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A Spatiotemporal-Adaptive-Network-Based Method for Predicting Axial Forces in Assembly Steel Struts with Servo System of Foundation Pits

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Abstract: The axial force in assembly steel struts with servo systems is a critical indicator of stability in foundation pit support systems. Due to its high sensitivity to temperature variations and direct influence on the lateral deformation of the foundation pit enclosure structure, accurate prediction is essential for safety monitoring and early warning. This study proposes a novel method for predicting the axial force in assembly steel struts with servo systems based on a spatiotemporal adaptive network. The method begins by feeding historical axial force data from multiple steel struts into an LSTM network to extract temporal sequence features. A self-attention mechanism is then employed to capture the global dependencies within the axial force data, enhancing the feature representation. Concurrently, a convolutional neural network (CNN) is utilized to extract local spatial features. Additionally, excavation depth and excavated soil stratification data are processed through convolutional operations to derive stratification-related features. Subsequently, the temporal and spatial features of axial force are fused with stratification-related features derived from excavation data and further refined through a CNN, enabling more accurate predictions. Validation using deep foundation pit data from a metro station in Zhejiang Province demonstrated the method's reliability and improved performance across multiple metrics compared to the existing approaches.

Keywords: deep excavation; axial force prediction; deep excavation safety early warning; neural network model

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1. Introduction

With the rapid development of the nation and society, the urbanization process has accelerated, leading to a significant increase in the utilization of underground space [1,2]. In foundation pit engineering, the scale and depth of deep excavations continue to grow, often situated in densely populated urban centers with complex and variable surroundings [3,4]. These characteristics greatly amplify the challenges and risks associated with construction. Any accidents involving deep foundation pits can result in substantial socioeconomic losses and pose serious threats to the safety of construction workers and nearby structures [5,6].

In deep foundation pit construction, the axial force of assembly steel struts is a critical indicator of the stability of the support system, directly reflecting the overall safety of the excavation [7]. However, it is significantly influenced by various external factors, including complex environmental conditions and varying excavation scenarios, with weather changes being particularly prominent [8–10]. For instance, during rain or snow, drastic temperature fluctuations can cause thermal expansion and contraction of metal materials, leading to axial force deviations around the design value [11–13]. Similarly, excavation processes, such as changes in excavation depth or speed, can introduce additional variability in axial forces. In extreme cases, these deviations may become substantial, potentially exceeding safe limits and increasing the risk of excavation instability and construction hazards [14,15]. To address this challenge, it is essential to conduct in-depth research on the behavior of axial forces in assembly steel struts under varying environmental and excavation conditions, enabling precise prediction and early warning of potential issues. Such advancements can help to mitigate the risk of safety incidents caused by abnormal axial forces, reduce casualties, enhance the overall efficiency and reliability of deep foundation pit projects, and allow experts ample time to make informed decisions.

In prediction methods, machine learning and neural networks have been widely applied for forecasting and early warning in engineering monitoring data. Support Vector Machines (SVMs) [16] and Random Forests (RFs) [17] have been used for predicting foundation pit deformation and safety risks. Backpropagation (BP) [18] neural networks and Artificial Neural Networks (ANNs) [19] have been employed for foundation pit settlement prediction. Furthermore, researchers have improved these basic networks to enhance prediction accuracy. For instance, Liu et al. [20] optimized BP neural networks using the Grey Verhulst model, while Liu et al. [21] introduced genetic algorithms to optimize ANN models, achieving higher accuracy in settlement prediction. Despite these advancements, such methods struggle to adequately capture the dynamic variations in monitoring data under complex working conditions. In recent years, the development of deep learning has led to the application of recurrent neural networks, such as Long Short-Term Memory (LSTM) [22] and Gated Recurrent Unit (GRU) [23], for predicting engineering monitoring data due to their strengths in handling time-series data. Li et al. [24] proposed an LSTM-based method for foundation pit deformation prediction, while Liu et al. [25] enhanced the GRU model by incorporating a Variational Mode Decomposition (VMD) method optimized with Particle Swarm Optimization (PSO), resulting in the VMD-PSO-GRU model, which achieved high prediction accuracy.

However, the stability of foundation pit support systems is influenced not only by temporal factors but also by spatial distribution characteristics, geological conditions, and external environmental factors such as temperature variations. The traditional methods have not considered the joint modeling of temporal and spatial dimensions. Addressing the influence of environmental conditions and the coupled effects of excavation implementation on the axial forces of assembly steel struts, this study integrates time series, spatial distribution, and geological features to construct an accurate predictive model based on a spatiotemporal adaptive network. This method can capture the complex variation patterns of axial forces, enabling effective early warning support for deep foundation pit construction. By reducing safety incidents caused by abnormal axial forces, it helps to ensure construction safety and improve economic efficiency.

2. Methodology

2.1. Overview

To address the issue of axial force fluctuations in assembly steel struts during foundation pit construction caused by temperature variations and excavation processes, particu-

larly in severe cases where significant deviations from the design value may pose safety risks, this study proposes an axial force prediction method for assembly steel struts based on a spatiotemporal adaptive network, as illustrated in Figure 1. By enabling accurate axial force prediction and early warning, this approach aims to identify potential anomalies caused by multi-factor coupling during construction, reduce safety risks, and enhance the stability and reliability of foundation pit projects. The proposed method comprises two main steps: feature extraction and fusion-based prediction.

