Integration of Building Information Modeling and Gated Recurrent Units for Enhanced Risk Management in Subway Foundation Pits

Xiaozheng Li*, Yaping Tao, Weiliang Gao, Lu Han, Yanming Zhao
School of Traffic Engineering, Huanghe Jiaotong University, Jiaozuo 454950, China
E-mail: 2019080956@zjtu.edu.cn, 2016101903@zjtu.edu.cn, gwl0216@126.com, m13674975106@163.com, 2021090101@zjtu.edu.cn
*Corresponding author

Keywords: foundation pit support risk, building information modeling, gated recurrent unit, risk monitoring, fuzzy comprehensive evaluation method

Received: June 11, 2025

To address issues such as low safety factors and difficulty in predicting the force variation of support systems in subway station foundation pit construction, this study develops a subway foundation pit support risk management system based on a risk data monitoring method combining Building Information Modeling technology and gated recurrent neural networks. In constructing the risk management system, a fuzzy analytic hierarchy process model is also used to assess and analyze the foundation pit risks. Experimental results show that the average absolute error of displacement prediction is 0.089 millimeters, the root mean square error is 0.112 millimeters, and the coefficient of determination is 0.947. The surface settlement error is within ±1.0 millimeters, and the early warning delay does not exceed 1.8 seconds. Compared with RCGAN, GRA and cooperative game weighting methods, the discrimination error rate decreased between 37% and 140%, which was statistically significant (p<0.05). This hybrid system significantly enhances the accuracy and real-time performance of safety control in metro foundation pit construction, which is of great significance for the future safety control of foundation pit excavation and support and the improvement of dynamic risk management level.

Povzetek: Hibridni sistem za upravljanje tveganj v metrojskih gradbenih jamah (BIM + GRNN + mehki AHP) omogoča zelo natančne napovedi pomikov in posedkov ter hitro zgodnje opozarjanje, s čimer bistveno izboljša varnostno kontrolo v realnem času.

1 Introduction

With the continuous development of metro rail transit, people's travel is more efficient and convenient, but it also brings some safety risks [1]. In the construction of rail transit, there are many causes of foundation pit collapse accidents, such as deep excavation, urgent construction schedules, and complex surrounding buildings [2]. Among them, the deep foundation pit support design and risk management is the focus of engineering research. The survey classification of rock and soil types such as artificial fill layer and quaternary alluvium should be considered in the design of deep foundation pit protection structure [3]. All kinds of deep foundation pit support forms, including underground continuous walls, soil nailing walls, and other support forms, need to pay attention to the management of enclosure structure deformation and collapse risk [4-5]. At present, VA risk system and fuzzy mathematics theory are mostly used in the risk management of foundation pit support [6]. Although these measures have positive effects, they are insufficient in risk monitoring and identification. Aiming at problems such as the lack of targeted risk management and control and inaccurate identification of collapse risk, this study constructed a risk management system for subway foundation pit support based on BIM and Gated Recurrent Unit (GRU), and simultaneously used FAHP for comprehensive risk evaluation, in order to reduce the risk frequency and improve the effect of collapse risk control. The innovation of this study is to combine BIM model with the GRU neural network to realize multi-source data fusion and dynamic monitoring, and effectively improve the risk prediction accuracy of subway foundation pit support. At the same time, the proposed model integrates the functions of real-time monitoring, risk assessment and dynamic early warning, which enhances the safety and efficiency of subway foundation pit support construction. The contribution of the research is to effectively combine the advantages of BIM technology and GRU neural network to realize the comprehensive and real-time dynamic monitoring of the subway foundation pit support construction process, break through the limitations of traditional monitoring methods, and provide more comprehensive and accurate risk information for construction personnel. The FAHP model is introduced to evaluate the risk of foundation pit support, which effectively solves the problems of excessive subjectivity and unreasonable weight distribution of evaluation indexes in the process of risk assessment, makes the risk assessment results more scientific, and provides strong support for construction decision-making.

2 Related works

In order to ensure the safety of foundation pit support structures and surrounding environments after excavation, as well as to provide better security on construction sites, research on risk data monitoring is essential [7]. In order to coordinate and optimize the mine stratigraphic structure and pre-detection analyses, Ma X and Dou Y proposed a water accumulation area detection model for goaf areas based on swarm intelligent perception computing. The model analyzes multi-source data in real-time through swarm intelligent perception computing. The results show that the model has a fast response speed and high sensitivity [8]. Aghamohammadi A et al. proposed a visual ergonomic assessment technology using multi-frame and multi-path convolutional neural networks to enhance human health risk identification. This technology uses four continuous frames to overcome joint missing issues and categorizes the inputs into risk categories [9]. Liu B's team designed a three-dimensional intelligent control platform for shield tunnel construction near major risk sources in order to establish an analysis model for calculating the immediate settlement of existing buildings. The model combines BIM, geographic information system (GIS), urban information model (CIM), geoscience model (GEO model), and the Internet of Things (IoT), and calculates the long-term settlement considering the influence of soil consolidation. The results show that this method effectively solves the problems of construction information management, early warning, and construction risk control in the construction process [10]. Brintrup A's team, to mitigate supply chain risks, redefined digital supply chain monitoring technology, helping companies detect supply chain risks and unethical practices in unsustainable environments. Experimental results show that supply chain digitization can supplement visibility solutions from the bottom up [11]. Xu X et al. proposed an in-situ measurement method to comprehensively understand the environmental impact of deep foundation pit engineering for target soil layer permeability. This method also employs precipitation head and constant head recharge tests to determine actual permeability, providing monitoring of the site. Experimental results show that this method can effectively monitor foundation pit risks and strengthen construction environment protection measures [12].

In conclusion, experts both domestically and internationally have conducted detailed research on subway construction, with achievements in foundation pit risk management. However, there is still limited research on subway foundation pit support risk management and risk data monitoring. Therefore, this study constructs a BIM-GRU-based subway foundation pit support risk management system for real-time monitoring and management of factors such as pit depth, surface settlement, and axial force. The system also utilizes the advantages of FAHP for constructing decision matrices and effectively assessing risks, further improving the level of risk management in underground transportation construction.

