

Article

A Deep Learning Framework for Deformation Monitoring of Hydraulic Structures with Long-Sequence Hydrostatic and Thermal Time Series

Hui Li ^{1,2,*} , Jiankang Lou ³, Fan Li ¹ , Guang Yang ⁴ and Yibo Ouyang ^{1,2}

¹ Department of Hydraulic Engineering, Henan Vocational College of Water Conservancy and Environment, Zhengzhou 450008, China

² Engineering Quality Testing and Materials Research Center, Zhengzhou 450008, China

³ Henan Water Planning and Design Research Co., Ltd., Zhengzhou 450002, China

⁴ School of Water Conservancy, North China University of Water Resources and Electric Power, Zhengzhou 450046, China

* Correspondence: lhui_hhu@163.com

Abstract: As hydraulic buildings are constantly subjected to complex interactions with water, particularly variations in hydrostatic pressure and temperature, deformation structural behavior is inherently sensitive to environmental fluctuations. Monitoring dam deformation with high accuracy and robustness is critical for ensuring the long-term safety and operational integrity of hydraulic structures. However, traditional physics-based models often struggle to fully capture the nonlinear and time-dependent deformation responses in hydraulic structures driven by such coupled environmental influences. To address these limitations, this study presents an advanced deep learning (DL)-based deformation monitoring for hydraulic buildings using long-sequence monitoring data of hydrostatic pressure and temperature. Specifically, the Bidirectional Stacked Long Short-Term Memory (Bi-Stacked-LSTM) is proposed to capture intricate temporal dependencies and directional dynamics within long-sequence hydrostatic and thermal time series. Then, hyperparameters, including the number of LSTM layers, neuron counts in each layer, dropout rate, and time steps, are efficiently fine-tuned using the Gaussian Process-based surrogate model optimization (GP-SMO) algorithm. Multiple deformation monitoring points from hydraulic buildings and a variety of advanced machine-learning methods are utilized for analysis. Experimental results indicate that the developed GP-SMO-optimized Bi-Stacked-LSTM dam deformation monitoring model shows better comprehensive representation capability of both past and future deformation-related sequences compared with benchmark methods. By approximating the behavior of the target function, the GP-SMO algorithms allow for the optimization of critical parameters in DL models while minimizing the high computational costs typically associated with direct evaluations. This novel DL-based approach significantly improves the extraction of deformation-relevant features from long-term monitoring data, enabling more accurate modeling of temporal dynamics. As a result, the developed method offers a promising new tool for safety monitoring and intelligent management of large-scale hydraulic structures.

Keywords: hydraulic buildings; hydrostatic pressure; temperature time series; deformation monitoring; deep learning



Academic Editor: Giuseppe Oliveto

Received: 26 April 2025

Revised: 13 June 2025

Accepted: 14 June 2025

Published: 17 June 2025

Citation: Li, H.; Lou, J.; Li, F.; Yang, G.; Ouyang, Y. A Deep Learning Framework for Deformation Monitoring of Hydraulic Structures with Long-Sequence Hydrostatic and Thermal Time Series. *Water* **2025**, *17*, 1814. <https://doi.org/10.3390/w17121814>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Hydraulic buildings like dams play a critical role in sustainable water resource management and hydropower generation, serving as key infrastructures for water storage, flood control, and energy supply in water-scarce and hazard-prone regions [1–4]. Hydraulic buildings are often built in regions with complex geological conditions, requiring advanced engineering techniques to ensure structural stability and longevity [5,6]. Given the immense scale and complexity of these structures, even small deformations can have significant impacts on the safety and operational efficiency of hydraulic buildings [7]. Therefore, effective deformation monitoring and predictive maintenance of hydraulic structures are essential to prevent potential failures that could lead to catastrophic consequences, both economically and environmentally.

Statistical regression methods, such as multiple linear regression (MLR) and generalized linear models are widely used in deformation monitoring for hydraulic structures due to the simplicity and ability to fit relationships between monitoring variables and deformation [8–10]. These methods rely on historical and real-time data collected from structural health monitoring systems, such as deformation, strain, temperature, rainfall, and water pressure, to establish predictive models that can estimate dam deformation behavior under different operational and environmental conditions [11,12]. However, statistical modeling methods rely on the assumption of linearity between the independent and dependent variables. In real-world applications, the relationship between the deformation-related variables is highly non-linear, leading to reduced prediction accuracy [13]. Statistical models struggle to capture complex, high-dimensional interactions between deformation-related variables, but they may oversimplify these interactions, potentially overlooking critical deformation mechanisms.

With the rapid advancement of information technology, the research and application of artificial intelligence (AI) and deep learning (DL) techniques in dam deformation prediction have become increasingly prominent [14–16]. Unlike traditional statistical approaches, DL-based methods can automatically extract and learn deep features from monitoring data without relying on predefined functional relationships, making them more suitable for addressing the complex, multi-factor coupling issues involved in dam deformation [17]. For instance, Zhang et al. [18] integrated densely connected convolutional networks and Long short-term memory (LSTM) networks to demonstrate superior accuracy and generalization in predicting the dynamic deformation of concrete gravity dams, achieving a correlation coefficient above 0.99. Xu et al. [19] employed Max-Relevance and Min-Redundancy and Lasso for feature selection and Convolutional Neural Network (CNN)-LSTM for dam deformation and crack opening prediction, thus providing a robust framework for the safe monitoring of cracked concrete arch dams. Lu et al. [20] proposed an Inception-ResNet-Gated Recurrent Unit (GRU) model that integrates feature extraction with long-term dependency learning, significantly improving dam deformation prediction accuracy for enhanced safety monitoring. Pan et al. [5] developed a CNN-based spatiotemporal deformation field model incorporating temperature, water pressure, and constraint fields for arch dams without the need for inverse analysis or parameter adjustment. Based on the above analysis, it can be inferred that DL-based methods show potential values in capturing the temporal and spatial dependencies within dam monitoring data. However, traditional single-layer DL networks, such as LSTM, lack the depth and hierarchical learning capacity required to capture complex interactions influenced by water pressure, temperature variations, and structural stress, limiting the predictive performance in long-sequence, multi-variable contexts. Another major limitation of traditional LSTM-based models is their unidirectional nature, as they rely solely on past observations to predict future outcomes, overlooking the potential influence of future conditions on the current state [21]. In addition, the predictive

performance of LSTM architectures relies heavily on hyperparameter selection, including layer count, units per layer, dropout rates, learning rates, and time steps. Interactions among these hyperparameters greatly affect the convergence, generalization, and accuracy of predictive models [22]. As model complexity increases, so does computational cost, leading to longer training times and a heightened risk of overfitting if hyperparameter tuning is not carefully managed. Traditional methods like grid or random search are often inefficient for navigating the vast hyperparameter space of complex LSTM models.

Based on the above analysis, this study proposes a novel DL-based deformation monitoring model for utilizing high-dimensional and long-sequence hydrostatic and thermal time series. First, an improved dam deformation monitoring model considering actual long-sequence prototypical hydrostatic and thermal data is developed, incorporating extensive thermometer data specifically for high arch dams. Next, a hybrid DL network architecture, featuring a Bi-Stacked Long Short-Term Memory (Bi-Stacked-LSTM) network, is constructed to capture the intricate temporal dynamics and complex interdependencies inherent in deformation-related hydrostatic and thermal sequences. Then, the Gaussian Process-based Surrogate Model Optimization (GP-SMO) algorithm is implemented to efficiently navigate the extensive hyperparameter space of DL techniques, optimizing parameters such as the number of LSTM units per layer, LSTM layer count, dense layer structures, dropout rates, and time steps. Multiple deformation monitoring points from a 300 m-high arch dam are analyzed. Comparative analysis is conducted using a range of advanced statistical and machine learning (ML) models, with predictive performance evaluated through diverse qualitative and quantitative metrics.

The key contributions of this study are as follows:

1. The proposed Bi-Stacked-LSTM model can capture complex nonlinear relationships between deformation and long-sequence hydrostatic and thermal time series in hydraulic structures by integrating multiple bidirectional LSTM layers, enabling it to effectively leverage intricate temporal dynamics and dependencies within the deformation data.
2. The GP-SMO algorithm can efficiently identify the optimal parameter configurations within a high-dimensional space, aligning the DL-based model with the unique temporal dependencies and nonlinear relationships in dam deformation monitoring data.
3. Through extensive quantitative and qualitative evaluations across various advanced ML models, the developed DL-based method demonstrates robust predictive power and reliability in dam deformation forecasting, validated from multiple perspectives in a series of comparative experiments.

The structure of this paper is as follows: Section 2 presents the GP-SMO-based Bi-Stacked-LSTM deformation monitoring model for hydraulic structures, focusing on neuron configurations and hyperparameter optimization. Section 3 covers dam monitoring data sources and preprocessing for training. Section 4 discusses the training process, hyperparameter optimization, and model evaluation across multiple monitoring points. Finally, Section 5 summarizes the contributions, advantages, limitations, and future research directions.

2. Proposed Method

2.1. Flowchart of the Developed Model

Figure 1 shows the flowchart of the proposed deformation prediction framework for high arch dams, comprising predictive model construction and hyperparameter optimization process of DL methods. In the predictive model stage, the Bi-Stacked-LSTM architecture is constructed and employed to capture the nonlinear and long-term dependencies

within environmental monitoring data and dam deformation sequences. Environmental monitoring data (water level, temperatures, and rainfall) and historical deformation data are normalized and partitioned into training and testing sets, which are then fed into DL models, allowing the model to learn temporal patterns effectively. In the hyperparameter optimization process, the GP-SMO algorithm is utilized to optimize critical hyperparameters of DL models (e.g., the number of LSTM layers, neuron counts in each layer, dropout rate, and time steps). The developed surrogate model guides the sampling and updating of hyperparameters to enhance model performance iteratively, ensuring that the optimal parameters are achieved for accurate predictions.

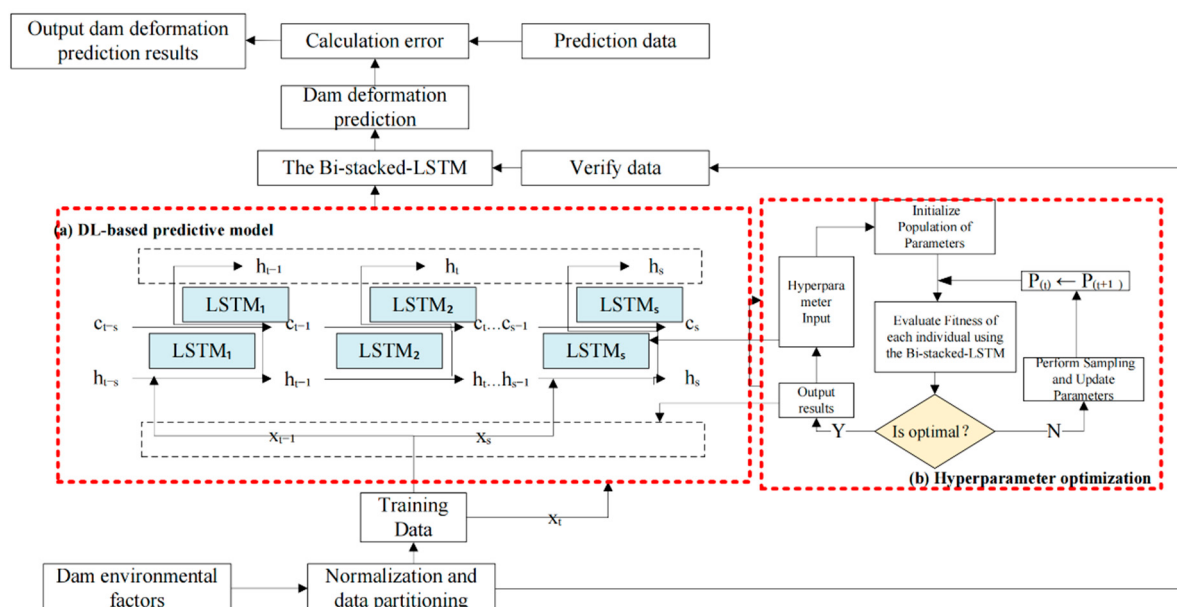


Figure 1. Flowchart of the proposed framework.

2.2. Deformation Monitoring Model for Dam Structures

Dam deformation, a characteristic structural response, can be divided into recoverable components—influenced by water pressure and temperature—and irrecoverable components, which are affected by creep, alkali-aggregate reactions, and material aging [23]. The loads and environmental impacts of dams in long-term service can be seen in Figure 2.

