

Article

A GB-RAR Deformation Early Warning Method Based on a Hybrid Algorithm for Optimizing Prediction Models

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Highlights

What are the main findings?

- A hybrid denoising method combining Median Absolute Deviation (MAD) outlier removal and Savitzky–Golay filtering effectively suppresses both transient pulse disturbances and high-frequency random noise in GB-RAR monitoring data while preserving critical structural vibration characteristics.
- The proposed PSO-GA-BP neural network model achieves superior prediction accuracy compared to BP, GA-BP, PSO-BP, and LSTM models, as evaluated by RMSE, MAE, and R^2 metrics on deformation data from a 447 m super-tall building.

What are the implications of the main findings?

- The integrated denoising and PSO-GA-BP prediction workflow provides a reliable and accurate deformation forecasting framework for super-tall buildings under complex environmental conditions, supporting practical structural health assessment.
- An adaptive early warning mechanism was developed based on a hybrid optimization machine learning model. By integrating multi-factor dynamic thresholds with a three-state finite state machine, the model successfully distinguished between transient disturbances and persistent hazardous deformations, achieving virtually zero false alarms under normal conditions and a recall rate of over 98% in simulations of trend and composite conditions.



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Abstract

To address the key challenges in GB-RAR monitoring of super-tall buildings—namely, complex noise interference (transient pulse disturbances coupled with high-frequency random fluctuations), the difficulty of distinguishing normal wind-induced vibrations from hazardous deformations, and the propensity of single-algorithm prediction models to converge prematurely—this paper proposes an integrated monitoring data processing workflow that combines status assessment and deformation early warning, using Wuhan Greenland Center as a case study. A denoising method combining Median Absolute Deviation outlier removal and Savitzky–Golay filtering was designed for preprocessing, quantitatively

validated through signal-to-noise ratio analysis. Based on filtered data, a spatio-temporal trajectory model was established to visualize and evaluate building movement. Furthermore, a GB-RAR-oriented residual-driven warning framework was developed by coupling a PSO-GA-BP deformation prediction model with adaptive sliding-window thresholding and finite-state warning decisions. Simulation results demonstrate that the PSO-GA-BP model outperforms other neural network models in prediction accuracy, and the derived early warning system exhibits strong feasibility and sensitivity. This workflow proves suitable for GB-RAR deformation monitoring of super-tall buildings, offering valuable reference for future research.

Keywords: GB-RAR; deformation monitoring; data denoising technology; neural network; spatiotemporal warning model

1. Introduction

Recent years have witnessed a surge in the construction of super-tall buildings in China, driven by continuous technological advancement. However, these structures are subjected to multiple deformation-inducing factors, including external construction vibrations, wind loads, diurnal temperature fluctuations, and inherent instability due to their height. Once the resulting deformation exceeds permissible thresholds, serious safety incidents may occur [1]. Establishing an effective monitoring and early-warning system is therefore crucial for obtaining accurate deformation data, assessing structural behavior in real time, and ultimately ensuring building and personnel safety.

Conventional building deformation monitoring techniques, including geodetic surveying, GNSS, and photogrammetry, exhibit inherent limitations for large-scale, continuous applications. Geodetic surveying, while accurate, is labor-intensive and environmentally constrained [2]. Advances in electronic technology and computer image processing have significantly improved deformation monitoring techniques. Since Tarchi's pioneering application of ground-based radar for dam monitoring in 1999, GB-RAR technology has been extensively employed in monitoring landslides, glaciers, and dams, with engineering practice confirming its accuracy and reliability [3,4]. Nevertheless, given the inherent instability of super-tall structures, effective deformation monitoring requires not only high-precision sensing for current state assessment but also reliable early-warning platforms to proactively identify potential safety hazards. In slope stability research, Cai et al. compared multiple machine learning models and adopted the high-accuracy CatBoost model as the foundation for their early-warning system. By calculating instability probabilities for correctly identified stable slopes, they established a risk classification-based warning framework, though the model remains constrained by the subjectivity of risk threshold determination [5]; Nie et al. integrated multi-source data—including high-resolution optical imagery, UAV, radar, video surveillance, and displacement sensors—and developed a multi-level environmental warning platform based on an improved empirical mode decomposition (IEMD) and LSTM model. While demonstrating strong predictive accuracy for PM2.5 levels, the system is limited by its structural complexity and integration challenges [6].

Drawing on numerous engineering examples of early warning model applications, this paper will select machine learning models with high fitness based on monitoring data. It will construct a highly sensitive early warning system tailored to the characteristics of the data and the features of the models [7].

Machine learning has gained extensive applications across numerous disciplines [8–10], with prevalent models generally categorized into four types: linear models (e.g., SVM), tree-

based models (e.g., random forests, XGBoost), probabilistic models (e.g., Naive Bayes) [11], and neural networks (e.g., LSTM, CNN). However, individual models often fail to satisfy the efficiency and accuracy requirements of contemporary engineering applications. To address this limitation, metaheuristic algorithms—including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimizer (GWO)—are increasingly integrated into prediction tasks, enhancing model performance through parameter optimization and weight refinement. These hybrid strategies have demonstrated significant success in engineering, mechanical, and chemical domains [12–15]. Recently, researchers have further combined hybrid metaheuristic algorithms with neural networks, developing advanced frameworks such as PSO-GWO and ACO-GA to overcome the constraints of single-algorithm optimization and achieve higher predictive accuracy [16–19].

For GB-RAR-based deformation monitoring of super-tall buildings, reliable early warning depends not only on the prediction model itself but also on the quality of the deformation sequence used for model training and residual analysis. In practical monitoring, transient pulse outliers may arise from temporary reflection changes, intermittent construction activities, or short-term signal instability, while high-frequency fluctuations are often associated with wind-induced vibration, temperature variation, atmospheric disturbance, and radar measurement uncertainty. The former may be misidentified as abrupt deformation, whereas the latter may obscure slow deformation trends and increase prediction residuals. Therefore, these two types of noise can directly affect deformation identification and warning reliability.

Based on the above monitoring characteristics and the requirements of deformation early warning, three critical gaps remain in GB-RAR-based deformation monitoring of super-tall buildings. First, existing denoising methods cannot simultaneously handle transient pulse outliers and high-frequency random noise, risking either ineffective removal or loss of genuine signals. Second, fixed empirical thresholds for anomaly detection fail to balance sensitivity and robustness due to pronounced ambient vibrations in super-tall structures. Third, the application of hybrid PSO-GA optimization to BP neural networks for deformation prediction remains underexplored, despite the demand for models combining global search with local refinement to handle nonlinear, non-stationary monitoring data.

This study employs the IBIS-S remote monitoring system—a GB-RAR technology developed by IDS and the University of Florence—to conduct continuous high-precision deformation monitoring of Wuhan Greenland Center. Through multi-directional scanning and interferometric processing, displacement values along the radar line-of-sight direction are derived. To address noise interference, structural assessment, and risk warning challenges in GB-RAR monitoring, an integrated methodology is introduced combining motion visualization with neural network-based warning simulation. A hybrid denoising technique integrating Median Absolute Deviation (MAD) outlier removal and Savitzky–Golay filtering is applied for data preprocessing [20–23]. Furthermore, a PSO-GA-BP prediction model is developed to optimize the initial weights and thresholds of the BP neural network. In this hybrid structure, PSO guides candidate solutions toward promising regions through velocity and position updates based on individual and global best information, while GA crossover and mutation operations enhance population perturbation and exploration capability when diversity decreases. This cooperative mechanism helps reduce the risk of premature convergence and improves the stability of nonlinear deformation prediction [19,24]. Through the above strategies, this study aims to establish an application-oriented GB-RAR deformation monitoring and early-warning workflow for super-tall buildings. The main contributions are reframed as follows:

- (1) An integrated GB-RAR deformation monitoring workflow is established for super-tall buildings. The workflow links data preprocessing, deformation trajectory analysis, prediction modeling, residual analysis, and adaptive warning decision-making, providing a practical technical route for short-term, high-frequency deformation monitoring.
- (2) According to the characteristics of GB-RAR monitoring data, traditional denoising and prediction techniques were adapted and coupled: MAD-based outlier removal and Savitzky–Golay filtering were used to suppress transient pulse disturbances and high-frequency random fluctuations, while the PSO-GA-BP model was employed for nonlinear deformation sequence prediction by combining deformation state variables and environmental factors. The workflow integrating data cleaning with deformation learning serves as a functional module within the integrated monitoring and early warning framework.
- (3) A residual-driven adaptive early-warning mechanism is developed as the core methodological contribution of this study. The mechanism combines an adaptive sliding window, a multi-factor dynamic threshold incorporating trend, volatility, and stability factors, and a three-state finite state machine. This design enables the system to distinguish transient disturbances from sustained deformation trends and to support graded warning decisions under complex GB-RAR monitoring conditions.
- (4) The proposed workflow is validated using field monitoring data from the Wuhan Greenland Center and semi-synthetic abnormal scenarios, including noise interference, pulse disturbances, trend deformation, and composite conditions. The validation results demonstrate the feasibility, robustness, and practical applicability of the integrated framework for short-term, high-frequency GB-RAR monitoring scenarios.

These three components form a unified, practically applicable framework, validated through comprehensive experiments under various scenarios using field data from Wuhan Greenland Center. The main contribution is the development of a GB-RAR-oriented deformation warning framework in which these components are specifically coupled according to the characteristics of high-frequency super-tall building monitoring data. In this framework, denoised displacement sequences are transformed into deformation-state features, the prediction residuals of the PSO-GA-BP model are further used to construct adaptive thresholds, and a finite-state decision mechanism is introduced to distinguish transient disturbances from sustained deformation trends. This integrated residual-driven warning strategy is designed for short-term, high-frequency GB-RAR monitoring scenarios where real failure samples are generally unavailable.

2. Materials and Methods

2.1. Principles of GB-RAR Deformation Monitoring

The core principle of ground-based interferometric radar integrates two key technologies: Ground-Based Real Aperture Radar (RAR) imaging and differential interferometry. The system first utilizes pulse compression to enhance range resolution and accurately determine target distances. Subsequently, differential interferometry compares phase variations in corresponding pixels in multi-temporal image sequences, enabling detection of minor surface displacements and comprehensive recording of deformation evolution. This provides robust technical support for geohazard monitoring and infrastructure safety assessment. The phase difference is calculated as follows:

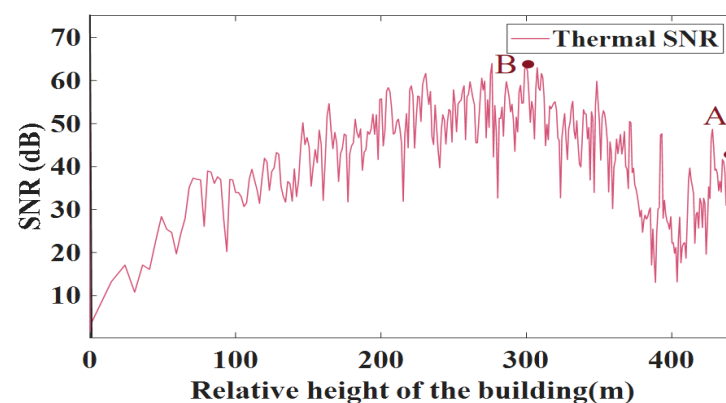
$$\Delta\varphi = \frac{4\pi d_{\text{Defo}}}{\lambda} + \varphi_{\text{Atm}} + \varphi_{\text{Noise}} \quad (1)$$

In the equation, λ represents wavelength, $\Delta\varphi$ represents interference phase, d_{Defo} represents deformation displacement, φ_{Atm} represents atmospheric delay phase, and φ_{Noise} represents noise phase.

This paper employs the IBIS-S system (IDS Ingegneria Dei Sistemi S.p.A., Pisa, Italy) to acquire radar signals. The equipment utilizes high-frequency monitoring with a frequency setting of 20 Hz. Since the acquisition of phase difference is confined to an extremely short time interval, component φ_{Atm} can be neglected. After subsequent noise reduction processing attenuates component φ_{Noise} , the displacement along the line of sight to the building structure can be obtained using Equation (1) [25].

