

Research Article

Intelligent Early Warning System for Construction Safety of Excavations Adjacent to Existing Metro Tunnels

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Received 16 June 2020; Revised 16 November 2020; Accepted 28 December 2020; Published 15 January 2021

Academic Editor: Elhem Ghorbel

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With the increasing exploitation and utilization of underground spaces, the excavation of deep foundation pits adjacent to existing metro tunnels is becoming increasingly common. These excavations have the potential to cause safety problems for the operation of the nearby metro. Therefore, to prevent metro tunnel accidents from occurring during the construction process and to ensure the safety of lives and property, it is necessary to establish a risk-based early warning system. During the excavation process, the main methods for preventing accidents in excavations adjacent to existing metro tunnels are manual analyses based on on-site monitoring data. However, these methods make it difficult to enact effective control measures in a timely manner owing to the lag of information processing. However, the trial application of artificial neural networks (ANNs) and building information modelling (BIM) for engineering projects provides a new method for solving such problems. This study uses a backpropagation neural network to predict the real-time deformation of the tunnel based on monitoring data from the adjacent construction site. A safety risk assessment model is then established based on the relevant specifications. Through the establishment of an intelligent warning system, the safety risk to the metro tunnel during the construction process can be displayed in a three-dimensional (3D) form using the BIM. The operation results of the ANN-BIM system show that it can effectively present the safety risk to existing metro tunnels in a 3D manner, which can provide managers with rapid and convenient visual information to inform their decision-making.

1. Introduction

With the building of numerous metro tunnels in cities and continuous urban construction and development, available land is becoming increasingly scarce, resulting in more frequent excavation of deep foundation pits adjacent to existing metro tunnels [1, 2]. During excavation, the retaining wall will be displaced into the pit, while the soil outside the wall will be deformed, and the surrounding surface will settle accordingly. As the excavation depth increases, the settlement and deformation will increase with the deformation of the retaining structure and will gradually be transferred outward. When these effects encounter a nearby existing metro tunnel, the balanced stress state around the tunnel will be changed, causing deformation and displacement of the metro tunnel. However, the safety

requirements governing the displacement and deformation of tunnels for metro operation are very strict, which complicates the construction process. During the construction process, not only the safety of the construction itself but also the safe operation of the adjacent metro should be carefully considered. Therefore, during the construction process, effective safety risk warnings are particularly important to ensure the safety of the construction project and the adjacent metro. However, it is difficult to visualize safety risk warnings for the whole construction period using conventional methods. Moreover, it is difficult to determine the source of the risk in a timely manner before an accident occurs. Artificial neural networks (ANNs), with their strong nonlinear prediction and reasoning abilities, are highly suitable for complex prediction, assessment, and identification tasks. ANNs have been widely used to perform

deformation predictions, risk assessments [3, 4], and cost estimations [5] during construction. In addition, Lai et al. [6] noted that ANNs have been applied as a new tool for analyzing difficult geotechnical problems and have successfully solved a series of engineering problems, including the deformation caused by tunnel excavation in various types of rock masses. Unlike the classical regression method, ANNs do not require complex constitutive models to solve these geotechnical problems, thus improving the convenience of obtaining their solutions. Zheng et al. [7] used a back-propagation (BP) neural network to integrate complex environmental factors and proposed a visualisation method to evaluate the deformation risk level of underground spaces. The deformation risk level was combined with the red, green, blue color space model to achieve real-time visualisation displays. Cao et al. [8] used an ANN to identify the most important parameters in the horizontal deformation of a deep foundation pit, thus providing a general paradigm for analyzing the sensitivity of influencing parameters. Wang and Huang [9] established a monitoring model for deep foundation pit deformation using an ANN, and the proposed model could realize nonlinear prediction of the deformation caused by excavation. Xu et al. [10] proposed an intelligent self-feedback and safety early warning system for underground caverns based on a BP neural network and the finite element method; the inversion of the mechanical parameters and the subsequent prediction were achieved using the BP neural network.

To date, building information modeling (BIM) technology has been applied for planning, architectural design, structural design, construction, operation management, etc. Moreover, BIM has gradually been applied in construction safety management. Sacks [11] demonstrated the feasibility and importance of the three-dimensional (3D) visualization and analysis of BIM in realizing construction safety management. Ruppel and Schatz [12] used BIM to transform a 3D model into a virtual reality model and employed various hardware to simulate the main senses of the human body in the event of a fire; finally, a “game” simulating a fire evacuation was designed. Cheng et al. [13] built a BIM-based intelligent fire protection and disaster reduction system and created an intelligent, two-way fire prevention system framework that could display real-time dynamic fire information in 3D. Zou et al. [14] showed that BIM can not only be used as a systematic risk management tool to support project development but also be used as a core data generator and platform for further risk analysis by other BIM-based tools. Li et al. [15] proposed a Chinese metro construction safety risk identification system and early warning system based on the BIM platform.

This study adopts the BIM platform for visualization, employs an intelligent monitoring system and manual monitoring as data sources, and utilizes the strong prediction capability of a BP neural network to predict safety risks. In addition, Navisworks software provided by Autodesk is used as the development platform to integrate these aspects into the BIM. By connecting to a mobile phone terminal through the network, the proposed system can notify managers in a timely manner when safety risks occur, to achieve the goal of providing real-time visualized warnings.

2. Research Approach

This study aims to establish an intelligent early warning system for construction projects involving excavation adjacent to existing metro tunnels. The early warning system is composed of four subsystems: data monitoring, deformation prediction, safety risk assessment, and safety risk early warning. Here, the data monitoring subsystem (DMS) is composed of wireless sensors and manual monitoring. The deformation prediction subsystem (DPS) realizes deformation prediction through a BP neural network. The safety risk assessment subsystem (SRAS) refers to the provisions of national or local codes related to the existing tunnels to assess safety risks. The safety risk early warning subsystem (SREWS) uses the BIM information model as a platform and integrates the other three systems on this platform through application programming interface (API) development to realize visual early warnings. The implementation process is shown in Figure 1.