In the statistical model, dam deformation δ can be described using hydraulic component δ_H , thermal component δ_T , and time-varying component δ_θ . Specifically, δ_H denotes the elastic deformation under hydraulic load, δ_T denotes the recoverable deformation affected by temperatures, and δ_θ denotes the irreversible dam deformation caused by dam material aging. The details are as follows:

$$\delta = \delta_H + \delta_T + \delta_\theta \quad (1)$$

$$\delta_H = \sum_{i=1}^{n_1} a_i H^i \quad (2)$$

where for gravity dams, $n_1 = 3$; for arch dams, $n_1 = 4$. In this study, the object of this study is an arch dam, so the coefficient is 4.

The difference between the Hydraulic–Seasonal–Time (HST) and Hydraulic–Temperature–Time (HTT) models mainly exists in the interpretation and simulation of temperature-related variables [24]. In the HST model, the temperature effect is mainly simulated by

simple harmonics, while the HTT model is mainly simulated by a large number of thermometer monitoring data. The specific contents are as follows:

$$\delta_T = \begin{cases} HST : \sum_{i=1}^2 \left[b_{1i} \sin \frac{2\pi it}{365} + b_{2i} \cos \frac{2\pi it}{365} \right] \\ HTT : \sum_{i=1}^{m_1} b_i T_i \end{cases} \quad (3)$$

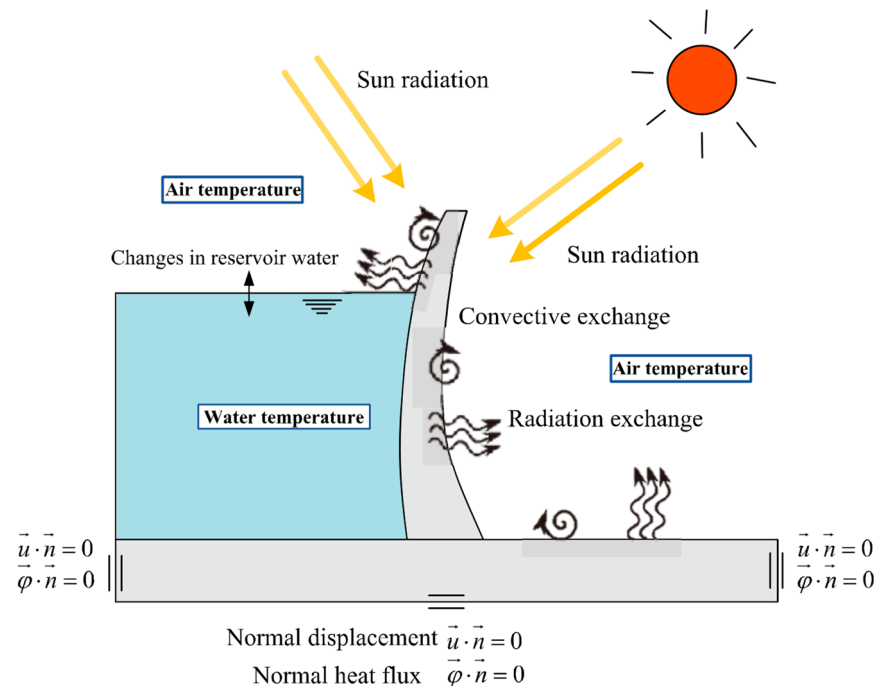


Figure 2. Schematic diagram of environmental loads impacting dam deformation.

The time-varying component δ_θ of the deformation of a high arch dam can be expressed by the following formula:

$$\delta_\theta = c_1 \theta + c_2 \ln \theta \quad (4)$$

Based on the HST and HTT deformation monitoring models, the deformation of high arch dams can be characterized as follows:

$$\delta = \sum_{i=1}^4 a_i H^i + c_1 \theta + c_2 \ln \theta + \begin{cases} \sum_{i=1}^2 \left[b_{1i} \sin \frac{2\pi it}{365} + b_{2i} \cos \frac{2\pi it}{365} \right], & HST \\ \sum_{i=1}^{m_1} b_i T_i, & HTT \end{cases} \quad (5)$$

where $n_1 = 4$; t denotes the cumulative days from the initial monitoring date to the current one and represents the total number of thermometers embedded within the dam and its foundation; m_1 represents the number of lag components; and a_i , b_{1i} , b_{2i} , b_i , b_1 , c_1 , and c_2 denote the regression coefficients. The relevant models can be obtained from Table 1.

Table 1. Composition of factor variables in dam deformation monitoring.

Models	Hydraulic Component	Temperature Component	Time-Varying Component
HST	H^i ($i = 1, 2, 3, 4$)	$\sin \frac{2\pi it}{365}, \cos \frac{2\pi it}{365}$ ($i = 1, 2$)	$\theta, \ln \theta$
HTT	H^i ($i = 1, 2, 3, 4$)	T_i ($i = 1, 2, \dots, 14$)	$\theta, \ln \theta$

2.3. Multi-Layer Bi-Stacked-LSTM Network

LSTM networks, a type of Recurrent Neural Network (RNN), are widely studied in time series forecasting for effectively addressing the vanishing and exploding gradient issues common in traditional RNNs. Figure 3 depicts the architecture of LSTM architectures. It can be seen that LSTMs are equipped with memory cells and gating mechanisms (input, forget, and output gates) that control information flow, enabling the model to capture long-term dependencies in sequential data. These gates determine which information to retain or discard at each time step, allowing LSTMs to effectively model long-term patterns in the data.

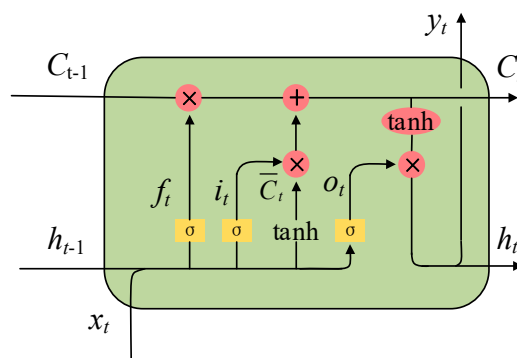


Figure 3. Intuitive diagram of LSTM network.

At this moment, the forget gate is determined by x_t and h_{t-1} , and is expressed as follows:

$$f_t = \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \quad (6)$$

where $\sigma(x)$ is a function of *logistic*, W_f , U_f , and b_f are the weight and bias vector of the forget gate, respectively.

The input gate comprises two components: the gate signal and the candidate state, both generated by activation functions. These components are then combined through element-wise multiplication to update the cell state. The input gate controls the inflow of new information, selectively updating the cell state. The calculation formula is as follows:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \bar{C}_t \quad (7)$$

where C_{t-1} is the cell state from the previous time step, whose value output is modulated by the activation function to control the degree of forgetting of the previous cell state; i_t is the input gate, the value output by the activation function, which controls the degree of retention of the candidate cell state $\bar{C}_t$, output by the activation function.

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \quad (8)$$

where O_t is the gate value of the output gate, which is output by the activation function *sigmoid*; W_o is the weight matrix of the output gate; h_{t-1} is the hidden layer state at the previous moment; x_t is the input data at the current moment; b_o is the bias of the output gate; and σ is the activation function. The output gate value, calculated by this expression, determines which part of the current cell state is passed to the external state. This controlled portion of the cell state is then output as the final result.

In the context of high arch dam deformation, which is influenced by multi-dimensional time series data (e.g., water levels, rainfall, and temperature), a single LSTM model often falls short in capturing the intricate interactions between these environmental factors and the dam's deformation behavior. Furthermore, single LSTMs struggle to effectively model

both short-term and long-term dependencies within the data, such as the immediate impact of rainfall versus the seasonal effects of temperature fluctuations.

To address these challenges, this study designs a Bi-Stacked-LSTM network architecture specifically for predicting multi-dimensional, long-sequence time series related to high arch dam deformation. Figure 4 depicts the schematic diagram of the developed Bi-Stacked-LSTM model. It can be seen that the developed model could better capture the intricate, multi-scale dependencies in the deformation-related time series, allowing for more accurate predictions of dam deformation under the influence of diverse and interdependent environmental factors. The Bi-Stacked-LSTM model processes dam deformation-related time series data in both forward and backward directions, capturing insights from past and future trends. This bi-directional and stacked-layer architecture enhances the model's ability to learn both short-term and long-term patterns in high arch dam deformation, effectively addressing the complex interactions between environmental factors and deformation monitoring data for more accurate predictions.

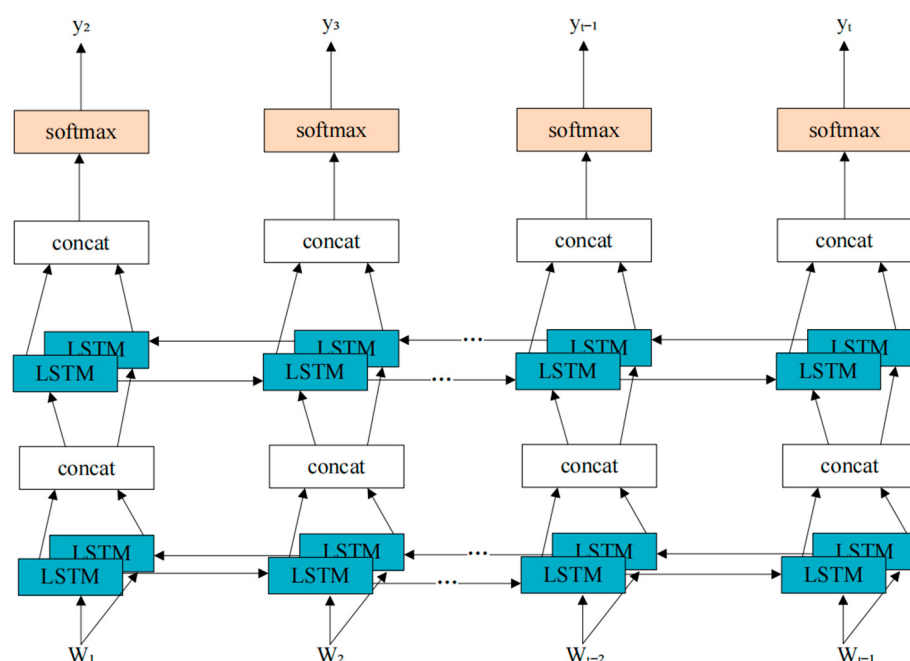


Figure 4. The Bi-Stacked-LSTM network.

2.4. The Improved GP-SMO Algorithm

In the context of dam deformation analysis, environmental factors (e.g., water levels, temperature, rainfall, and time-varying factors) have complex, nonlinear relationships with structural deformation. Traditional physics-based models often struggle to capture these relationships accurately. A Gaussian Process (GP)-based surrogate model, grounded in Bayesian theory, can effectively represent the statistical dependency between observed environmental factors and dam deformation, offering a predictive approach for assessing dam deformation performance under varying conditions.

A Gaussian Process is a non-parametric Bayesian model that assumes any finite set of function observations follows a multivariate normal distribution. For a given target function $f(x)$, where $x \in \mathbb{R}^d$ represents a d -dimensional input vector of environmental variables, GP assumes the following:

$$f(x) \sim \mathcal{GP}(m(x), k(x, x')) \quad (9)$$

where $m(x)$ is the mean function, often set to zero for simplicity, and $k(x, x')$ is the covariance (or kernel) function, which defines the similarity between two input points x and x' .

Commonly used kernels, such as the Radial Basis Function (RBF) or Matern kernel, capture dependencies among environmental variables, which are crucial for modeling their impact on deformation.

Given a set of n observed dam deformation monitoring points $\{(x_i, y_i)\}_{i=1}^n$, where x_i represents the observed environmental factors and y_i the corresponding dam deformation measurements, Bayesian inference enables us to make predictions at new input locations. Specifically, for an unobserved point x_{n+1} , the posterior distribution of the predicted deformation $y(x_{n+1})$ given all observations is as follows:

$$y(x_{n+1}) \mid X, Y, x_{n+1} \sim \mathcal{N}(\mu(x_{n+1}), \sigma^2(x_{n+1})), \quad (10)$$

$$\mu(x_{n+1}) = k(x_{n+1}, X)^\top [K(X, X) + \sigma_n^2 I]^{-1} Y, \quad (11)$$

$$y(x_{n+1}) \mid X, Y, x_{n+1} \sim \mathcal{N}(\mu(x_{n+1}), \sigma^2(x_{n+1})), \quad (12)$$

$$\sigma^2(x_{n+1}) = k(x_{n+1}, x_{n+1}) - k(x_{n+1}, X)^\top [K(X, X) + \sigma_n^2 I]^{-1} k(x_{n+1}, X). \quad (13)$$

where $k(x_{n+1}, X)$ is the covariance vector between the new point x_{n+1} and the observed points; $K(X, X)$ denotes the covariance matrix among the observed points; and σ_n^2 is the noise variance associated with observation noise.