3 Subway foundation pit support risk management based on BIM-GRU

3.1 Optimization of BIM-GRU risk data monitoring method

During urban underground construction, deep foundation pits are often excavated, and inaccurate excavation can lead to surface deformation and frequent collapse accidents [13]. Therefore, to ensure the safety of foundation pit support structures and surrounding pipelines, a dynamic risk assessment method based on BIM technology is proposed to guarantee the safe implementation of urban rail transit operations. BIM technology, as a digital technology, can create three-dimensional models with attributes such as building geometry, spatial relationships, and geographic information, integrating data throughout its entire life-cycle. The dynamic risk assessment method based on BIM technology is shown in Figure 1.

As shown in Figure 1, the dynamic evaluation of construction safety risks mainly consists of risk probability analysis, sensitivity analysis, and most likely cause chain analysis performed by the construction safety risk dynamic evaluation Bayesian network. The construction safety information database is used for collecting accident, project, and risk information, while urban rail transit projects use BIM technology for information reporting, risk quantification, and analysis. This improves the overall effectiveness of risk evaluation work and provides more valuable reference data for construction safety risk management. The data received by the BIM technology platform is processed using the Bayesian learning method for risk identification, and the calculation equation is shown in Equation (1).

$$P(R|X)=\frac{P(X|R)\cdot P(R)}{P(X)} \tag{1}$$

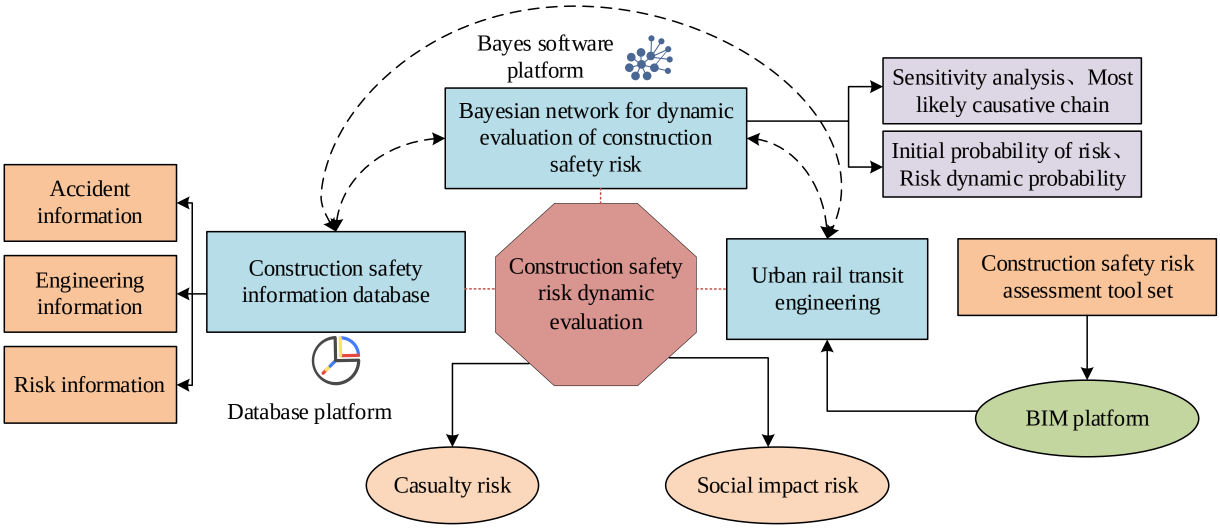


Figure 1: Method framework of dynamic risk assessment based on BIM technology

In Equation (1), $P(R|X)$ represents the data feature probability under the known risk state. X represents the real-time data feature vector, $P(R)$ denotes the prior conditions under the risk state, and $P(X)$ represents the marginal probability of the feature. Since there are also various constraints during the construction process, such as material costs and architectural design, the study proposes, based on the BIM risk dynamic evaluation method, a cost control framework based on BIM technology to ensure reasonable construction practices. The cost control framework based on BIM technology is mainly divided into two parts: the construction project cost control phase and the project optimization phase. In the cost control phase, the project database is used for drawing optimization, collision detection, and virtual design. Then, BIM technology is applied for dynamic site and resource management, construction process, and real-time tracking simulation. Finally, project optimization is carried out through measures such as schedule plan optimization, monitoring, and adjustments. The specific expression for calculating the cost-benefit of subway-related engineering projects using BIM technology is shown in Equation (2).

$$\begin{cases} \begin{bmatrix} \dot{\xi} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} -\xi / \upsilon \\ \frac{1}{2} \otimes \bar{\xi} \end{bmatrix} + \begin{bmatrix} -\varepsilon / \upsilon \\ 0 \end{bmatrix} \\ \begin{bmatrix} \dot{\xi} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} \xi \\ \dot{\omega} \end{bmatrix} + \begin{bmatrix} \varsigma \\ \phi \end{bmatrix} \end{cases} \tag{2}$$

In Equation (2), $\bar{\xi}$ represents the mean value of the project cost vector in subway construction projects, $\dot{\xi}$ indicates the first-order derivative of the feature vector in subway-related engineering, ξ is the cost feature vector in construction engineering, and ω and $\dot{\omega}$ represent the material market cost and the first-order derivative value in subway construction. ε, ς, and ϕ represent the observed change values. The comprehensive model for construction project cost control is shown in Equation (3).

$$U_{k+1} = T \cdot \sigma_k \cdot \phi_k \cdot I_k / I_{k+1} \tag{3}$$

In Equation (3), k represents the construction project cost control phase, ϕ_k and σ_k denote the intensity-stress ratio matrix and the observed noise present in the control phase, while I_k and I_{k+1} represent the benefit diffusion index of adjacent construction projects. Although the cost control and risk assessment method improved based on BIM technology provides effective management of the construction process, issues such as missing monitoring data may arise as the number of measurement points increases and monitoring frequency intensifies [14]. Therefore, based on the BIM technology-improved cost control and risk assessment methods, a BIM-GRU risk data monitoring method is proposed to analyze and provide early warnings for deformation and other states of construction materials. Among them, GRU can handle missing data such as concrete deformation monitoring, and its improved update gate operation equation is shown in Equation (4).

$$z_t = \sigma\left(\left[W_z x\right]_t + \left[U_z h_{t-1}\right]_t\right) \tag{4}$$

In Equation (4), x_t represents the deformation monitoring data sample, W_z and U_z are the weight matrices, and h_{t-1} denotes the hidden layer. The output equation of the reset gate is shown in Equation (5).

