MIMF_{1,SIF5}, H^1, H^2, H^3, H^4, MIMF_{1,SIF6}, \theta, \ln\theta, MIMF_{1,SIF2}$
$MIMF_{2,TP}$	14	$MIMF_{2,SIF5}, MIMF_{2,SIF3}, MIMF_{2,SIF7}, MIMF_{2,SIF6}, MIMF_{2,SIF4}, H^4, H^3, H^2, H^1, MIMF_{2,SIF2}, \theta, \ln\theta, T_{16-30}, T_{7-15}$
$MIMF_{3,TP}$	15	$MIMF_{3,SIF3}, MIMF_{3,SIF4}, MIMF_{3,SIF7}, MIMF_{3,SIF6}, MIMF_{3,SIF5}, MIMF_{3,SIF2}, MIMF_{3,SIF1}, T_{7-15}, T_{3-6}, T_{16-30}, T_2, T_1, T_0$
$MIMF_{4,TP}$	5	$MIMF_{4,SIF3}, MIMF_{4,SIF4}, MIMF_{4,SIF5}, MIMF_{4,SIF6}, MIMF_{4,SIF7}$

The CNN-BiGRU-AM prediction model is constructed for the MIMF components. Establishing hyperparameters is pivotal for constructing a deep learning model. For different components, improved north hawk optimization is used to find the optimum for the hyperparameters [35], and the detailed parameters of the deep learning for each component are shown in Table 5. After the hyperparameters are determined, the MIMF components are trained, fitted, and predicted sequentially. The final horizontal displacement prediction result of the TP was achieved by stacking each component. Figure 7 shows that each component has good fitting ability and low prediction error. The overall trend is consistent with the actual trend, the linear fit is within the 95% confidence interval, and there are almost no outliers, indicating that the developed framework can predict high-arch dam deformations.