2.2. Equipment Deployment Plan

This study selected Wuhan Greenland Center (WGC) as its research subject. The monitoring team employed two IBIS-S systems to conduct high-precision continuous deformation monitoring of the building. Specifically, two working reference points, S1 and S2, were established along the north–south and east–west axes of the structure, respectively, with IBIS-S systems installed at these locations. Through radar scanning of the Wuhan Greenland Center using the IBIS-S system, high-spatial-resolution and high-temporal-resolution radar imagery was successfully captured. Interferometric techniques were applied to process this data, precisely capturing the building’s displacement along the observation line of sight. During monitoring, the radar system operated in high-frequency data acquisition mode (sampling frequency of 20 Hz) from 12:21 on 5 July 2017, to 9:38 on 7 July 2017, totaling approximately 45 h. Since the deformation information provided by the IBIS-S system is limited to the radar line-of-sight direction, this paper selects representative study points based on the thermal signal-to-noise ratio measured by GB-RAR monitoring along the line-of-sight. The power map along the radar line-of-sight is shown in Figure 1. Point A, representing the highest point of the building at the time with a relative height of 447 m above S2, holds significant research value. The thermal signal-to-noise ratio at Point A is 39.0 dB in the east–west direction and 37.4 dB in the north–south direction. Point B, located at the building’s midpoint (300 m above reference point S2), exhibited a thermal signal-to-noise ratio of 60.8 dB in the north–south direction and 62.2 dB in the east–west direction. Its radar monitoring data demonstrated high quality. Subsequent analysis will focus on points A and B of the building. In addition, the research team installed a weather station on the roof to monitor changes in meteorological parameters (temperature, humidity, atmospheric pressure, and wind speed) during the deformation monitoring process; the data collection period for this weather station coincided with the operational period of the IBIS-S. As illustrated in Figure 2, the deployment plan establishes a comprehensive monitoring network through the platform configuration.



(a) Monitoring power in east–west direction

Figure 1. Cont.

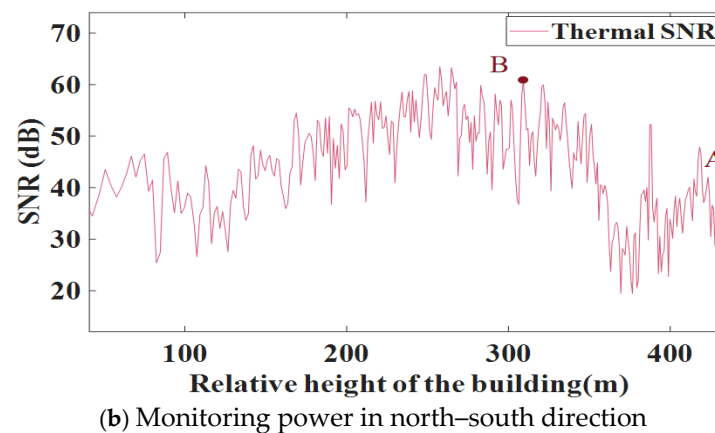


Figure 1. Thermal signal-to-noise ratio (SNR) distribution along the relative height of the building. The red dots indicate the two representative monitoring points selected for subsequent deformation analysis. Point A represents the top monitoring point at a relative height of 447 m, while Point B represents the middle monitoring point at a relative height of 300 m. The letters A and B correspond to the two selected monitoring positions on the Wuhan Greenland Center.

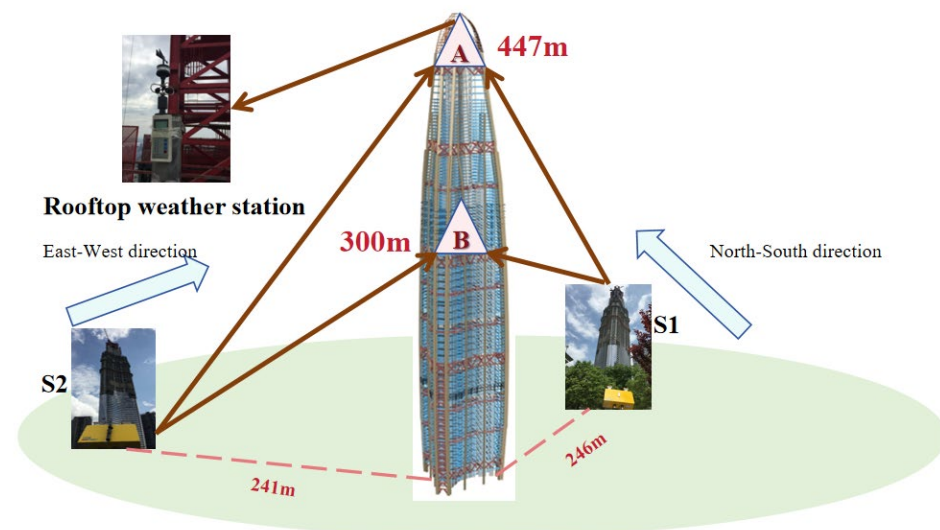


Figure 2. Layout diagram of reference stations S1 and S2. Points A and B denote the two representative monitoring positions on Wuhan Greenland Center, corresponding to the top monitoring point at 447 m and the middle monitoring point at 300 m, respectively. S1 and S2 denote the two radar reference stations deployed along the north–south and east–west directions, respectively. The red dashed lines denote the approximate horizontal distances between the reference stations and the building.

2.3. Data Preprocessing

GB-RAR structural monitoring data are inevitably contaminated by outliers and environmental noise, primarily caused by transient disturbances such as intermittent construction activities and sudden wind load variations. To enhance data quality, this study introduces a hybrid denoising approach integrating Median Absolute Deviation (MAD) outlier removal with Savitzky–Golay polynomial filtering. The proposed strategy combines the advantages of outlier suppression and local trend preservation, enabling effective noise reduction for GB-RAR monitoring data.

2.3.1. Median Absolute Deviation Outlier Removal (MAD)

The MAD outlier removal method is a robust anomaly detection technique based on the Median Absolute Deviation (MAD). Due to its strong robustness, it is widely employed for eliminating outliers in time series data within monitoring projects [21,26].

In this experiment, the method treats abnormal radar signal pulses as gross errors while considering residual noise as normal observations, with the MAD calculated according to Equation (2).

$$MAD = bM(|U_i - U_M|) \quad (2)$$

In the formula, b is a constant typically set to 1.4826. $M(\cdot)$ denotes the median of the internal sequence, U_i represents the monitored time-series data, and U_M indicates the median of the monitored time-series data.

To investigate outliers in an observation sequence, the criterion coefficient C for U_i must be calculated using the following formula:

$$C = \frac{|U_i - M(U_j)|}{MAD} > 2.5 \quad (3)$$

In the formula, when the value of C exceeds a given threshold, it is identified as an outlier. Based on extensive literature review and experimental results, setting the threshold to 2.5 is considered appropriate for this study [20,27].

The use of MAD effectively removes outliers and impulse noise, which proves particularly effective for addressing abrupt change points in monitoring data. Linear interpolation is then applied to fill the gaps resulting from outlier removal. For the remaining noise in the data, this study employs the Savitzky–Golay polynomial filtering method to achieve smooth noise reduction.

The hybrid denoising strategy combines the complementary advantages of MAD filtering and Savitzky–Golay (SG) filtering. MAD filtering is mainly used to identify and remove transient pulse outliers and abrupt abnormal spikes caused by sudden disturbances or measurement interference. However, MAD filtering alone is insufficient for suppressing the remaining high-frequency random fluctuations.

Therefore, SG filtering is further applied to smooth high-frequency random noise while minimizing excessive distortion of local deformation trends and dynamic vibration characteristics. For GB-RAR deformation monitoring data, the proposed MAD-SG strategy achieves a balance between noise suppression and signal preservation.

2.3.2. Savitzky–Golay Polynomial Filtering

The Savitzky–Golay filter is a method that employs a sliding window and local least-squares polynomial fitting. By performing polynomial fitting around data points and computing polynomial derivatives, it not only smoothens the data but also preserves local features, thereby reducing excessive distortion of deformation data caused by over-smoothing during filtration. This technique has been widely and successfully applied in numerous studies related to SAR data preprocessing [22,23]. The fundamental principle is illustrated in Equation (4):

$$Y_i^* = \sum_{i=-m}^{i=m} \frac{C_i Y_{j+i}}{N} \quad (4)$$

Among these, Y_i^* denotes the filtered monitoring sequence function, Y_{j+i} represents the raw sequence monitoring data, C_i indicates the filtering function, and N signifies the data points contained within the sliding window.

The polynomial coefficient C_i is obtained via local least squares fitting, as expressed in Equation (5):

$$Y_i = c_0 + c_1 x_i + c_2 x_i^2 + \dots + c_m x_i^m + \varepsilon_i \quad (5)$$

In the above equation, x_i corresponds to position Y_i ; c_k represents the polynomial coefficients ($k = 0, 1, 2, \dots, m$); ε_i denotes the error term.

By employing the least squares method, the corresponding coefficients of the filtering polynomial can be precisely calculated. These coefficients provide a reliable basis for efficient smoothing of sequence data, thereby optimizing the accuracy and processing workflow of noise reduction analysis.

2.4. Noise Reduction Performance Evaluation

To validate the effectiveness of the proposed denoising algorithm, this study will evaluate the performance of the processed data using two metrics: Signal-to-Noise Ratio (SNR), Energy Share of Noise-Reduced Data in Original Data (ESN). The formulas for SNR and ESN are provided below:

$$SNR = 10 \lg \left(\frac{\sum_{i=1}^n X^2(t)}{\sum_{i=1}^n [X(t) - X'(t)]^2} \right) \quad (6)$$

$$ESN = \frac{\sum_{i=1}^N (x'(t))^2}{\sum_{i=1}^N (x(t))^2} \quad (7)$$

In Equations (6) and (7), $X(t)$ denotes the original data, while $X'(t)$ represents the denoised data. SNR is the ratio of useful signal power to noise signal power; a higher value indicates a greater proportion of useful signal and better denoising performance. ESN represents the energy content of the true monitoring signal in the denoised signal; a larger ESN indicates that the denoised signal better preserves the characteristics of the monitored vibration signal [28].

2.5. Neural Network Model Selection

Based on the measured deformation data, this study employs an improved back-propagation (BP) neural network for time series forecasting to establish an accurate early warning model. This algorithm was selected because it maintains stable performance even with limited datasets and requires fewer parameters; these characteristics are particularly crucial for GB-RAR monitoring data, which is subject to environmental influences and often exhibits fluctuations in quality. Therefore, this study developed a variant of the enhanced BP neural network to process GB-RAR monitoring sequences.

While traditional Back Propagation (BP) neural networks offer advantages for temporal data processing, they suffer from slow convergence, susceptibility to local optima, and gradient instability when handling complex models [29]. Although Genetic Algorithm (GA) optimized BP networks can accelerate training and improve stability through approximate gradient calculation, they often require excessive iterations and still face premature convergence issues [30,31].

To address these limitations, this paper proposes a hybrid PSO-GA-BP prediction model. The rationale for adopting the PSO-GA-BP hybrid structure is closely related to the characteristics of GB-RAR deformation monitoring data. Super-tall building deformation sequences are strongly nonlinear, non-stationary, and highly sensitive to environmental disturbances such as wind loads, temperature fluctuations, and construction vibrations. Under such conditions, traditional BP neural networks relying solely on gradient descent are prone to slow convergence and local optima.

Within the proposed framework, BP neural networks are responsible for nonlinear mapping between deformation-related variables and structural responses, while PSO is used to optimize the initial weights and thresholds of the BP network to reduce the influence of random initialization and improve convergence performance. GA crossover and mutation operations are additionally introduced during the optimization process to reduce

the possibility of premature convergence. Specifically, each particle or individual in the PSO-GA optimization process represents a candidate set of BP network weights and thresholds. PSO updates the position of each candidate solution according to its own historical best solution and the global best solution, which accelerates convergence toward high-fitness regions. However, when particles become overly concentrated around local optima, the search diversity may decrease. To alleviate this problem, GA crossover and mutation operations are introduced to recombine candidate solutions and generate new search directions. The crossover operation exchanges information between high-quality individuals, while the mutation operation introduces random perturbations into selected genes, thereby enhancing global exploration and reducing the probability of premature convergence. In this way, PSO mainly improves convergence efficiency and local exploitation, whereas GA enhances population diversity and global exploration. The optimized weights and thresholds are then assigned to the BP network for deformation prediction. Compared with traditional BP, GA-BP, and PSO-BP models, the proposed framework improves convergence stability and increases robustness for nonlinear deformation time-series prediction.

