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Research on an intelligent monitoring system for the entire tunnel construction process based on IoT and digital twin

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Abstract. There are high-risk problems, such as peripheral rock instability and palm face collapse, during tunnel construction, and the traditional monitoring methods are difficult to meet the safety management needs due to sparse data and lagging response. This paper proposes an intelligent monitoring system for the whole process of tunnel construction based on Internet of Things (IoT) and digital twin, which integrates a multi-source sensor network, BIM dynamic modeling, and risk intelligent analysis. The system realizes an all-around perception of environment, equipment, and surrounding rock status through real-time fusion of heterogeneous data, and uses digital twin technology for 3D visualization and risk trend prediction. It adopts the improved D-S evidence theory for multi-source risk assessment, and improves the early warning accuracy through the effectiveness factor and conflict weakening strategy. The actual engineering experiments show that the system achieves 100% monitoring coverage and 100% warning accuracy, and successfully captures the whole process of palm face collapse and the time-sequence evolution of enclosing rock deformation, which significantly improves the safety and management efficiency of tunnel construction. The study verifies the high accuracy and stability of the proposed system, which provides an intelligent solution for the safety of complex underground projects.

Keywords: Tunnel construction / Internet of Things (IoT) / digital twin / BIM dynamic modeling / multi-source information fusion / risk intelligent warning

1 Introduction

As an important part of modern urban transportation, energy pipeline and water conservancy facilities construction, with the acceleration of urbanization and infrastructure construction, the scale of tunneling projects has been expanding, the geological conditions have become more and more complicated, and the construction safety problems have become more and more prominent [1,2]. Especially in the case of uneven geological structure, abundant groundwater, and strong construction disturbance, risk events such as deformation of tunnel surrounding rock, instability of palm face, and sudden water and mud surge occur frequently, which pose serious threats to construction safety, schedule, and economic benefits [3,4]. Therefore, how to realize the safety control and risk prevention in the whole process of construction has become a core research problem in the field of tunnel engineering. In recent years, the rapid development of emerging technologies such as Internet of Things (IoT), big data, and Digital Twin has provided new opportunities for intelligent tunnel construction management. Through real-time data collection, intelligent monitoring, risk prediction, and decision support, it is expected to break through the limitations of traditional manual monitoring and single-point sensing technology, and realize dynamic monitoring and intelligent risk management and control of the whole process of tunnel construction [5,6].

The open system, which is known as the proposed system, consists of IoT sensors that are placed in different areas of the tunnel. The sensors can collect data concerning the environment and the structure in real-time, which will then be sent through a wireless gateway and cloud-based data bus. The different data streams are combined and shared in the digital twin framework in order to provide a united and immediate virtual representation of the site conditions for all the monitoring modules.

There are several factors that affect the surrounding rock during tunnel construction, and they all interact with each other. Some of these factors include geological heterogeneity, the disturbance caused by excavation, and groundwater activity. The interplay of these factors results in variations in stress and deformation over time and in different locations; hence, there is considerable uncertainty regarding the stability of rock masses. Thus,

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the use of smart technology for continuous monitoring must be implemented to safeguard construction sites and avert accidents that might not be detected otherwise.

The proposed system incorporates Internet of Things (IoT) sensors that are strategically positioned throughout the construction site to monitor and collect various kinds of data, e.g., environmental conditions, stress, and displacement, in real-time and without interruption. The digital twin platform receives the data streams of these measurements, which, in turn, updates a dynamic virtual tunnel model and thus reflects the real-time status of the actual construction site.