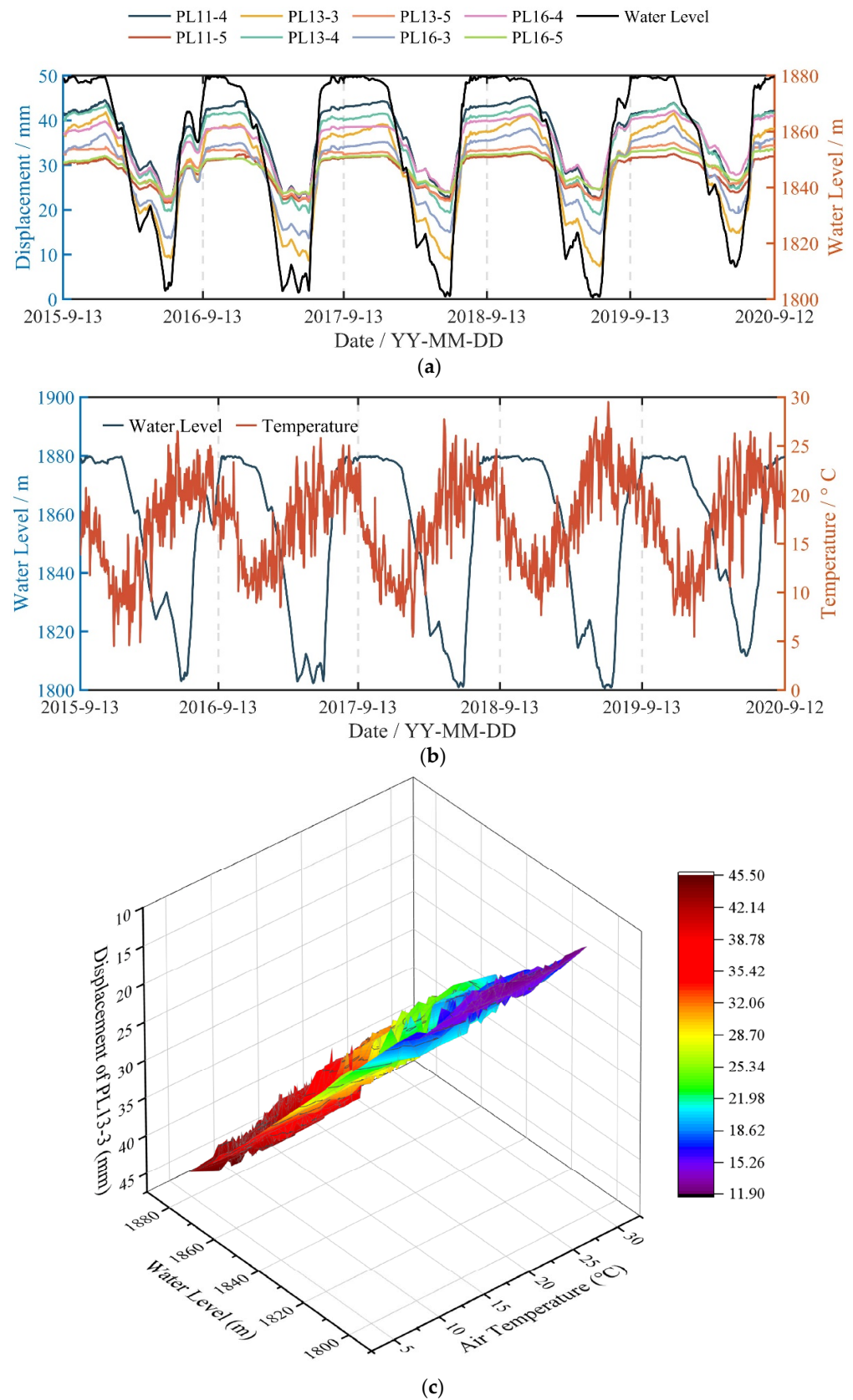


Figure 4. Changes in the deformation and environmental quantities in zone 3. (a) Deformation changes of points in zone 3; (b) environmental quantity changes; (c) relationship of PL13-3 with environmental quantity.

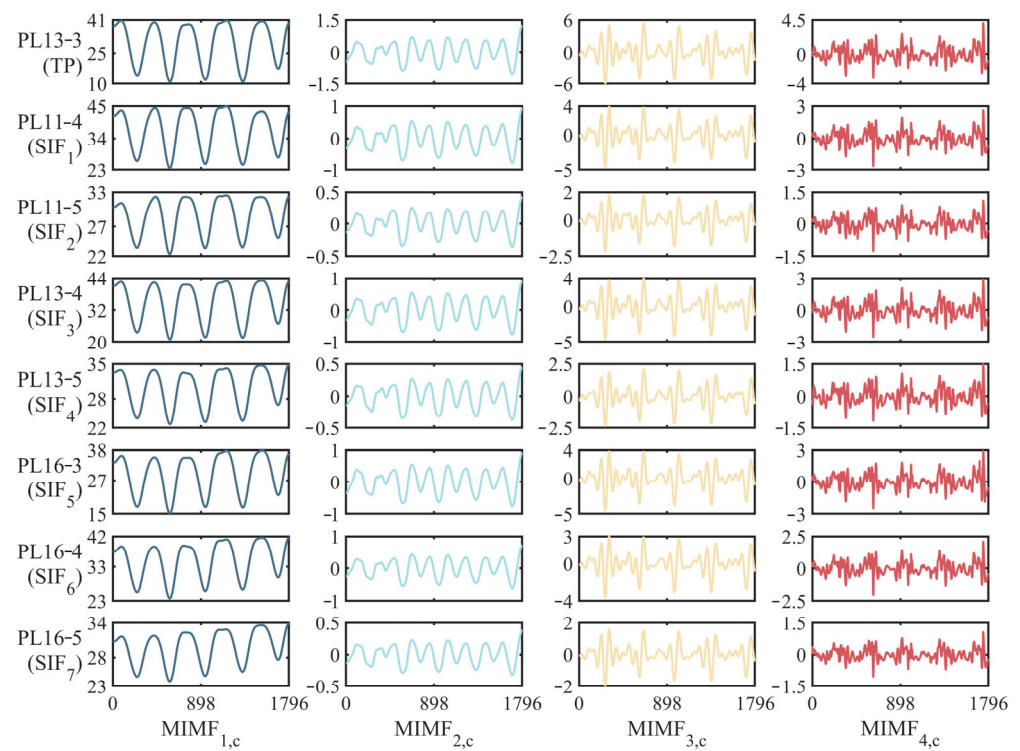


Figure 5. Decomposition results for TP and its SIFs.