3. Methodologies

3.1. Analysis of Factors Influencing the Safety Risk. To determine the main factors that cause the deformation of metro tunnels, it is necessary to first determine the factors causing changes in the stress field of the soil. Evidently, the size, depth, shape, and methods of support of the foundation pits should be considered [6]. The change in the stress field of the soil is also related to properties of the soil and groundwater [8]. In addition, when an existing tunnel is deformed under external forces, the deformation is related to the stiffness, strength, and embedded depth of the tunnel [16], and thus the characteristics of the tunnels themselves are also important factors. Through analysis of these three aspects, the factors influencing the safety risk of an excavation adjacent to an existing metro tunnel can be obtained, as summarized in Table 1. Of these factors, some change gradually during the construction process and are defined as variable factors, while others remain constant during the construction process and are defined as constant factors. For example, although the properties of the soil change gradually with varying soil depth, the soil characteristics of each layer remain almost unchanged. Thus, its impact on the safety risk can be reflected by the soil depth, and thus this factor is defined as a constant factor.

3.2. Real-Time Prediction Module for Existing Tunnel Deformation. To more rapidly control the safety risk to adjacent existing tunnels, it is necessary to effectively predict the real-time deformation of adjacent tunnels during the construction process (for example, using the excavation condition today to predict the deformation of existing tunnels tomorrow). The analysis in Section 3.1 demonstrates that the factors causing tunnel deformation are very complex, and thus, it is difficult to use conventional prediction methods. BP neural networks have strong adaptability for complex nonlinear predictions, which allows the real-time prediction of tunnel deformation using this method. During

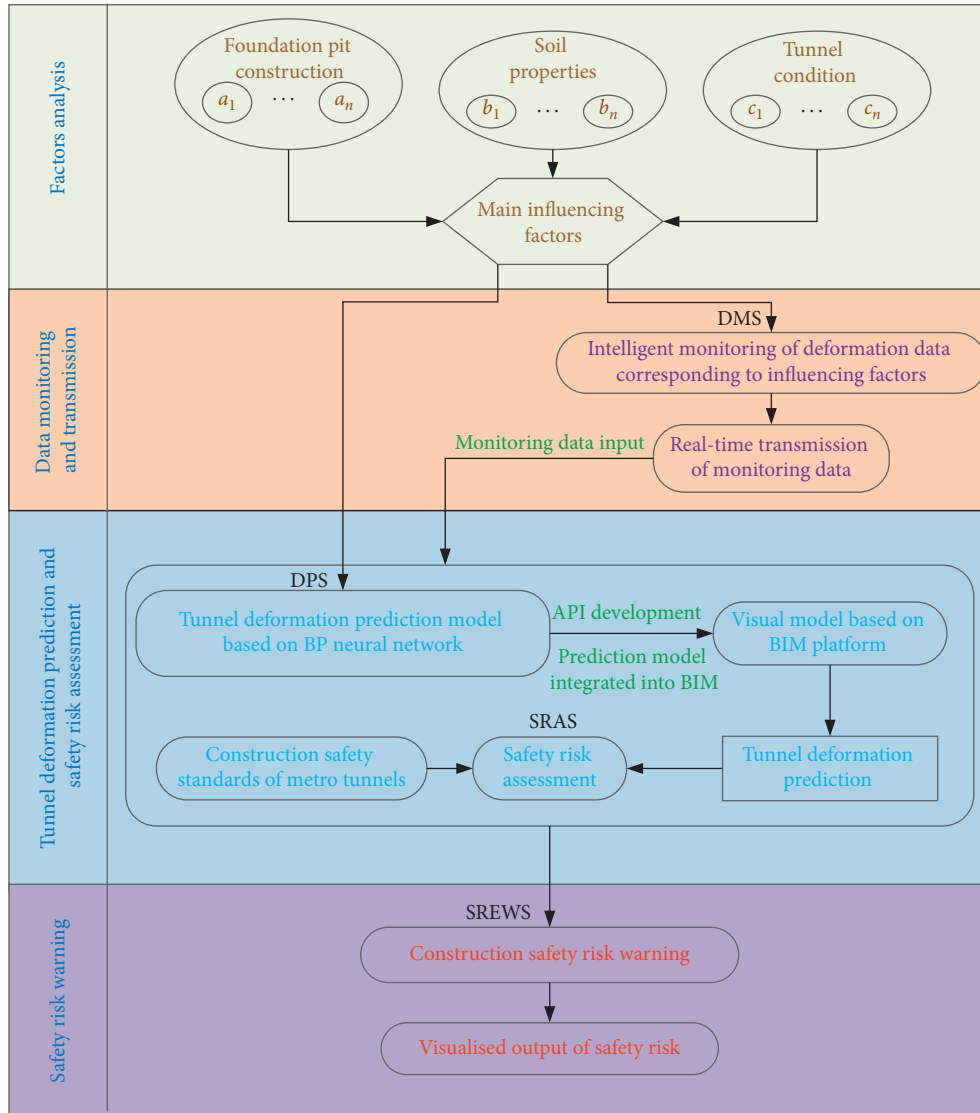


FIGURE 1: Intelligent early warning system process.

application of the deformation prediction model, the variable factors are used as inputs. For the constant factors, real-time monitoring data of the tunnel deformation were used as training samples to integrate the internal law governing the influence of the constant factors into the model and reduce human intervention. The trained prediction model can then be used to predict the deformation of the tunnels. The real-time monitoring data can be continuously inputted into the real-time updated prediction model. The operating mechanism of the real-time prediction model for tunnel deformation is shown in Figure 2.

3.3. Safety Risk Assessment Module. After the real-time deformation of the tunnel is predicted by the model in Section 3.2, the limit values for tunnel deformation referring to the Chinese specification *technical code for protection of existing structures of urban rail transit* are used as the warning thresholds for the deformation of the existing tunnel. When the tunnel deformation reaches 30%, 50%, and 70% of the

warning threshold, the corresponding risk level and corresponding warning level are obtained. The classification of the risk levels and corresponding warning levels are summarized in Table 2.