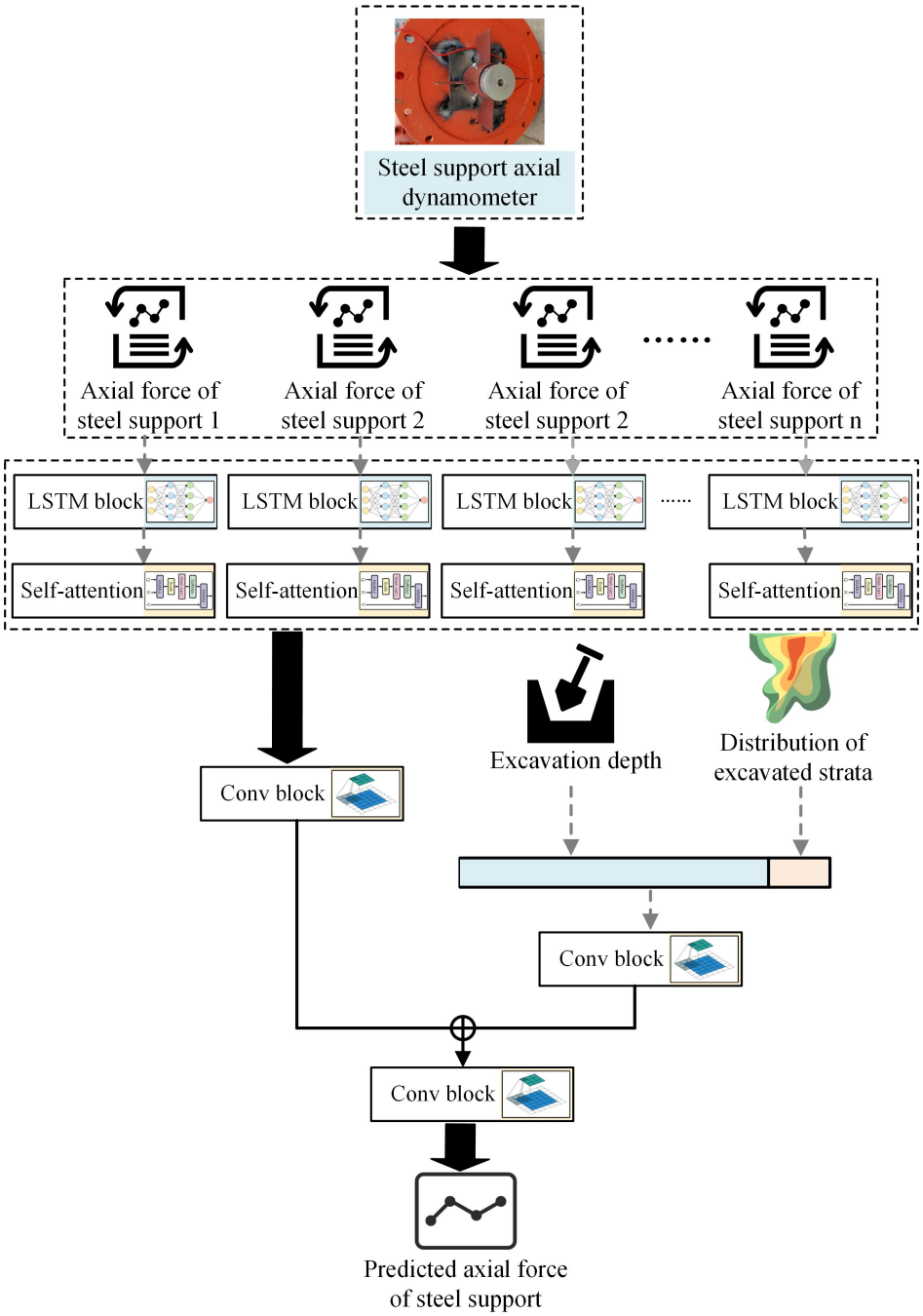


Figure 1. Spatiotemporal adaptive prediction network framework.

In the feature extraction phase, an LSTM network is first employed to capture the temporal sequence features from the historical axial force data of each assembly steel strut. To further enhance its ability to capture long-range dependencies, a self-attention mechanism is integrated with the LSTM, enabling it to selectively focus on hidden states

across different time steps. Additionally, excavation depth and stratification distribution data are incorporated, with convolutional operations applied to extract features relevant to geological conditions. This combination of enriched temporal and spatial characteristics yields a comprehensive and robust feature representation for prediction. In the fusion prediction phase, the extracted temporal, spatial, and geological features are integrated to form a unified representation. This integrated feature set is then input into a deep learning network that models and predicts the axial forces of the assembly steel struts, leveraging the complementary strengths of the multidimensional features to ensure accurate and robust predictions.

2.2. Spatiotemporal Adaptive Prediction Network

2.2.1. LSTM Network

To effectively extract the temporal features of assembly steel strut axial force data, this study constructs an LSTM model. The model is designed to capture the dynamic temporal variations in historical axial force data, providing high-quality temporal feature representations for subsequent prediction tasks. LSTM networks, known for their significant advantage in handling long-term dependencies in time-series data, are widely used in dynamic trend prediction applications.

As shown in Figure 2, the historical axial force data for each assembly steel strut are processed independently through separate LSTM modules. Leveraging the coordinated operation of the input, forget, and output gates, the LSTM effectively retains key features, enabling it to capture the temporal patterns and regularities of axial force variations. After processing through the LSTM network, the output temporal feature representations encapsulate the critical variation trends of assembly steel strut axial forces across different time steps. The computation process of the LSTM network can be described as follows:

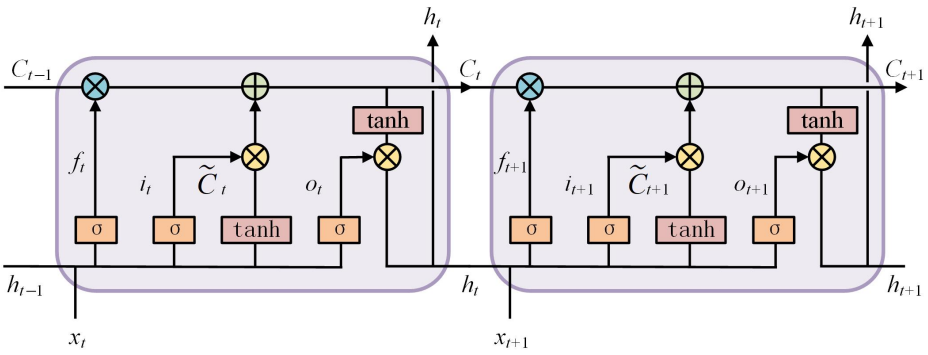


Figure 2. Overall structure of LSTM.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

where x_t is the current input vector, h_{t-1} and h_t denote the previous and current hidden states, respectively, and $[h_{t-1}, x_t]$ denotes their concatenation for computing gate activations and candidate states; W_f, W_i, W_C, and W_o together with b_f, b_i, b_C, and b_o are the weight

matrices and bias vectors for the forget, input, candidate, and output gates; σ and tanh are the sigmoid and hyperbolic tangent functions, respectively; f_t, i_t, and o_t are the outputs of the forget, input, and output gates; and $\tilde{C}_t$ is the candidate cell state used to update and form the new cell state C_t.

2.2.2. Self-Attention Mechanism

To further enhance the representation capability of assembly steel strut axial force data features, a self-attention mechanism is integrated into the LSTM network to refine the hidden states across time steps by focusing on the most relevant information. As illustrated in Figure 3, the self-attention mechanism not only captures long-range dependencies but also highlights critical temporal features, overcoming the limitations of traditional methods that predominantly focus on local characteristics. By applying self-attention to the LSTM's hidden states, the model selectively accentuates key information, yielding a more comprehensive and focused depiction of the global dynamic changes in the data. Moreover, this approach enables the model to uncover and prioritize potential spatial correlations within the axial force data, thereby optimizing the feature representation derived from the LSTM. The enhanced representation effectively combines the temporal dynamics captured by the LSTM with the essential dependencies revealed by the self-attention mechanism, ultimately providing enriched and precise feature information for the subsequent prediction module.

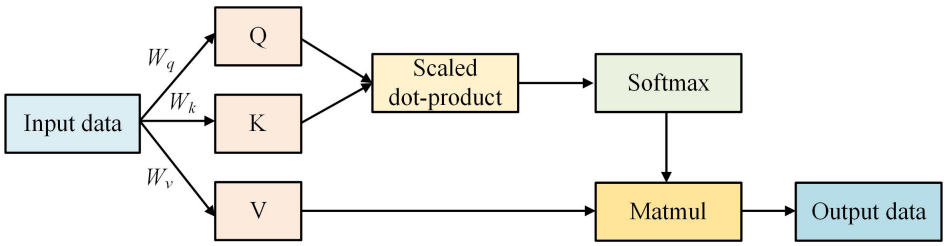


Figure 3. Structure of the self-attention mechanism.