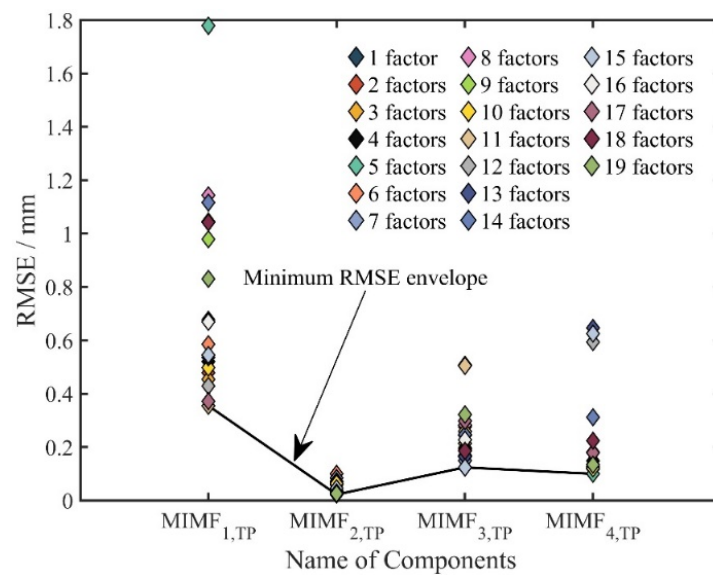


Figure 6. Relationship between number of input factors and RMSE for MIMF components.

Table 5. Model hyperparameter details.

Hyperparameters	Value			
	MIMF _{1,TP}	MIMF _{2,TP}	MIMF _{3,TP}	MIMF _{4,TP}
Conv1D units	64	64	64	64
Kernel size	3	3	3	3
Learning rate	0.0017	0.0019	0.0016	0.0016
BiGRU units	49	19	48	44