3.4. Establishment of the Safety Risk Early Warning System. The safety risk early warning system employs BIM as the platform, wireless sensors and manual monitoring as the data collection methods, the prediction model for deformation of the adjacent existing tunnel caused by deep foundation pit construction as the basis for data processing, and the allowable deformation limits given in tunnel-related specifications as the early warning thresholds. The data monitoring module, real-time tunnel deformation prediction module, safety risk assessment module, and safety risk early warning module are integrated into Navisworks with the help of API development to establish the early warning system. This system is connected to the BIM collaborative management platform to realize data sharing. The system

TABLE 1: Summary of factors affecting safety risks.

Primary factors	Secondary factors	Factor categories
Characteristics of the foundation pit	Real-time depth of excavation point (a) Real-time width of excavation point (b) Real-time length of excavation point (h)	Variable factors
	Horizontal distance from an excavation point to a tunnel section (d) Vertical distance between an excavation point and tunnel (v) Excavation time (t)	
Support methods for the excavation	Parameters related to the diaphragm wall Parameters related to soil stabilization Parameters related to anchorages Parameters related to the supporting structure	
Construction scheme	Construction technology Construction procedure Loads outside the pit	
Soil properties	Soil density (γ) Internal friction angle (ψ) Cohesive force (c) Static lateral pressure coefficient (k) Compressive modulus (E)	Constant factors
Characteristics of existing metro tunnels	Structural strength of the tunnel Structural cracking degree of the tunnel Embedded depth of the tunnel	

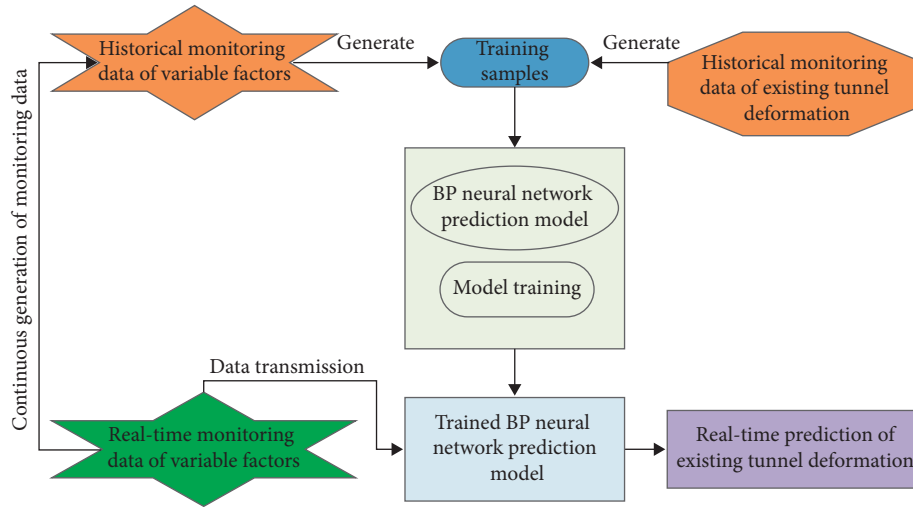


FIGURE 2: Operation mechanism of the real-time prediction model for metro tunnel deformation.

TABLE 2: Security risk classification and alarm signal selection.

Risk level	Total deformation/threshold	Risk alarm signal	Signal color
Low level (I)	$\delta < 0.3$	Risk ignored	Blue
Moderate level (II)	$0.3 \leq \delta < 0.5$	Risk concerned	Green
High level (III)	$0.5 \leq \delta < 0.7$	Risk controlled	Yellow
Extreme level (IV)	$0.7 \leq \delta$	Risk prevented	Red

δ = deformation amount/threshold.

has the ability to provide dynamic, visual, and real-time risk warnings. This allows for optimization of the safety risk warning method for excavation adjacent to existing metro tunnels, which can ensure a smooth construction process and safe operation of the existing metro tunnels. The overall operation framework of the built early warning system is shown in Figure 3, and a specific demonstration of the

early warning system will be given through a case study (Section 4).

4. System Operation and Case Study

4.1. Engineering Background. A square construction project located on the east side of the Zhengzhou high-speed railway

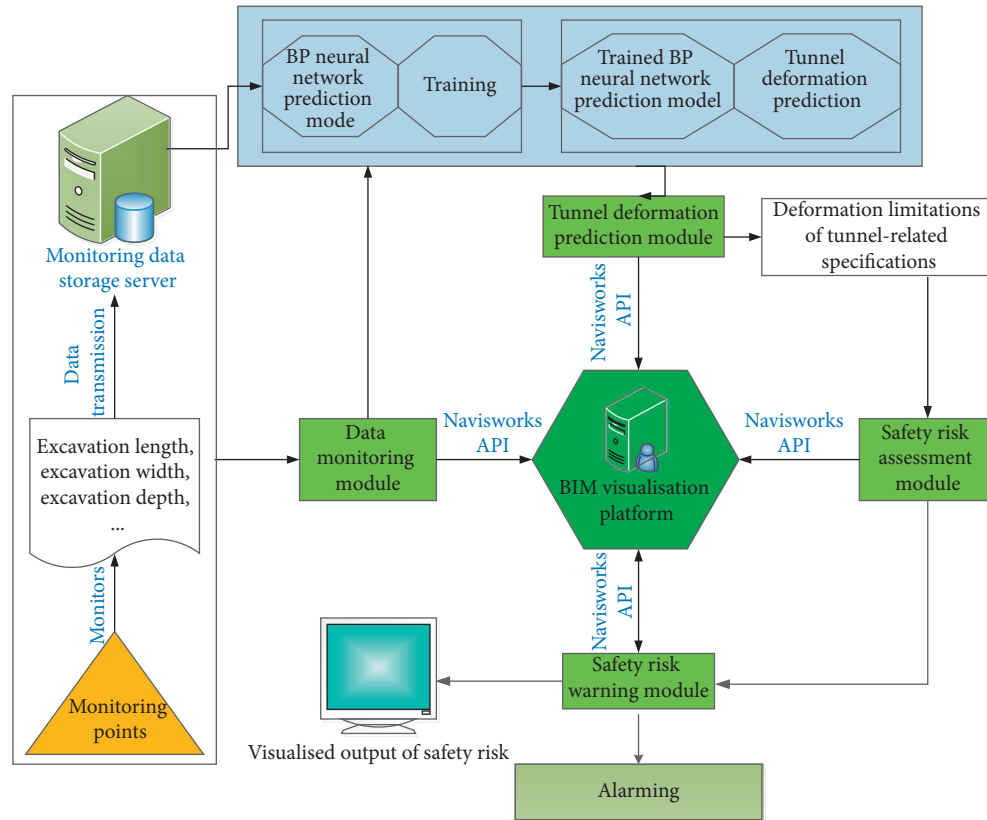


FIGURE 3: Operation framework for the intelligent early warning system.