$$r_t = \sigma\left(\left[W_r x\right]_t + \left[U_r h_{t-1}\right]_t\right) \tag{5}$$

In Equation (5), r_t represents the reset gate output, and x_t denotes the deformation data. The information to be retained is determined through the hidden layer, and the final output is shown in Equation (6).

$$h_t = z_t \times h_{t-1} + (1-z_t) \times h_t' \tag{6}$$

In Equation (6), h_t represents the hidden unit, and $1-z_t$ determines the information to be forgotten. In the integration of GRU and BIM, the BIM platform provides multi-dimensional monitoring data streams in real-time. Each data stream is a feature vector, which includes parameters such as position, settlement, axial force, stress, temperature, and equipment status collected at specific time points. First, standardize the raw data, handle missing values, and remove outliers. The preprocessed time series data is input into the trained GRU network. The GRU outputs predicted values and potential risk characteristics by learning the time series dependencies of historical data. Transmit the predicted values and potential risk characteristics back to the BIM platform in real-time. The predicted displacement, settlement values, etc. are mapped to the corresponding components or monitoring points of the BIM model to achieve dynamic association between the physical model and the predicted data. And through the BIM platform, the predicted values are compared with the preset early warning thresholds and control thresholds. If the predicted values exceed the early warning thresholds, the system automatically highlights the corresponding positions in the BIM model and sends alarm information to the management personnel through the cloud platform, indicating the potential risk locations and the predicted risk index values. In summary, GRU can predict and store data. The specific process of the BIM-GRU risk data monitoring method is shown in Figure 2.

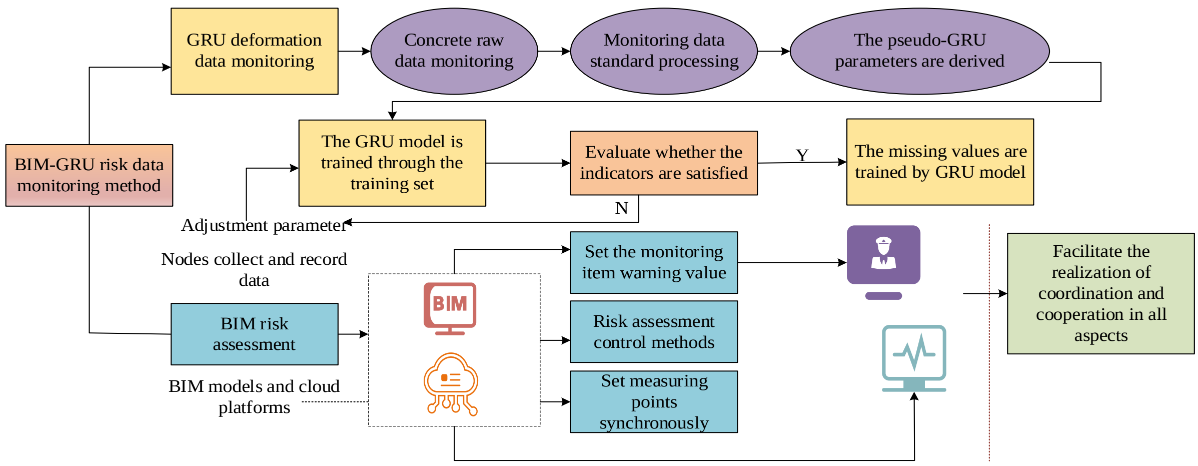


Figure 2: Diagram of BIM-GRU risk data monitoring methodology

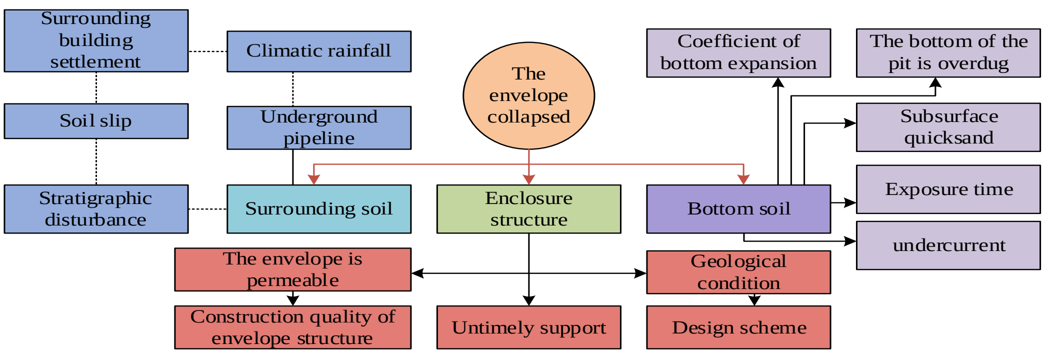


Figure 3: Schematic diagram of subway pit support collapse risk indicators

3.2 Design of subway foundation pit support risk management system based on

BIM technology and FAHP

While the BIM-GRU risk data monitoring method can promptly detect component conflicts and construction path obstacles during the construction process, it still has certain shortcomings in subway foundation pit support risk management. Therefore, based on the BIM-GRU risk data monitoring method, this research proposes a subway foundation pit support risk management system based on FAHP to achieve full control over the risk of foundation pit support collapse. FAHP can accurately reflect the fuzzy decision-making judgments among the risks of support collapse, ensuring that the evaluation results are scientific and reasonable [15]. The subway foundation pit support collapse risk indicators are shown in Figure 3.