The core computation process of the self-attention mechanism is as follows: For an input feature matrix $X \in \mathbb{R}^{n \times a}$ (where n represents the number of time steps and d is the feature dimension), linear transformations are first applied to obtain the query vector (Q), key vector (K), and value vector (V):

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V \tag{7}$$

where W_Q, W_K, $W_V \in \mathbb{R}^{d \times d'}$ are learnable weight matrices and d' is the reduced feature dimension. Next, the similarity between the query and key vectors is computed using a dot product, and the result is normalized with the Softmax function to generate the attention weight matrix A:

$$A = \text{Softmax}\left(\frac{QK^\top}{\sqrt{d'}}\right) \tag{8}$$

the attention weight matrix $A \in \mathbb{R}^{n \times n}$ represents the strength of spatial correlations within the input data. Finally, the attention weight matrix is multiplied with the value vector to produce the weighted output features O:

$$O = AV \tag{9}$$

the output O is the global feature representation processed by the self-attention mechanism, which incorporates the spatial correlation information within the input data.

2.2.3. CNN Framework

To extract the local spatial features of assembly steel strut axial force data and capture geological characteristics pertinent to foundation pit construction, this study employs a CNN for feature extraction. As illustrated in Figure 4, the temporal and spatial features of the axial force data are fused with geological features to form a unified representation that is subsequently processed by the CNN. This method facilitates the extraction of high-level features that capture complex spatial and geological relationships, ultimately enhancing the accuracy of assembly steel strut axial force predictions.

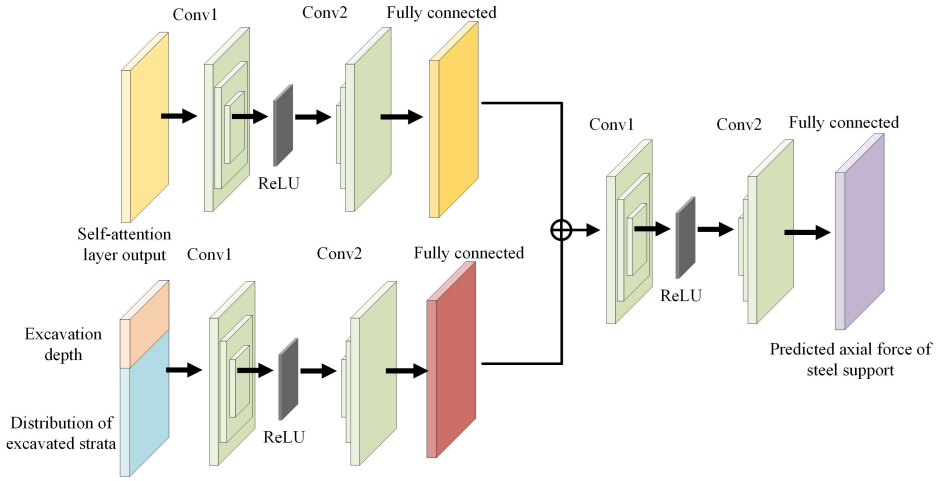


Figure 4. CNN structural framework.

The feature map $X \in \mathbb{R}^{H \times W \times C}$, generated from the self-attention-enhanced LSTM, where H and W denote the height and width of the feature map and C represents the number of channels, is used as input. A convolutional kernel $K \in \mathbb{R}^{k \times k \times C}$ is applied to perform convolution operations and extract local spatial features. The convolution calculation is defined as follows:

$$Y(i,j) = \sum_{p=1}^{C} \sum_{n=1}^{k} \sum_{m=1}^{k} X(i+m-1, j+n-1, p) \cdot K(m,n,p) + b \tag{10}$$

where $Y(i,j)$ is the value of the output feature map at position (i,j), b is the bias term, p is the input channel index, and m, n are indices along the spatial dimensions of the kernel. The convolution operation slides the kernel over the input feature map to extract spatial features, using the ReLU activation function to introduce nonlinearity and improve the model's capacity to capture complex patterns:

$$Y_{\mathrm{ReLU}}(i,j) = \max(0, Y(i,j)) \tag{11}$$

2.2.4. Model Performance Evaluation Metrics

To comprehensively evaluate the performance of the proposed model, three metrics are adopted: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). Smaller RMSE and MAE values indicate lower prediction errors, while an R^2 value closer to 1 signifies higher prediction accuracy and better model fit. The specific formulas for these metrics are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{12}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{13}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{14}$$

where n is the total number of data points, y_i is the observed value for the i-th data point, $\hat{y}_i$ is the predicted value for the i-th data point, and $\bar{y}$ is the mean of the observed values.

3. Case Study

3.1. Overview of the Engineering Project

The deep foundation pit in this project pertains to the main excavation of the Sanbao Station on the SG9-3 section of the Phase I civil construction of Hangzhou Metro Line 9. Sanbao Station serves as a "T"-shaped transfer station between Line 6 and Line 9. The Line 6 section of Sanbao Station (Zones 1 to 5) is an underground four-story island-style station with a total length of 175 m and a standard width of 25.7 m. The Line 9 section (Zones 6 to 11) is an underground three-story island-style station with a total length of 201.2 m and a standard width of 24.5 m. Both sections adopt a double-column, three-span reinforced concrete box-frame structure with full waterproofing. The diaphragm walls and interior lining walls are designed as composite walls. The station is primarily constructed using the open-cut method. Entrance passages, ventilation shafts, and other auxiliary structures are mainly constructed using the open-cut method after the main structure is completed. For Entrance C, where it connects to the already constructed underpass tunnel, the horizontal freezing method is employed, followed by underground excavation. During the excavation and underground construction, special consideration is afforded to minimizing the impact on the surrounding environment. A schematic diagram of the environment surrounding Sanbao Station is shown in Figure 5.

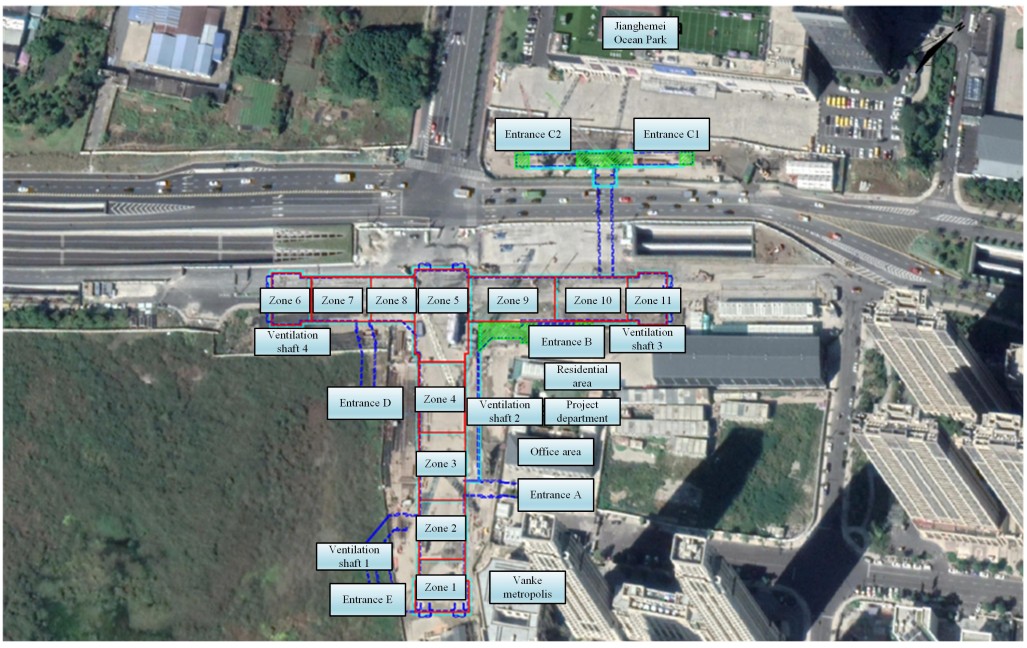


Figure 5. Schematic diagram of the project's surrounding environment.