station and the south side of the long-distance bus station is considered in this case study. The shield section of existing metro line 1 passes through the middle of the square plot. The main functions of the project are the construction of an underground garage and underground shopping mall, which are arranged symmetrically on either side of the metro shield. The depth of each foundation pit is approximately 20 m, the length is approximately 177 m, and the width is approximately 110 m. The vertical distance between the edge of the foundation pit and the tunnel is approximately 33 m, as shown in Figure 4.

4.1.1. Engineering Geology. According to the geological drilling results and in situ test results, the project scope comprises an exploration depth of 55 m. With the exception of a shallow part composed of miscellaneous fill, the excavation is mainly in quaternary Holocene and upper Pleistocene series of alluvial and diluvial formations. The exposed soil layers are shown in Figure 5.

4.1.2. Hydrogeological Survey. The aquifer in the exploration depth is divided into two layers: phreatic water in the upper layer and confined water in the lower layer. Phreatic water occurs mainly in silt and silty clay above 16.0–18.0 m (absolute elevation: 70.0 m), which are weakly permeable layers. Confined water mainly occurs in fine sand below 16.0–18.0 m. With high water content, strongly permeable layers, and a micro-confined aquifer, this layer has a certain

hydraulic connection with the upper phreatic water. The phreatic layer is separated from the confined water layer by the fifth silty clay layer.

The groundwater level at the site was measured using an exploration borehole. The static water level measured in the exploration borehole was between 10.3 and 17.0 m below the surface, corresponding to absolute elevations of between 74.81 and 76.79 m. The static water level of the lower confined water was approximately 12.0–19.0 m below the ground surface, corresponding to an absolute elevation of approximately 74.0 m.

4.2. Establishment of the Project BIM and Layout of the Monitoring System

4.2.1. Establishment of the Project BIM. The project BIM not only has a realistic appearance but also contains additional component characteristic information. The completed BIM is used in various stages of the construction process, replacing traditional communication based on two-dimensional drawings, which allows information to be transferred among project members more accurately, intuitively, and efficiently. In the construction process, the corresponding BIM structure model and electro-mechanical equipment model are established and applied for the layout of the precipitation well, collision inspection, and engineering quantity statistics, as shown in Figure 6.

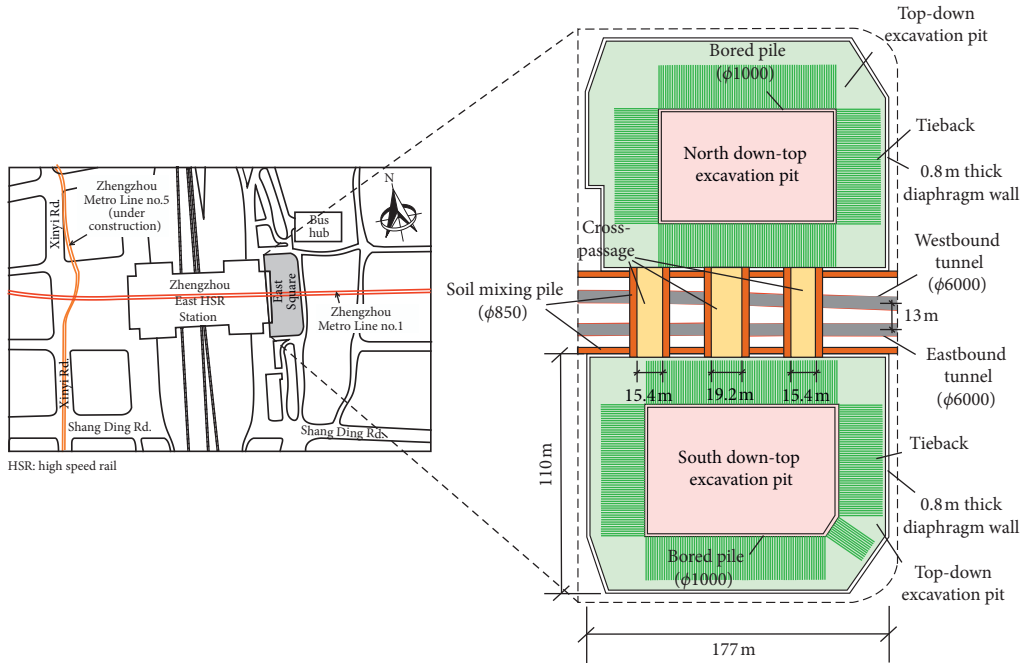


FIGURE 4: Location layout of the foundation pit.

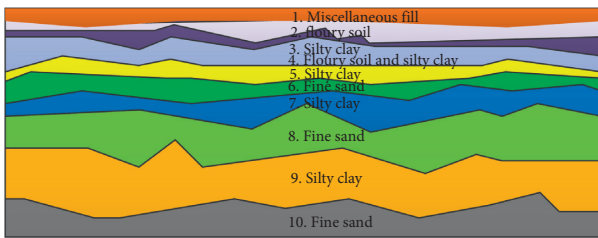


FIGURE 5: Geological sections.