The constant interaction between the physical site and the virtual model of the site not only provides real-time site condition visualization but also allows for smart analysis and early risk detection based on the continuously synchronized IoT data streams [7]. Traditional monitoring methods mainly rely on manual inspection or single measurement means (such as inclinometer, level meter), although to a certain extent it can reflect the deformation trend of the surrounding rock, but there are problems such as limited monitoring accuracy, response lag, sparse data distribution, etc., which is difficult to meet the requirements of modern tunneling projects for high time-efficiency and high-precision safety management [8,9]. The issue comes from the fact that conventional monitoring techniques rely on manual data gathering and point-by-point measurements, which yield discrete and low-frequency data. This kind of monitoring does not detect the quick fluctuations in stress and strain of the surrounding rock during construction. Besides, if people are involved and the environment is disturbed, then there are chances of delays and errors in measurements, which finally make it difficult to have modern tunneling projects with safety management that is timely, accurate, and automated. The usual methods for monitoring in the classical way are total station surveying, convergence gauges, extensometers, piezometers, and manual visual inspection. These methods usually offer point and low-frequency data, which results in the difficulty of obtaining continuous real-time monitoring and early detection of possible deformation or instability in the course of construction.

In addition, most of the existing construction management systems remain at the level of Informa ionization, lacking in-depth data integration and intelligent risk warning functions, resulting in a passive response to sudden disaster events. Based on this, there is an urgent need for a comprehensive monitoring platform that integrates multi-source information sensing, real-time data fusion, digital twin modeling, and intelligent risk warning to improve the safety management level of tunnel construction [10].

Scholars at home and abroad have proposed various technical routes to address the issue of safety monitoring in tunnel construction. Early research mainly relied on geological investigation and construction experience, and established empirical models or analytical models for risk assessment through limited monitoring data, such as the method based on Monitoring Measurement for predicting the stability of surrounding rock, but its accuracy is limited by the sparsity of monitoring points. In recent years, the rise of sensor technology and the Internet of Things (IoT) has made real-time monitoring possible, and related research has realized the continuous collection of construction data by deploying sensors for stress, displacement, inclination, and water level [11,12]. However, due to the heterogeneity of sensors and the complexity of data, the fusion of multi-source information has become a technical bottleneck, and traditional data processing methods are difficult to effectively integrate multi-dimensional information.

In risk assessment, scholars have tried to introduce D-S evidence theory, fuzzy comprehensive evaluation, and Bayesian networks to solve the problem of risk discrimination under uncertain information. For example, D-S evidence theory shows good ability of multi-source information fusion in tunnel construction risk analysis, but its high conflict and unstable evidence reliability limit the practical application [13]. On the other hand, digital twin technology has been widely studied in recent years, which achieves dynamic mapping of engineering states by constructing virtual models synchronized with physical entities. However, most of the existing research stays in single-element modeling (e.g., static display of BIM models) and lacks deep coupling with real-time sensing data, which cannot give full play to the advantages of digital twins in prediction and early warning.

The Dempster–Shafer (D-S) evidence theory is compared with traditional risk assessment methods and is seen as a stronger tool in the handling of multi-source uncertainty information in tunnel construction. D-S theory is different from fuzzy evaluation, which mostly concerns itself with fuzziness, and Bayesian networks, which demand prior probability distribution, because it does not require complete prior knowledge and permits a flexible assignment of belief to multiple possible risk states. It allows the fusion of evidence from various monitoring sources such as stress, deformation, and environmental data, thus enhancing the robustness of the system under sparse, conflicting, or unreliable measurement inputs. Therefore, D-S theory has greater applicability in real-time decision-making in complex underground conditions where risks change over time and information conflicts are common.

In summary, the existing studies are still deficient in the integration degree of multi-source information, the ability of intelligent identification of risks, and the level of dynamic visualization, and have not yet formed a complete set of intelligent monitoring systems for the whole process of tunnel construction [14,15].

Although the development of IoT and digital twin technology provides new possibilities for intelligent tunnel monitoring, there are still many challenges in practical applications: (1) efficient fusion of heterogeneous data from multiple sources: with many types of sensors and complex data formats, how to realize real-time, highly reliable data integration is the primary challenge; (2) uncertainty handling of risk warning models: the construction environment is dynamically changing, how to give stable and reliable risk determination under uncertainty and information conflict needs to be studied; (3) insufficient 3D