3.2. Geological Conditions and Steel Support Layout

The foundation soil layers in the station area, from top to bottom, consist of filling layers (plain filling and miscellaneous filling), sandy silt layers, clay layers (mucky clay, silty clay, and silty clay containing sand), silty layers, gravelly medium sand layers, rounded

gravel layers, and mud siltstone layers (ranging from completely weathered to moderately weathered). Specifically, the base slab of Sanbao Station (Zones 1 to 5) is situated within the silty clay layer, while the walls are founded in the moderately weathered mud siltstone stratum. The detailed geological profile is shown in Figure 6.

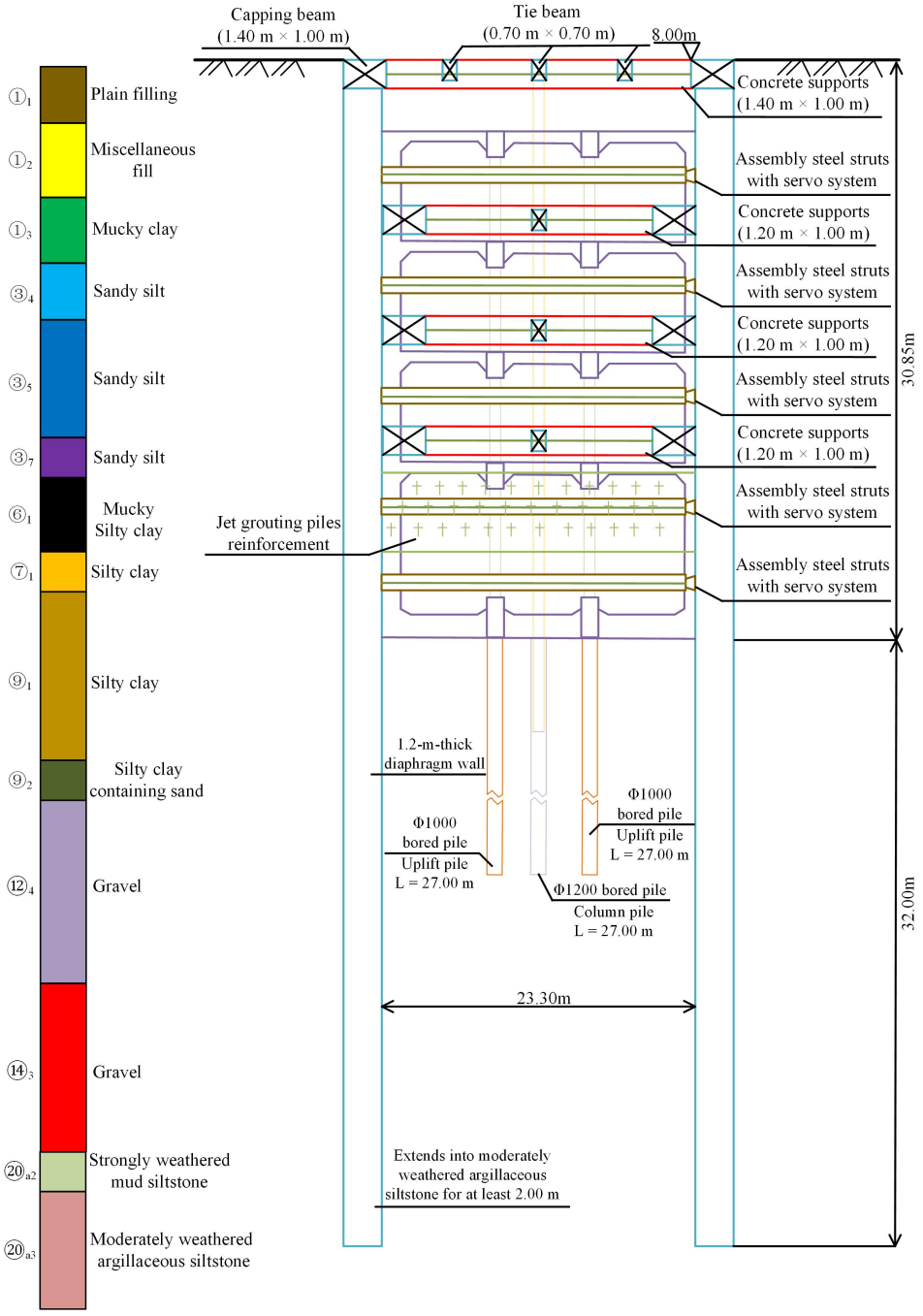


Figure 6. Typical geological profile of zones 1 to 5 at Sanbao Station.

The standard section width of Zones 1 to 5 at Sanbao Station is 23.3 m, while the end shaft width is 27 m. Each steel strut weighs approximately 11.5 tons. The installation process for the steel struts involves pre-assembly on the ground, followed by segmented hoisting into the foundation pit using a 20-ton gantry crane, where the assembly is completed. In certain areas, manual chain hoists are used to assist with assembly adjustments. For the transfer nodes, steel struts are segmented and hoisted into the foundation pit using a 50-ton

crawler crane, where they are subsequently assembled. The layout of the second layer of steel struts within the foundation pit is illustrated in Figure 7.