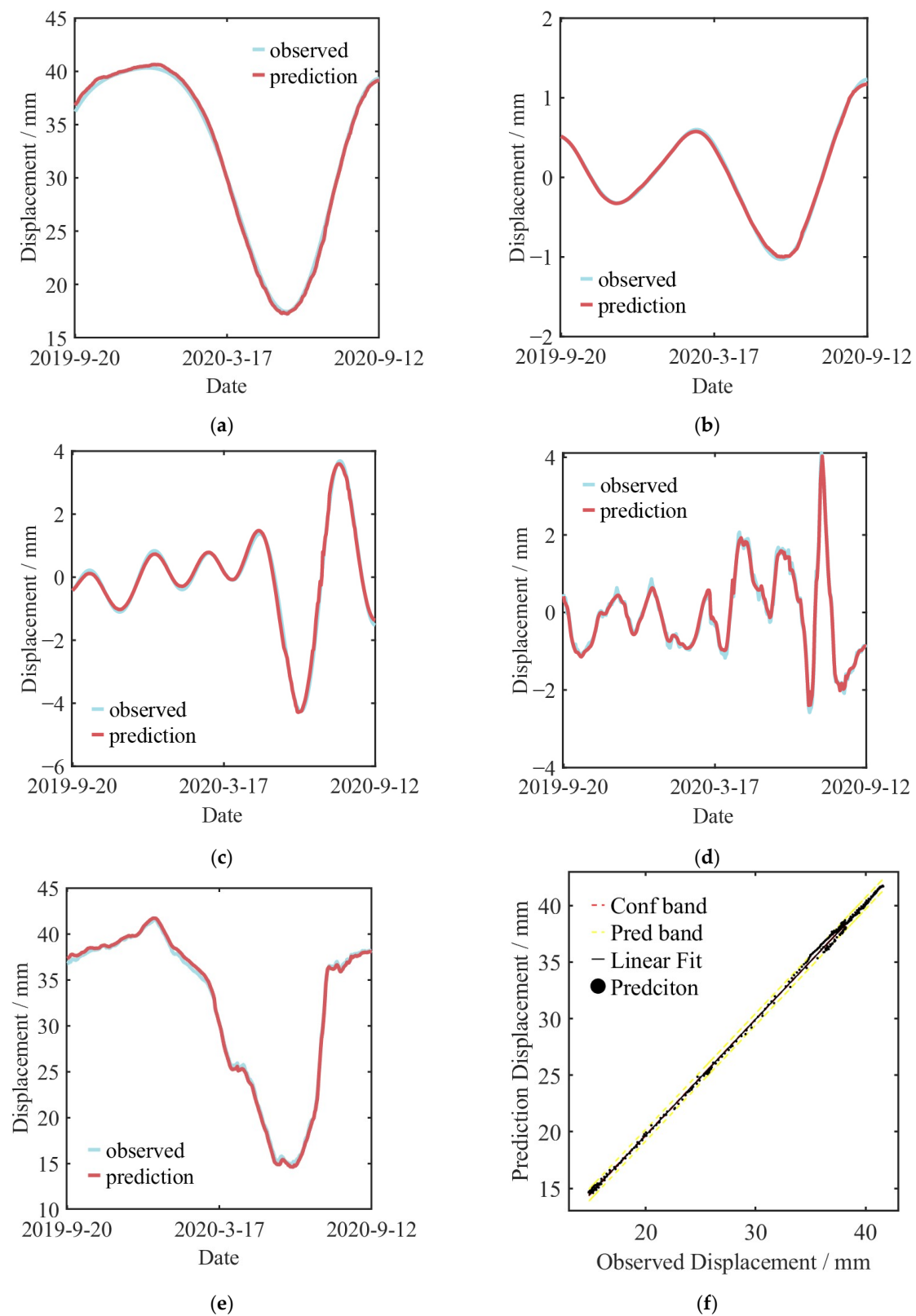


Figure 7. Predicted results for each component of the TP. (a) MIMF1; (b) MIMF2; (c) MIMF3; (d) MIMF4; (e) TP; (f) linear fit.

4.5. Comparison of Model Prediction Performance

To further validate the performance of the framework, the PL13-3 in zone 3 is again used as an example to compare it with M1~M10. The experimental model has machine

learning components, consistent with the framework of this paper, using improved north hawk optimization to obtain the optimal parameters. Table 6 shows the optimal hyperparameter values of the adopted machine learning components.

Table 6. Hyperparameter settings for machine learning components in ablation tests.

Model	Parameters	Optimal Parameter
SVR	C	64.44
	Gamma	1.73
GRU	Number of units	[18;80;108;30]
	Learning rate	[0.015;0.01;0.01;0.0055]

Note: [;] represents the hyperparameters corresponding to each MIMF component.

Table 7 illustrates the prediction indices of various models, with the best values highlighted in bold. Moreover, Figures 8–10 show the process line, box plot, and Talor plot of different models to more intuitively depict the results of the prediction performance comparison. The results reveal that the predicted values are consistent with the measured data, but the other benchmark models are weak when capturing the fluctuations in the data series. In contrast, the proposed framework significantly improves the prediction ability in the peak deformation and the ability to handle nonlinear correlations, with higher accuracy in predicting long periods and more accuracy in predicting details such as local inflection points. Figure 9 reveals that the residuals of the framework are more concentrated, and the middle line of the residuals is close to 0, with no discrete values. In contrast, the residual distribution of the other benchmark models is larger than the proposed framework. Some benchmark models have discrete values, which indicates that the benchmark models are not as good as the proposed framework. The model prediction performance indices in Table 7 and Figure 10 intuitively demonstrate that the framework outperforms the benchmark model in terms of prediction accuracy.

Next, the effectiveness and impact level of each module in the framework on the performance improvement of the framework were analyzed. Firstly, the effectiveness of the spatiotemporal clustering of measurement points for the model was determined by comparing the results of M0 and M1 (Figure 8a). M1 did not cluster the deformation measurement points. All the prediction indexes were inferior to those of M0, which indicated that considering all the deformation measurement points of the arch dams was not conducive to the modeling. The uncorrelated characteristics between some of the measurement points make the model complex, which increases the modeling difficulty and reduces the prediction accuracy.

Secondly, the results of M0 and M2, M5, M6, and M7 (Figure 8b) indicate that M0 has the best results, M6 has the worst results, and the performance decreases in the order of M7, M5, and M2, which shows that SIFs have a great influence on the model, followed by LFs. It indicates that it is not enough to consider only the deformation data to construct the autoregressive model or to consider only the LFs, and the spatiotemporal characteristics of the deformation should be considered in calculations. Compared with M0 and M7, the indexes of M0 are better than those of M7, which proves that the reasonable selection of factors can improve the model prediction performance.

Thirdly, the results of M0 with M3 and M4 (Figure 8c) reveal that the decomposition strategy improves the performance of the hybrid framework, which is because the decomposition strategy can efficiently extract the information of different scales and reduce mode interference. In addition, M0 outperforms M4 because MEMD has inherent defects, such as modal aliasing, while SMVMD does not.

Fourthly, the results of M0 and M8 (Figure 8d) show that by replacing the deep learning components with other deep learning algorithms, the overall performance decreases, reflecting the effectiveness of the developed model.

Finally, the comparison results between M0 with M9 and M10 (Figure 8e) validate the effectiveness of the spatiotemporal clustering, decomposition, factor screening, and deep learning components of the prediction framework.