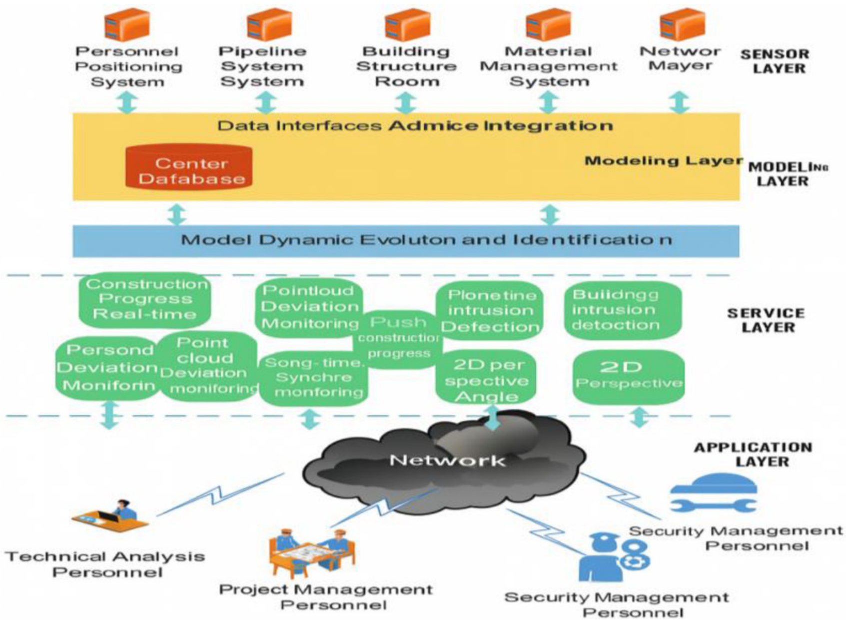


Fig. 1. System functional module structure diagram.

visualization and decision support capabilities: existing BIM applications mostly stay at the static display stage, lacking the ability to integrate with real-time monitoring and risk prediction. And information conflicts, how to give a stable and reliable risk determination under uncertainty and information conflict needs to be studied; (3) Insufficient 3D visualization and decision-making support capability: existing BIM applications mostly stay in the static display stage, and there is a lack of a dynamic digital twin model that is deeply integrated with the real-time monitoring and risk prediction; (4) System stability in the complex on-site environment: high humidity, dusty, and highly disturbed construction environments put forward strict requirements on the stable operation of the system. Requirements. Therefore, there is an urgent need to design a full-process monitoring system with multi-source data fusion, intelligent warning, 3D visualization, and high stability [16,17].

The integration of Internet of Things (IoT), digital twin technologies, and multiple data sources has given rise to communication among the monitoring systems at different levels that is very easy and comfortable. The IoT sensors are real-time measuring stress, deformation, and environmental conditions constantly; this data is sent through the service layer to the digital twin platform for visual inspection and simulation. Then, the multi-source data fusion unit combines the different sensor data streams to ensure that the whole monitoring process has uniformity, correctness, and time synchronization.

Aiming at the above problems, this paper proposes an intelligent monitoring system for the whole process of tunnel construction based on the Internet of Things and digital twin, whose core innovations include the following aspects:

- Multi-source information fusion mechanism: integrating personnel positioning system, tube sheet quality monitoring system, shield propulsion parameter monitoring, and environmental sensing network, real-time collection and standardized processing of multi-dimensional data through data interface adapter, and adopting heterogeneous data fusion strategy to improve information reliability;
- Digital twin-driven BIM dynamic modeling: combining real-time monitoring data and BIM models to build a digital twin of the construction state, realizing three-dimensional dynamic visualization and multi-perspective construction progress display.
- Intelligent Risk Warning and Decision Support: Adopt the improved D-S evidence theory for fusion of multi-source risk indicators, and introduce a conflict weakening strategy to improve the stability of assessment, combined with the validity factor for risk determination verification.