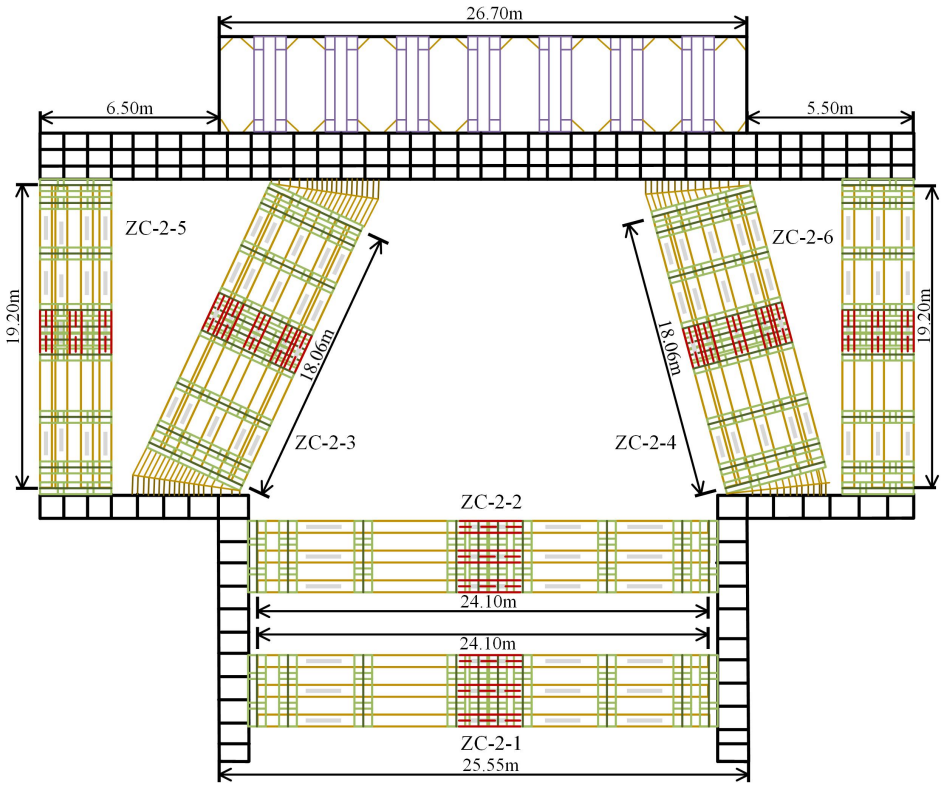


Figure 7. Layout of the second layer of assembly steel struts with servo system in zone 5 of Sanbao Station.

4. Results Analysis

4.1. Data Description

Temperature fluctuations can lead to variations in assembly steel strut axial force, particularly under the influence of diurnal temperature differences, causing the axial force to oscillate around its design value to a certain extent. If these fluctuations are not effectively predicted and controlled, they may threaten the stability of the foundation pit support system and even pose safety risks. To analyze the relationship between assembly steel strut axial force and temperature changes in greater detail and to validate the effectiveness of the proposed method, this study uses axial force monitoring data from six assembly steel struts in the second layer of Zone 5 at Sanbao Station as experimental data.

This study utilizes monitoring data from assembly steel struts ZC2-1 to ZC2-6 collected between 22 October 2019 and 26 December 2019. The data were recorded hourly, capturing daily temperature variations and their corresponding impact on the axial force of assembly steel struts over consecutive days, as illustrated in Figure 8. To ensure the scientific validity of the model training and evaluation, the dataset was divided into three parts: 70% for model training, 10% for validation, and 20% for testing. By modeling and analyzing this dataset, the study uncovers the fluctuation patterns of assembly steel strut axial forces under daily temperature changes. Furthermore, the prediction results provide 4 h forecasts of axial force, offering technical support and data-driven insights for safety monitoring during foundation pit construction and stability assessment of the support system.

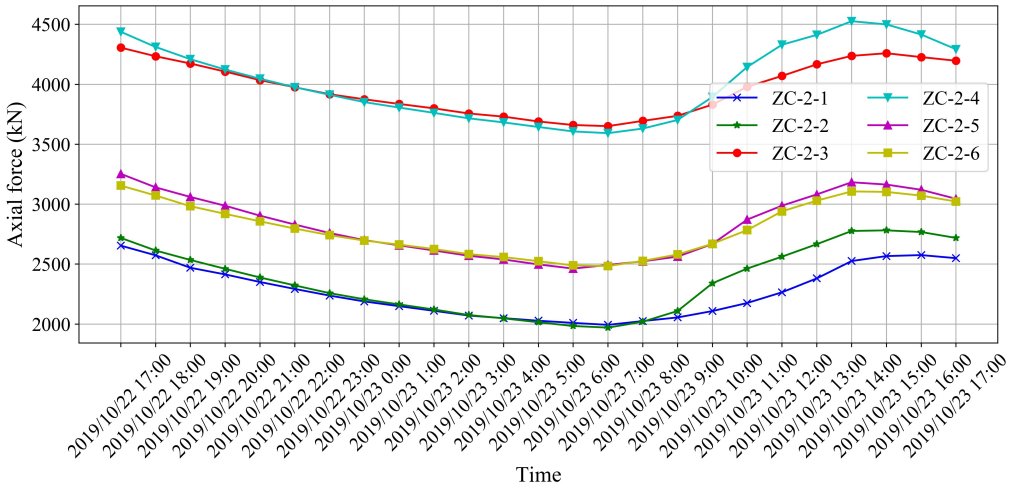


Figure 8. Axial force variation curves of assembly steel struts with servo system in the second layer.

4.2. Prediction Performance

As shown in Figures 9 and 10, the dashed-box areas correspond to the period between December 17 and 18, 2019, during which the axial forces of the assembly steel struts with a servo system exhibit a gradual decrease. This trend can be attributed to the progressive increase in the axial-force-bearing capacity of the newly cast concrete struts. Following the casting process, the concrete struts underwent a curing period during which their strength steadily increased, enabling them to take on more of the applied load. As a result, the load previously borne by the assembly steel struts with a servo system was gradually redistributed to the concrete struts, leading to a reduction in the axial forces of the steel struts.

This phenomenon is effectively captured by the spatiotemporal axial force predictions generated using the spatiotemporal adaptive network (STAN) model. As detailed in the figures, the predicted axial forces for struts ZC2-2 and ZC2-3, derived from the past 5 h of axial force data, excavation depth, and stratigraphic distribution, align well with the observed trends. Subplots (a–d) in Figures 9 and 10 compare the predicted and actual axial force values for 1 h, 2 h, 3 h, and 4 h forecasting intervals, respectively. The STAN model demonstrates high accuracy in tracking the variations in axial forces, particularly for shorter-term predictions (Figure (a) and (b)), while maintaining consistency in longer-term forecasts (Figure (c) and (d)) despite slight deviations. The alignment between the STAN model's predictions and the observed reduction in axial forces underscores its effectiveness in capturing the spatiotemporal dynamics of axial force redistribution during construction. This validates the model's applicability in monitoring and predicting the behavior of support systems under dynamic load conditions.

Table 1 presents the evaluation results of the axial force predictions for the overall performance across six assembly steel struts over the next 1 to 4 h. The model's performance is quantitatively analyzed using RMSE, MAE, and R^2. The results show that the model achieves low errors and high prediction accuracy for forecasts. However, as the prediction time steps increase, the errors gradually grow, leading to a slight decline in accuracy. For the 1 h prediction, the RMSE is 20.77, the MAE is 14.88, and R^2 reaches 0.99, indicating an excellent fit between the predicted and actual values. This level of accuracy effectively meets the monitoring requirements for dynamic changes in assembly steel strut axial forces in practical engineering scenarios. The low error within the first hour demonstrates that the model effectively leverages historical data to capture both local trends and overall fluctuations in axial force variations.