As shown in Figure 4, the foundation pit support collapse indicators are mainly divided into enclosure structure, surrounding soil, and bottom pit soil. The enclosure structure includes factors such as construction quality, delayed support, and geological conditions. The surrounding soil includes factors such as settlement of nearby buildings and underground pipelines. The settlement factors of the bottom pit soil mainly include underground quicksand and seepage. When using FAHP for decision-making, the first step is to establish a hierarchical structure model, including the objective layer, criterion layer, and indicator layer. The target layer is the risk of collapse of subway foundation pit support, while the criterion layer includes the risk of enclosure structure, surrounding soil, and bottom soil. The risk of enclosure structure includes horizontal displacement of support structure, vertical settlement of support structure, abnormal axial force of support structure, and development of cracks in support structure. The risk of surrounding soil includes settlement of adjacent buildings, deformation of underground pipelines, and surface settlement rate. The risk of soil at the bottom of the pit includes the amount of uplift at the bottom of the pit, changes in groundwater level, and risk of soil seepage and damage. Then, triangular fuzzy numbers (a, b, c) are used to pairwise compare the importance of each factor within the same level relative to a factor in the previous level, where a is the most pessimistic value, b is the most likely value, and c is the most optimistic value. The scale range is from (1, 1, 1) to (7, 8, 9), and the reciprocal is used to represent the opposite importance level. By integrating the fuzzy judgments of multiple experts, the geometric average of the fuzzy judgment values of n experts is taken to construct a comprehensive fuzzy judgment matrix; Then, the extended analysis method is used to calculate the fuzzy weights of each factor. The fuzzy product of each row element in the matrix is calculated, the nth root is taken, and the fuzzy sum of the preliminary fuzzy weights of all factors is obtained to obtain the fuzzy weights of each factor. The centroid method is used for deblurring processing to obtain clear weights, which are then normalized. At the same time, the fuzzy weights of the criterion layer relative to the target layer and the indicator layer relative to the criterion layer are calculated, and the fuzzy comprehensive degree value of the indicator layer relative to the target layer is obtained through fuzzy synthesis operation; Subsequently, the fuzzy judgment matrix is transformed into a clear judgment matrix composed of the median value b, and its consistency index CI and consistency ratio CR are calculated. CR=CI/RI, RI is the average random consistency index. When CR<0.1, the judgment matrix meets the consistency requirement, otherwise it needs to be adjusted. Finally, a fuzzy relationship matrix is established to determine the membership degrees of each factor to the five risk levels of "extremely low", "low", "medium", "high", and "extremely high". The weighted average method is used to synthesize the weight vectors with the fuzzy relationship matrix, and the final comprehensive risk level is determined based on the principle of maximum membership degree. The judgment matrix is shown in Equation (7).

$$AW = \lambda_{\max} W \tag{7}$$

In Equation (7), $\lambda_{\max}$ represents the maximum value of the matrix, W represents the eigenvector, and A is the judgment matrix. When the probability value is $0 < P < 0.01$, it indicates that accidents rarely occur, and the level is A. When the probability value is $0.1 \le P \le 1$, it indicates that accidents occur occasionally, and the level is C, with relatively minor risk losses. When the probability value is $P \ge 10$, it indicates that accidents frequently occur, resulting in significant losses. Therefore, the study uses the risk probability table for further judgment of risk losses. The algorithm for single-factor evaluation using FAHP is shown in Equation (9).

$$R = \begin{bmatrix} r_{11} \cdot \cdot r_{1m} \\ \cdots \\ \cdots \\ r_{n1} \cdot \cdot r_{nm} \end{bmatrix} \tag{9}$$

In Equation (9), R represents the relationship matrix, and r_{ij} corresponds to a specific factor within the evaluation factor set. The equation for determining the factor weight vector is shown in Equation (10).

$$\begin{cases} A = \{a_1, a_2, a_3, ...a_n\} \\ \sum_{i=1}^{n} a_i = 1 \end{cases} \tag{10}$$

In Equation (10), a_i represents the weight, and A indicates the weight vector. The comprehensive evaluation and analysis are shown in Equation (11).

$$E_0 = \frac{1}{2} K_0 \gamma H^2 \tag{11}$$

In Equation (11), E_0 represents the static soil pressure, γ represents the soil density, and H and K_0 represent the height of the retaining wall and the static soil pressure coefficient, respectively. In summary, using FAHP to evaluate the risks of subway foundation pit support can provide effective risk warnings. The framework of the metro foundation pit support risk management hybrid system based on FAHP is shown in Figure 4.

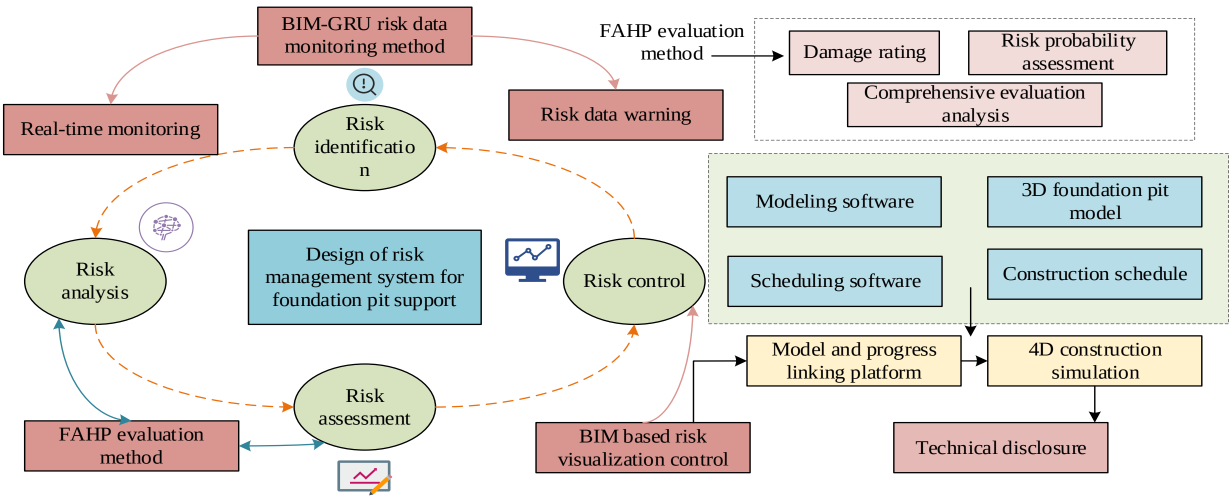


Figure 4: Risk management hybrid system of subway foundation pit support based on FAHP