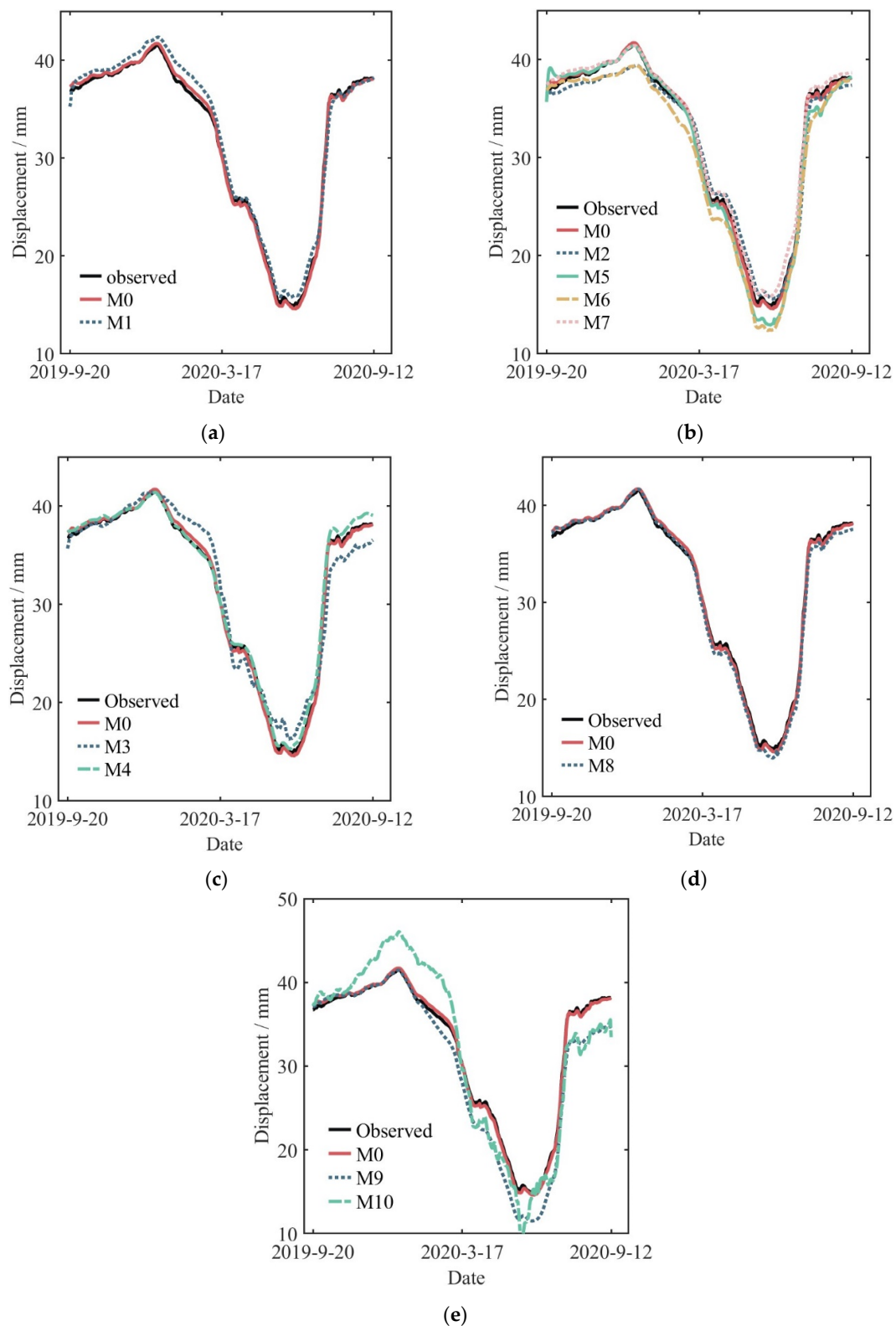


Figure 8. Process line comparison of ablation test models. (a) Clustering module; (b) factor screening module; (c) decomposition module; (d) deep learning module; (e) all modules.

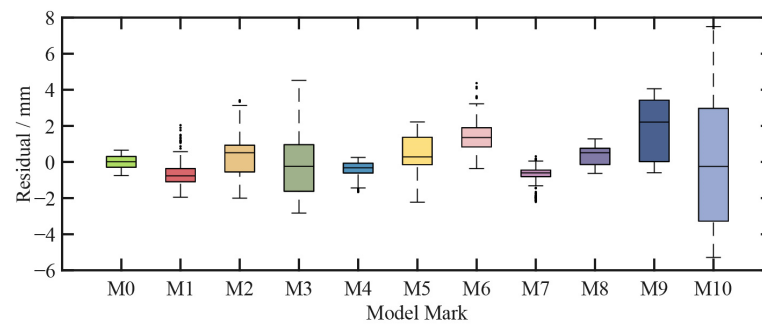


Figure 9. Residual comparison of ablation test models.