To enhance the predictive accuracy for dam deformation under new environmental conditions, Bayesian optimization is often applied in tandem with the GP surrogate model. Bayesian optimization uses an acquisition function to determine where to sample next. These acquisition functions balance exploration and exploitation, thereby achieving efficient global optimization even with limited sampling.

Figure 5 illustrates the iterative process of the GP-SMO optimization algorithm, often applied in scenarios such as dam deformation analysis, where experimental costs are high and the objective function is complex and nonlinear. The process consists of two main phases: Inference and Planning, which operate in a loop to iteratively refine the model and optimize the target objective. This approach combines Bayesian inference with strategic experimental planning to enhance model performance in predicting target outcomes with limited deformation-related data. The specific calculation steps are as follows:

Step 1: Initial Experiments: The process begins with a set of initial experiments $X = \{(x_i, y_i)\}$, where x_i represents the environmental inputs, and y_i represents the measured responses, such as dam deformation.

Step 2: Updating the Surrogate Model: The surrogate model f is then updated based on the initial data, mapping x to predictive mean $\mu(x)$ and variance $\sigma(x)$. These statistical outputs represent the expected behavior of the response and the uncertainty around it, respectively, under different environmental conditions.

Step 3: Planning with Acquisition Functions: Using the posterior predictions $\mu(x)$ and $\sigma(x)$, an acquisition function $\alpha(\mu, \sigma)$ is computed. Common acquisition functions can help to balance exploration (searching in uncertain regions) and exploitation (focusing on promising regions) in the search for optimal solutions. The next experimental point x^* is selected by maximizing $\alpha(x)$.

Step 4: Iterative Experimental Updates: The selected experiment x^* is added to the dam environmental monitoring dataset, and its outcome y^* is recorded. The surrogate model is then updated with this new data, thereby improving its accuracy and refining its predictions iteratively.

Step 5: Objective Optimization and Benchmarking: This cycle continues, iteratively updating the surrogate model and refining the acquisition function until the optimal input

$x_{\text{opt}} = \operatorname{argmin}_{x \in X} y$ is found. The process concludes with benchmarking using evaluation metrics to assess effectiveness and accuracy.

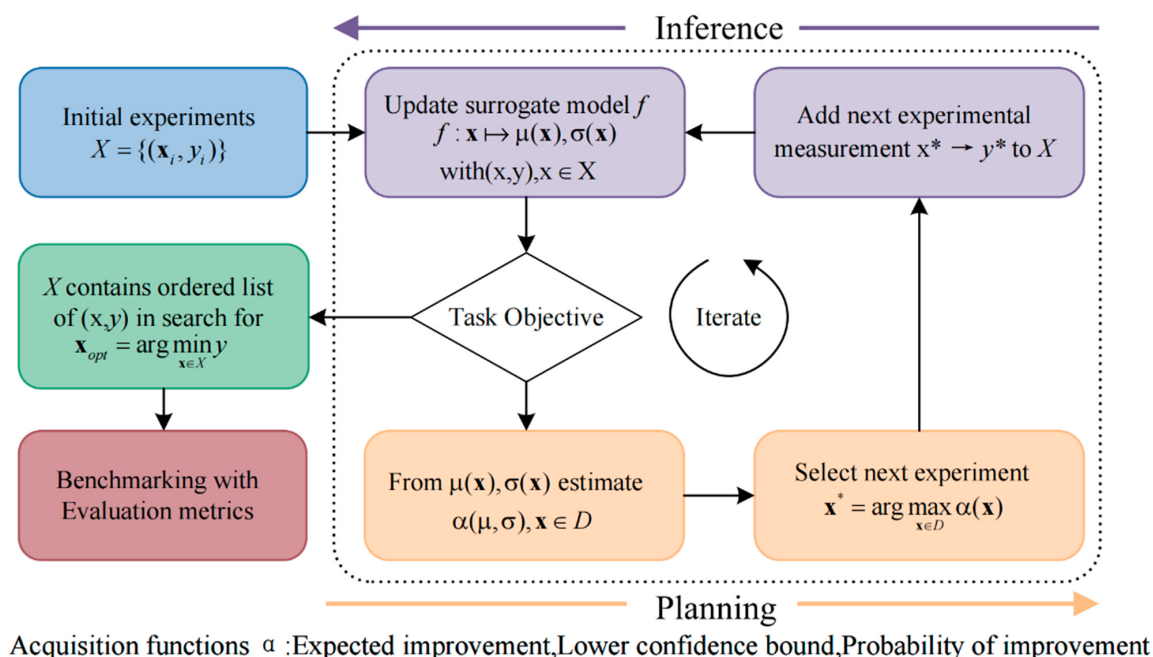


Figure 5. The developed GP-SMO algorithm for hyperparameter optimization.

3. Case Study

3.1. Project Background Description

The water conservancy project used in this study is located in Sichuan Province, China, which comprises barrages, flood discharge, energy dissipation, water conveyance structures, and underground powerhouses. Figure 6 demonstrates the overview of the project and its structural health monitoring system. Note that TCN represents the horizontal displacement vertical monitoring system, and C represents the crack opening measuring meter. As observed in Figure 6, the main water-retaining structure of this project is a 300-m-level concrete parabolic double-curvature arch dam. To monitor the operation behavior of the dam in service, the project is equipped with automated dam safety monitoring systems. Among them, dam horizontal displacements are mainly observed through the plumb line and inverted plumb line systems, composed of 10 vertical lines and 8 inverted vertical lines.

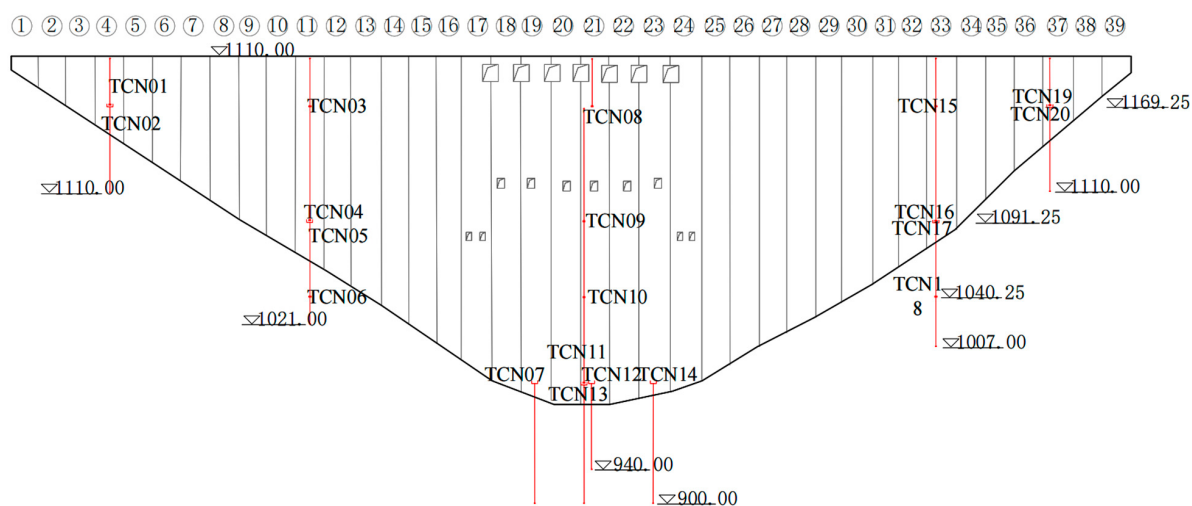


Figure 6. Overall view of dam deformation monitoring system.

3.2. Prototypical Monitoring Data Analysis

Figure 7 illustrates the time series monitoring data of key environmental variables related to dam operations. Figure 7a shows that the upstream water level displays notable seasonal variation, with peaks above 220 m during periods of high inflow. In contrast, the downstream water level remains more stable, fluctuating between 38 and 50 m, likely due to dam discharge and natural downstream hydrological processes. Figure 7b shows the rainfall data (in millimeters) over time. The rainfall peaks are periodic, with multiple spikes indicating heavy rainfall events. Rainfall intensity appears to be highly variable, with some extreme events exceeding 300 mm.

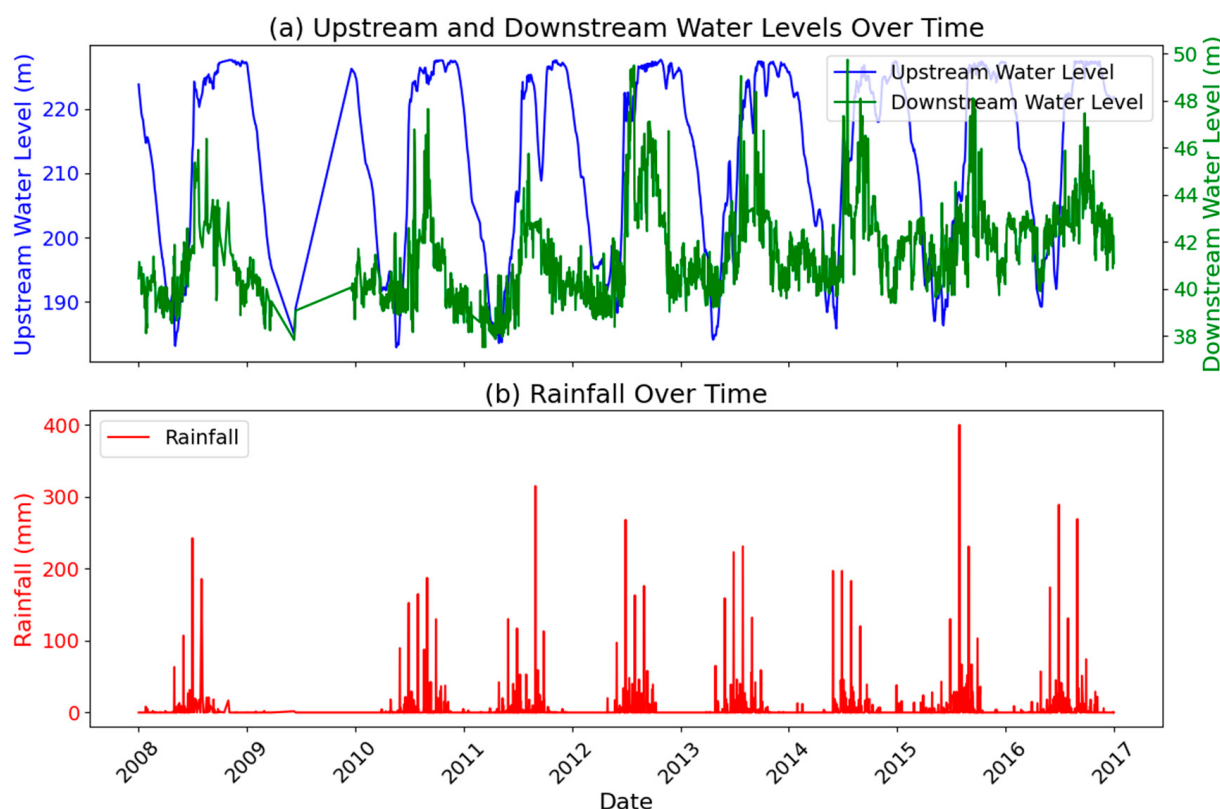


Figure 7. Processed upstream and downstream water levels and rainfall.

Figure 8 presents temperature data from 12 randomly selected thermometers out of 44, spanning the period from 2008 to 2017. The data exhibits clear seasonal patterns, with temperatures peaking around 30 °C during warmer months and dropping below 10 °C in colder months. Significant variability is observed among the thermometers, indicating potential differences in local environmental conditions or exposure.

Figure 9 shows the process line display of multiple deformation monitoring sequences. The deformation time series data of the high arch dam shows clear seasonal periodicity, with deformation peaking in summer and dipping in winter, reflecting environmental influences such as temperature and water level fluctuations. The magnitude of deformation varies across monitoring points, with TCN08 showing the highest values and TCN10 the lowest.

The Pearson correlation coefficients were computed and are presented as a ranked bar plot (Figure 10), along with the corresponding numerical values. As shown in Figure 10, the upstream water level and some temperature variables exhibit a high positive correlation with TCN08 deformation, suggesting a strong hydrostatic influence on the structural response. In contrast, several air temperature-related variables show moderate to weak negative correlations ($r \approx -0.3$ to -0.6), indicating potential thermal contraction effects.

Parameters such as downstream water level and rainfall show minimal or near-zero correlation, suggesting a limited direct contribution to the observed deformation at this specific location. The results indicate that upstream hydraulic loading is the primary factor influencing dam deformation, with ambient thermal conditions playing a secondary role.