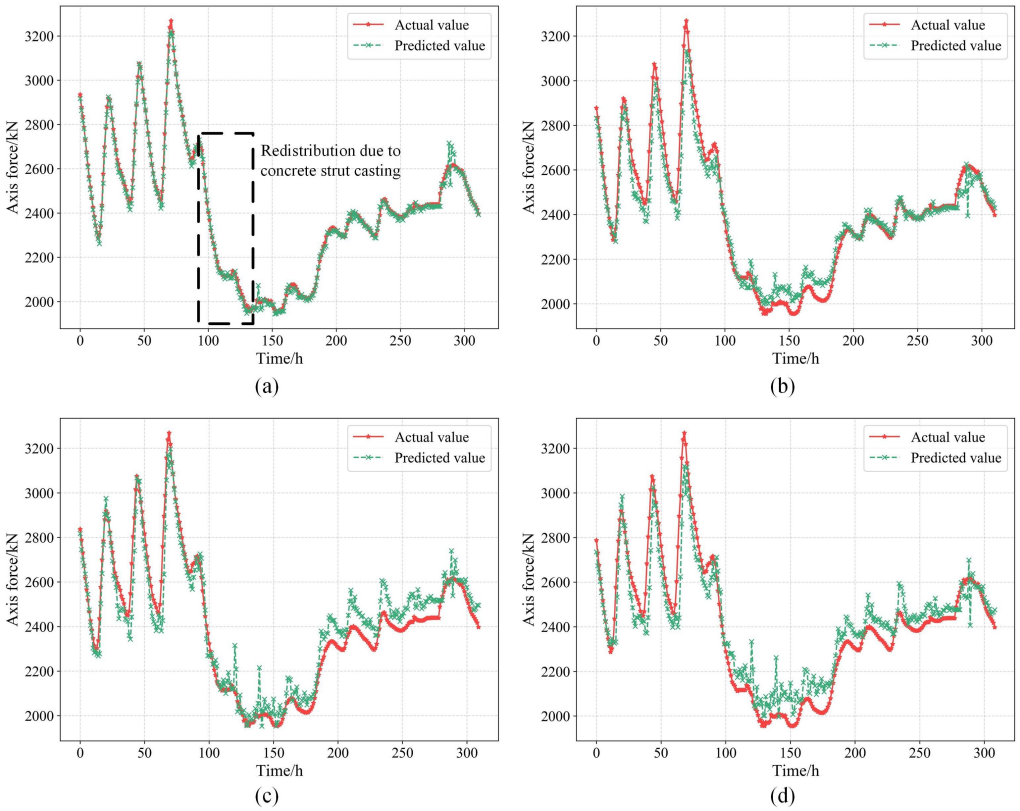


Figure 9. Comparison of predicted and actual axial forces of ZC2-2 for the next four hours: (**a**) next 1st hour; (**b**) next 2nd hour; (**c**) next 3rd hour; (**d**) next 4th hour.

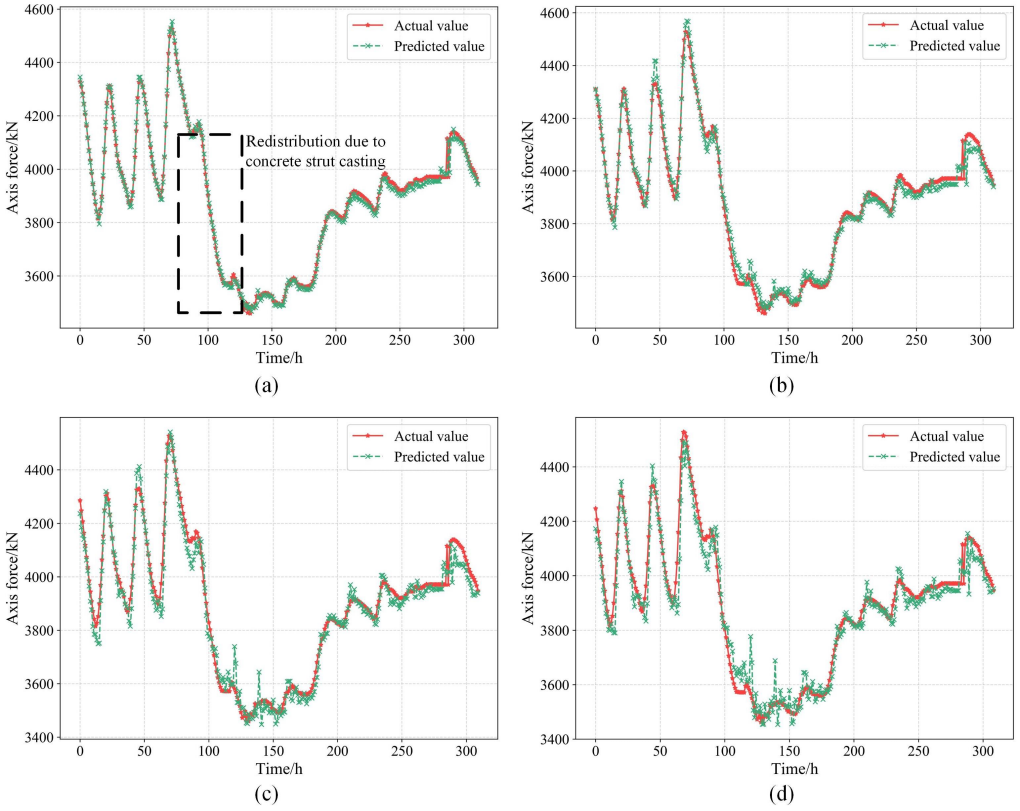


Figure 10. Comparison of predicted and actual axial forces of ZC2-3 for the next four hours: (**a**) next 1st hour; (**b**) next 2nd hour; (**c**) next 3rd hour; (**d**) next 4th hour.

However, in the 2 h and 3 h predictions, the errors increase, with RMSE reaching 51.22 and 62.23, MAE rising to 38.39 and 46.60, and R^2 dropping to 0.93 and 0.91, respectively. Although the error growth is significant, the overall accuracy remains acceptable, and the predictions effectively capture the trends in assembly steel strut axial forces. For the longer-term 4-h prediction, the RMSE rises to 83.81, MAE increases to 59.94, and R^2 drops to 0.86, indicating a higher level of error. This suggests that, for longer prediction time steps, the model's ability to capture local fluctuations diminishes, although it still accurately reflects the overall trend. The experiments demonstrate that the STAN model achieves low errors in predictions, meeting the accuracy requirements for monitoring and early warning of assembly steel strut axial forces. For medium- to long-term predictions, while the error increases, the model retains a certain degree of predictive capability, providing valuable references for trend analysis.

Table 1. Evaluation of overall predicted axial force performance for assembly steel struts with servo system over the next four hours.

Predicted Axial Force (Future Hours)	Evaluation Metrics		
	RMSE	MAE	R^2
Next 1st Hour	20.77	14.88	0.99
Next 2nd Hour	51.22	38.39	0.93
Next 3rd Hour	62.23	46.60	0.91
Next 4th Hour	83.81	59.94	0.86

The decline in prediction accuracy over time can be attributed to two main factors. First, the fluctuation in assembly steel strut axial forces is influenced by various complex factors, such as temperature changes, excavation progress, and stratigraphic conditions. These factors tend to exhibit greater complexity and uncertainty over longer prediction time steps, reducing the relevance of historical data for future predictions and increasing the difficulty and error in forecasting. However, the proposed STAN method leverages the joint modeling of temporal and spatial features to effectively extract dynamic patterns under multi-factor influences, enabling it to capture overall trend changes even over extended time steps. Second, short-term predictions typically rely on the local trends and overall fluctuation characteristics of historical data, which exhibit strong continuity and predictability within shorter periods, leading to higher accuracy. In contrast, long-term predictions require the model to possess stronger nonlinear fitting and generalization capabilities to address more unknown factors and complex dependencies in dynamic changes. Although errors increase gradually in long-term predictions, the STAN method significantly enhances the ability to model complex nonlinear relationships by extracting global features through the self-attention mechanism and integrating local features via multi-layer convolutional networks.