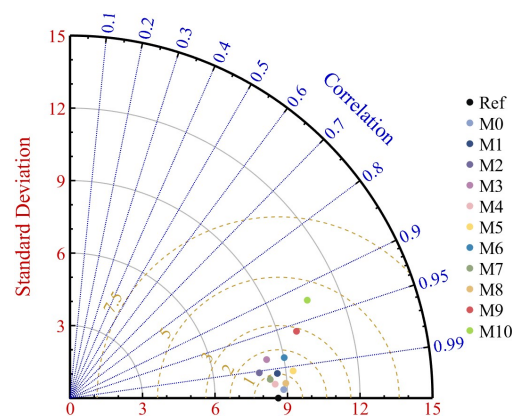


Figure 10. Prediction performance Taylor chart of ablation test models.

Table 7. Prediction performance comparison of ablation test models.

Model Mark	R^2	MAE (mm)	RMSE (mm)	MAPE (%)	Model Mark	R^2	MAE (mm)	RMSE (mm)	MAPE (%)
M0	0.998	0.304	0.344	1.086	M6	0.966	1.393	1.601	5.315
M1	0.986	0.869	1.019	2.959	M7	0.991	0.667	0.801	2.674
M2	0.982	0.959	1.142	3.274	M8	0.995	0.486	0.591	1.941
M3	0.963	1.356	1.658	5.008	M9	0.919	1.920	2.439	7.865
M4	0.995	0.429	0.584	1.619	M10	0.854	2.836	1.814	9.190
M5	0.985	0.776	1.043	3.34					

4.6. Comparison of Different Deformation Prediction Methods

To assess the superiority of a proposed framework, its performance is commonly compared with existing constructed novel model methods. In this paper, XGBoost (M11) [36], stacking ensemble learning method (M12) [37], and EMD-LSTM (M13) [38] were selected as benchmark models. PL13-3 is still used as an example in this section. Consistent with the framework of this paper, using improved north hawk optimization to obtain the optimal parameters, the LFs and SIFs are the same as Equation (7). Figure 11 shows the prediction results of the four models. Table 8 shows the prediction performance comparison results. Figure 11 and Table 8 show that the proposed framework outperforms the benchmark model in terms of prediction accuracy. And for the same benchmark model, the effect of prediction when considering SIFs is superior to that of prediction without considering SIFs. Models considering SIFs are more likely to capture deformation features and trends.

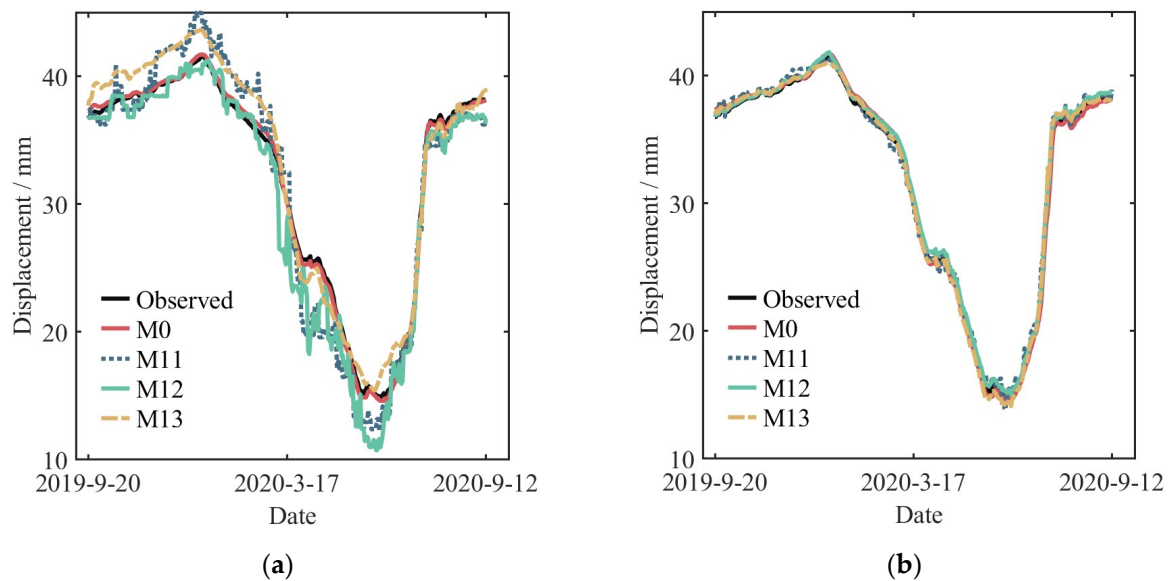


Figure 11. Process line comparison with benchmark models. (a) Without SIFs; (b) with SIFs.