The proposed PSO-GA-BP prediction model uses environmental variables and deformation state variables as inputs, including wind speed, temperature, displacement, deformation rate, and acceleration. Among them, deformation rate and acceleration are calculated from the denoised displacement sequence using first-order and second-order temporal differences, respectively, to characterize the dynamic evolution of structural deformation. The detailed network structure and optimization procedure are introduced in the following subsections.

The prediction error of the BP network is defined as the fitness function of particle optimization. PSO performs iterative optimization of network parameters by updating particle velocity and position, while GA operations are additionally introduced to reduce the risk of premature convergence during optimization. Through repeated parameter updates and fitness evaluation, the optimized BP network is finally used for deformation trend prediction and subsequent warning analysis.

2.5.1. Particle Swarm Optimization-Genetic Algorithm-Back Propagation Neural Network Model (PSO-GA-BP)

PSO-GA-BP is a hybrid algorithm that integrates Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Back Propagation (BP) neural networks. The algorithm consists of two main components: first, a BP algorithm is employed to establish a fundamental prediction model for deformation time series data; second, based on this BP framework, the weights and thresholds are optimized using the PSO-GA.

In a standard BP neural network architecture, the design typically comprises three structural components: an input layer, a hidden layer, and an output layer. The corresponding mathematical expression is as follows:

$$I_{out1} = f_1(w_1 I_{in} + b_1) \quad (8)$$

$$I_{out2} = f_2(w_2 I_{out1} + b_2) \quad (9)$$

$$h = \sqrt{Z_1 + Z_2} + a_e, a_e \in [1, 10] \quad (10)$$

In the above equation, Equation (8) represents the functional relationship between the input layer and the hidden layer. I_{out1} denotes the output variable of the hidden layer, f_1 denotes the activation function of the hidden layer, w_1 denotes the connection weight between the input layer and the hidden layer, I_{in} denotes the input variable entering the input layer of the neural network, and b_1 denotes the connection threshold between the input layer and the hidden layer; Equation (9) describes the functional relationship between

the hidden layer and the output layer, where I_{out2} denotes the output variable of the output layer, f_2 denotes the activation function of the output layer, w_2 denotes the connection threshold between the hidden layer and the output layer, and b_2 denotes the connection threshold between the hidden layer and the output layer; Equation (10) is the functional expression concerning the number of hidden layer nodes relative to the number of input layer nodes and output layer nodes. h denotes the number of hidden layer nodes, Z_1 denotes the number of input layer nodes, Z_2 denotes the number of output layer nodes, and a_e denotes a constant whose value is typically determined through simulation experiments.

In this experiment, to more intuitively visualize the planar movement of the building relative to the initial monitoring time, the line-of-sight displacement measurements were processed by calculating the square root of the sum of squares to derive the planar displacement distance. The formula is presented below:

$$\Delta S_i = \sqrt{(X_i - X_0)^2 + (Y_i - Y_0)^2} \quad (11)$$

ΔS_i represents the planar displacement of the building at time i relative to the initial time. X_i denotes the east–west direction data of the building at time i . X_0 indicates east–west direction data of the building at the initial time. Y_i shows the north–south direction data of the building at time i . Y_0 reflects the north–south direction data of the building at the initial time.

The instantaneous deformation state of super-high-rise buildings depends not only on historical displacements but is also closely related to current movement trends and external loads. Based on this physical context, this paper no longer limits the input for the predictive model to a simple stacking of time-series displacements. Instead, it constructs a feature system comprising “state variables” and “action variables”: at the state variable level, based on denoised data, the instantaneous displacement, deformation rate, and deformation acceleration at the current time are selected to form dynamic indicators reflecting the building’s motion state. The deformation rate and deformation acceleration are derived from the denoised displacement sequence using first-order and second-order temporal differences, respectively. For the “action” dimension, real-time temperature, atmospheric humidity, wind speed, and air pressure in the monitoring area are selected as the primary external environmental factors. A neural network deformation prediction model, using deformation time-series data (GB-RAR deformation time-series data that has undergone outlier removal, data filling, and filtering) as the prediction output, is trained using a constructed historical sample dataset. The neural network deformation prediction model outputs deformation prediction time series data. In this study, the *tansig* function is selected as the activation function from the input layer to the hidden layer, and the *purelin* function is selected as the activation function from the hidden layer to the output layer. The structure of the BP network model is shown in Figure 3.

The Genetic Algorithm (GA) optimizes the Back Propagation (BP) neural network through selection, crossover, and mutation operations. These operations iteratively update the population to identify the individual with the minimum fitness value—representing the optimal weights and biases for the BP network. Population initialization is performed using the *initializega* function, with each individual encoding a complete set of network parameters. The fitness function is defined as the sum of squared errors between predicted and actual values, driving the optimization process. The corresponding mathematical formulations are specified as follows:

$$P_i = \frac{k_e \times N_i}{F_i \sum_{j=1}^N N_j} \quad (12)$$

$$a_{kj} = a_{kj}(1 - b_e) + a_{ij}b_e \quad b_e \in [0, 1] \quad (13)$$

$$a_{ij} = a_{ij}(1 - b_e) + a_{kj}b_e \quad b_e \in [0, 1] \quad (14)$$

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max})f(g) & r > 0 \\ a_{ij} + (a_{\min} - a_{ij})f(g) & r \leq 0 \end{cases} \quad (15)$$

$$f(g) = r_2(1 - g/G_{\max})^2 \quad b_e \in [0, 1]$$

In the above equation, Equation (12) represents the functional relationship concerning the selection operation. This paper employs a roulette wheel selection strategy based on fitness ratios, where individuals with lower fitness values have a higher probability of being selected. In the equation, P_i denotes the probability of each individual i being selected, F_i represents the fitness value of individual i , k_e denotes the coefficient, and N_i denotes the population size, which can be determined through simulation experiments. Equations (13) and (14) represent the functional expressions for the crossover operation. This paper employs a real-number crossover method to cross the genes of two individuals, generating a new individual. Here, a_{kj} and a_{ij} respectively denote the genes of the k th chromosome and the i th chromosome after crossover at position j , while b_e is a coefficient; Equation (15) represents the functional expression for mutation operations. This paper employs a single-point mutation method to mutate a specific gene of an individual. Here, $a_{\max}$ and a_{ij} denote the maximum and minimum values of a_{ij} , respectively; r_2 and r denote a random number, whose magnitude is typically determined through multiple experiments to select the optimal value; g represents the current iteration count; and $G_{\max}$ denotes the maximum number of purification iterations.

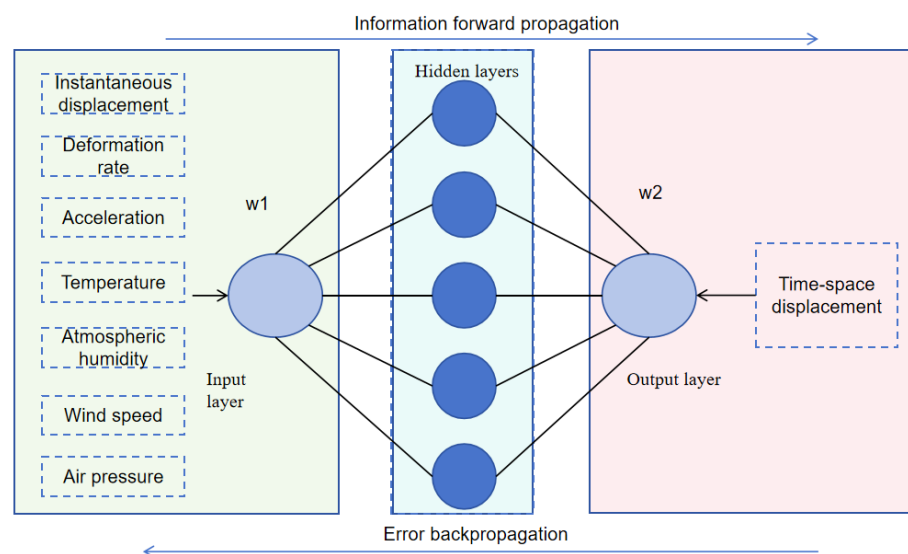


Figure 3. BP Neural Network error prediction model. The light-green, light-cyan, and light-pink background regions represent the input layer, hidden layer, and output layer, respectively. The blue circles denote neurons, where the larger circles indicate the input and output neurons and the smaller circles indicate hidden-layer neurons. The solid black lines represent the weighted connections between adjacent layers. The blue arrow at the top indicates forward information propagation, while the blue arrow at the bottom indicates error backpropagation during training. The dashed rectangles mark the input variables and the output variable. Here, w_1 and w_2 denote the connection weights from the input layer to the hidden layer and from the hidden layer to the output layer, respectively.

Particle Swarm Optimization (PSO) is a swarm intelligence algorithm inspired by collective behaviors like bird flocking. It locates optimal solutions through information sharing among particles, which continuously update their velocities and positions. In

this study, PSO optimizes the weights and thresholds of the GA-BP neural network by identifying the global best particle. The mathematical formulation is as follows:

$$v_i^k = \omega v_i^{k-1} + c_1(pbest_i^{k-1} - x_i^{k-1}) + c_2(gbest^{k-1} - x_i^{k-1}) \quad (16)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (17)$$

In Equations (16) and (17), the default time is 1, where v_i^k represents the velocity or displacement of individual i during iteration k ; ω , c_1 , and c_2 denote the inertia weight, individual learning factor, and social learning factor, respectively; $pbest_i^{k-1}$ denotes the individual optimal solution recorded by individual i during iteration $k - 1$; $gbest^{k-1}$ represents the global optimal solution recorded by the entire population during iteration $k - 1$.

This paper determines the key parameter settings for the PSO-GA cooperative optimization algorithm through literature review and comprehensive consideration of deformation data characteristics as follows in Table 1:

Table 1. Optimized Parameter Settings Table.

Parameters	Scope
Number of Populations (N)	[0, 30]
Individual Learning Factor (c_1)	[0, 3]
Social learning factor (c_2)	[0, 3]
Probability of mutation (P_m)	[0, 1]
Cross-probability (P_c)	[0, 1]
Inertial weighting (ω)	[0, 1]
GA ratio (r_{GA})	[0.3, 0.9]
Population Diversity (D)	[0, 1]

In this study, the collaboration between PSO and GA is designed as an embedded hybrid optimization process rather than a simple progressive process. Specifically, PSO is used as the main iterative search framework to update the candidate weights and thresholds of the BP neural network through velocity and position updating. During this process, each particle represents a candidate set of BP network weights and thresholds, and the prediction error of the BP network is used as the fitness function.

As the PSO iteration proceeds, particles may gradually concentrate around the current optimal region, which improves convergence efficiency but may also reduce population diversity and increase the risk of premature convergence. To address this problem, GA operations are embedded into the PSO process. When the population diversity decreases to a predefined threshold, crossover and mutation operations are introduced to recombine candidate solutions and generate new search directions. The crossover operation promotes information exchange among high-quality individuals, while the mutation operation introduces random perturbations to enhance global exploration.

Therefore, the proposed PSO-GA-BP model follows an embedded collaborative mechanism: PSO provides efficient convergence and local exploitation, whereas GA maintains population diversity and strengthens global exploration during the iterative search. The optimized weights and thresholds obtained through this embedded PSO-GA process are then assigned to the BP neural network for deformation prediction.

The algorithmic flow for generating the PSO-GA-BP neural network model is illustrated in Figure 4:

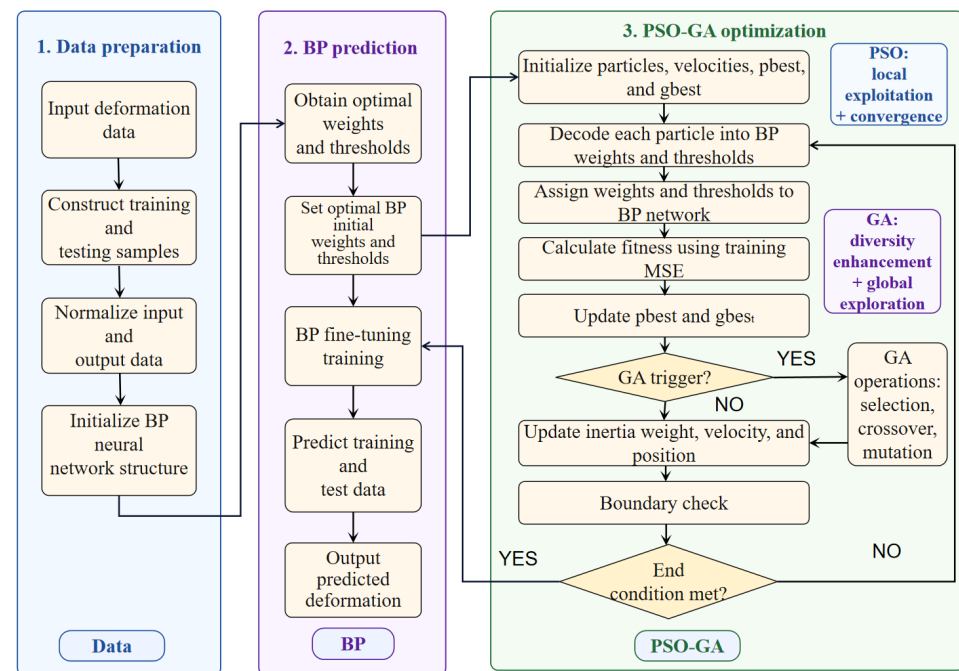


Figure 4. Flowchart of the PSO-GA-BP hybrid algorithm.