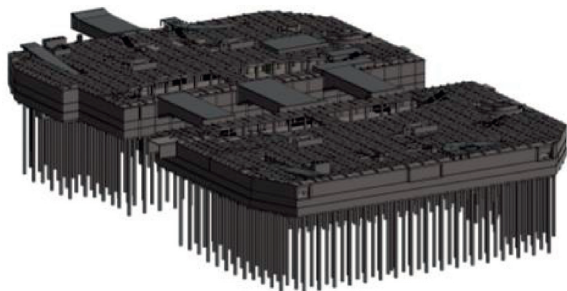


FIGURE 6: An integrated model of structure and electromechanical equipment.

4.2.2. *Layout of the Monitoring System.* To obtain real-time monitoring data of the tunnel deformation, which is used to train the prediction model and allow the prediction model to be updated in real time, reasonable monitoring of the tunnel deformation is required. During excavation, the adjacent existing tunnel deformation (convergent deformation and uplift deformation) was synchronously monitored. The monitoring locations are shown in Figure 7. There were 31 automatic monitoring sections in each tunnel; the distance between the monitoring sections at the three cross-passages

was 5 m, while the rest of the monitoring sections were separated by 10 m.

4.3. Establishment of the Prediction Model Based on the BP Neural Network

4.3.1. *Establishment of the Prediction Model.* The real-time monitoring data for the variable factors (manual monitoring or automatic monitoring) are used as the input values. The real-time deformation (uplift deformation and convergent deformation) and deformation rate (uplift deformation rate and convergent deformation rate) of the tunnels are used as the output values. The corresponding monitoring data for deformation of the tunnels are used as the training set for the training model to establish a BP neural network prediction model that can predict the deformation of the tunnels in real time. The training set consisted of 3224 data sets obtained from the monitoring of 31 tunnel sections for 104 d. The design of the BP neural network includes defining the number of nodes in the input layer, number of neurons in the output layer, number of hidden layers, and number of neurons in each hidden layer. According to Kolmogorov's theory, a three-layer neural network such as the one used in this study can guarantee a complex mapping from any dimension, n , to output dimension, m . Therefore, a three-layer neural network model is ideal for conditions in which the training set is not large and the dimensions of the input and output layers are also not large. The network topology of the prediction model is shown in Figure 8. The number of nodes in the input layer is equal to the number of input variables, the number of neurons in the output layer is equal to the number of output variables, and the number of neurons in the hidden layer is preliminarily determined by ①; the final number of neurons in the hidden layer is determined by trial

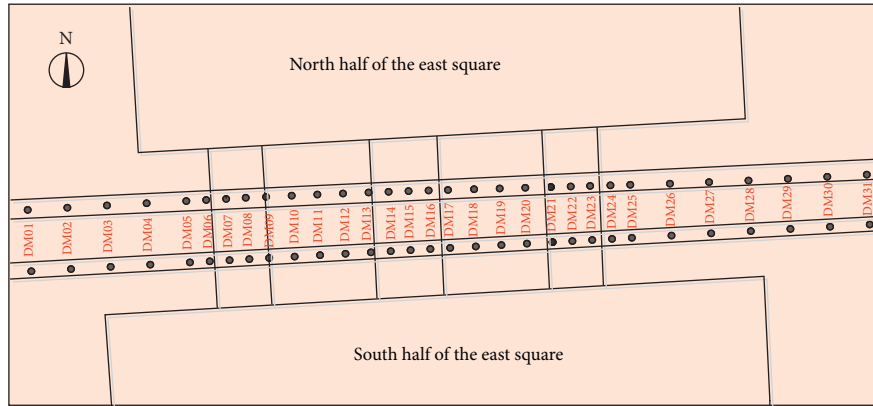


FIGURE 7: Distribution of automatic monitoring sections in the tunnels.

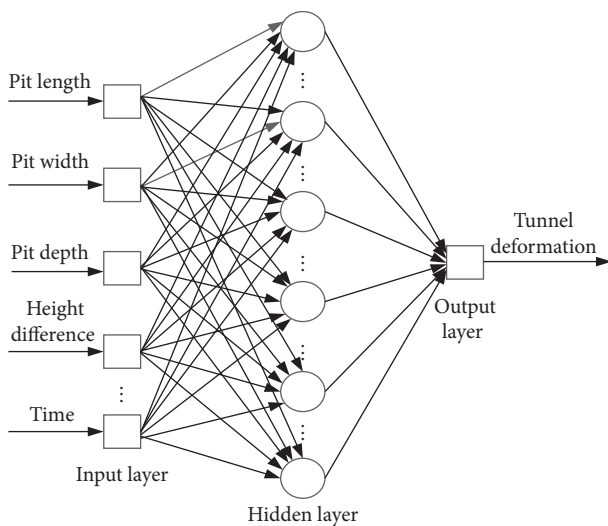


FIGURE 8: Network topology of the prediction model.

calculations. During the trial calculations, the model including 13 hidden layer neurons produced the smallest mean squared error and the highest precision; therefore, the optimal number of hidden layer neurons was determined to be 13.

$$M = \sqrt{n + m} + a, \quad (1)$$

where m and n are the number of output layer and input layer neurons, respectively, and a is a constant between 0 and 10.

4.3.2. Validation of the Prediction Results. To test the effectiveness of the developed model, the prediction model was used to predict the uplift deformation of tunnel section DM12 during the excavation process from 9 March 2016 to 1 June 2016, and the prediction results were compared with the actual monitoring results to evaluate the prediction accuracy. The results showed that the maximum absolute error of the prediction was 1.22 mm, and the maximum relative error was 8.1% (under normal circumstances, an error within 2 mm is considered acceptable), which satisfies the accuracy requirement. The comparison between the prediction data and the monitoring data and the

corresponding error curve are shown in Figures 9 and 10, respectively.

4.4. Development and Operation of the ANN-BIM-Based Early Warning System

4.4.1. Navisworks Development Platform.

(1) Selection of development platform

In this study, Navisworks is selected as the platform, and development is carried out to realize each functional module of the safety risk early warning system. In addition, .NET API is used to develop the safety risk early warning system on the Navisworks platform.

(2) Implementation of Navisworks API

This study uses the Navisworks API to implement custom family lookup, access object properties, modify model parameters, and perform other operations. Through the permutation and combination of these basic operations, the basic functions of the safety risk early warning system can be realized. The specific methods are described below.