Table 8. Prediction performance comparison with benchmark models.

Model Mark	Without SIFs				Model Mark	With SIFs			
	R^2	MAE (mm)	RMSE (mm)	MAPE (%)		R^2	MAE (mm)	RMSE (mm)	MAPE (%)
/	/	/	/	/	M0	0.998	0.304	0.344	1.086
M11	0.927	1.936	2.331	6.92	M11	0.995	0.442	0.563	1.631
M12	0.943	1.444	2.057	5.875	M12	0.996	0.363	0.479	1.377
M13	0.960	1.501	1.732	4.846	M13	0.997	0.343	0.476	1.339

To verify the proposed framework, the Diebold–Mariano (DM) test was applied in this study. M0 was used as the target model, M11–M13 was used as the benchmark model, and MSE was employed as the loss function. Table 9 shows that M0 significantly outperforms all benchmark models in all cases, which statistically verifies the developed framework.

Table 9. Results of DM test.

Model Mark	DM Value	Model Mark	DM Value
M11 (without SIFs)	14.2395 *	M11 (with SIFs)	6.6259 *
M12 (without SIFs)	9.482 *	M12 (with SIFs)	2.9003 *
M13 (without SIFs)	22.5113 *	M13 (with SIFs)	3.0211 *

Note: * represents that the proposed framework outperforms the benchmark model at 1% significance level.

4.7. Generality Analysis

To explore the generality of the model, four other representative measurement points, PL13-1, PL13-5, PL5-3, and PL19-3, were selected for analysis. These monitoring points reflect the deformation of the arch dam's top and bottom arch crown beam and the arch dam's left and right 1/4 sections. Figure 12 shows the prediction results of the four points. Table 10 shows the prediction performance of the framework. Figure 12 and Table 10 show that the proposed framework has good prediction performance at all points, both in terms of local detail prediction and overall trend, and the prediction indexes are better than M9. This shows that the proposed framework has strong robustness and generalization.