2.5.2. Prediction Performance Evaluation

To scientifically evaluate the prediction performance of the PSO-GA-BP model, three metric parameters are selected to investigate model accuracy: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The functional expressions for each metric are provided below:

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

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

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (20)$$

In the above three equations, n represents the number of samples, y_i denotes the true value of the i -th sample, $\hat{y}_i$ indicates the predicted value of the i -th sample, and $\bar{y}$ signifies the mean value of the sample population. Among these, RMSE is commonly used to measure the deviation between predicted and true values. However, this model is highly sensitive to outliers, as shown in Equation (18). A smaller RMSE indicates higher prediction accuracy. MAE represents the average absolute difference between predicted and actual values, providing a metric for the average prediction error. As shown in Formula (19), a smaller MAE indicates higher prediction accuracy. R^2 serves as an indicator measuring the model's ability to explain the variability of the dependent variable. As shown in Formula (20), the closer R^2 is to 1, the greater the variability explained by the model, signifying superior predictive performance [32–34].

2.5.3. Model Parameter Configuration

In the PSO-GA-BP model, this experiment utilized a monitoring dataset from nearly two days for predictive analysis, with 70% allocated for training and 30% for testing. Re-

garding the setting of the number of hidden-layer nodes, when the number of hidden-layer nodes is small, the network may have insufficient nonlinear fitting capability, resulting in underfitting. However, when too many hidden-layer nodes are used, the model complexity increases, and the network may begin to fit local fluctuations or residual noise in the training data, thereby reducing its generalization ability and leading to increased prediction error on the test set. Therefore, the increase in test error observed in Figure 5 indicates a tendency toward overfitting when the network structure becomes overly complex. Considering RMSE, MAE, and R^2 together, five hidden-layer nodes provide a better balance between prediction accuracy and generalization performance, and were therefore selected as the final configuration.

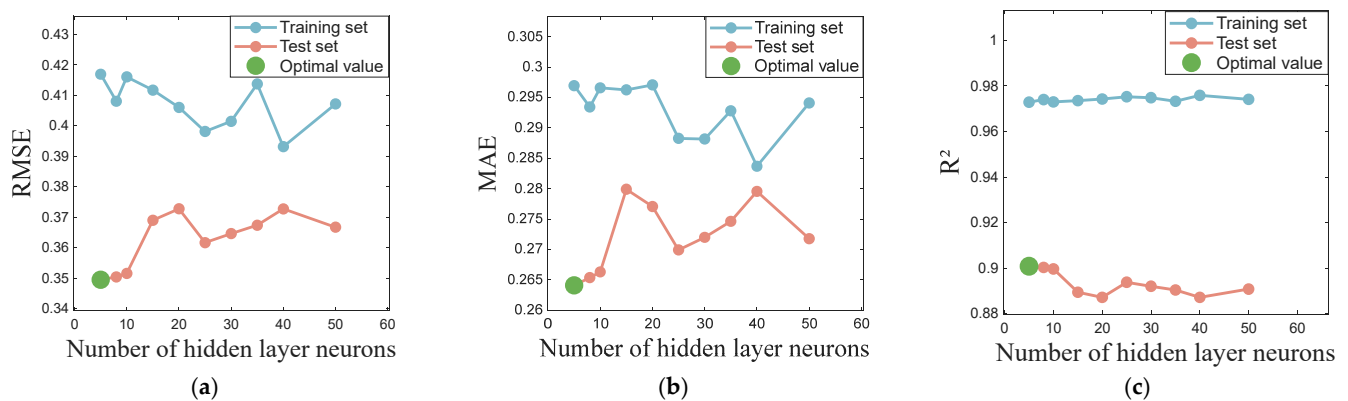


Figure 5. Accuracy comparison under different numbers of hidden-layer nodes. (a) Comparison of hidden-layer nodes based on RMSE; (b) Comparison of hidden-layer nodes based on MAE; (c) Comparison of hidden-layer nodes based on R^2 .

Input variables were standardized to ensure they were on the same quantitative level. Subsequently, the PSO-GA was employed to explore and discover the optimal parameter combination capable of enhancing the BP model's performance. The optimization process utilized a fitness function as the criterion for evaluating model performance. The Figure 6 below illustrates the relationship between the evaluation metric and the number of optimization searches. It can be observed that after 47 iterations, the model reached a plateau phase:

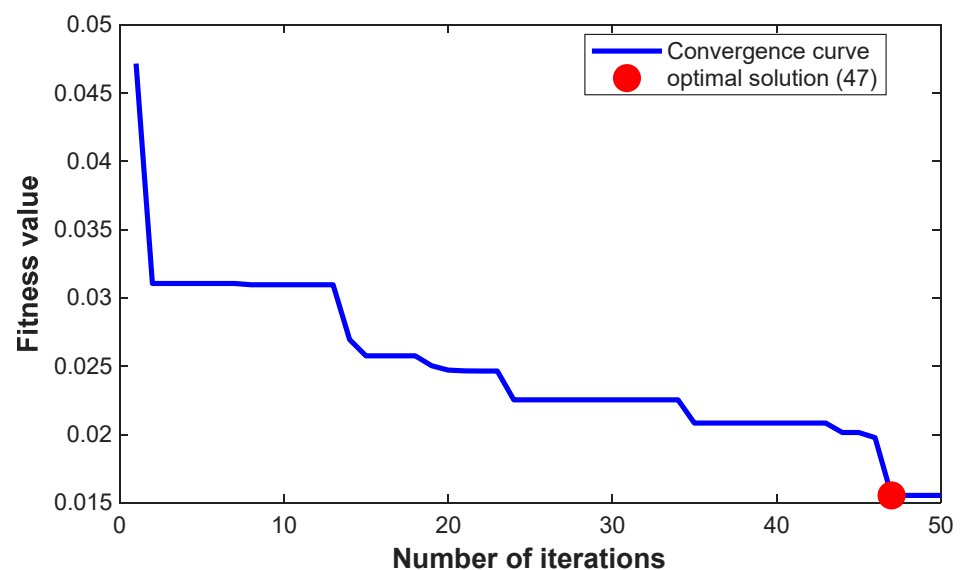


Figure 6. Relationship between fitness value and optimization iterations.

To enhance understanding of the model optimization process, this study visually presents the interrelationship between optimization parameters in the PSO-GA process and the overall model fitness. As shown in the Figure 7, each set of optimization parameters is color-coded based on the magnitude of the evaluation metric, with blue representing the minimum and red the maximum. By observing the degree of color gradient, one can assess the impact of parameter changes on the fitness function. This also provides a basis for parameter selection during the optimization process:

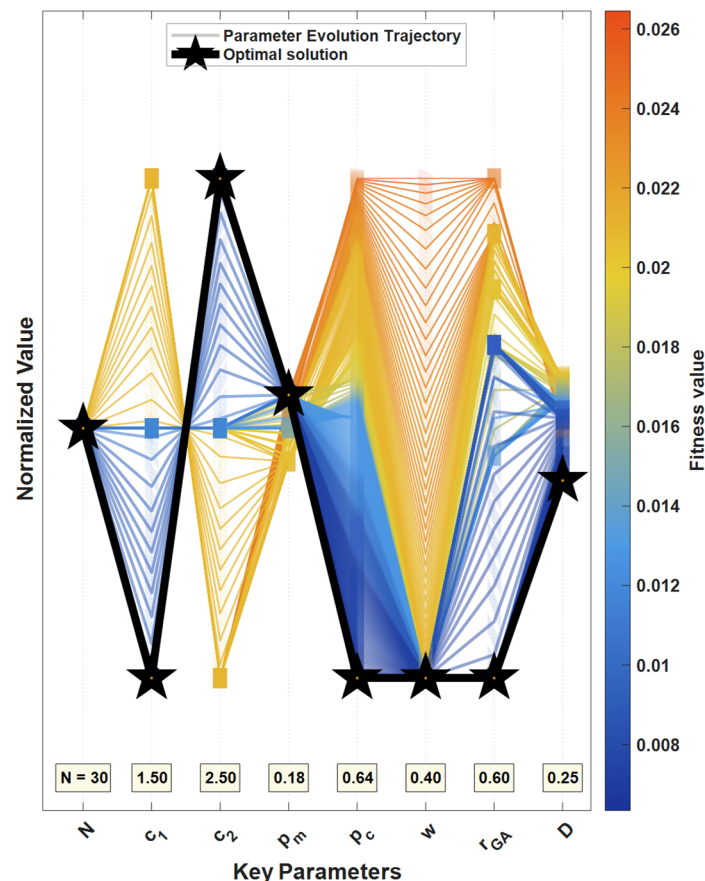


Figure 7. PSO-GA optimization results and parameter–fitness relationship.

The final parameter configuration was determined by comprehensively considering the parameter search results, prediction accuracy, and convergence behavior, with the objective of minimizing the network prediction error. In the PSO-GA hybrid optimization module, the particle population size was set to 30. The individual learning factor c_1 and social learning factor c_2 were set to 1.5 and 2.5, respectively. The inertia weight was set to 0.4 to enhance local refinement during the optimization process. For the GA component, the crossover probability was set to 0.6, the mutation probability was set to 0.18, and the population diversity threshold was set to 0.25. In addition, the two best individuals were retained directly into the next generation to preserve high-quality solutions. The optimization process was then iteratively performed to obtain the optimal weights and thresholds of the BP neural network, thereby constructing the final PSO-GA-BP prediction model [19,32].

2.6. Early Warning Platform Development Based on PSO-GA-BP

Under stable structural conditions, the PSO-GA-BP model produces accurate predictions with minimal error. However, when deformation exceeds safe thresholds, prediction errors increase significantly, providing a basis for anomaly detection [35,36]. While this

principle enables warning model construction, practical GB-RAR monitoring is susceptible to environmental interference, causing deviations between predictions and measurements. Direct residual comparison with fixed thresholds often yields false alarms. To enhance reliability, this study establishes an early-warning system incorporating dynamic threshold detection and consecutive triggering mechanisms, with sensitivity and robustness validated through scenario simulations.

Integrating these concepts, this study develops a dynamic standard deviation-based warning approach. The methodology employs an adaptive sliding window to capture real-time data dynamics and mitigate random fluctuations. The warning threshold automatically adjusts according to the residual standard deviation within each window, overcoming the limitations of fixed thresholds. To address the issue of false alarms caused by random factors temporarily disrupting the early warning system within a short period, the alert mechanism is configured to trigger an alarm only when the current window threshold is exceeded continuously for a specified number of times.

2.6.1. Adaptive Sliding Window

The sliding window size critically affects early-warning performance: oversized windows delay alerts, while undersized windows impair feature capture and increase instability. Given the irregular movements and variable data quality in super-tall buildings, this study adopts an adaptive sliding window approach. By applying Fast Fourier Transform (FFT) to identify dominant frequencies, the method dynamically adjusts window size and step length according to principal periods, ensuring alignment with data characteristics and enhanced prediction accuracy [37,38].

The Fast Fourier Transform (FFT) efficiently computes the discrete Fourier transform, converting signals from the time domain to the frequency domain. The method involves sampling monitoring data at frequency f to obtain N points, which are transformed via FFT into N complex values. Each complex number corresponds to a frequency component, with its magnitude representing amplitude and phase indicating temporal shift. The dominant period of the time series is determined as the reciprocal of the frequency showing maximum amplitude in the resulting spectrum. The mathematical principle is expressed as follows:

$$\hat{x}(k) = \sum_{n=0}^{N-1} x(n) e^{-i \frac{2\pi}{N} nk} \quad (21)$$

$$T_{\text{dominant}} = \frac{1}{f_{\text{dominant}}} \quad (22)$$

Here, e is the base of the natural logarithm, N is the number of sampling points, f_{dominant} is the frequency corresponding to the maximum amplitude, and T_{dominant} is the main period.