4.3. Method Comparison

To demonstrate the superiority of the proposed STAN method in predicting assembly steel strut axial forces, a comparative analysis was conducted against the RNN method proposed by Borandag [26], the LSTM method proposed by Guo et al. [1], and the GRU method proposed by Zhang et al. [27]. As shown in Figures 11 and 12, the performance of each method was evaluated by comparing the predicted and actual axial forces of assembly steel struts ZC2-2 and ZC2-3 over the next 1, 2, 3, and 4 h. These comparisons highlight the performance of each method across different prediction time steps.

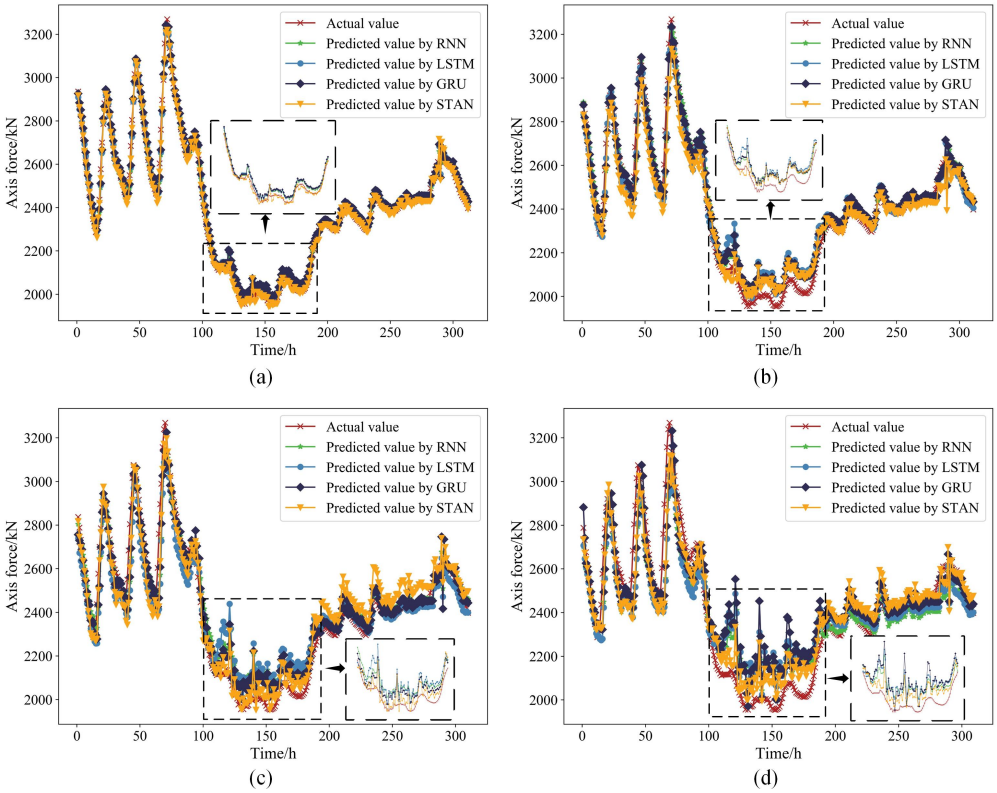


Figure 11. Comparison of the performance of different methods in predicting axial forces of ZC2-2 over the next four hours: (**a**) next 1st hour; (**b**) next 2nd hour; (**c**) next 3rd hour; (**d**) next 4th hour.

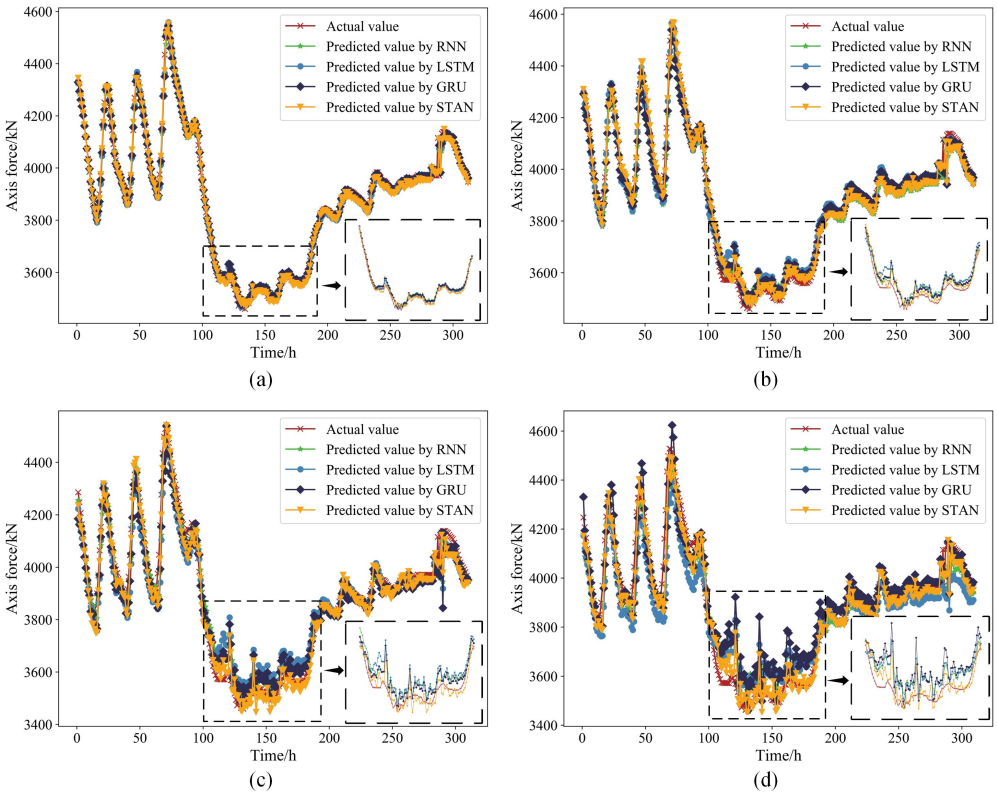


Figure 12. Comparison of the performance of different methods in predicting axial forces of ZC2-3 over the next four hours: (**a**) next 1st hour; (**b**) next 2nd hour; (**c**) next 3rd hour; (**d**) next 4th hour.