4 Performance analysis of subway foundation pit support risk hybrid management system based on BIM technology

4.1 Verification of the effectiveness of the BIM-GRU risk data monitoring method

To highlight the superior performance of the BIM-GRU risk data monitoring method, Mean Square Error (MSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2) were selected as evaluation indexes. The displacement corresponds to the engineering thresholds of ±10 mm for early warning and ±20 mm for control. The strain results are normalized to a 0–100% early warning margin ratio based on the maximum allowable strain of the enclosure, to ensure comparability across methods. The experiment used MIDAS/GTS as the finite element analysis software, with an Intel i7-12650H CPU@2.30GHz, and was connected through built-in ports of the cloud platform. The 3D model of the foundation pit was built through Autodesk Revit 2023, and the model integration and data association were carried out through Navisworks Manage2023. The Revit model and the monitoring database were connected through the ODBC interface to achieve real-time binding of monitoring data and model components. Set up a data visualization template in Navisworks, display displacement monitoring values using color mapping, and simulate the risk evolution trend during the foundation pit excavation process through the TimeLiner function. Develop a data interaction plugin through the Revit API. The operation of the plugin requires. NET Framework 4.8 environment support. The experimental data are sourced from the open-cut section foundation pit project of Metro Line 5 in a certain city. The collection period is from June to December 2023, and it includes real-time monitoring data of 16 monitoring sections, with monitoring sections set every 50 meters. The collected data includes 144,000 original records, with five types of parameters: horizontal displacement, vertical settlement, axial force of the support, stress of the retaining structure and groundwater level. The data is divided into a training set and a test set in a 7:3 ratio. In the experiment, the hidden layer dimension of the GRU network was set to 64, the hidden layer activation function adopted tanh, the output layer adopted a linear activation function, and the AdamW optimizer was selected. The initial learning rate was 0.01 with a decay factor of 0.95, the weight decay was 0.0001, the maximum number of iterations was 200, and the batch processing size was 32. In each iteration, the mean square error between the predicted and true values is first calculated through forward propagation. Then, the parameters are updated using the Mini-batch gradient descent method. Meanwhile, an early stop mechanism is introduced. Training is terminated when the loss of the validation set does not improve after 10 consecutive rounds to avoid overfitting. During the training process, the data needs to be preprocessed. The Lida criterion is adopted to identify outliers, and the cubic spline interpolation method is used for filling. The interpolation interval is set at 5 to 15 minutes, and the maximum interpolation error is ≤0.08mm. Normalize the data to the range [-1, 1] using min-max scaling. The sliding window method is adopted to extract temporal features and generate a feature matrix, where the window size is set to 30 and the step size is set to 5. To ensure the feasibility of the experiment, a subway station foundation pit with dimensions of 198×20.1×17m was selected, and the calculation range for the experiment extended 2-3 times the side wall of the pit. In this study, SPSS 26.0 was used for statistical analysis. All monitoring data were tested by Shapiro-Wilk normality test to determine whether they conformed to the normal distribution. One-way analysis of variance (ANOVA) was used to compare the significance of the differences among the four methods, with a significance level of 0.05. If $p<0.05$, the differences between groups were significant. In order to verify the reliability of bim-gru risk data monitoring method for displacement monitoring, the displacement prediction results were compared with cooperative game empowerment, relative conditional generation countermeasure network (rcgan) and grey correlation analysis (GRA), and the comparison results are shown in Figure 5.

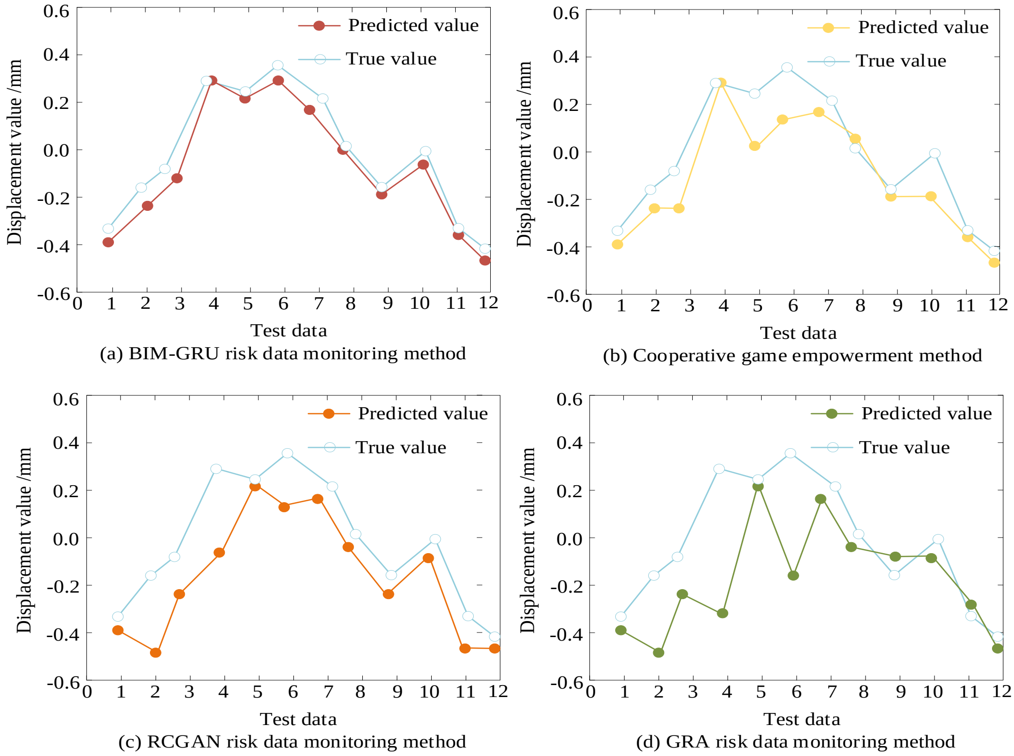
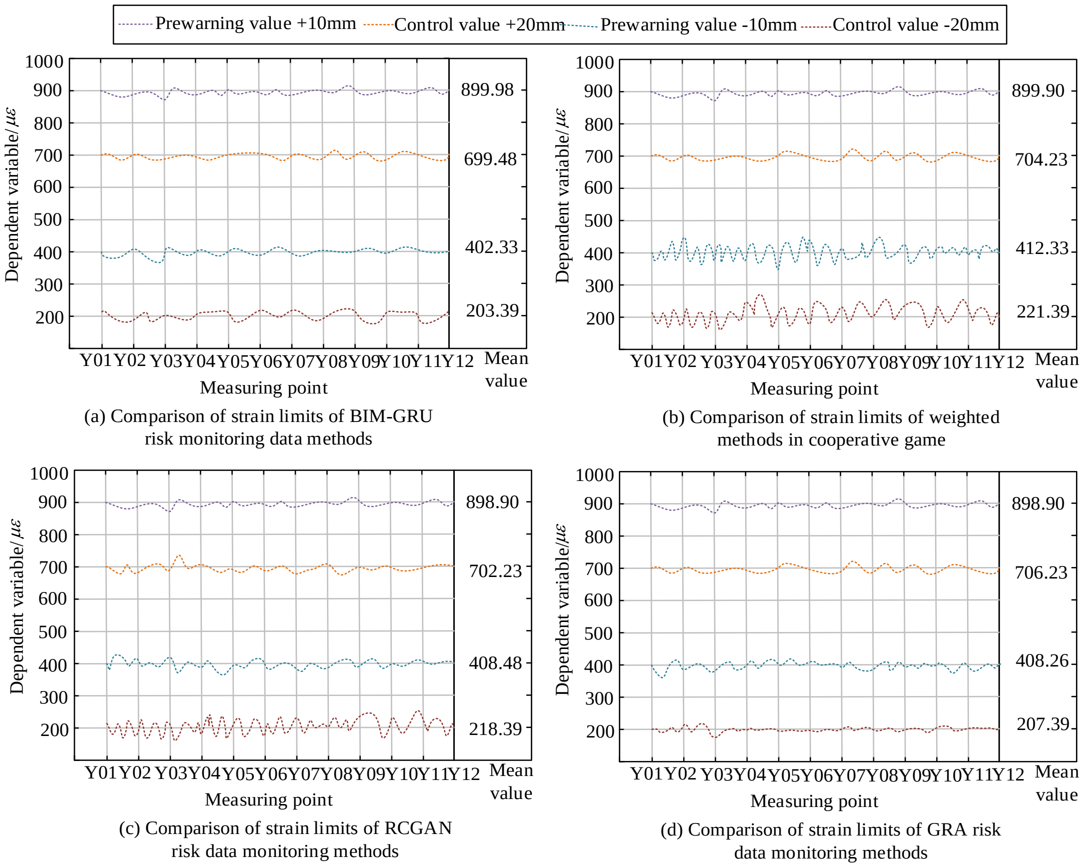