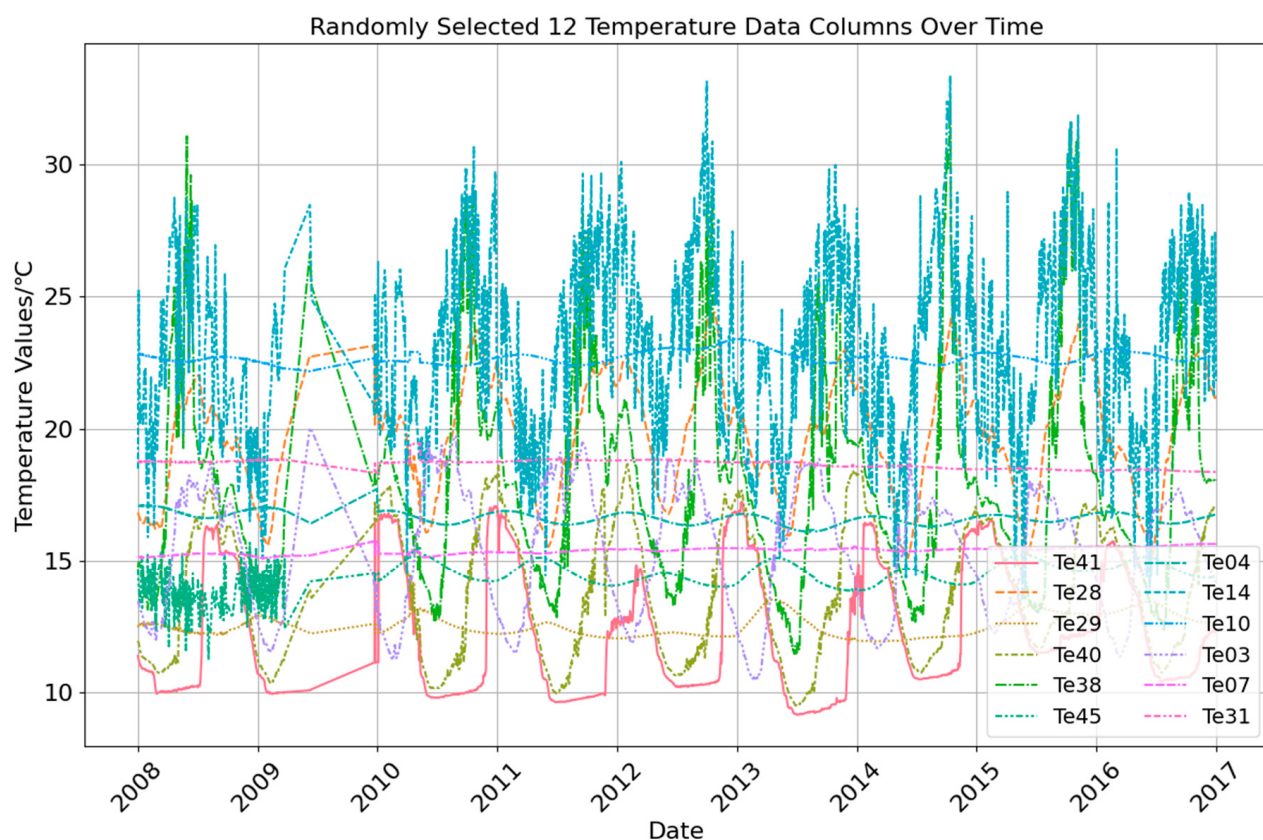


Figure 8. Visual display of environmental quantity monitoring data.

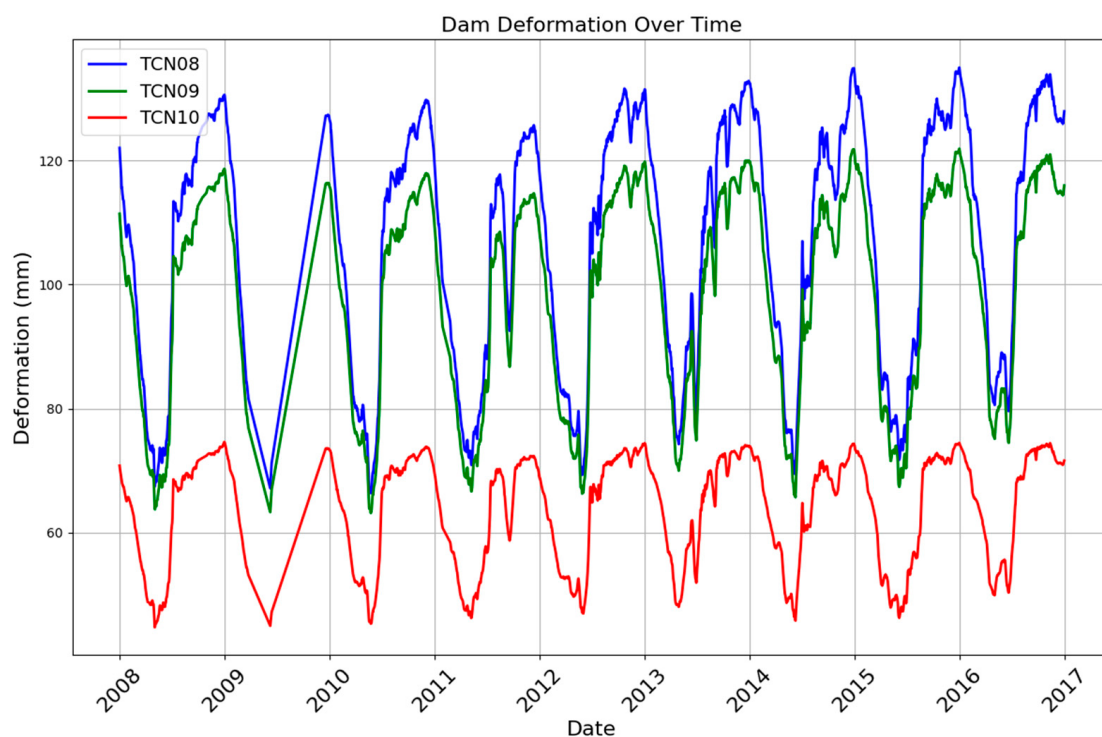


Figure 9. Process line display of multiple deformation monitoring sequences.

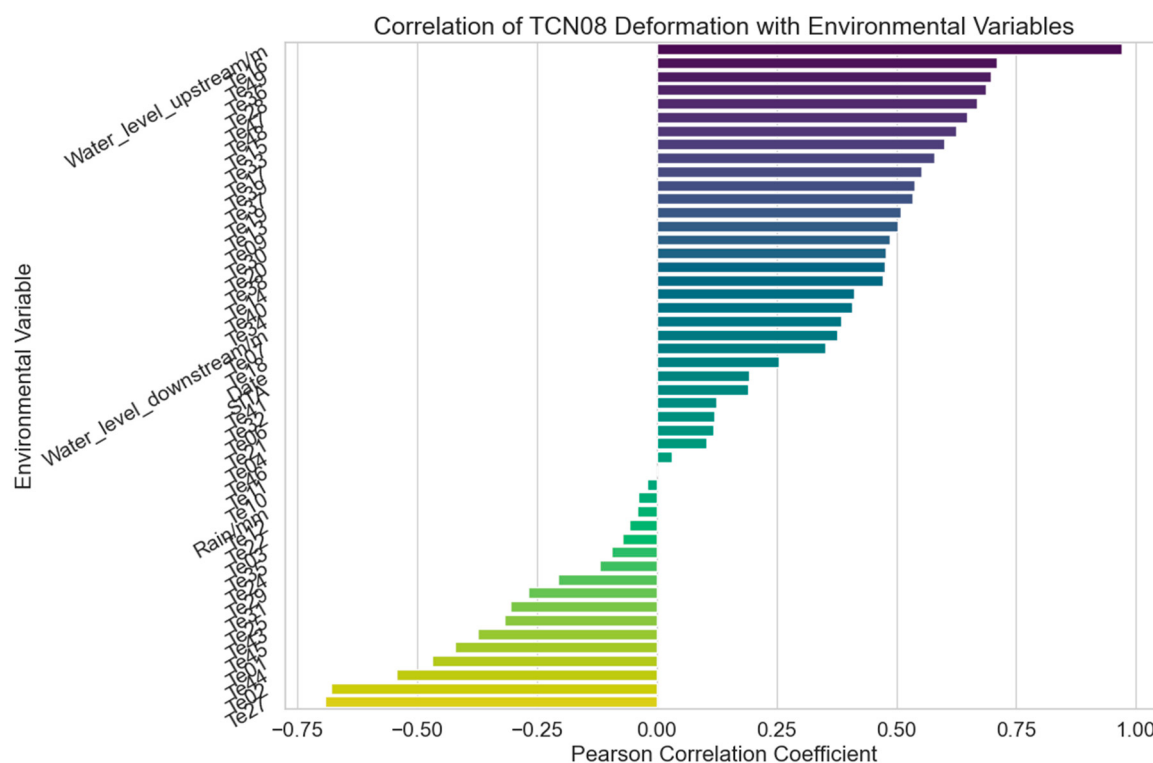


Figure 10. Correlation analysis of dam deformation-relevant environmental variables.

In response, a scatter plot with linear regression fitting is presented in Figure 11 to illustrate the relationship between deformation at monitoring point TCN08 and the upstream water level.

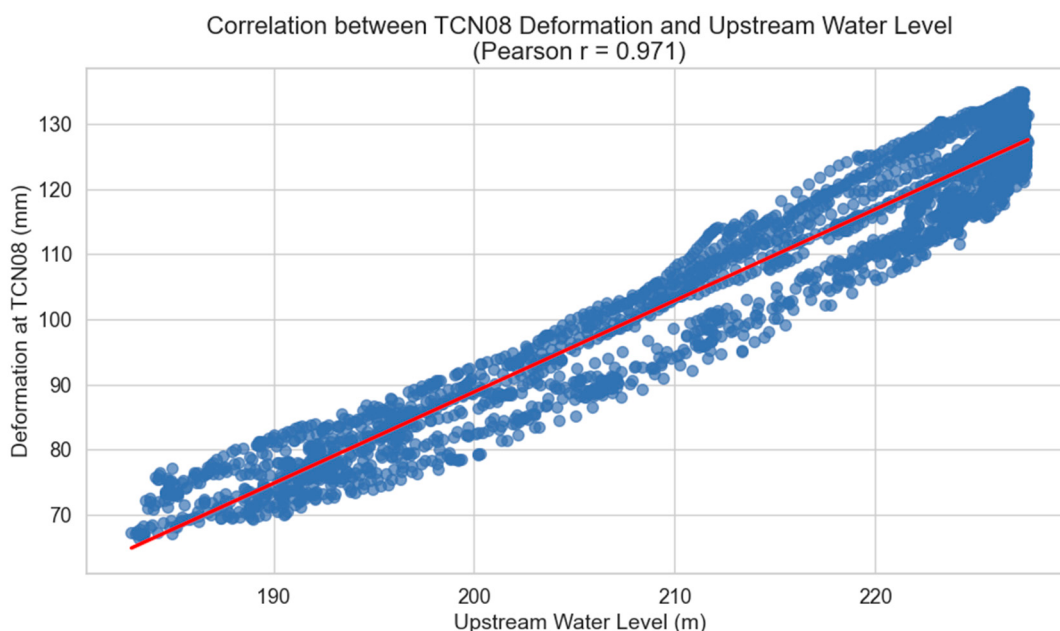


Figure 11. Correlation diagram of upstream water level and deformation monitoring point.

3.3. Experimental Design and Parameter Setting

Table 2 shows the selected hyperparameters of the proposed DL-based method and their impacts on predictive performance. The LSTM units per layer, ranging from 50 to 256, controls the hidden state size, impacting the model's ability to capture complex patterns and long-term dependencies. Increasing the number of LSTM layers (from 2

to 4) enables the model to learn hierarchical features, improving its ability to represent intricate temporal relationships in deformation-related sequences. The dense units, set between 50 and 256, control the neuron count in the fully connected layers, allowing the model to learn non-linear combinations of deformation-related features extracted by the LSTM layers. A dropout rate of 0.1 to 0.4 is applied as a regularization method to prevent overfitting by temporarily deactivating neurons during training, thereby enhancing the model's generalization on unseen data. Time steps, ranging from 3 to 14, determine the input sequence length for predictions, which is essential for capturing temporal patterns in time-series data and balancing short-term and long-term dependencies.

Table 2. Impact analysis of DL-based model hyperparameter.