Following the Nyquist sampling criterion requiring at least two signal cycles for adequate characterization [39], the window length is set to twice the principal period. To maintain stability, window size is constrained between 5–10 h (300–600 min), with a 50% overlap between consecutive windows to ensure comprehensive temporal coverage and prevent critical information loss.

2.6.2. Dynamic Residual Threshold

The model dynamically adjusts alarm thresholds based on residual standard deviation and window stability, replacing fixed empirical values. This adaptive approach enhances robustness under data fluctuations by analyzing residual standard deviation sequences

from both training and test sets within each sliding window of size N [40]. The formula for the mean $\bar{X}$ and standard deviation σ_w of residuals e_i under the window is as follows:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N e_i \quad (23)$$

$$\sigma_w = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (e_i - \bar{X})^2} \quad (24)$$

Traditional threshold calculation methods are based on the sigma principle, which sets the threshold at three times the standard deviation to cover approximately 99.7% of the fluctuating data. However, in complex monitoring scenarios, this approach struggles to adapt to the time-varying characteristics of the data, often leading to false alarms during periods of high data volatility or missed alarms during periods of data stability. To address this, this section proposes a multi-factor fusion dynamic threshold calculation method that comprehensively considers short-term fluctuations in residuals, trend changes, and window stability. This is achieved by introducing the following three influencing factors:

- (1) Trend factor α_{trend} : This reflects changes in deformation trends by comparing the ratio of the recent residual mean to the historical residual mean. When the residual mean rises significantly, it indicates a possible entry into a sustained deformation phase; in this case, the threshold should be appropriately lowered to increase sensitivity. Conversely, when the residual mean decreases, the threshold should be appropriately raised to reduce false positives.
- (2) Volatility factor $\alpha_{volatility}$: By comparing the ratio of the recent residual standard deviation to the residual standard deviation of the training set, this factor reflects changes in local volatility. When local volatility intensifies, the threshold should be appropriately increased to avoid misclassifying normal fluctuations as anomalies; conversely, when local volatility subsides, the threshold should be appropriately lowered to capture subtle deformations.
- (3) Stability factor $\alpha_{stability}$: By comparing the standard deviation of data in the current window with the median standard deviation of historical windows, this factor reflects the stability of the window itself. A lower threshold is used for stable windows to enhance sensitivity, while a higher threshold is used for volatile windows to enhance robustness [41].

The formula for calculating the composite threshold is as follows:

$$T = \sigma \cdot k_{base} \cdot (1 + \alpha_{trend} + \alpha_{volatility} + \alpha_{stability}) \quad (25)$$

$$\alpha_{trend} = \frac{\bar{r}_{hist} - \bar{r}_{recent}}{\bar{r}_{hist} + \varepsilon} \quad (26)$$

$$\alpha_{volatility} = \frac{\sigma_{recent} - \sigma_{train}}{\sigma_{train} + \varepsilon} \quad (27)$$

$$\alpha_{stability} = \frac{\sigma_{window}}{\text{median}(\sigma_{hist}) + \varepsilon} - 1 \quad (28)$$

Here, k_{base} is the reference coefficient, determined based on the 95th percentile of the residuals from the training set, ensuring that the threshold covers 95% of the fluctuation range under normal conditions. Each adaptation factor is calculated in real time using a sliding window, allowing the threshold to dynamically respond to changes in data characteristics. $\bar{r}_{recent}$ and $\bar{r}_{hist}$ denote the recent residual mean and the historical residual mean, respectively. σ_{recent} denotes the recent residual standard deviation, σ_{train} denotes the

residual standard deviation of the training set, and σ_{window} denotes the standard deviation of the monitoring data within the current sliding window. σ_{window} denotes the median standard deviation of historical sliding windows. ε is a small positive constant introduced to avoid division by zero.

However, suppose the data within the window is generally in a stable state at a certain time, with minimal fluctuations and a small residual standard deviation. If a high threshold calculated using a larger window is used for testing, minor abnormal changes—such as the sudden widening of a micro-crack in a building under stable weather conditions—will fail to trigger an alarm, often resulting in missed incidents; Additionally, when the data within the window is in a period of natural fluctuation—such as wind noise caused by typhoon conditions—the data itself exhibits significant volatility and large residuals. If a fixed threshold is used in this scenario, the system will frequently trigger alarms, but most of these will be normal, intense fluctuations rather than actual anomalies, leading to false alarms. To prevent frequent false alarms caused by an excessively low threshold or missed detections caused by an excessively high threshold, and given that 1.8 times the standard deviation of the training set residuals falls between 1.64σ (90% confidence interval) and 1.96σ (95% confidence interval), the threshold is set to ensure that it covers no less than 92% to 93% of the data during normal fluctuations, thereby avoiding frequent false alarms caused by an excessively low threshold. The upper limit is set at 5.0 times the standard deviation of the training set residuals. Based on the 5σ principle, this corresponds to an extremely low-probability event of approximately 1 in 1.7 million in a normal distribution. This effectively prevents threshold divergence caused by local severe fluctuations while reserving sufficient detection capacity for extreme anomalies. These upper and lower limits ensure that the threshold remains within a statistically reasonable range, balancing the sensitivity and robustness of the early warning system.

2.6.3. State Machine Early Warning Mechanism

To distinguish between transient disturbances and sustained deformation, this paper introduces a three-state finite state machine (FSM) as an early warning decision-making mechanism. The state machine comprises three states: normal state (0), alert state (1), and alarm state (2). State transitions are determined based on the proportion of samples exceeding the dynamic threshold within a sliding window [41,42]. The proportion of samples exceeding the threshold is defined as the ratio of sample points within the current window whose residuals exceed the dynamic threshold:

$$r_{exceed} = \frac{\text{count}(|e_i| > T)}{N} \quad (29)$$

The transition between deformation states is based on the assessment of the exceedance ratio:

- (1) When the exceedance ratio exceeds the normal threshold three consecutive times, the system enters the alert state; otherwise, it remains in the normal state.
- (2) When the exceedance ratio exceeds the alarm threshold, an alarm is triggered and the system enters the alarm state; When the exceedance ratio falls below 80% of the normal threshold for five consecutive times, the system returns to the normal state; otherwise, it remains in the alert state.
- (3) The alarm signal is continuously output until the exceedance ratio falls below the normal threshold for three consecutive times, at which point the system returns to the alert state.

In the proposed dynamic threshold model, the reference coefficient k_{base} is determined from the 95th percentile of the absolute training residuals. Therefore, k_{base} provides

a baseline statistical reference for the residual threshold. Under relatively stable residual conditions, where no significant trend growth, abnormal volatility, or window instability is observed, the baseline threshold corresponds to an expected exceedance proportion of approximately 5%.

Based on this reference level, the normal threshold is set to 0.15 and the alarm threshold is set to 0.30 in the FSM, which are used to represent exceedance proportions substantially higher than the normal reference level. The threshold of 0.15, approximately three times the baseline exceedance reference, was used for the transition from the normal state to the alert state. The threshold of 0.30, approximately six times the baseline exceedance reference, was used for the transition from the alert state to the alarm state. Therefore, these two thresholds provide a hierarchical decision rule for distinguishing isolated residual fluctuations from persistent abnormal residual growth.

In the normal monitoring data used in this study, no false alarm was generated under this threshold combination, indicating that the selected thresholds provided acceptable false-alarm suppression for the current dataset. When the proposed framework is applied to longer monitoring periods or other structures, the FSM thresholds can be recalibrated according to site-specific monitoring data.

2.6.4. Semi-Synthetic Validation Experiment

According to the deformation control and serviceability performance requirements specified in the Technical Specification for Concrete Structures of Tall Buildings (JGJ 3-2010) [43] and the Engineering Measurement Standard (GB 50026-2020) [44], horizontal displacement, settlement, and inclination are important indicators for deformation monitoring of super-tall buildings. Furthermore, the Load Code for the Design of Building Structures (GB 50009-2012) [45] provides the engineering background for wind loads and temperature effects, which are significant environmental factors affecting structural deformation monitoring. These deformation control and monitoring principles were used as engineering references for displacement control and warning level design in the validation experiments.

Based on measured GB-RAR monitoring data, and in order to simulate structural failure or abnormal deformation events that have not yet occurred to test the effectiveness of the warning model, this study designed five sets of controlled and semi-synthetic validation experiments (Groups A–E). Abnormal conditions were constructed by superimposing controllable disturbance signals onto the original monitoring sequence, including Gaussian noise, Gaussian envelope pulse disturbances, linear deformation trends, and composite disturbances. This design enables quantitative evaluation of the warning system's performance under different controllable disturbance conditions while preserving the characteristics of the measured monitoring data:

Group A (Steady-State Control): Used measured monitoring data without artificial interference as the baseline control. This group verifies the system's false alarm rate under normal conditions and establishes baseline performance metrics.

Group B (Noise Interference): Superimposed Gaussian white noise on the test set at three signal-to-noise ratio (SNR) levels—15 dB (mild), 10 dB (moderate), and 5 dB (severe). This evaluates the system's resistance to random noise interference and its ability to distinguish noise from actual deformation.

Group C (Pulse disturbance): Semi-synthetic Gaussian-envelope pulse signals were superimposed at 180, 330, and 480 min of the test set. Each pulse lasted 10 min, with amplitudes set at 3σ , 4σ , and 5σ the background noise standard deviation. These pulse signals were used to represent short-duration pulse-like disturbances. This group tests the

fault-tolerance mechanism of the warning system and its ability to suppress short-duration disturbances without triggering false alarms.

Group D (Trend Deformation Group): This group was designed to evaluate the sensitivity of the warning system to sustained cumulative deformation trends. According to the displacement control requirements in relevant engineering codes, for a monitored structure with a height of 447 m, the code-related displacement limit is estimated to be 894 mm. In this paper, 10% of this limit, i.e., 89.4 mm, is adopted as a conservative warning reference value for semi-synthetic validation. The training set remained unchanged, while a linear trend was superimposed on the test set starting from the 30% position of the sequence. Three deformation rates—0.02 mm/min, 0.05 mm/min, and 0.10 mm/min—were set as progressively intensified semi-synthetic trend deformation levels. These rates were used to evaluate whether the warning system could identify sustained deformation development before the cumulative displacement approached the warning reference value.

Group E (Composite conditions): A semi-synthetic composite disturbance condition was constructed by simultaneously superimposing a linear trend of 0.05 mm/min, a pulse disturbance of 5σ lasting 10 min, and Gaussian noise with SNR = 10 dB onto the test set. This group evaluates the overall robustness of the warning system under coupled disturbance conditions and its ability to identify sustained deformation trends in the presence of multiple interference sources.

Each experimental group was repeated 50 times, with Recall and Accuracy statistically analyzed. This comprehensive evaluation framework—with Group A providing baseline reference, Group B testing noise resistance, Group C testing fault tolerance, Group D testing sensitivity, and Group E testing comprehensive robustness—provides a basis for evaluating the performance of the early warning system and establishes a foundation for parameter optimization and practical application.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (30)$$

$$\text{Accuracy} = \frac{TP}{TP + TN + FP + FN} \quad (31)$$

Here, TP refers to the number of correct alarms; FP refers to the number of false alarms; FN refers to the number of missed alarms; and TN refers to the number of instances where the model did not trigger an alarm under normal conditions.

2.7. Technical Approach

Through integrated data denoising, motion trajectory analysis, time-series prediction, and early-warning modeling, this study establishes a systematic framework for building deformation assessment and risk forecasting. The comprehensive data processing workflow proceeds as follows:

- (1) Deploy dual IBIS-S systems to acquire high-precision continuous deformation data of WGC, simultaneously collecting temperature records for subsequent analysis.
- (2) Implement hybrid denoising combining Median Absolute Deviation and Savitzky–Golay filtering, followed by spatiotemporal trajectory analysis to evaluate current structural deformation states.
- (3) Develop a PSO-GA-BP neural network for deformation prediction, with dataset partitioning for model training and comparative performance validation.
- (4) Establish adaptive sliding windows within the PSO-GA-BP framework, dynamically adjusting warning thresholds through residual standard deviation analysis, and validate system sensitivity via simulated hazard scenarios.