Figure 5: Comparison of measuring point displacement prediction and real value

As shown in Figure 5(a), the BIM-GRU risk data monitoring method's displacement predictions for test data points 4, 5, 8, and 9 were nearly identical to the actual values, with relatively small errors. In Figure 5(b), Cooperative Game Empowerment's prediction for test data point 4 showed a small error, while predictions for test data points 5 and 10 exhibited significant discrepancies from the actual values. In Figure 5(c), the RCGAN risk data monitoring method predicted -0.18mm for test data point 4, with a difference of 0.48mm from the actual value. In Figure 5(d), the GRA risk data monitoring method's overall prediction curve fluctuated significantly, with predictions for test data points 5 and 6 showing discrepancies of 0.68mm and 0.54mm from the actual values, respectively. In summary, the BIM-GRU risk data monitoring method was better at fitting data trends and offered higher prediction accuracy. To further highlight the strain measurement capability of the BIM-GRU risk data monitoring method, its strain limit testing results were compared with those of Cooperative Game Empowerment, RCGAN, and GRA. The testing results are shown in Figure 6.



(a) Comparison of strain limits of BIM-GRU risk monitoring data methods

(b) Comparison of strain limits of weighted methods in cooperative game

(c) Comparison of strain limits of RCGAN risk data monitoring methods

(d) Comparison of strain limits of GRA risk data monitoring methods

Figure 6: Strain limit test results comparison chart

As shown in Figure 6(a), when the BIM-GRU risk data monitoring method was tested with warning values of +10mm and control values of +20mm for 12 measurement points, the average strain values were 699.48 $\mu\varepsilon$ and 899.98 $\mu\varepsilon$, respectively. In Figure 6(b), for Cooperative Game Empowerment, when the 12 measurement points were tested with a warning value of -10mm, the average strain value was 412.33 $\mu\varepsilon$. In Figure 6(c), for the RCGAN risk data monitoring method, the average strain value was 218.39 $\mu\varepsilon$ when tested with a control value of -20mm for the 12 measurement points. In Figure 6(d), the GRA risk data monitoring method produced an average strain value of 207.39 $\mu\varepsilon$ when tested with a control value of -20mm for the 12 measurement points. In summary, the BIM-GRU risk data monitoring method provided a preliminary assessment of the internal structure of the subway foundation pit. To further demonstrate the predictive capability of the BIM-GRU risk data monitoring method for risk data, comparisons were made between the predicted and actual values using the Cooperative Game Empowerment method, the RCGAN risk data monitoring method, the GRA risk data monitoring method, and additional comparisons with the Vehicle Driving State-GAN (VDS-GAN) based on dynamic traffic change feature sequence data generation, as well as the WaveGAN, an audio generation model based on deep learning. The comparison results are shown in Table 1.

Table 1: Comparison of discriminant and predicted values

Different risk data monitoring methods	Discriminant value	The t value of the discrimination value compared with BIM-GRU	The P-value of the discrimination value compared with BIM-GRU	Predicted value	The t value of the predicted value compared with BIM-GRU	The p value of the predicted value compared with BIM-GRU
BIM-GRU	0.196±0.012	/	/	0.213±0.004	/	/
Cooperative	0.312±0.019	6.932	<0.05	0.294±0.005	8.256	<0.05

game empowerment method						
RCGAN	0.403±0.013	10.247	<0.05	0.375±0.008	9.873	<0.05
GRA	0.412±0.014	11.568	<0.05	0.312±0.007	7.635	<0.05
VDS-GAN	0.288±0.004	5.896	<0.05	0.301±0.007	6.427	<0.05
WaveGAN	0.472±0.010	14.329	<0.05	0.461±0.006	12.758	<0.05

As shown in Table 1, the sample error rate generated by the BIM-GRU risk data monitoring method is 0.196±0.012. Statistical analysis shows that the discrimination error rates of RCGAN, GRA, cooperative game weighting method, VDS-GAN and WaveGAN are all significantly higher than those of BIM-GRU, and the differences among the methods are statistically significant ($p<0.05$). The sample error rate of the RCGAN risk data monitoring method was 0.312±0.019, and the predicted value was 0.294±0.005, which was 37.1% higher than the error rate of the BIM-GRU risk data monitoring method. The sample error rate of the GRA risk data monitoring method was 0.403±0.013, and the predicted value was 0.375±0.008, which was 51.3% higher than that of the BIM-GRU risk data monitoring method. Moreover, the predicted values of RCGAN, GRA, cooperative game weighting method, VDS-GAN and WaveGAN were significantly different from those of BIM-GRU ($p<0.05$). In conclusion, the BIM-GRU risk data monitoring method performs better in terms of data correlation within the same frame.