Hyperparameter	Range	Value Type	Reason for Selection
LSTM Units per Layer	[50, 256]	Integer	The hidden state size in each LSTM layer determines the model's ability to capture complex patterns and long-term dependencies.
Number of LSTM Layers	[2, 4]	Integer	Increasing the model depth enables the learning of hierarchical features from sequential data.
Dense Units	[50, 256]	Integer	The number of neurons in the fully connected layers controls the model's capacity to learn non-linear combinations of extracted features, with higher units offering greater flexibility.
Number of Dense Layers	[1, 2]	Integer	Adds depth to fully connected layers for processing features learned from LSTM layers.
Dropout Rate	[0.1, 0.4]	Real	A regularization method that temporarily deactivates a portion of neurons during training to reduce overfitting.
Time Steps	[3–14]	Integer	Specifies the number of time steps used for prediction in each input window, crucial for capturing patterns in time-series data.

The dam safety monitoring dataset used for model construction consists of 2782 entries with 45 variables, including upstream and downstream water levels, rainfall, two time-varying effects, and prototypical data from 40 thermometers. To ensure robust model evaluation, the data is split into training and test sets, with the test set divided by year, where each year is set as 365 days years. The training and validation sets are constructed using 5-fold random cross-validation, allowing for better model tuning and performance evaluation while maintaining a random distribution of data in the folds. Figure 12 illustrates the process of k-fold cross-validation. In this approach, the dataset is split into five equal-sized folds, where, in each iteration, one fold serves as the validation set and the remaining four folds are used for training.

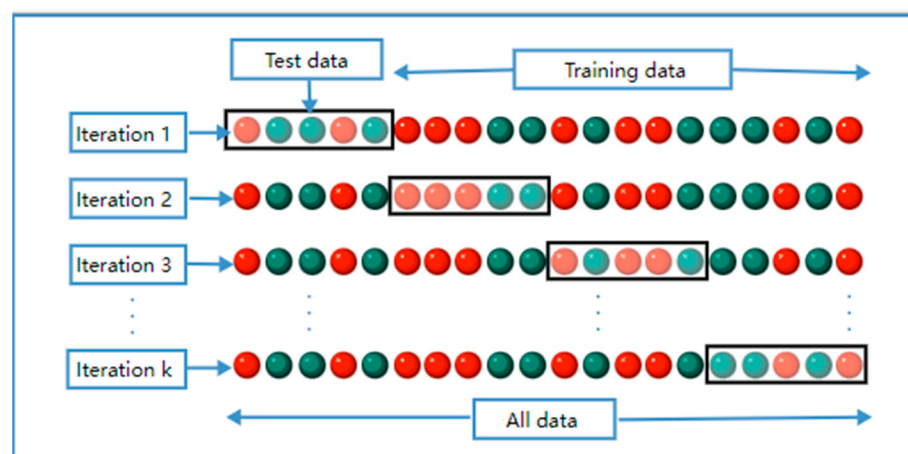


Figure 12. Randomized cross-validation diagram.

4. Experimental Results Analysis

The DL-based dam deformation prediction model and comparative methods were implemented on a graphics workstation featuring an AMD Ryzen 9 5900X CPU, NVIDIA RTX 4080 GPU, 64 GB RAM, and 2 TB SSD, running TensorFlow on an Ubuntu Linux OS optimized for GPU-accelerated tasks and high-level computations. Multiple evaluation metrics, including Mean Absolute Error (MAE), symmetric Mean Absolute Percentage Error (sMAPE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R_{squared}), were employed to comprehensively assess and compare the performance of dam deformation predictive methods.

4.1. The Model Hyperparameter Optimization Process

Figure 13 demonstrates the changes in loss values and R_{squared} evaluation metrics during the GP-SMO parameter tuning process. It can be seen from Figure 13a that the parameter optimization process has achieved a significant loss reduction, particularly after around 90 epochs, where the minimum value of 0.0035 is observed. This suggests that the developed GP-SMO algorithm can accurately identify a set of hyperparameters that significantly improve the model's predictive ability to generalize to the training data. The fluctuation in loss before reaching the optimal point indicates that the model was undergoing a phase of exploration in the parameter space, leading to a better configuration. It can be seen from Figure 13b that the highest R_{squared} value of 0.9548 occurs at epoch 97, coinciding with the point where the loss reaches its minimum. The R_{squared} score reflects the proportion of variance explained by the model, and a value close to 1 signifies an excellent fit of the model to the data.

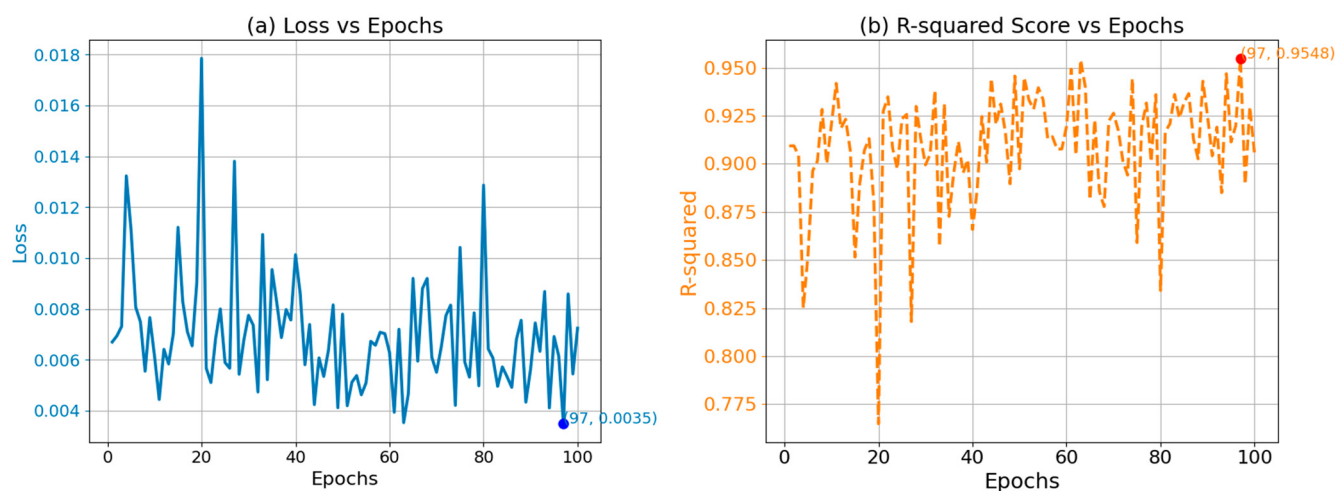


Figure 13. Changes in loss values and evaluation indicators during model parameter optimization.

Figure 14 depicts the variation of the loss function during the training process of the proposed Bi-Stacked-LSTM model using the obtained optimal hyperparameters. It can be seen that the loss starts at a relatively high value of approximately 0.45, initially reflecting the initial prediction error of the model when the training begins. However, the loss quickly decreases within the first 50 epochs, indicating that the model rapidly learns from the data and reduces the prediction error. As the epochs progress beyond 50, the loss continues to decrease but at a much slower rate, suggesting that the model is converging and refining its predictions with each additional epoch. By around epoch 100, the loss stabilizes and approaches a very low value close to zero, remaining nearly constant for the remainder of the training period up to 500 epochs. The relevant optimized deep learning model hyperparameters are shown as Table 3.

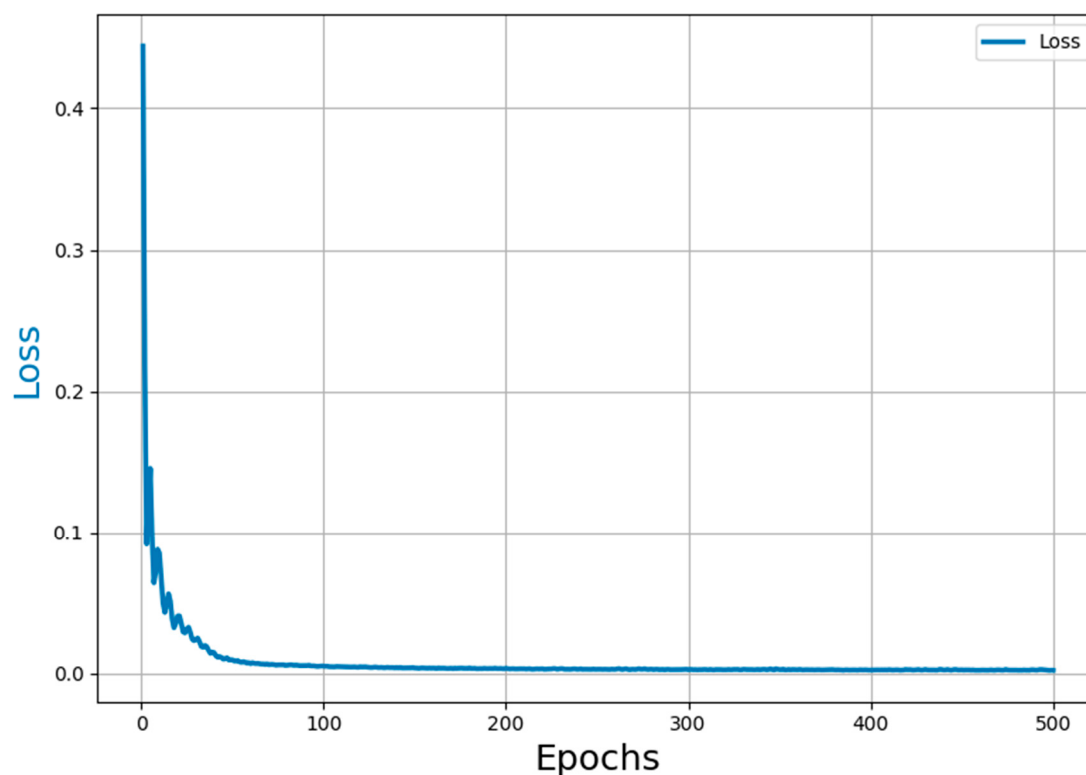


Figure 14. Changes in loss values during the training phase of the proposed method.

Table 3. The obtained optimal hyperparameters of DL-based models.

Hyperparameter	Optimal_Values_TCN08	Optimal_Values_TCN09	Optimal_Values_TCN10
LSTM_layers	4	2	2
LSTM_units_layer1	256	53	122
LSTM_units_layer2	122	256	230
LSTM_units_layer3	50	-	-
LSTM_units_layer4	256	-	-
Dense_units	64	252	117
Dense_layers	1	1	1
Dropout_rate	0.05	0.14	0.09
Time_step	7	10	6

4.2. Model Ablation Experiment

Referring to the optimal hyperparameters obtained based on the GP-SMO algorithm in the previous section, the GP-SMO-Bi-Stacked-LSTM model for high arch dam deformation prediction was constructed. To further verify the effectiveness of the various components of the GP-SMO-Bi-Stacked-LSTM proposed in this study for the accuracy of dam deformation prediction, five comparative algorithms, namely GP-SMO-Stacked-LSTM, GP-SMO-Bi-LSTM, Stacked-LSTM, GP-SMO-LSTM model, and single LSTM model, were introduced to conduct ablation experiments on each component.

Table 4 shows the ablation test evaluation results of each component of the proposed method on the test set. It should be noted that the evaluation results are based on the average apple index results of the prediction results of three typical measurement points. As can be seen from Table 4, the GP-SMO-Bi-Stacked-LSTM neural network model learns long-term dependencies and trend change laws based on dam deformation-related data for sample training and has better prediction ability on the deformation prediction in the test sets. The prediction accuracy is significantly higher than other algorithms. This further

verifies the advantages of the GP-SMO algorithm in optimizing the hyperparameters of the Bi-Stacked-LSTM model. In other words, the GP-SMO optimization algorithm effectively explores the parameter architecture and optimal hyperparameters of the constructed Bi-Stacked-LSTM model and thus obtains a more reasonable parameter and architecture model of the Bi-Stacked-LSTM.

Table 4. Ablation experimental results of the developed DL-based method.

Models	Optimized	Bi	Stacked	LSTM	R_Squared	RMSE	sMAPE
LSTM				✓	0.920	2.864	2.876
GP-SMO-LSTM	✓			✓	0.947	2.575	2.693
GP-SMO-Stacked-LSTM	✓		✓	✓	0.951	2.468	2.472
GP-SMO-Bi-LSTM	✓	✓		✓	0.949	2.542	2.558
Bi-Stacked-LSTM		✓	✓	✓	0.948	2.684	2.778
GP-SMO-Bi-Stacked-LSTM	✓	✓	✓	✓	0.974	2.205	1.883

In contrast, the prediction effect of other models may be limited by insufficient hyperparameter tuning or the limitations of the model itself. The single LSTM model has problems of insufficient model fitting ability and inappropriate eigenvalues because it fails to fully utilize the causal feature information of multiple factors, resulting in lower dam deformation prediction accuracy than the proposed method. The prediction accuracy of the GP-SMO-LSTM model under various indicator evaluations is higher than that of the single LSTM model. This is mainly because the GP-SMO-LSTM model better balances the complexity and prediction ability of the model, so its performance on the training set is more accurate. However, since the GP-SMO-LSTM model still uses a single LSTM hidden layer, the feature extraction ability is insufficient, resulting in limited generalization performance on dam deformation prediction. The prediction accuracy of the GP-SMO-Stacked-LSTM and GP-SMO-Bi-LSTM models is higher than that of the GP-SMO-LSTM model, which shows that under the premise of parameter optimization, the bidirectional transmission mechanism and stacking strategy can improve the feature extraction ability of the network model to a certain extent, thereby improving the model dam deformation prediction ability.