This paper presents denoising, prediction, and early warning as a progressive processing workflow, connected through a residual-driven mechanism: denoising improves the reliability of deformation state feature construction; prediction residuals provide a quantitative basis for abnormal deviations; and the adaptive threshold combined with the state machine further transforms residual evolution into early warning decisions. Following the above steps, a complete monitoring data processing and early warning system is formed. The technical flowchart is presented below in Figure 8:

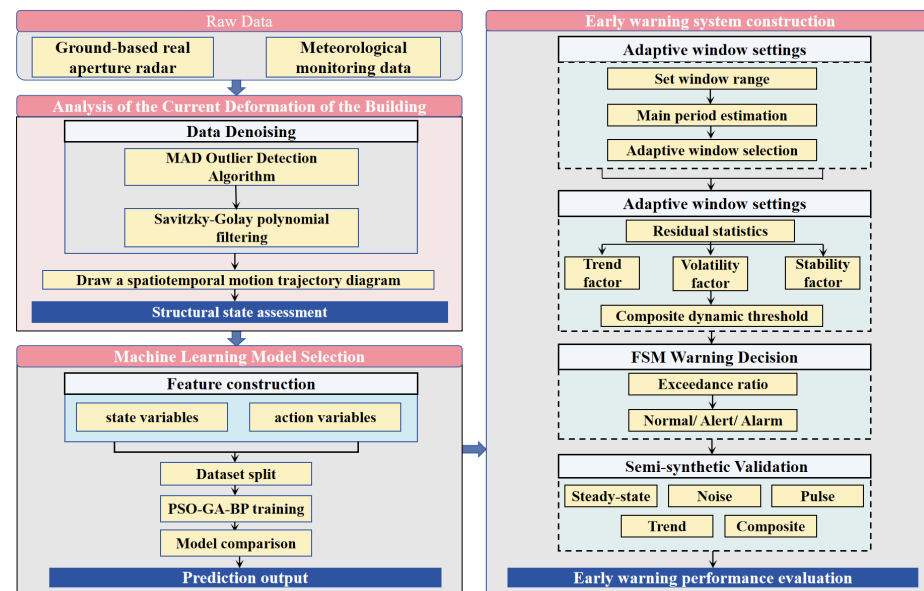


Figure 8. Overall research flowchart.

3. Results

3.1. Data Denoising Results

Based on GB-RAR monitoring data from Points A and B (447 m and 300 m elevation), raw deformation sequences were obtained totaling approximately 3,261,600 epochs per point (equivalent to 2720 min at 20 Hz sampling).

Data preprocessing followed the established workflow: outlier removal using Median Absolute Deviation (MAD) with a threshold coefficient of 2.5, gap filling via linear interpolation, and subsequent smoothing through Savitzky–Golay filtering. The denoising results are presented in the following Figures 9 and 10, with time zero corresponding to 12:21 on 5 July 2017:

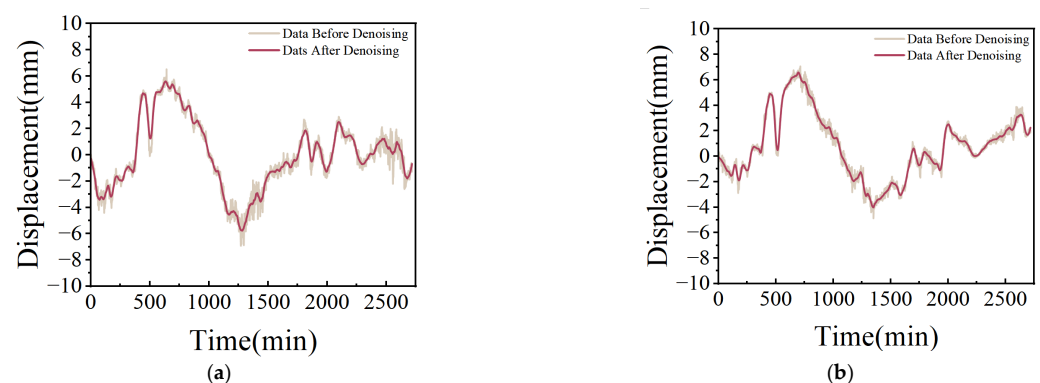


Figure 9. Denoising effect diagram of monitoring data at 300 m height. (a) Comparison diagram of north–south direction displacement before and after denoising; (b) Comparison diagram of east–west direction displacement before and after denoising.

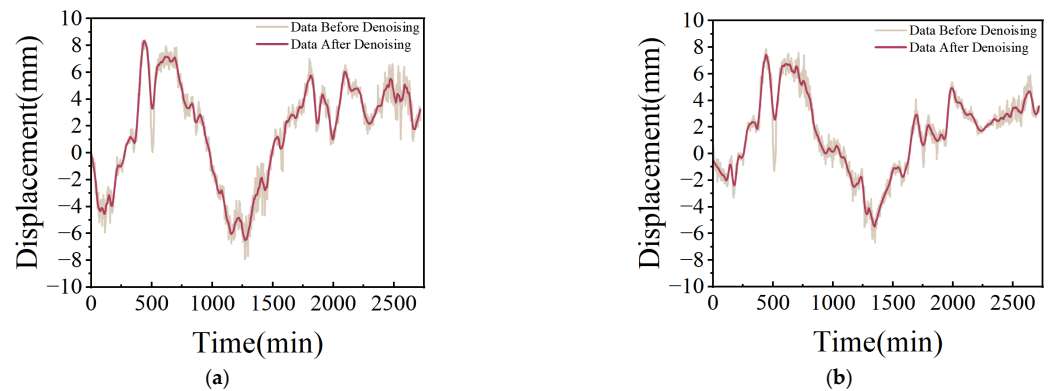


Figure 10. Denoising effect diagram of monitoring data at 447 m height. (a) Comparison diagram of north–south direction displacement before and after denoising; (b) Comparison diagram of east–west direction displacement before and after denoising.

The statistical analysis of data before and after denoising was conducted by calculating the SNR and ESN coefficients for each location and orientation. The results are presented in the Table 2 below.

Table 2. Denoising Accuracy Evaluation Table.

Points	Monitoring Orientation	SNR	ESN
300 m	North–South direction	16.6941	97.16%
	East–west direction	19.7047	97.96%
447 m	North–South direction	17.0262	98.33%
	East–west direction	16.3153	98.03%

Analysis of the raw GB-RAR monitoring data revealed significant fluctuations and sharp spikes in displacement measurements. Application of the combined MAD and Savitzky–Golay filtering technique substantially improved curve smoothness and reduced anomalous jagged features. For instance, at the 447 m level around the 500 min mark, prominent outliers were effectively eliminated and reconstructed through interpolation, enhancing data reliability for subsequent predictive modeling.

Nevertheless, residual fluctuations persist in the denoised data, particularly at the 447 m height where variation amplitude significantly exceeds that at the 300 m level. These fluctuations likely originate from combined effects of construction vibrations, instrumental errors, and environmental interference during the monitoring period.

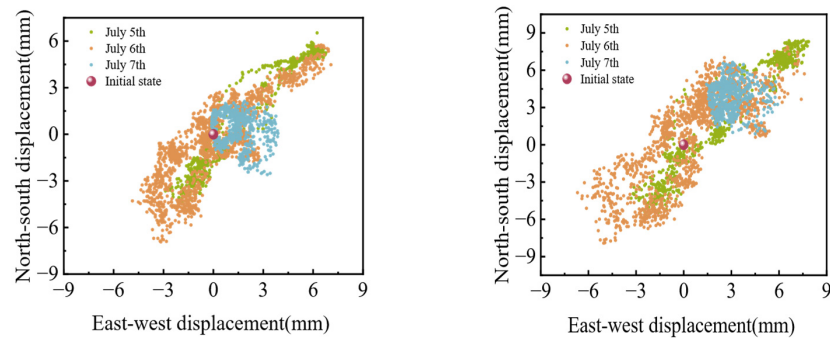
3.2. Data Visualization Analysis and Status Assessment

To visually characterize the dynamic deformation behavior and operational status of Wuhan Greenland Center, this study employs preprocessed GB-RAR monitoring data to generate spatiotemporal graphical representations for structural condition assessment and deformation analysis.

A quantitative model was developed to analyze displacement relative to the base state—defined as the initial measurement at 12:21 on 5 July 2017. The relative displacement of Points A (447 m) and B (300 m) was computed by comparing subsequent monitoring data with this reference, enabling spatiotemporal trajectory visualization based on correction term aggregation. In Figure 11, the red sphere denotes the base state, while colored points represent displacement magnitudes at different timestamps.

Analysis of spatiotemporal displacement trajectories from 5 July 2017, 12:21 to 7 July 2017, 09:38 reveals the following deformation characteristics: both the 300 m and 447 m levels exhibit symmetrical displacement distributions around the base state, with deformation

magnitudes generally within 5 mm, indicating minor structural deformation. The building demonstrates periodic swaying in the southwest-northeast direction with temporal regularity. Notably, displacement distribution at the 447 m level shows greater dispersion than at 300 m, reflecting more pronounced movement at the building's summit. These elevated deformations are likely attributable to combined effects of construction vibrations and wind loads during the monitoring period.



(a) Displacement trajectory at 300 m Height (b) Displacement trajectory at 447 m Height

Figure 11. Operation trajectory diagram.

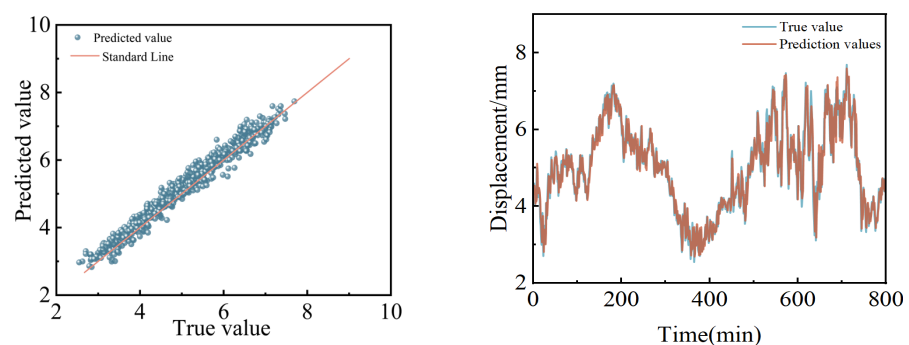
3.3. Analysis of PSO-GA-BP Results

To concisely validate model robustness, subsequent analysis focuses on the most critical deformation point. Based on variance comparisons in Table 3, the 447 m level—exhibiting the most significant displacement—is selected to demonstrate the early-warning model's performance.

Table 3. Correlation between height and deformation.

Building point	300 m	447 m
variance	4.403	5.512

This study selects the deformation monitoring data from the 447 m height of the building as the test sample for evaluating the robustness and reliability of the PSO-GA-BP model. By incorporating meteorological data collected during the monitoring period as model inputs, the prediction results for the top-level point are presented in the Figure 12 below:



(a) Scatter diagram of test set prediction results (b) Comparison of prediction results between test sets

Figure 12. Prediction Results of the PSO-GA-BP Model.

The prediction results for both the training and test sets are tightly clustered near the baseline in the scatter plot, with the actual values and predicted values curves exhibiting high consistency—this fully validates the high accuracy and applicability of the PSO-GA-BP model. Quantitative evaluation using Equations (18) to (20) further confirms its

precision. Comparative experiments against BP, GA-BP, PSO-BP, and the commonly used LSTM model for prediction will effectively validate the effectiveness of the proposed hybrid method.

3.4. Predictive Model Comparison Study

3.4.1. Baseline Model Configurations and Hyperparameter Tuning

To ensure a fair comparison, all baseline models (BP, GA-BP, PSO-BP, and LSTM) were trained and tested using the same preprocessed dataset, input variables, normalization procedure, and training/testing split as the proposed PSO-GA-BP model.

For BP, GA-BP, and PSO-BP, the number of hidden layer nodes was adjusted within the range of 3–10 nodes using repeated experiments based on RMSE performance. The optimal hidden node number was determined as 5 for all three models.

For the LSTM model, hyperparameters including the number of LSTM layers, hidden units, learning rate, time-step length, batch size, and dropout rate were adjusted through grid-search-based repeated experiments. The final parameter configuration was selected according to prediction performance under the current monitoring dataset. The hyperparameter search ranges and final parameter settings are summarized in Table 4:

Table 4. Hyperparameter configurations of LSTM.