- (1) Custom family lookup: in the safety risk early warning system, the monitoring point for each early warning indicator will bind a corresponding family component. After opening the model document, the primary task is to distinguish the component corresponding to the monitoring point from the common components. Navisworks API provides three methods to find objects: the search class built into the .NET API and traversal and LINQ database lookup in .NET itself. To identify the early warning indicator components more rapidly, the search class and LINQ methods are selected in this study.
- (2) Access to object properties: during use of the safety risk early warning system, several monitoring points are often required for each early warning indicator. To enable the system to identify the monitoring points and type of early warning monitoring indicator corresponding to each monitoring component,

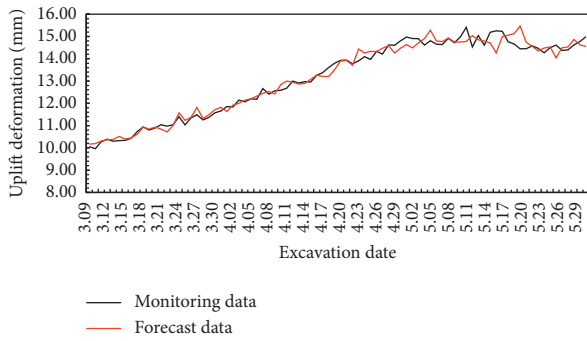


FIGURE 9: Predicted and measured uplift deformation of tunnel section DM12.

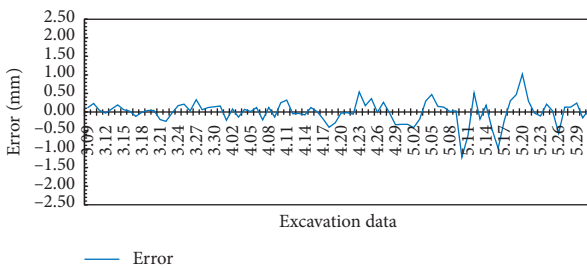


FIGURE 10: Prediction error in the uplift deformation of tunnel section DM12.

the monitoring component in the Revit model should be described in detail according to the component type properties, as shown in Figure 11. In this case, the monitored tunnel is divided into nine sections, each of which will present the maximum deformation value in the section.

- (3) Modification of model parameters: the most important feature of the BIM technology is to provide a visual means of browsing. To make full use of the advantages of visualization in the safety risk early warning system, it is necessary to modify the model parameters; the corresponding spatial position, color, and other appearance parameters of the model are modified according to the monitoring data for the variable factors, which allows the risks to be directly reflected in the BIM model.

4.4.2. Integration of the Safety Risk Prediction Model.

The tunnel deformation prediction module based on the BP neural network and the safety risk assessment module are integrated into the BIM-based early warning system with the help of computer language to improve the efficiency and accuracy of the safety risk prediction. In the process of computer realization, the tunnel deformation prediction module is divided into two parts: prediction model training and tunnel deformation prediction. The first step is to implement the prediction model based on the BP neural network into a computer language, train the model, and integrate the model into the BIM platform. Then, the DataReader function is used to read the monitoring data in

the database and input them into the trained prediction model to obtain the prediction results for the tunnel deformation. The third step is to read the prediction results into the safety risk assessment module, evaluate the safety risk, and make a signal alarm to realize integration of the safety risk prediction model.

4.4.3. Operation of the Early Warning System. The menu for the safety risk early warning system is embedded in the “Windows” bar under the “View” menu in Navisworks. The safety risk early warning system menu consists of two parts: the default function of the early warning system and the browsing function of early warning signals, as shown in Figure 12.

To cope with different engineering environments and different national or local standards, the threshold values of different indicators are preset in the early warning system to ensure the safety risk assessment models run correctly, as shown in Figure 13.

The browsing function for the early warning signals is the core function of the system. According to the description in Section 4.3, the safety risk is divided into four levels, corresponding to safety risk warning signals shown in red, blue, yellow, and green from high to low risk. If a safety manager wants to quickly check the specific safety risk signal of a tunnel section, he or she can select the section, click the “Early Warning System” menu, and input the latest data for the variable factors based on a large amount of data entered in the previous period (Figure 14). According to the early warning signals, the safety manager can then take corresponding risk countermeasures, as shown in Figure 15.

For example, on 29 April 2016, the safety risk early warning system issued a red warning signal indicating “extreme risk”. When one red section was selected, the uplift deformation exceeded the threshold value (Figure 15). According to the warning signal for the safety risk, corresponding countermeasures should be taken promptly to prevent a further increase in the risk.

5. Discussion

Predicting the deformation of adjacent existing metro tunnels caused by the construction of deep foundation pits is an important task. Although the conventional finite element simulation method is usually carried out before excavation, the environmental conditions of the excavation are often different from the ideal conditions determined by the numerical simulation method, which will introduce certain errors, leading to serious safety problems, including fatalities.

Compared to some risk assessment methods with insufficient prediction accuracy [17] or timeliness [18], the above case study demonstrates that the BP neural network can effectively solve this problem. This method uses the variable factors affecting the deformation of existing metro tunnels as input variables, and the existing deformation data as the training signal, in order to integrate the internal law for the effect of the constant factors (or those with small