The figures reveal significant differences in the ability of the three methods to predict assembly steel strut axial forces. The RNN method captures the overall trend of the axial force variations but responds more slowly to regions with rapid fluctuations and shows limitations in fitting local details. As the prediction time steps increase, the RNN method's capacity to model complex dynamic changes becomes increasingly constrained, making it difficult to maintain stable performance in long-term predictions. The LSTM method, by incorporating a gating mechanism, effectively captures temporal dependencies in the time series. Compared to RNN, it demonstrates improved performance in short-term predictions, particularly excelling in capturing rapid fluctuations. As the prediction time steps increase, LSTM maintains relatively stable performance in modeling global trends, but its fitting capability in regions with pronounced local fluctuations remains somewhat limited. The GRU method, similar to LSTM, also leverages gating mechanisms to manage long-term dependencies while reducing computational complexity. It achieves comparable performance to LSTM in predicting axial force variations but exhibits slightly better generalization in long-term forecasts, capturing local fluctuations more effectively. However, like LSTM, it still faces challenges in maintaining high accuracy under the influence of temperature fluctuations.

In comparison, the STAN method demonstrates significant advantages in both short-term and long-term predictions. For the 1 h and 2 h predictions, the STAN method accurately captures the overall trend of the assembly steel strut axial forces while effectively characterizing the local fluctuation features. The predicted curves align closely with the actual values, reflecting its high precision. For the longer-term 3 h and 4 h predictions, despite the increased demands placed on the model due to the increase in prediction time steps, the STAN method continues to effectively capture the overall trends and maintains a high degree of consistency in regions with local fluctuations. This highlights its strong adaptability and stability across different prediction time steps.

The quantitative analysis in Table 2 highlights the significant advantages of the STAN method in predicting assembly steel strut axial forces, particularly in handling long-term predictions, where its performance far surpasses that of the other methods. This superiority arises from the STAN method's spatiotemporal adaptive mechanism, which effectively integrates temporal features, spatial characteristics, and geological information, enabling a more comprehensive capture of the dynamic patterns in assembly steel strut axial forces. In long-term predictions, the STAN method mitigates the impact of error accumulation by leveraging joint modeling of temporal dependencies and spatial distribution characteristics, thereby enhancing the robustness of the model.

Table 2. Comparison of overall predicted axial force performance for assembly steel struts with servo system using various methods.

Model	Next 1st Hour			Next 2nd Hour			Next 3rd Hour			Next 4th Hour		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
RNN	30.47	22.48	0.96	60.58	48.37	0.87	94.48	74.18	0.71	127.03	99.25	0.62
LSTM	28.04	20.83	0.97	56.71	42.78	0.92	91.42	66.86	0.81	124.74	95.74	0.67
GRU	27.41	21.04	0.98	53.09	42.45	0.93	84.99	68.03	0.73	123.02	91.94	0.65
STAN	20.77	14.88	0.99	51.22	38.39	0.93	62.23	46.60	0.91	83.81	59.94	0.86

The LSTM method performs well in short-term and mid-term predictions and significantly outperforms the traditional RNN method. By introducing a gating mechanism, LSTM captures temporal dependencies in time-series data more effectively, demonstrating stronger modeling capability for complex temporal patterns. For instance, in the 1 h and 2 h predictions, while the performance differences among the methods are relatively minor,

LSTM achieves slightly lower RMSE and MAE values than RNN, indicating that its gating mechanism effectively improves trend fitting for assembly steel strut axial forces. The GRU method, similar to LSTM, incorporates a gating mechanism to manage long-term dependencies while offering a more simplified architecture with fewer parameters. It demonstrates comparable performance to LSTM in short-term and mid-term predictions, achieving slightly better accuracy in longer time steps due to its improved generalization ability. However, like LSTM, it remains limited in its ability to fully capture local fluctuations over extended time horizons.

However, a shared limitation of the LSTM, GRU, and RNN approaches is their sole focus on the temporal relationships of assembly steel strut axial forces without considering the spatial correlations between struts. In the 3 h and 4 h predictions, this limitation significantly reduces their ability to capture local fluctuation characteristics, causing the predicted results to deviate substantially from the actual trends. In contrast, the STAN method comprehensively integrates temporal features, spatial characteristics, and geological information, enabling more holistic modeling of the dynamic variations in assembly steel strut axial forces. By capturing both the overall trends and local details, the STAN method significantly outperforms the LSTM, GRU, and RNN methods. Its performance advantage becomes even more pronounced in long-term predictions, showcasing remarkable adaptability and robustness.

5. Conclusions

This study proposes a spatiotemporal-adaptive-network-based method for predicting the dynamic variations in axial forces of assembly steel struts with a servo system during foundation pit excavation. The following conclusions are drawn:

(1) The STAN model integrates the self-attention mechanism with a convolutional neural network, effectively combining temporal features, spatial characteristics, and geological information. This integration significantly enhances the model's ability to capture and predict the complex dynamic variations in axial forces of assembly steel struts with a servo system.

(2) The STAN model was validated using monitoring data of axial forces from assembly steel struts with a servo system in an actual engineering project. The results demonstrate that the STAN model effectively captures the dynamic variation trends of axial forces in both short-term and long-term predictions, with the predicted curves closely aligning with the actual values. In short-term predictions, the model excels at accurately capturing local fluctuation characteristics. For long-term predictions, despite the increased challenges posed by longer time steps, the STAN model continues to effectively reflect the overall trends, showcasing strong stability and adaptability.

(3) The comparative analysis with the RNN, LSTM, and GRU methods demonstrates that the STAN model offers significant advantages in capturing the dynamic variation patterns of axial forces in assembly steel struts with a servo system. Particularly in long-term predictions, the STAN model, through joint modeling of spatiotemporal features, provides a more comprehensive reflection of the overall trends and local fluctuation characteristics. In contrast, the RNN, LSTM, and GRU methods, which only consider temporal relationships and fail to incorporate spatial features, exhibit a gradual decline in prediction accuracy as the prediction time steps increase. While the GRU approach performs similarly to the LSTM method and achieves slightly better accuracy in long-term predictions due to its improved generalization ability, both methods still struggle to fully capture local fluctuations and spatial dependencies. This further validates the adaptability and stability of the STAN model in complex

engineering environments, demonstrating its superiority in effectively predicting axial force variations in deep excavation projects.

Fluctuations in axial forces of assembly steel struts with a servo system are critical factors affecting the stability of foundation pit support systems, with abnormal variations potentially leading to structural instability and severe safety incidents. Accurate prediction and effective early warning of axial forces are therefore essential for ensuring construction safety and reducing the risk of accidents during foundation pit excavation. The proposed STAN model achieves precise modeling and prediction of dynamic changes in axial forces of assembly steel struts with a servo system, providing technical support for axial force early warning during construction. This method has theoretical significance and offers a potential solution for early warning in practical engineering, serving as a reference for related research and engineering applications.

Future research will explore the integration of physical constraints associated with temperature fluctuations regarding neural network frameworks to further enhance the accuracy of long-term axial force predictions. This will be achieved by embedding key thermal–mechanical principles and material behavior, particularly the effects of temperature-induced expansion and contraction of steel supports, directly within the model architecture. The enhanced hybrid approach is expected to better capture the complex interactions between temperature variations and axial force dynamics. This strategy aims to overcome the limitations of purely data-driven models by improving both interpretability and robustness, ultimately providing a more reliable early warning system for foundation pit support stability under conditions of temperature variation.

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