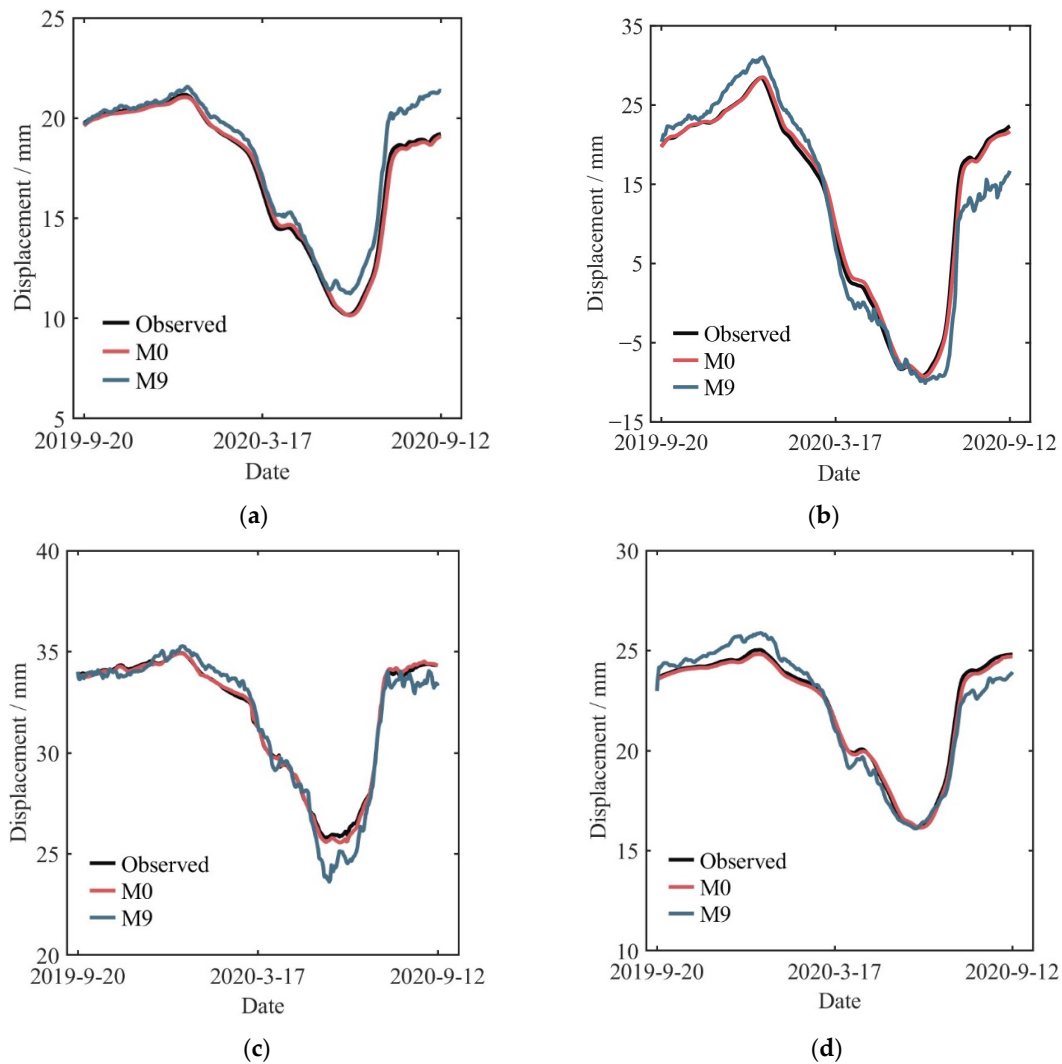


Figure 12. Prediction results at different points. (a) PL5-3; (b) PL13-1; (c) PL13-5; (d) PL19-3.

Table 10. Prediction performance comparison of different points.

Point	M0				Point	M9			
	R^2	MAE (mm)	RMSE (mm)	MAPE (%)		R^2	MAE (mm)	RMSE (mm)	MAPE (%)
PL5-3	0.997	0.166	0.223	1.058	PL5-3	0.918	0.761	1.022	4.907
PL13-1	0.996	0.608	0.808	2.092	PL13-1	0.928	2.606	3.289	6.028
PL13-5	0.998	0.099	0.132	0.332	PL13-5	0.946	0.549	0.706	1.836
PL19-3	0.996	0.152	0.196	0.944	PL19-3	0.942	0.598	0.696	2.623

5. Conclusions

The present study focuses on high-arch dam deformation monitoring, comprehensively using the methods of spatiotemporal clustering, multivariate decomposition, factor screening, and deep learning, and a multi-point joint monitoring framework is proposed. Combined with the long-term monitoring data of high arch dams, an ablation test model analysis was carried out, and the model's prediction accuracy was evaluated with multiple indicators to verify the framework from various aspects. Our main achievements can be summarized as follows:

(1) Based on the similarity of the time series, the K -means clustering method is used to study the partitioning of the high-arch dam deformation points. The spatially correlated

measuring points are considered as the SIFs of the target point to be introduced into the model, which achieves the extension of single-point time series data analysis to multi-point spatiotemporal joint data analysis. When the model considers the SIFs of the measurement points, its prediction accuracy outperforms the model that only considers the environmental factors or the time autocorrelation.

(2) The use of SMVMD on the multi-point deformation sequence can effectively solve the influence of high fluctuation and nonlinearity on the prediction results. The factor preference strategy reduces the redundancy of model training and improves the prediction accuracy. Compared with each benchmark model in the ablation test, the framework proposed based on decomposition–factor screening–prediction–stacking has the best prediction results under all evaluation indexes.

(3) Multiple point analyses in various sections of the high-arch dam verify the model. Meanwhile, the comparison results between the developed framework and each benchmark model designed by the ablation test proved the superiority of the proposed prediction framework in this paper. The hybrid framework can better achieve the long-term deformation prediction of high-arch dams and also provides a new idea for the spatiotemporal deformation prediction of similar concrete structures.

(4) The model-fitting factors proposed in this paper are still based on the conventional statistical model; for ultra-high-concrete-arch dams in special environments, such as high-arch dams in cold regions at high latitudes or at high altitudes, special characterization factors should also be taken into account for model construction, as well as special spatiotemporal correlations, which is the subject of our next in-depth study.

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