4.2 Evaluation of the BIM-GRU-based subway foundation pit support risk management system

To verify the superior performance of the subway foundation pit support risk management system based on the BIM-GRU risk monitoring data method, the study compared it with three other subway foundation pit support risk management systems: Cooperative Game Empowerment, RCGAN, and GRA. Risk events can be classified into three types: retaining structure risks, geological and hydrological risks, and construction operation risks. Among them, retaining structure risks include excessive displacement of underground continuous walls, which can lead to soil collapse behind the walls and rupture of adjacent pipelines. Geological and hydrological risks can cause water accumulation in the foundation pit and delay the excavation process. Construction operation risks include deviations in support installation and damage to monitoring points, which can distort data collection, delay risk warning responses, and increase the risk of instability of the support structure. Since the materials used in the subway foundation pit support structure can limit soil deformation and surface settlement, the study selected surface settlement monitoring points DBC3294-Z1Z4 and DBC32493-Y1Y4 as representative monitoring points for the experiment. The four risk management systems—Cooperative Game Empowerment, RCGAN, GRA, and BIM-GRU—were compared for surface settlement analysis, with the results shown in Figure 7.

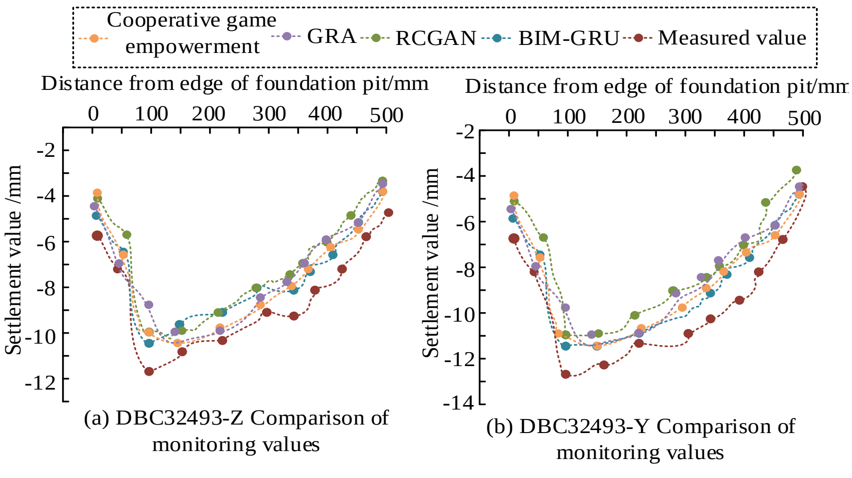
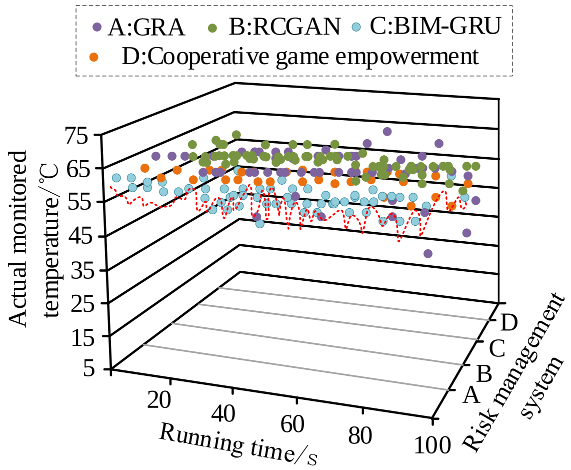


Figure 7: Comparative analysis of surface settlement map

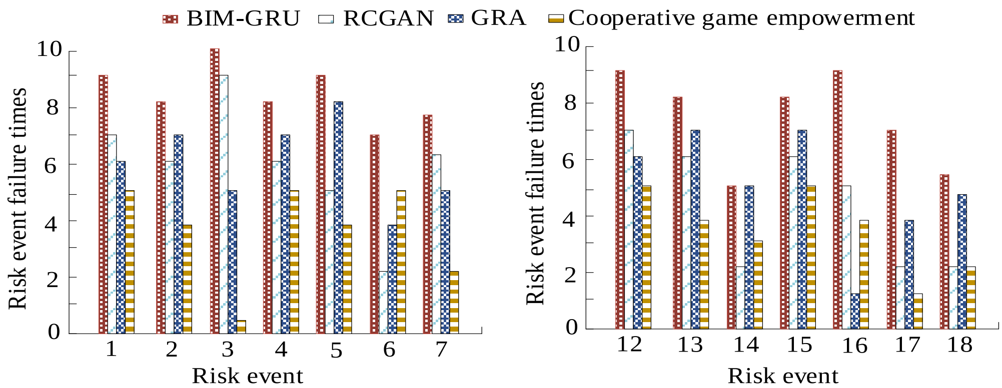


Temperature equipment monitoring of different systems

Figure 8: Comparison of temperature monitoring in different risk management systems of subway foundation pit support

As shown in Figure 7(a), when the distance from the edge of the foundation pit was approximately 100mm, the measured settlement value was -12.12mm, the BIM-GRU subway foundation pit support risk management system recorded a settlement value of -10.83mm, and the RCGAN subway foundation pit support risk management system recorded a maximum settlement value of -10.11mm. As shown in Figure 7(b), when the distance from the edge of the foundation pit was approximately 100mm, the measured settlement value was -12.88mm, and the BIM-GRU subway foundation pit support risk management system recorded a settlement value of -11.83mm, which was close to the measured value. In summary, as the distance from the foundation pit edge increased, the settlement value monitored by the BIM-GRU subway foundation pit support risk management system decreased. To demonstrate the monitoring accuracy of the BIM-GRU subway foundation pit support risk management system, its results were compared with those of the Cooperative Game Empowerment, GRA, and RCGAN subway foundation pit support risk management systems for subway equipment temperature monitoring. The monitoring results are shown in Figure 8.