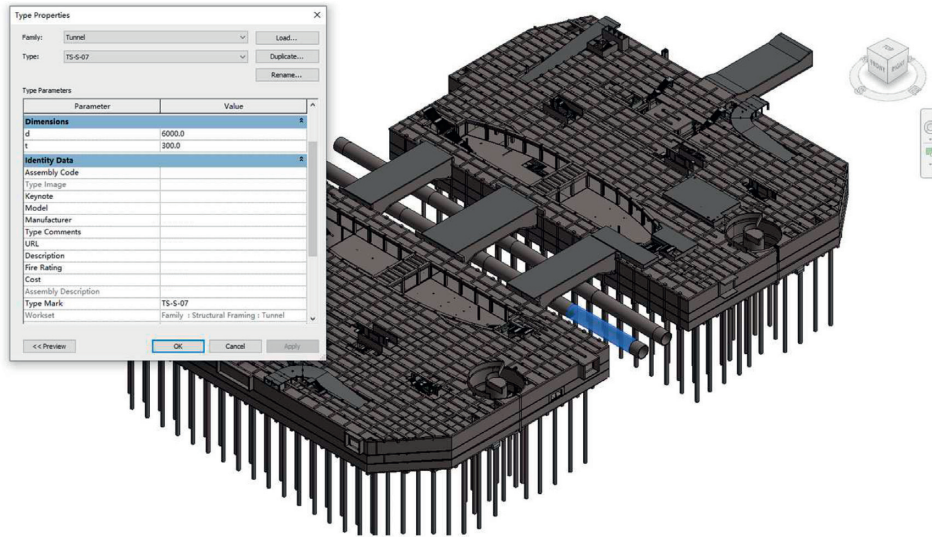


FIGURE 11: Revit component type parameter setting.

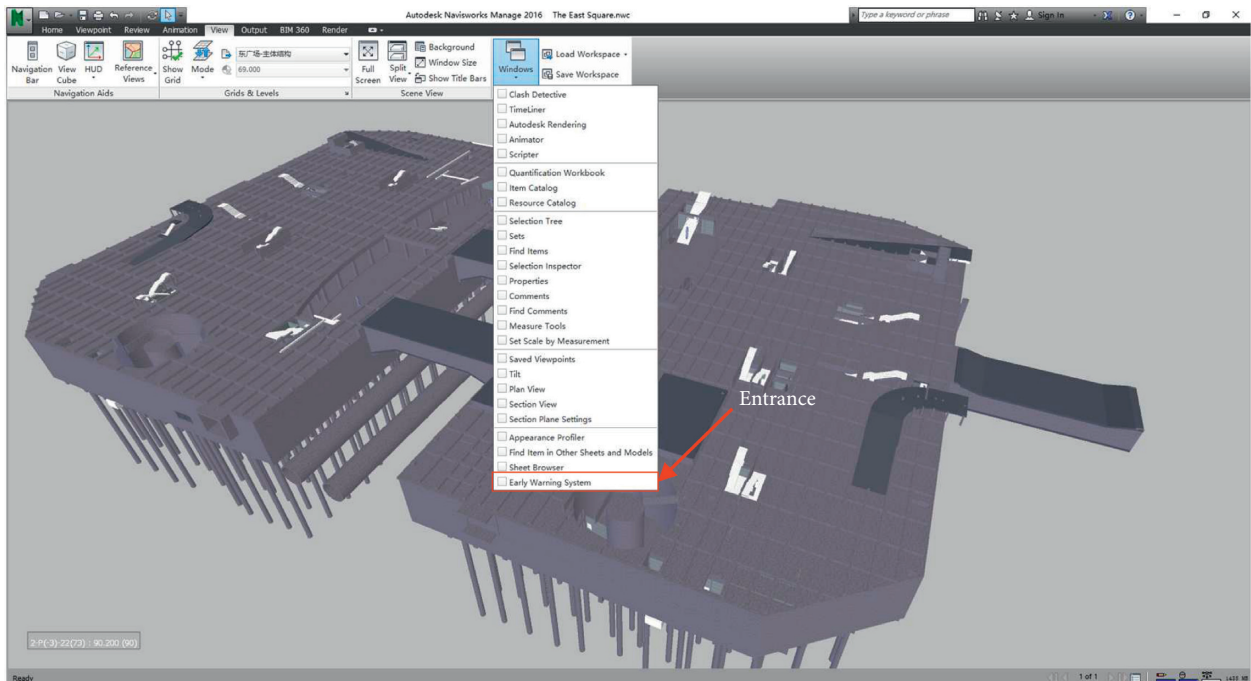


FIGURE 12: Menu of the safety risk early warning system.

changes) on tunnel deformation into the model. In addition, the BP neural network prediction model can also realize real-time prediction, thus providing data support for the early warning of safety risks.

In the building of the BP prediction model, the design of the input and output neurons of the model is determined by the number of input and output variables. The numbers of neurons in the input and output layers of this model are six and four, respectively. For the number of hidden layers and the number of neurons in each layer, because a three-layer BP network structure can complete any m -to n -dimensional complex mapping, one hidden layer is used in the model, which can ensure effective operation and reduce the model

complexity and calculations. Based on an empirical method, the approximate number of hidden layer neurons is initially determined, and then the optimal number is determined through trials. To balance the accuracy of each output value and observe its advantages and disadvantages, the mean squared error of each output value is used as a reference standard in the trial calculation. By changing the number of neurons in the hidden layer, the mean square error of the output was at a minimum with 13 neurons in the hidden layer. Therefore, as a whole, the network structure of the model was optimized.

After establishing the network structure of the BP prediction model, through development with the API, the

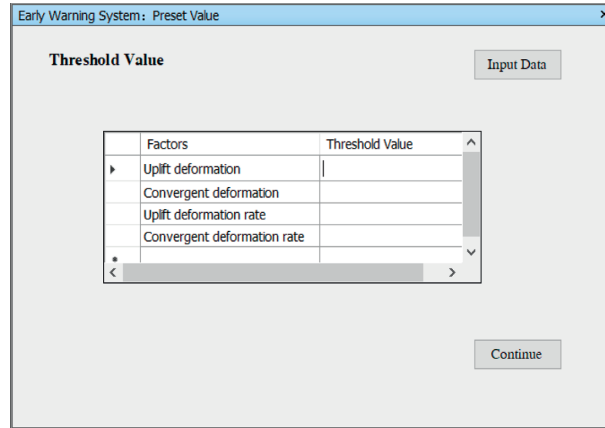


FIGURE 13: Interface for the preset threshold values.