Hyperparameter	Search Range	Optimal Value
Number of LSTM layers	[1, 5]	2
Hidden units per layer	[32, 128]	64
Learning rate	[0.001, 0.01]	0.005
Time steps (look-back window)	[5, 30]	15
Batch size	[16, 64]	32
Dropout rate	[0.1, 0.5]	0.2

Considering the relatively limited scale of the current monitoring dataset, a lightweight LSTM structure with dropout regularization was adopted to reduce the risk of overfitting. This helps improve the fairness of comparative experiments under the current monitoring conditions.

3.4.2. Model Comparison Results

Using identical input variables, BP, GA-BP, PSO-BP, and LSTM models were applied to the preprocessed top-level deformation data. Their performance was quantitatively compared with the proposed PSO-GA-BP model using RMSE, MAE, and R^2 metrics. The comparative results are presented in Figure 13:

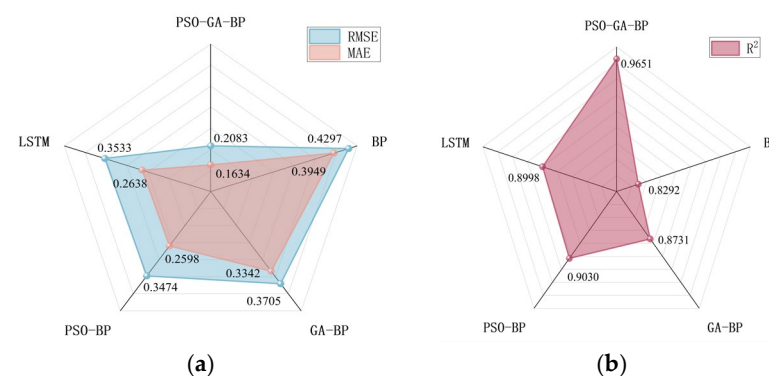


Figure 13. Comparative experiments of different prediction models. (a) Quantitative comparison of prediction performance based on RMSE and MAE; (b) Quantitative comparison of prediction performance based on R^2 .

Comparative experiments based on RMSE, MAE, and R^2 indicate that the proposed PSO-GA-BP model achieved higher prediction accuracy than the comparative neural network models under the current monitoring conditions. The prediction results generated by the PSO-GA-BP model were closer to the measured deformation sequence, demonstrating stable nonlinear deformation prediction capability for GB-RAR monitoring data.

The results further indicate that the proposed framework provides a useful basis for subsequent adaptive warning threshold determination and dynamic early warning analysis.

3.4.3. Deformation Response Analysis

To further analyze the deformation response mechanism and support the physical rationality of the selected input features, this study conducted Pearson correlation analysis and time-lag correlation analysis among deformation-related variables and environmental factors. The analyzed variables included temperature, humidity, wind speed, atmospheric pressure, measured deformation, predicted deformation, prediction residual, deformation rate, and deformation acceleration.

The Pearson correlation results show that the environmental variables exhibit measurable relationships with the measured deformation. Specifically, temperature shows a moderate negative correlation with measured deformation ($r = -0.421$), while humidity shows a moderate positive correlation ($r = 0.452$). Wind speed presents a weaker but still observable positive correlation with measured deformation ($r = 0.260$), whereas atmospheric pressure shows a relatively weak global correlation ($r = 0.093$). These results indicate that the deformation response of the super-high-rise building is not controlled by a single environmental variable, but is influenced by the combined effects of thermal variation, humidity variation, wind excitation, and structural motion state.

The predicted deformation is highly correlated with the measured deformation ($r = 0.998$), indicating that the PSO-GA-BP model effectively captures the main deformation trend of the monitored structure. In addition, the prediction residual shows relatively strong correlations with deformation rate ($r = 0.603$) and deformation acceleration ($r = 0.521$). This suggests that residual variations are closely related to changes in the structural motion state, providing quantitative support for using prediction residuals as the basis for dynamic thresholding and early warning.

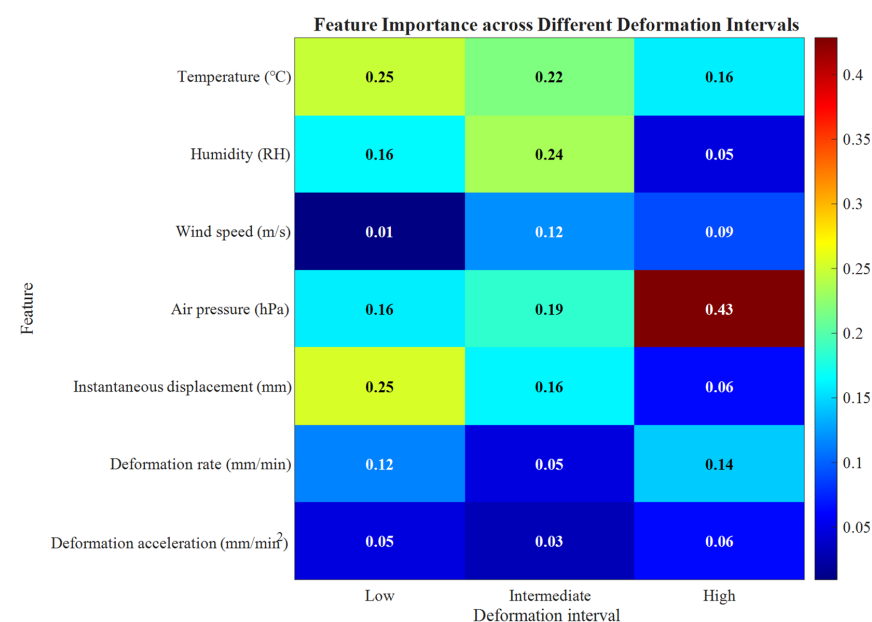
A time-lag correlation analysis was further conducted between environmental variables and measured deformation to examine the delayed response characteristics of the structure. The results show that temperature reaches its maximum correlation with measured deformation at a lag of 48 min ($r = 0.464$), indicating a delayed thermal response of the super-tall building. Humidity shows the strongest correlation at zero lag ($r = 0.452$), suggesting a more synchronous relationship with deformation during the monitoring period. Wind speed reaches its maximum correlation at a lag of approximately 1 min ($r = 0.261$), reflecting the relatively rapid response of the structure to wind excitation. Atmospheric pressure reaches its maximum correlation at a lag of approximately 3 min ($r = 0.170$), indicating a weak but observable delayed association. These results demonstrate that different environmental factors affect structural deformation with different temporal response characteristics. The relationship between the deformation state and environmental variable responses is shown in the following Table 5.

To understand the PSO-GA-BP model's decision-making in predicting super-high-rise building deformation, this study employed the Local Interpretable Model-agnostic Explanations (LIME) method. By providing local explanations for typical samples, LIME quantifies each feature's contribution to individual predictions through perturbed data and locally interpretable linear models.

Table 5. Pearson and time-lag correlation analysis between environmental variables and measured deformation.

Variable	Pearson Correlation with Measured Deformation	Maximum Lag Correlation	Best Lag (Min)
Temperature	−0.421	0.464	48
Humidity	0.452	0.452	0
Wind speed	0.260	0.261	1
Atmospheric pressure	0.093	0.170	3

LIME analysis was conducted on deformation predictions at the Wuhan Greenland Center’s summit (447 m) during a typical period. The results are shown in Figure 14. The analysis categorized test set displacements into low, medium, and high levels based on quartiles, examining seven input features. Feature importance varies significantly across deformation stages:

**Figure 14.** Input Variable Importance Heatmap.

During the low-deformation stage, the building exhibits elastic recovery, with current displacement primarily depending on residual vibration from previous time steps. Thus, historical displacement autocorrelation dominates.

In the moderate-deformation stage, temperature and humidity changes cause uniform expansion or contraction of structural materials (concrete and steel). This volumetric effect superimposes on dynamic displacement, increasing the contribution of temperature and humidity features.

During the high-deformation stage (e.g., sudden strong winds), abrupt atmospheric pressure changes accompany intense wind pressure pulsations, directly causing significant dynamic deformation and acceleration responses. Consequently, deformation rate and atmospheric pressure become dominant factors.

These findings reveal how the model adaptively weighs different features based on deformation intensity, providing interpretability crucial for understanding building behavior under varying conditions. The LIME-based interpretation is generally consistent with the quantitative correlation and time-lag correlation analyses. Temperature and humidity show relatively strong correlations with measured deformation and also present high LIME contributions in the low- and moderate-deformation intervals. Wind speed shows a weaker

global correlation, which is consistent with its relatively lower LIME contribution. Atmospheric pressure shows a weak global Pearson correlation but a high LIME contribution in the high-deformation interval, indicating that it may play a more important local role under specific deformation states. Therefore, the interpretability analysis is supported by both quantitative variable-relationship analysis and local model explanation.

3.5. Sensitivity Testing of the Early Warning Model

Five groups of semi-synthetic validation scenarios (Groups A–E) were introduced. The model was primarily evaluated for its adaptive alarm mechanism, and the graph showing changes in the model's thresholds is presented below. To ensure the scientific rigor of the model testing, this section designates the preprocessed normal data as the control group, while the mutation-based and incremental deformation tests serve as the experimental groups. The model's accuracy is verified by comparing the automatic alarm test results between the control group and the experimental groups. The results are illustrated in the Figure 15 below:

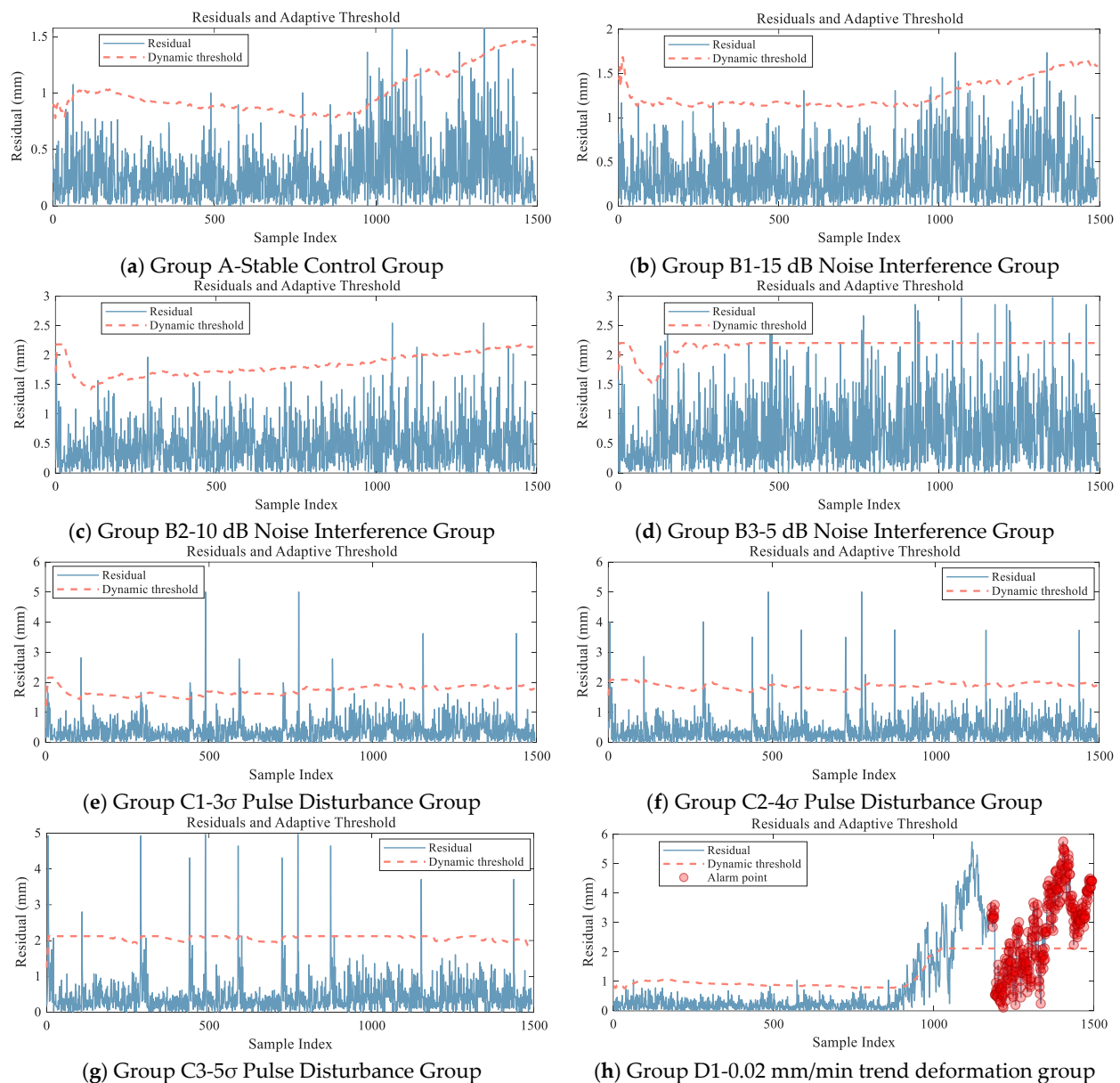


Figure 15. Cont.