4.3. Performance Evaluation of Comparative Methods

To validate the effectiveness of the proposed DL-based deformation prediction model for high arch dams, a series of statistical and ML-based comparative methods were introduced. These methods included HST-based multiple linear analysis (HST-MLR), Light Gradient Boosting Machine (LGBM), Random Forest (RF), Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Gradient Boosting Machine (GBM). To ensure a fair comparison, all comparative methods and the proposed DL-based model were trained and evaluated on the same dataset under identical environmental conditions. This approach guarantees that the observed differences in model performance are attributable solely to the model architectures and algorithms rather than variations in data or experimental setup. The principles of the relevant methods are introduced as follows:

- (1) HST-MLR model. The HST-based MLR model is widely used in dam safety monitoring, which analyzes the relationship between multiple independent variables and a single dependent variable. It assumes a linear relationship, where each predictor has a unique coefficient indicating its contribution to the outcome [25].
- (2) LGBM model. LGBM is a high-performance gradient-boosting framework optimized for large datasets and high-dimensional data. Unlike traditional boosting, LGBM grows trees leaf-wise, thus improving computational speed and memory efficiency.

This makes it suitable for applications requiring rapid, accurate predictions with reduced computational cost [26].

- (3) RF model. An ensemble learning method, RF constructs multiple decision trees and aggregates their outputs, resulting in robust generalization and reduced overfitting. It is highly effective for handling feature interactions and noisy data, making it a popular choice for regression tasks [27].
- (4) MLP model. MLP is a type of feedforward neural network consisting of multiple layers of neurons, enabling it to capture complex, non-linear relationships within the data. It performs well in both regression tasks but requires significant computational resources and training data for optimal performance [28].
- (5) SVR model. An extension of Support Vector Machines, SVR is designed for regression tasks and minimizes an epsilon-insensitive loss function. This method is particularly effective in handling high-dimensional data and ensuring robust performance in the presence of noise [29].
- (6) LSTM model. LSTM, a specialized recurrent neural network architecture, effectively captures sequential dependencies by mitigating the vanishing gradient problem. It uses memory cells and gating mechanisms, allowing it to retain long-term information, making it ideal for time-series prediction [30].
- (7) GBM model. The GBM model ensemble method builds models sequentially, with each new model aiming to correct errors made by previous ones using gradient descent on a specified loss function [31].

Table 5 shows the hyperparameter range settings and optimization results of comparison methods. It can be inferred that corresponding hyperparameters have been added to this manuscript to list the specific values or search ranges used for each key hyperparameter (e.g., number of estimators, learning rate, maximum depth, number of hidden units, etc.), along with the optimization method (e.g., grid search, default setting, or manual tuning based on validation performance).

Three representative monitoring points (TCN08 to TCN10) were selected as study targets to illustrate distinct deformation patterns that are directly indicative of the dam's structural response under varying hydrostatic and thermal influences. Figure 15 shows the prediction and residual analysis for dam deformation at three monitoring points from TCN08 to TCN10. It consists of six subplots, where subplots (a), (b), and (c) show the predicted deformation results, and subplots (d), (e), and (f) display the residuals associated with these predictions. The evaluation index calculation results of the proposed and compared methods are shown in Table 6. It can be inferred from Figure 15a–c that the proposed GP-SMO-based Bi-Stacked-LSTM method demonstrates superior performance in capturing the temporal trends of dam deformation in the prediction results for monitoring points TCN08, TCN09, and TCN10. Compared to other benchmark comparative methods such as GBM, HST-MLR, LGBM, LSTM, MLP, RF, and SVR, the proposed method aligns more closely with the observed values, indicating higher predictive accuracy. Figure 15d–f demonstrates the residual plots, which indicate the error distribution for each method's predictions relative to the actual deformation values. In terms of residuals, the proposed method consistently shows smaller and less dispersed residuals around the zero line across all monitoring points. This suggests fewer and smaller prediction errors, as well as improved stability relative to other methods. The lower variability in the residuals further supports the robustness and reliability of the proposed method in accurately predicting dam deformation. Consequently, the proposed method offers a more reliable tool for predicting dam deformation, providing critical insights for the safety monitoring of high arch dams and decision-making processes.

Table 5. Hyperparameter range settings and optimization results of comparison methods.

Model	Hyperparameter	Search Range	Selected Value
HST-MLR	–	–	Standard MLR
LGBM	learning_rate	[0.01, 0.05, 0.1]	0.05
	n_estimators	[50, 100, 200, 500]	200
	num_leaves	[20, 31, 50]	31
	max_depth	[−1, 5, 10]	−1 (no limit)
RF	n_estimators	[50, 100, 200]	100
	max_depth	[None, 10, 20, 30]	None
	min_samples_split	[2, 5, 10]	2
	min_samples_leaf	[1, 2, 4]	1
MLP	hidden_layer_sizes	[(100,),(100, 50), (128, 64, 32)]	(100, 50)
	activation	['relu', 'tanh']	relu
	solver	['adam', 'sgd']	adam
	alpha	[0.0001, 0.001, 0.01]	0.0001
SVR	learning_rate	['constant', 'adaptive']	constant
	C	[1, 10, 100]	10
	epsilon	[0.01, 0.1, 0.5]	0.1
	kernel	['rbf', 'linear']	rbf
LSTM	gamma	['scale', 'auto']	scale
	layers	[1, 2, 3]	2
	hidden_units	[32, 64, 128]	64
	dropout	[0.1, 0.2, 0.3]	0.2
	optimizer	['adam', 'rmsprop']	adam
	learning_rate	[0.0005, 0.001, 0.005]	0.001
	epochs	[50, 100, 200]	100
	batch_size	[16, 32, 64]	32
GBM	learning_rate	[0.05, 0.1, 0.2]	0.1
	n_estimators	[100, 200, 300]	100
	max_depth	[3, 5, 7]	3
	subsample	[0.8, 1.0]	1.0

Table 6. Comparative evaluation of prediction results of different methods.

Monitoring Points	Methods	R_Squared	MAE	RMSE	sMAPE
TCN08	Proposed_method	0.980	2.139	2.591	1.939
	HST-MLR	0.920	4.610	5.255	4.272
	LGBM	0.949	3.861	4.168	3.446
	RF	0.960	2.833	3.707	2.395
	MLP	0.714	8.556	9.902	8.094
	SVR	0.949	3.066	4.196	2.640
	LSTM	0.961	2.754	3.655	2.322
	GBM	0.831	6.317	7.609	5.348
TCN09	Proposed_method	0.973	1.999	2.598	1.846
	HST-MLR	0.871	5.007	5.656	4.844
	LGBM	0.922	3.652	4.417	3.341
	RF	0.939	3.376	3.886	3.395
	MLP	0.721	7.841	8.331	7.884
	SVR	0.946	2.646	3.649	2.488
	LSTM	0.940	3.275	3.857	3.157
	GBM	0.847	5.105	6.161	4.726
TCN10	Proposed_method	0.970	1.231	1.427	1.866
	HST-MLR	0.732	3.749	4.271	5.739
	LGBM	0.901	2.176	2.598	3.239
	RF	0.939	1.704	2.039	2.611
	MLP	0.726	3.611	4.314	5.628
	SVR	0.851	2.569	3.187	3.920
	LSTM	0.939	1.697	2.031	2.602
	GBM	0.914	1.817	2.417	2.741

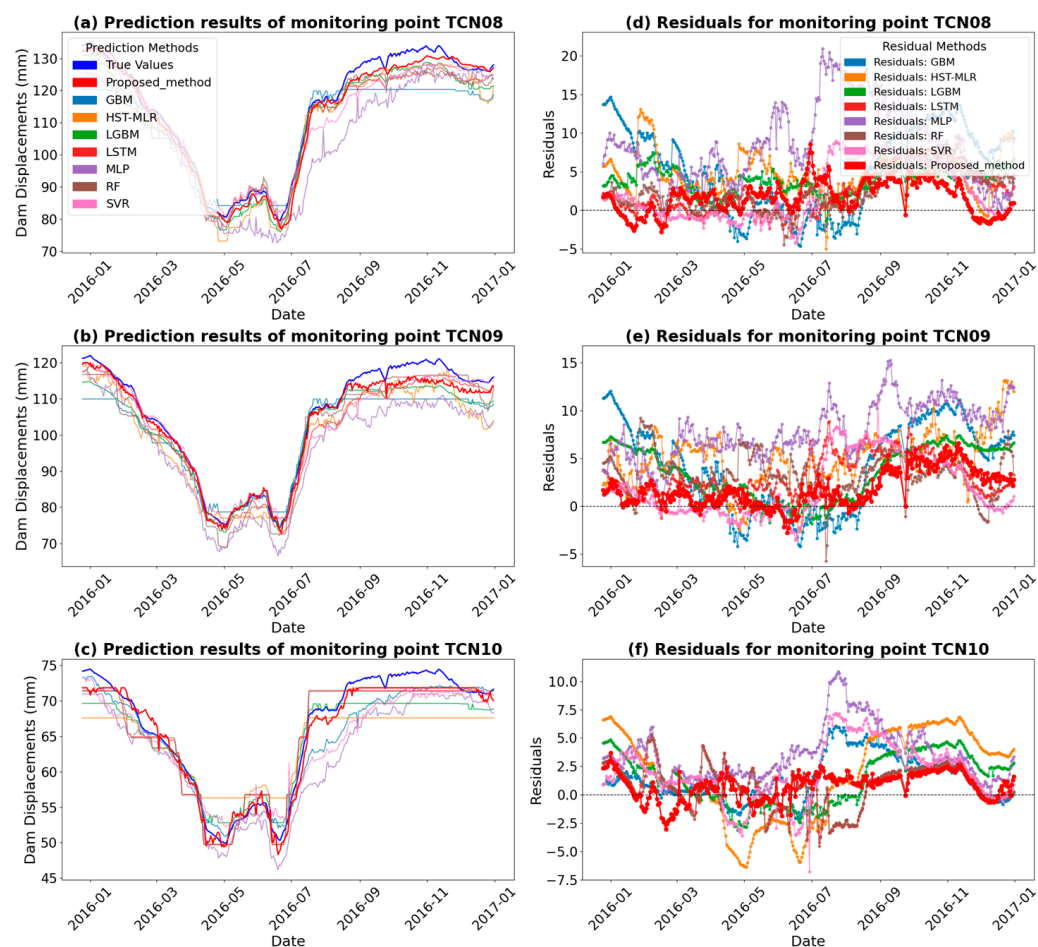


Figure 15. Prediction results and residual distribution process lines of different monitoring points.

4.4. Graphical Visualization Evaluation Comparison

Figure 16 presents radar charts comparing the performance of different ML-based models across R-squared, RMSE, and sMAPE metrics at three monitoring points. In terms of R-squared (subplots a, d, g), which reflects the proportion of variance explained by each model, the proposed method generally covers the largest area, indicating superior performance in capturing variance in dam deformation data. For RMSE (Subplots b, e, h), a metric assessing the standard deviation of prediction errors, the proposed method consistently shows lower values, suggesting higher predictive accuracy and reduced error spread. Lastly, for sMAPE (Subplots c, f, i), which focuses on percentage errors, the proposed method achieves the lowest values across monitoring points, further demonstrating its advantage in prediction accuracy over other models.

In summary, the radar charts provide a comparative view of model performance across multiple metrics and monitoring points. The proposed method consistently shows superior performance in terms of higher R-squared values and lower RMSE and sMAPE values, indicating its effectiveness in predicting dam deformation more accurately than the other models tested.

Figure 17 demonstrates the residual box plots of the proposed and other benchmark methods at monitoring points TCN08, TCN09, and TCN10, respectively. It can be inferred that the proposed method consistently exhibits lower median residuals and a narrower interquartile range across all monitoring points, highlighting its accuracy and stability in dam deformation prediction. Additionally, the proposed method has fewer extreme outliers, particularly when compared to methods such as HST-MLR, RF, and LSTM, which display higher variability and a wider spread of residuals. This suggests that the proposed method

not only reduces prediction error but also enhances robustness by minimizing residual dispersion, making it a more reliable choice for high-precision deformation monitoring in dam safety assessments.