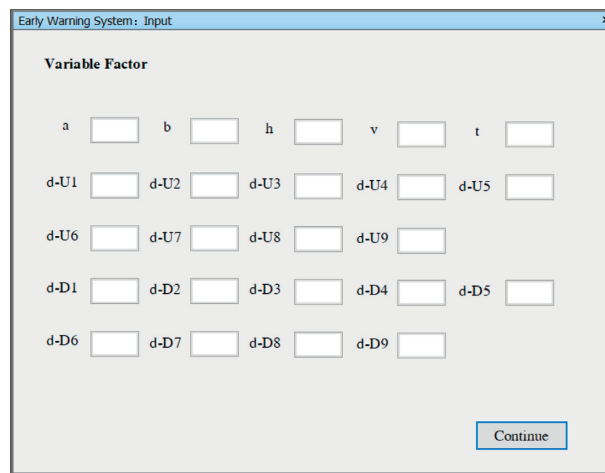


FIGURE 14: Manual input interface for variable factors.

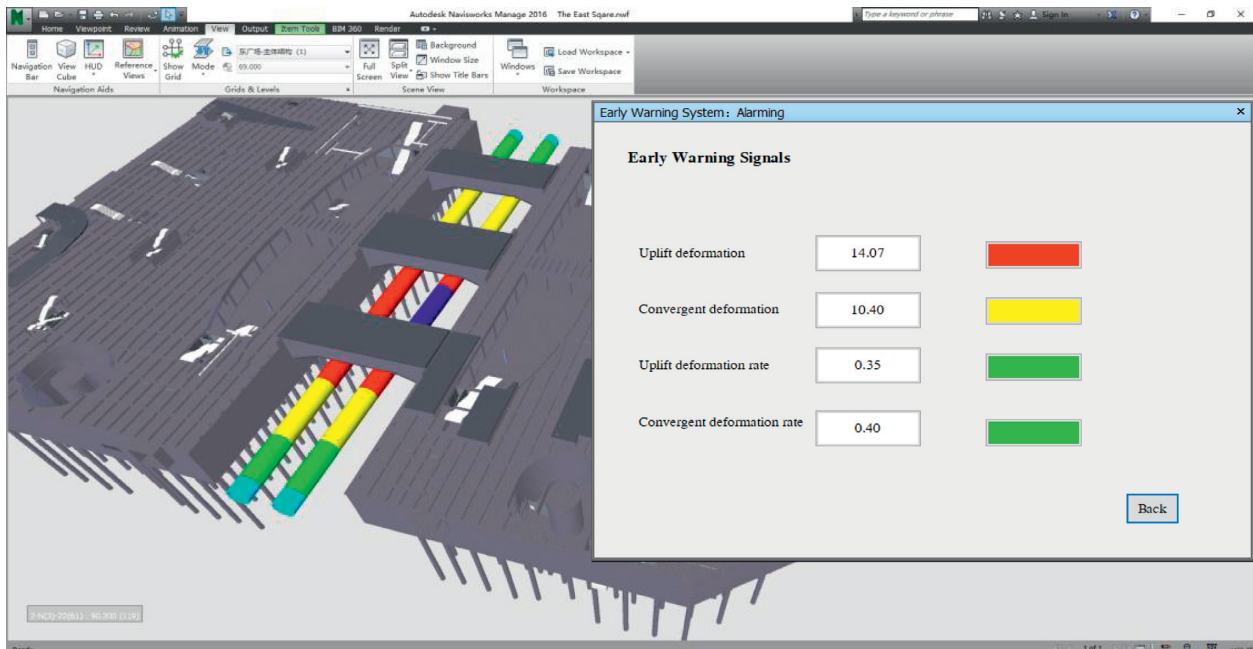


FIGURE 15: Overview of risk indicators on 8 April.

model is connected to the BIM-based early warning system. The model is trained using samples taken from actual monitoring data, and then the trained model is used to predict the deformation risk of the tunnels. Based on the prediction results of the model, the prediction accuracy can satisfy the construction requirements.

For common safety risk early warning systems [9, 10], when a safety risk occurs, the system can only provide a risk alarm, and it is difficult to visualize the safety risk. In the case study, when the safety risk early warning system for excavation adjacent to an existing metro tunnel is established, BIM is used as the data platform, which provides support for visualizing the safety risk. When a safety risk is identified, the system can provide visual outputs including the risk level, location, and other information, thus greatly improving the efficiency of the risk control decision-making.

6. Conclusion

The excavation of a deep foundation pit will cause deformation of any adjacent existing metro tunnels. When the deformation exceeds a certain range, it will create serious safety risks for the metro operation. To effectively reduce this risk, a BP neural network prediction model is established in this study, and the proposed model can predict the deformation of the existing metro tunnel in advance.

To achieve effective real-time early warnings, this study employs the visualization characteristics of BIM, takes BIM as the data platform, and utilizes the .NET API interface and corresponding information technology to carry out development in Navisworks. Four submodules (DMS, DPS, SRAS, and SREWS) are integrated into Navisworks, and an intelligent early warning system for the construction safety risk of deep excavations adjacent to existing metro tunnels is established.

To validate the feasibility and effectiveness of the proposed system, this system is applied to predict the safety risk of the East Square excavation of the Zhengzhou high-speed railway station adjacent to existing Metro 1 tunnel. The accuracy of short-term (more than 7 days) prediction of safety risks can reach 98% and the accuracy of long-term (more than 60 days) prediction can reach 92%. The corresponding early warning signals can be simultaneously and accurately presented in the BIM model. The results presented in this study demonstrate that this system can accurately predict the safety risk.

Enacting the risk-based early warning system to reduce the on-site accident rate will require further research to be undertaken to simplify the information flow of the system and optimize the system structure. Furthermore, we try to use control-based applications to access the API and develop an independent safety risk early warning system. In addition, although the remote monitoring data transmission module has been integrated into the system, its application is not widespread in those excavations adjacent to existing metro tunnels. It seems that the stability and accuracy of this module need to be further improved.

Data Availability

Some data used to support the findings of this study are included within the article. All datasets generated during the current study are not publicly available because the data also form part of an ongoing study but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors sincerely thank Zhengzhou Transportation Construction Investment Co. Ltd. for providing data support for this research. This research was financially supported by the Ministry of Housing and Urban-Rural Development of China (Grant no. 2015-R3-003) and China Scholarship Council.

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