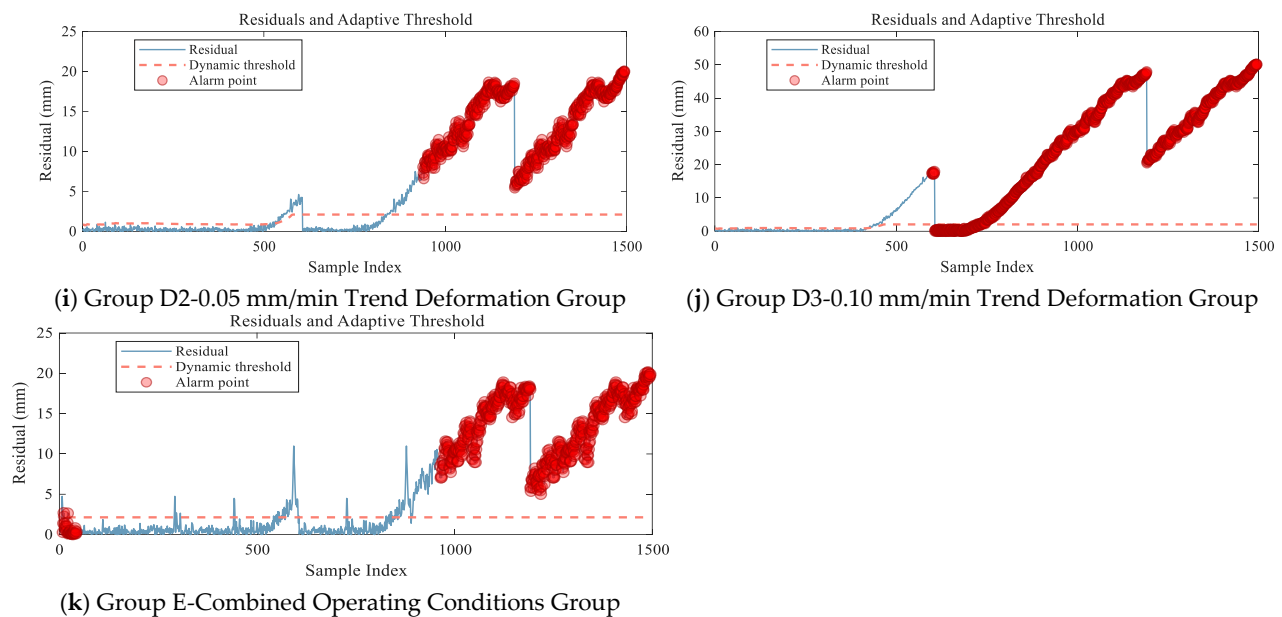


Figure 15. Display of Dynamic Thresholds and Alarm Points.

Based on statistical analysis of 50 experimental runs over approximately 45 h, the following results were obtained:

In Group A (normal conditions), the model threshold fluctuated stably within 0.7–2 mm, and the residual sequence remained stable. The state machine stayed in normal state (0) with zero alarms, verifying the system's false alarm-free performance under normal operating conditions and meeting practical engineering requirements.

Group B (Noise Interference): As the signal-to-noise ratio (SNR) of Gaussian white noise decreased from 15 dB to 5 dB, the threshold exhibited an adaptive upward trend. When the SNR was 15 dB, the threshold rose slightly but remained stable, with no false alarms observed across 50 experiments; when the signal-to-noise ratio (SNR) drops to 10 dB or even 5 dB, the fluctuation amplitude increases. Although the threshold rises significantly, the state machine remains capable of effectively distinguishing between noise and actual deformation, with only one false alarm in 50 experiments. This demonstrates that the dynamic threshold mechanism possesses excellent noise immunity.

In Group C (pulse disturbance), pulse signals at 180, 330, and 480 min caused instantaneous residual surges and brief threshold elevations. However, with only 10 min pulse durations and the exceedance proportion failing to meet the warning trigger condition (exceeding 0.15 for three consecutive times), the state machine remained normal, successfully suppressing all false alarms from single-pulse disturbances. This confirms effective fault tolerance against transient disturbances.

Group D (trend deformation) served as the primary test scenario. Under slow deformation (0.02 mm/min), the model detected sustained residual deviation at index 918, transitioning to alert state (1) after three consecutive exceedances and triggering the first alarm at minute 763 (cumulative displacement 7.42 mm). Under moderate deformation (0.05 mm/min), alarms triggered at minute 565 (19.96 mm). Under rapid deformation (0.10 mm/min), alarms triggered at minute 483 (27.20 mm). Notably, all alarm-time cumulative displacements (7.42–27.20 mm) remained far below 40% of the code limit (89.4 mm), providing ample emergency response time and demonstrating high sensitivity to continuous deformation.

Group E (composite conditions) involved linear trend (0.05 mm/min) coupled with pulse disturbances and Gaussian noise. The model accurately identified the true deformation trend despite multiple interferences, triggering an alarm at minute 11 of the test

set while successfully suppressing all pulse disturbances with zero false alarms. This demonstrates excellent robustness and practicality in complex real-world environments.

Quantitative performance metrics from the 50 independent experiments across all five groups are summarized in Table 6, confirming the system's reliability and effectiveness for deformation monitoring and early warning applications.

Table 6. Performance Statistics for the Early Warning Model.

Experimental Group	TP	FP	FN	TN	Recall Rate (%)	Accuracy (%)
A (Steady-state control)	0	0	0	50	-	100
B1 (Noise, SNR = 15 dB)	0	0	0	50	-	100
B2 (Noise, SNR = 10 dB)	0	1	0	49	-	98
B3 (Noise, SNR = 5 dB)	0	1	0	49	-	98
C1 (Pulse, 3σ)	0	0	0	50	-	100
C2 (Pulse, 4σ)	0	0	0	50	-	100
C3 (Pulse, 5σ)	0	0	0	50	-	100
D1 (Trend, 0.02 mm/min)	49	0	1	0	98	98
D2 (Trend, 0.05 mm/min)	50	0	0	0	100	100
D3 (Trend, 0.10 mm/min)	50	0	0	0	100	100
E (Composite conditions)	50	0	0	0	100	100

4. Discussion

The results demonstrate that the proposed GB-RAR-based framework can effectively support short-term, high-frequency deformation prediction and adaptive early warning for super-tall buildings. Compared with conventional deformation monitoring workflows that mainly focus on data acquisition or displacement description, the proposed framework links data preprocessing, deformation prediction, residual analysis, dynamic thresholding, and finite-state warning decisions into an integrated process.

The MAD-SG hybrid denoising strategy improved the quality of GB-RAR deformation sequences by suppressing both transient outliers and high-frequency random fluctuations. This preprocessing step is important because residual-based early warning depends strongly on the reliability of the input deformation sequence. After denoising, the trajectory analysis showed that the monitored deformation of the Wuhan Greenland Center remained within a small range during the observation period, and the displacement mainly oscillated along the southwest–northeast direction. This indicates that the structure was in a stable state during the monitoring period.

For deformation prediction, the PSO-GA-BP model showed better prediction performance than BP, GA-BP, PSO-BP, and LSTM under the current monitoring conditions. This result suggests that the embedded collaboration between PSO and GA can improve the optimization of BP network weights and thresholds. PSO mainly improves convergence efficiency and local exploitation, while GA crossover and mutation help maintain population diversity and reduce the risk of premature convergence. Therefore, the proposed model is suitable for nonlinear and non-stationary deformation sequences obtained from GB-RAR monitoring.

The early warning results further show that the residual-driven adaptive warning mechanism can distinguish transient disturbances from sustained deformation trends. In the steady-state, noise-disturbed, and pulse-disturbed groups, the model showed strong false-alarm suppression ability. In the trend-deformation and composite scenarios, the model successfully identified sustained abnormal deformation trends, demonstrating sensitivity to cumulative deformation development. These results indicate that combining adaptive thresholds with an FSM decision mechanism is effective for improving warning robustness under complex monitoring conditions.

It should be noted that the actual monitoring data used in this study covered approximately 45 h, from 12:21 on 5 July to 9:38 on 7 July. For a 447 m super-tall building, such a monitoring period mainly captures short-term structural responses associated with diurnal temperature variation, wind-induced vibration, and other temporary environmental disturbances.

Therefore, the proposed model aims to establish a short-term, high-frequency deformation prediction and adaptive warning framework based on GB-RAR monitoring. In practical monitoring applications, GB-RAR systems continuously acquire high-frequency deformation observations, and the proposed framework is intended to operate in a rolling-update manner, where model inputs, residual statistics, and warning thresholds can be updated as new monitoring data become available. This rolling mechanism helps maintain warning sensitivity under changing short-term environmental conditions. However, for long-term warning applications involving seasonal effects, settlement evolution, or material creep, longer monitoring records and periodic model recalibration are still required. In addition, the current validation is based on a specific super-tall building in a case study, and the obtained results may, to some extent, reflect the structural characteristics, surrounding environment, and radar deployment geometry of the Wuhan Greenland Center itself. Therefore, when applying the proposed framework to other buildings, the model parameters, warning thresholds, and feature sensitivity may be influenced by structural form, height, stiffness, environmental constraints, and instrument deployment. Consequently, parameter calibration and validation based on site-specific monitoring data are still required.

Future work will further incorporate longer-term continuous monitoring datasets covering seasonal temperature variations, foundation settlement evolution, and long-term structural deformation characteristics, in order to further improve the engineering applicability and generalization capability of the proposed framework.

5. Conclusions

Based on GB-RAR technology, this study systematically analyzed deformation monitoring data from the Wuhan Greenland Center at 300 m and its summit (447 m). The analysis addressed data denoising, motion trajectory assessment, deformation prediction, and adaptive early warning, providing insights into the behavior of super-high-rise buildings. The main conclusions follow:

- (1) A combined denoising method integrating Median Absolute Deviation (MAD) outlier removal and Savitzky–Golay filtering effectively eliminated gross errors and noise from GB-RAR data. Using the denoised data, a spatiotemporal trajectory map was constructed with the monitoring start as reference. Results show that the building's displacement oscillates predominantly in the southwest–northeast direction, with amplitude within ± 8 mm, indicating minor deformation. Based on structural characteristics, the building remained safe throughout the monitoring period.
- (2) A PSO-GA-BP time-series prediction model was developed by jointly optimizing a BP neural network with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), enabling deformation forecasting for GB-RAR monitoring data. Compared with BP, GA-BP, PSO-BP, and LSTM models using RMSE, MAE, and R^2 metrics, the PSO-GA-BP model produced prediction results closer to the measured values under the current monitoring conditions. The results demonstrate that the proposed model provides stable prediction performance for nonlinear deformation sequences of super-high-rise buildings.
- (3) An adaptive early warning mechanism based on the PSO-GA-BP model was established. It integrates an adaptive sliding window, a multi-factor dynamic threshold (incorporating trend, fluctuation, and stability factors), and a three-state finite state

machine (normal–alert–alarm) to enable graded anomaly detection. Validation under steady-state, noise-disturbed, pulse-disturbed, trend-deformation, and composite conditions showed strong resistance to transient disturbances and high sensitivity to sustained deformation trends. Under the current experimental conditions, the proposed framework achieved stable warning performance and demonstrated good robustness and practical applicability for GB-RAR monitoring scenarios.

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Abbreviations

The following abbreviations are used in this manuscript:

GB-RAR	Ground-Based Real Aperture Radar
PSO-GA-BP	Particle Swarm Optimization—Genetic Algorithm—Back Propagation
MAD	Median Absolute Deviation
S-G Filter	Savitzky–Golay Filter
WGC	Wuhan Greenland Center
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R ²	Coefficient of Determination
FSM	Finite State Machine

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