2 Materials and methods

2.1 Three-dimensional visualization aid system

The intelligent monitoring system of tunnel construction based on Internet of Things and digital twin is shown in Figure 1. The overall structure adopts a four-layer system of data layer-model layer-service layer-application layer, which is combined with the optimization method of multi-source information fusion and risk assessment proposed in this paper to realize dynamic visualization monitoring and intelligent risk warning and decision-making support for the whole process of construction [18,19]. The synchronization of the data mechanism is the one that facilitates communication among the four layers in a seamless manner. The data layer's IoT sensors collect real-time data that is transmitted through the service layer, processed in the model layer, and finally displayed in the application layer, all having the same time stamps and using the same data protocols. This mechanism thus assures the uninterrupted and dependable flow of monitoring information all over the construction period. The system not only integrates various types of information from the construction site, but also provides a comprehensive and comprehensive system for the construction site. The system not only integrates all kinds of heterogeneous monitoring equipment at the construction site, but also realizes multi-dimensional visual display with the help of a BIM platform, and realizes intelligent safety management through D-S evidence theory, multi-source fusion algorithm, and risk optimization strategy [20]. BIM dynamic modeling is all about using Building Information Modeling (BIM) for the creation of a digital twin that is continuously updated and represents the current state of the construction site and geological conditions. The conflict weakening strategy is a data merging method that minimizes the effect of wrong or differing information coming from various sensors, whereas the effectiveness factor indicates the reliability of each risk warning output. The description of these mechanisms is provided in great depth.

Moreover, the BIM platform assisted multi-dimensional visualization and intelligent safety management through the coupling of D-S evidence theory and a multi-source data fusion algorithm. The integration allowed transforming and presenting the heterogeneous monitoring data related to the IoT sensors on the BIM model and thus visualizing the dynamic safety states for the surrounding rock and construction components. Fused and weighted risk indicators are monitored in real-time through a risk optimization technique, which was additionally supported by the BIM environment to provide early warning information and assist decision-making throughout tunnel construction.

IoT gateways, along with standardized data-exchange interfaces, act as a unifying force for heterogeneous monitoring devices and bring together data from different sources, which include but are not limited to sensors, laser scanners, and environmental monitors. The data streams are merged at the service layer and coupled with the BIM-digital-twin platform in real time, thus ensuring regular visualization and analysis during the whole construction process.

The system applies the ongoing collection of fresh sensor data and the updating of the digital twin model to correspond with the actual site conditions throughout the construction process. This way, the model can be altered along with the geological conditions, the operation of the machines, and the environmental state, while at the same time, the risk predictions and real-time visualization of the tunneling process are still accurate and consistent.

The onsite situation is represented in the digital twin model, which is updated continuously as the system collects new sensor data throughout the construction process. The model can go through the transformations that occur in geology, the equipment used, and other external factors, which implies that the real-time visualization and risk prediction during the whole tunnel construction period are reliable due to the uninterrupted synchronization.

In the data layer, the system aggregates real-time information from multiple subsystems, such as personnel positioning, tube sheet quality, shield propulsion, and material management, which are standardized by data interface adapters and unified through the heterogeneous data fusion service F $(\cdot)$. The fusion process can be expressed as follows:

$$D_f = F(A(D_1), A(D_2), \ldots, A(D_n)). \tag{1}$$

Among them, D_i Represents the original data from different sources, A $(\cdot)$ is the interface adaptation function, and D_f It is the unified dataset that can be directly used for model calculation after fusion. This layer ensures that all collected information can be stored in the central database in a highly current and consistent form, which provides the basis for subsequent modeling and analysis.

After entering the model layer, the fused data is input into the BIM data integration platform and the dynamic evolution operator. Φ generates the time-series digital twin modelM_t, whose mathematical form can be expressed as follows:

$$M_t = \Phi(D_f, t). \tag{2}$$

The system persistently modifies and improves the digital-twin model with the reception of new IoT data streams. Every inflow of instantaneous sensor data is merged, confirmed, and employed to re-adjust the deformation, stress, and environmental factors in the BIM-based model, thus ensuring that the virtual image constantly shows the current construction progress.

The service layer is like the bridge that links the model layer and the application layer, being the major part in between them. The real-time data outputs and the analytical results are first taken from the model layer, then, data fusion, risk evaluation, and decision analysis are conducted, and finally, the info is sent to the application layer for visualization and management. This interaction between the two layers allows for a continuous data flow, and hence, all layers are constantly updated during the building process. The model cannot only be organically organized for different construction conditions, but also supports multi-view display, enabling dynamic evolution and real-time visualization of construction status in both time and space dimensions. The core of this layer is to transform the static BIM model into a predictive and interactive digital twin, which provides an accurate model foundation for the subsequent service layer functions.