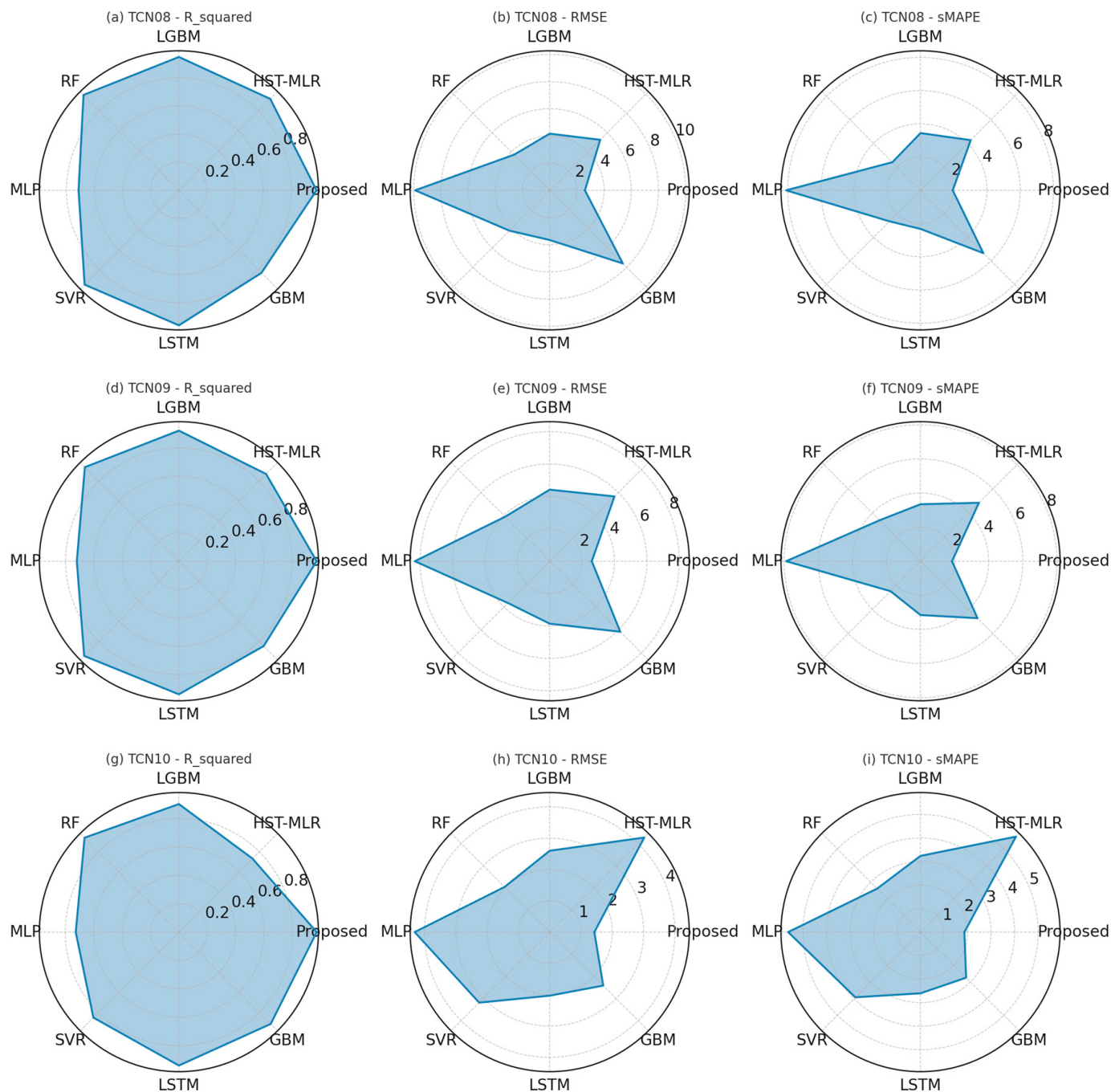


Figure 16. Radar chart of evaluation indicators for prediction results.

Figure 18 presents the long-term deformation prediction results of the proposed method at three monitoring points (TCN06, TCN07, and TCN08) from 2008 to 2017. The predicted values (red curves) exhibit strong agreement with the measured deformation data (blue curves), successfully capturing both seasonal fluctuations and long-term trends. The proposed model demonstrates consistent performance across different deformation magnitudes and monitoring locations, indicating its robustness and reliability in practical dam deformation structural health monitoring applications.

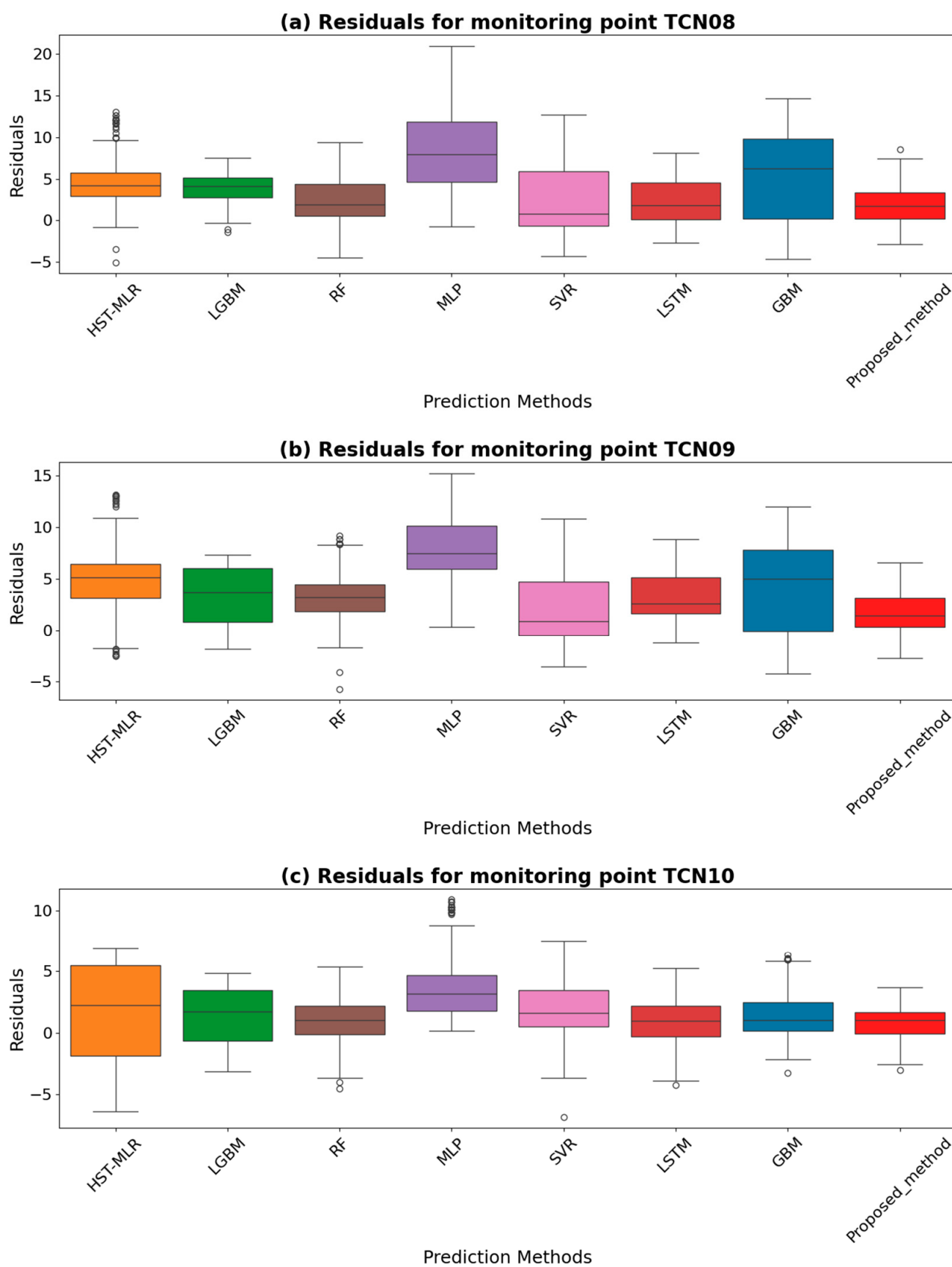


Figure 17. Residual box plot of prediction results of different deformation monitoring models.

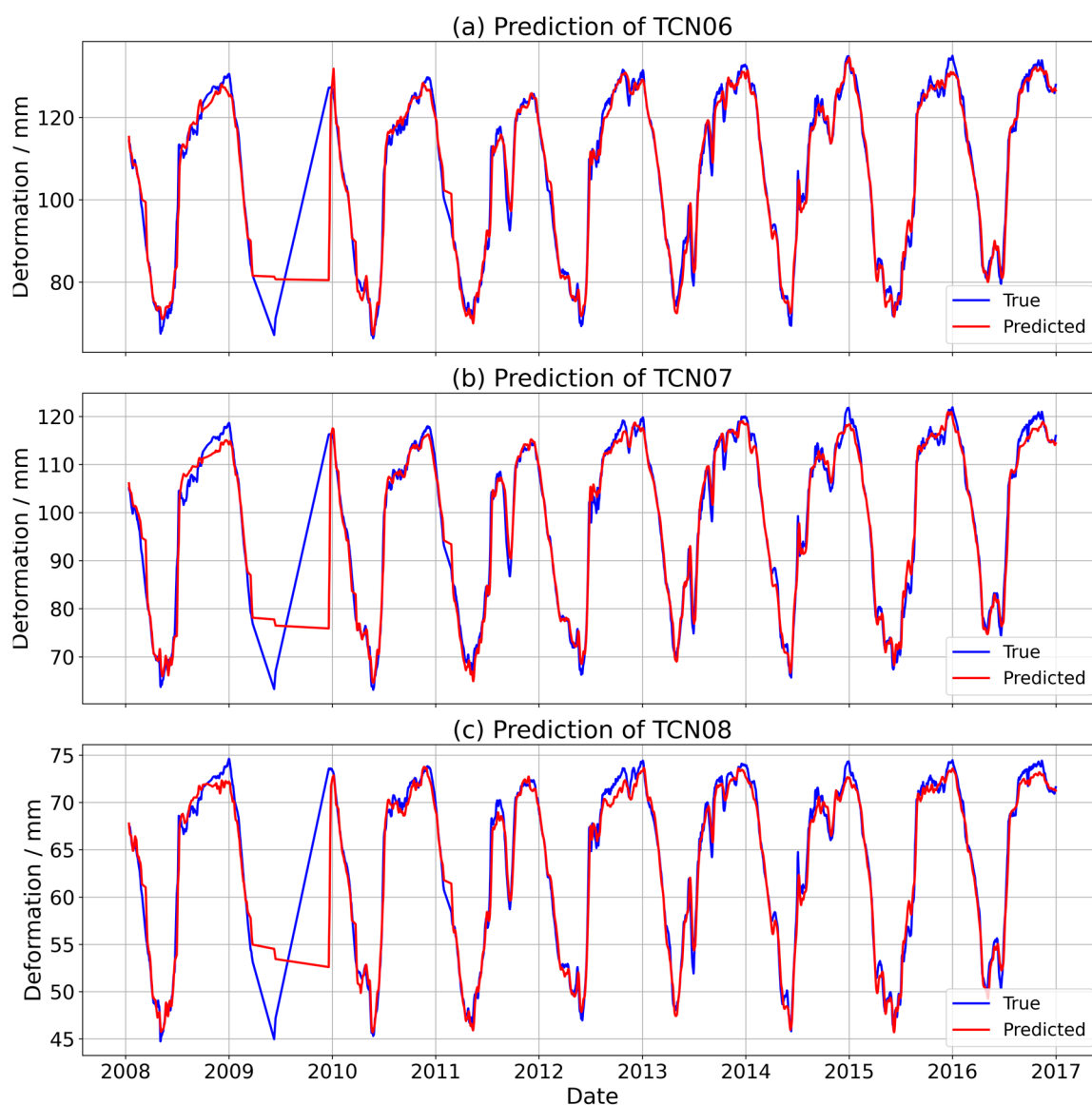


Figure 18. Display of prediction results of long sequence deformation data.