As shown in Figure 8, the BIM-GRU subway foundation pit support risk management system measured a temperature of 55.21°C after the equipment had been running for 20s, with an error of -0.05°C. The GRA subway foundation pit support risk management system measured a temperature of 58.21°C after the equipment had been running for 40s, with an error of -0.13°C. The RCGAN subway foundation pit support risk management system measured a temperature of 61.01°C after the equipment had been running for 60s, with an error of -0.12°C. In summary, the BIM-GRU subway foundation pit support risk management system was able to effectively monitor equipment operating temperature and demonstrated certain practical feasibility. To further highlight the risk avoidance capability of the BIM-GRU subway foundation pit support risk management system, its performance was compared with the Cooperative Game Empowerment, GRA, and RCGAN subway foundation pit support risk management systems in terms of risk event failure effects. The comparison results are shown in Figure 9.



(a) Foundation pit support risk test 1 (b) Foundation pit support risk test 2

Figure 9: Comparison of failure effects of risk events results plot

As shown in Figure 9(a), The BIM-GRU subway foundation pit support risk management system successfully avoided Risk Event 1 a total of 9 times, while the RCGAN subway foundation pit support risk management system managed to avoid Risk Event 1 a total of 7 times. The Cooperative Game Empowerment subway foundation pit support risk management system failed to avoid Risk Event 3. As shown in Figure 9(b), the BIM-GRU subway foundation pit support risk management system successfully avoided Risk Event 16 a total of 9 times. In summary, the BIM-GRU subway foundation pit support risk management system was able to effectively avoid different risks, with a high avoidance efficiency.

5 Conclusion

In order to improve the safety of subway construction, a risk management system for subway foundation pit support is constructed based on the BIM-GRU risk data monitoring method. In the process of building the system, the advantages of the FAHP multi-objective comprehensive evaluation are used to evaluate and analyze the risk of foundation pit support in real time. The experimental results show that the displacement of the BIM-GRU method at monitoring point 4 is 0.31 mm, and the accuracy is higher than that of the cooperative game empowerment method, GRA, and RCGAN. The system successfully avoided risks 19 times, which was better than the other three systems. The measured temperature was 55.21 ℃ and the deviation was -0.05 ℃ after the subway equipment operated for 20s. The overall performance was excellent. To sum up, the BIM-GRU metro foundation pit support risk management system can effectively manage the metro foundation pit support structure. Although the BIM-GRU system has high monitoring accuracy and risk control ability, it is highly dependent on data. If there are errors or incompleteness in the data collection process, it may affect the final monitoring and analysis results. Therefore, in future research, the data acquisition and processing program will be further optimized, and more advanced sensor technology and data cleaning algorithms will be introduced to improve data quality, thus enhancing the system's performance.

Acknowledgment

This study is supported by Henan Provincial Key Discipline of Transportation Engineering and Funded Program of Key Scientific Research Projects in Higher Education Institutions of Henan Province (No. 25A580010).

References

[1] Han X, Ye F, Han X, Ren C, Song J, Zhao R. Mechanical responses of underground carriageway structures due to construction of metro tunnels beneath the existing structure: A case study. Deep Underground Science and Engineering, 2024, 3(2):231-246.

[2] Liu K, Liu Y, Kou Y, Yang X, Hu G. Efficiency of risk management for tunnel security of megaprojects construction in China based on system dynamics. Journal of Asian Architecture and Building Engineering, 2024, 23(2):712-724.

[3] Xu N, Guo C, Wang L, Zhou X, Xie Y. A three-stage dynamic risk model for metro shield tunnel construction KSCE Journal of Civil Engineering, 2024, 28(2):503-516.

[4] Li X, Yuan J, Zhang L, Yang D. Risk assessment of subway station fire by using a Bayesian network-based scenario evolution model. Journal of Civil Engineering and Management, 2024, 30(3): 279–294.

[5] Chen D, Zhou J, Duan P, Zhang J. Integrating knowledge management and BIM for safety risk identification of deep foundation pit construction. Engineering, construction and architectural management, 2022, 30(8):3242-3258.

[6] Jiang M. Construction Technology and Safety Risk Control Measures of Deep Foundation Pit Excavation. Journal of World Architecture, 2023, 7(2):24-29.

[7] Li D, Ma J, Wang C, Gao X, Fang M. A new method for piping risk evaluation on unconfined aquifers under dewatering of deep foundation pits. KSCE Journal of Civil Engineering, 2022, 26(8):3275-3286.

[8] Ma X, Dou Y. Water Accumulation Area Detection Model Based on Multi-Source Data Fusion and Swarm Intelligence Perception. Informatica, 2024, 48(23): 33-45.

[9] Aghamohammadi A, Beheshti Shirazi S A, Banihashem S Y, Shishechi S, Ranjbarzadeh R, Jafarzadeh Ghoushchi S, Bendechache M. A deep learning model for ergonomics risk assessment and sports and health monitoring in self-occluded images. Signal, Image and Video Processing, 2024, 18(2):1161-1173.

[10] Liu B, Han Q, Fu C, Zhang G, He Y, Li W. Development and engineering application of intelligent management and control platform for the shield tunneling construction close to risk sources. Journal of Intelligent Construction, 2024, 2(2): 1-12.

[11] Brintrup A, Kosasih E, Schaffer P, Zheng G, Demirel G, MacCarthy B L. Digital supply chain surveillance using artificial intelligence: definitions, opportunities and risks. International Journal of Production Research, 2024, 62(13):4674-4695.

[12] Xu X, Zheng Y, Lan X, Pan J, Wen Y. Numerical simulation analysis of controlling settlement by water-resisting curtain combined with recharge in deep foundation pit. Journal of Civil Engineering and Management, 2024, 30(7):566–580.

[13] Luo Z, Guo J, Han J, Wang Y. Research on the construction safety risk assessment of prefabricated subway stations in China. Engineering, Construction and Architectural Management, 2024, 31(4):1751-1787.

[14] Li W, Lu X, Wu M. Safety risk assessment model of a subway tunnel collapse system based on improved DOW-FFTA method. International Journal of Low-Carbon Technologies, 2024, 19(2):171-184.

[15] Deng Y, Liu Z, Song L, Ni G, Xu N. Exploring the metro construction accidents and causations for improving safety management based on data mining and network theory. Engineering, construction and architectural management, 2024, 31(9):3508-3532.