5. Conclusions

The monitoring of deformation in hydraulic structures is critical for maintaining structural integrity and ensuring safe, continuous operation under varying hydraulic conditions. These structures are constantly subjected to environmental stressors, particularly long-term fluctuations in hydrostatic pressure and temperature. Thus, accurate prediction of deformation patterns becomes essential for proactive maintenance and water-related risk mitigation. However, traditional statistical regression and shallow ML-based approaches are often constrained by their linear modeling assumptions, dependency on hand-crafted deformation features, and limited capacity to capture complex temporal dynamics driven by environmental variability.

To overcome these limitations, this study proposes a Bidirectional Stacked Long Short-Term Memory (Bi-Stacked-LSTM) network, specifically designed to model intricate temporal dependencies and directional interactions embedded in multivariate deformation time series induced by hydrostatic and thermal conditions. To further enhance model performance, hyperparameters such as the number of LSTM layers, neurons per layer, dropout rate, and time steps are efficiently optimized using the Gaussian Process-based Surrogate Model Optimization (GP-SMO) algorithm. The framework is validated using

long-term monitoring data collected from multiple deformation measurement points in the crown beam region of high arch dams. The main conclusions drawn from this study are as follows:

- (1) The proposed Bi-Stacked-LSTM model effectively captures the complex nonlinear relationships between deformation and deformation-related environmental variables (e.g., long-sequence hydrostatic and thermal time series) in hydraulic structures by integrating multiple bidirectional LSTM layers. This architecture allows the developed model to leverage intricate temporal dynamics and dependencies within the deformation data, resulting in enhanced predictive accuracy.
- (2) The GP-SMO algorithm efficiently identifies optimal parameter configurations within a high-dimensional space, ensuring that the deep learning-based model aligns with the unique temporal dependencies and nonlinear relationships present in dam deformation monitoring data. This optimization process not only enhances model performance but also enables more accurate predictions, ultimately contributing to improved structural health monitoring and risk management strategies for high arch dams.
- (3) Through extensive quantitative and qualitative evaluations of various advanced ML-based models, the developed DL-based method demonstrates robust predictive power and reliability in forecasting deformation in hydraulic structures. This effectiveness is validated from multiple perspectives through a series of comparative experiments, highlighting its superiority in accurately capturing the complexities of deformation patterns.

However, this research is not without its limitations. First, while the developed GP-SMO-based Bi-Stacked-LSTM model shows improved performance, its complexity may pose challenges in terms of interpretability. Stakeholders may find it difficult to derive actionable insights from the model's predictions due to the intricate nature of its architecture. Additionally, the reliance on historical data to train the dam deformation model may lead to overfitting, particularly in scenarios with limited datasets. Future work could explore strategies to mitigate this risk, such as employing regularization techniques or expanding the dam monitoring dataset through synthetic data generation. Moreover, the prediction model of deformation is contingent upon the quality and granularity of the input data. In practice, variations in data collection methods, sensor accuracy, and environmental factors can significantly impact predictive performance. Thus, further research is needed to evaluate the model's robustness across diverse datasets and under varying conditions. In addition, the authors plan to further expand this analysis in future work by incorporating all available dam deformation monitoring points to investigate spatiotemporal dependencies and to enhance the model's generalization across the entire dam structure.

Lastly, while the focus of this study was on deformation prediction, the proposed framework could be adapted for other hydraulic structural response variables, such as seepage, crack opening, etc. Future studies may investigate its applicability to different types of dams like concrete face rockfill dams and gravity dams, further extending the contributions of this research. In conclusion, while the developed DL-based model offers significant advancements in dam deformation predictive accuracy, addressing the highlighted limitations will be essential for its successful implementation in real dam safety management applications.

Author Contributions: Conceptualization, methodology, experiment, software: J.L. and F.L. validation; formal analysis: H.L. and G.Y.; funding, investigation, experiment: Y.O. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the 2024 Henan Province Science and Technology Research Project (242102211010, 242102220091), the 2025 Henan Province Science and Technology Research Project (252102210090, 252102211032), the National Natural Science Foundation of China (52109155), the Open Research Fund Program of National Key Laboratory of Water Disaster Prevention (2024491911), the 2024 Henan Province Higher Education Teaching Reform Research and Practice Project (2024SJGLX0675), and the National Level General Project Cultivation Project (23HNCDXJ49, School Level).

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to data confidentiality laws in China.

Conflicts of Interest: Author Jiankang Lou was employed by the company Henan Water Planning and Design Research Co., LTD, Zhengzhou, Henan 450008, China. 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.

References

1. Fu, X.; Gu, C.; Qin, D. Deformation Features of a Super-High Arch Dam Structural System. *Optik* **2017**, *130*, 681–695. [\[CrossRef\]](#)
2. Li, J.; Bao, T.; Ventura, C.E. An Automated Operational Modal Analysis Algorithm and Its Application to Concrete Dams. *Mech. Syst. Signal Process.* **2022**, *168*, 108707. [\[CrossRef\]](#)
3. Li, Y.; Min, K.; Zhang, Y.; Wen, L. Prediction of the Failure Point Settlement in Rockfill Dams Based on Spatial-Temporal Data and Multiple-Monitoring-Point Models. *Eng. Struct.* **2021**, *243*, 112658. [\[CrossRef\]](#)
4. Li, H.; Wang, Y.; Wei, B. Inversion Algorithm for the Whole Prototype Dynamic Displacement Field of a High Arch Dam Based on Limited Measuring Points. *JVC/J. Vib. Control* **2017**, *23*, 3431–3447. [\[CrossRef\]](#)
5. Pan, J.; Liu, W.; Liu, C.; Wang, J. Convolutional Neural Network-Based Spatiotemporal Prediction for Deformation Behavior of Arch Dams. *Expert Syst. Appl.* **2023**, *232*, 120835. [\[CrossRef\]](#)
6. Wang, R. Key Technologies in the Design and Construction of 300 m Ultra-High Arch Dams. *Engineering* **2016**, *2*, 350–359. [\[CrossRef\]](#)
7. Yang, G. Deformation Similarity Characteristics-Considered Hybrid Panel Model for Multi-Point Deformation Monitoring of Super-High Arch Dams in Operating Conditions. *Meas. J. Int. Meas. Confed.* **2022**, *192*, 110908. [\[CrossRef\]](#)
8. Liu, X.; Li, Z.; Sun, L.; Khailah, E.Y.; Wang, J.; Lu, W.; Yahya, E.; Wang, J.; Lu, W. A Critical Review of Statistical Model of Dam Monitoring Data. *J. Build. Eng.* **2023**, *80*, 108106. [\[CrossRef\]](#)
9. Belmokre, A.; Mihoubi, M.K.; Santillán, D. Analysis of Dam Behavior by Statistical Models: Application of the Random Forest Approach. *KSCE J. Civ. Eng.* **2019**, *23*, 4800–4811. [\[CrossRef\]](#)
10. Li, M.; Si, W.; Ren, Q.; Song, L.; Liu, H. An Integrated Method for Evaluating and Predicting Long-Term Operation Safety of Concrete Dams Considering Lag Effect. *Eng. Comput.* **2021**, *37*, 2505–2519. [\[CrossRef\]](#)
11. Li, M.M.; Ren, Q.; Li, M.M.; Fang, X.; Xiao, L.; Li, H. A Separate Modeling Approach to Noisy Displacement Prediction of Concrete Dams via Improved Deep Learning with Frequency Division. *Adv. Eng. Inform.* **2024**, *60*, 102367. [\[CrossRef\]](#)
12. Li, Y.; Yin, Q.; Zhang, Y.; Qiu, W. Prediction of Long-Term Maximum Settlement Deformation of Concrete Face Rockfill Dams Using Hybrid Support Vector Regression Optimized with HHO Algorithm. *J. Civ. Struct. Health Monit.* **2023**, *13*, 371–386. [\[CrossRef\]](#)
13. Wang, S.; Xu, C.; Liu, Y.; Wu, B. Mixed-Coefficient Panel Model for Evaluating the Overall Deformation Behavior of High Arch Dams Using the Spatial Clustering. *Struct. Control Health Monit.* **2021**, *28*, 1–19. [\[CrossRef\]](#)
14. Zang, W.; Zheng, Y.; Zhang, Y.; Lin, X.; Li, Y.; Fernandez-Rodriguez, E. Numerical Investigation on a Diffuser-Augmented Horizontal Axis Tidal Stream Turbine with the Entropy Production Theory. *Mathematics* **2023**, *11*, 116. [\[CrossRef\]](#)
15. Zhu, Y.; Niu, X. Residual Correction-Based Dam Deformation Monitoring Method via Data Dimension Reduction and Optimized Bi-LSTM Algorithm. *Struct. Health Monit.* **2024**, 14759217241264098. [\[CrossRef\]](#)
16. Ren, Q.; Li, M.; Kong, T.; Ma, J. Multi-Sensor Real-Time Monitoring of Dam Behavior Using Self-Adaptive Online Sequential Learning. *Autom. Constr.* **2022**, *140*, 104365. [\[CrossRef\]](#)
17. Chen, W.; Wang, X.; Cai, Z.; Liu, C.X.; Zhu, Y.S.; Lin, W. DP-GMM Clustering-Based Ensemble Learning Prediction Methodology for Dam Deformation Considering Spatiotemporal Differentiation. *Knowl.-Based Syst.* **2021**, *222*, 106964. [\[CrossRef\]](#)
18. Zhang, Y.; Zhong, W.; Li, Y.; Wen, L. A Deep Learning Prediction Model of DenseNet-LSTM for Concrete Gravity Dam Deformation Based on Feature Selection. *Eng. Struct.* **2023**, *295*, 116827. [\[CrossRef\]](#)
19. Xu, B.; Chen, Z.; Su, H.; Zhang, H. A Deep Learning Method for Predicting the Displacement of Concrete Arch Dams Considering the Effect of Cracks. *Adv. Eng. Inform.* **2024**, *62*, 102574. [\[CrossRef\]](#)

20. Lu, T.; Gu, C.; Yuan, D.; Zhang, K.; Shao, C. Deep Learning Model for Displacement Monitoring of Super High Arch Dams Based on Measured Temperature Data. *Meas. J. Int. Meas. Confed.* **2023**, *222*, 113579. [[CrossRef](#)]
21. Qin, C.; Zhao, W.; Zhong, K.; Chen, W. Prediction of Longwall Mining-Induced Stress in Roof Rock Using LSTM Neural Network and Transfer Learning Method. *Energy Sci. Eng.* **2022**, *10*, 458–471. [[CrossRef](#)]
22. Yang, R.; Singh, S.K.; Tavakkoli, M.; Amiri, N.; Yang, Y.; Karami, M.A.; Rai, R. CNN-LSTM Deep Learning Architecture for Computer Vision-Based Modal Frequency Detection. *Mech. Syst. Signal Process.* **2020**, *144*, 106885. [[CrossRef](#)]
23. Yuan, D.; Wei, B.; Xie, B.; Zhong, Z. Modified Dam Deformation Monitoring Model Considering Periodic Component Contained in Residual Sequence. *Struct. Control Health Monit.* **2020**, *27*, 1–15. [[CrossRef](#)]
24. Wang, S.; Sui, X.; Liu, Y.; Gu, H.; Xu, B.; Xia, Q. Prediction and Interpretation of the Deformation Behaviour of High Arch Dams Based on a Measured Temperature Field. *J. Civ. Struct. Health Monit.* **2023**, *13*, 661–675. [[CrossRef](#)]
25. Tranmer, M.; Elliot, M. Multiple Linear Regression. *Cathie Marsh Cent. Census Surv. Res.* **2008**, *5*, 1–5.
26. Fan, J.; Ma, X.; Wu, L.; Zhang, F.; Yu, X.; Zeng, W. Light Gradient Boosting Machine: An Efficient Soft Computing Model for Estimating Daily Reference Evapotranspiration with Local and External Meteorological Data. *Agric. Water Manag.* **2019**, *225*, 105758. [[CrossRef](#)]
27. Rigatti, S.J. Random Forest. *J. Insur. Med.* **2017**, *47*, 31–39. [[CrossRef](#)]
28. Tang, J.; Deng, C.; Huang, G.-B. Extreme learning machine for multilayer perceptron. *IEEE Trans. Neural Netw. Learn. Syst.* **2015**, *27*, 809–821. [[CrossRef](#)]
29. Awad, M.; Khanna, R.; Awad, M.; Khanna, R. Support Vector Regression. *Effic. Learn. Mach. Theor. Concepts Appl. Eng. Syst. Des.* **2015**, *67–80*. [[CrossRef](#)]
30. Graves, A. Long Short-Term Memory. In *Supervised Sequence Labelling with Recurrent Neural Networks*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 37–45.
31. Ayyadevara, V.K.; Ayyadevara, V.K. Gradient Boosting Machine. In *Pro Machine Learning Algorithms: A Hands-On Approach to Implementing Algorithms in Python and R*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 117–134.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.