In the service layer, the system accomplishes risk identification and intelligent warning by fusing multi-source information and combining it with the D-S evidence theory. The D-S fusion rule calculates the comprehensive credibility of different risk levels through the basic probability assignments m_2:

$$m(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K} \tag{3}$$

where K denotes the conflict coefficient, the smaller it is, the higher the information fusion consistency is. To further enhance the credibility of the warning results, the system introduces the validity factor E for verification:

$$E = \frac{P_{\max} - P_{\text{second}}}{1 - P_{\text{second}}} \tag{4}$$

where $P_{\max}$ and P_{second} These are the maximum and second-largest affiliation probabilities, respectively. When E > 0.5, the warning conclusion has high validity. The service layer functionally realizes dynamic display of construction progress, real-time monitoring of the surrounding environment, tracking of personnel trajectory, quality detection of pipe sheet, as well as risk display and intelligent data retrieval in 3D/2D perspective to ensure the multi-dimensional safety posture of the construction site is fully controllable.

Ultimately, the application layer serves as the user interaction interface, delivering the above analysis and monitoring results to project managers, safety management personnel, and on-site construction workers in the form of visualization. Users can access risk information in real time through mobile terminals or consoles, and formulate countermeasures based on the decision optimization results provided by the system. The goal of risk decision-making is to form an optimal strategy by considering the trade-off between risk cost R(x)R(x) and construction cost. $C(x)$:

$$min_{x \in X} J(x) = \alpha R(x) + \beta C(x) \tag{5}$$

Where α and β These are the weighting coefficients to ensure that the construction achieves the optimal balance between safety and cost.

In summary, the architecture organically integrates real-time IoT sensing, digital twin dynamic modeling, multi-source fusion of D-S evidence theory, and risk optimization and control, realizing closed-loop intelligent management from data collection, information fusion, model evolution, to risk warning and decision support. Figure 1 clearly shows the whole process working principle of the modeling scheme proposed in this paper: the upper user can intuitively grasp the construction global situation, risk formation process, and warning level through the network access platform, which truly realizes the integration of digitalization, intelligence, and visualization of tunnel construction safety management.

2.2 Multisource fusion framework

A multisource fusion framework is proposed to improve the quality of decisions made in complicated multimodal data settings. This framework provides a one-stop shop for evidence by combining the diverse signals from different subsystems. The enhanced Dempster–Shafer (D–S) evidence theory, together with the conflict-weakening approach and the validity factor, guarantees the proper handling of inconsistency or disagreement in the information being fused. The conflict-weakening mechanism gives less power to the highly uncertain evidence, while the validity factor affects the data source's influence based on its trustworthiness. All these approaches together increase the reliability and precision of the fusion of the given multisource risk indicators, thus facilitating smart risk alerts and high-confidence decision-making.

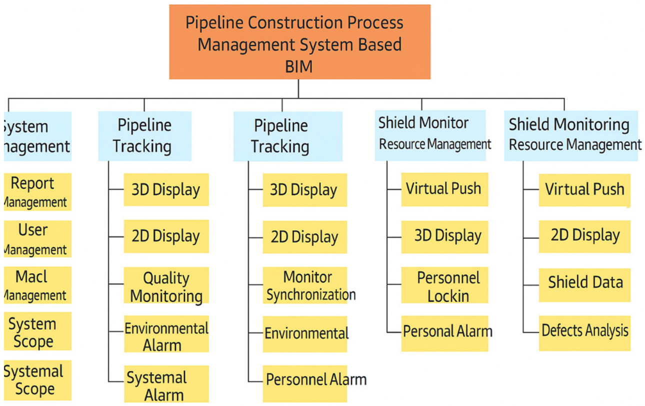


Fig. 2. Schematic structure of software functional modules.

The improved Dempster–Shafer (D-S) evidence theory presented in this paper not only increases the multi-source risk indicator fusion's correctness but also its stability. More precisely, the conflict-weakening strategy reduces the adverse effect of contradictory or inconsistent evidence to the extent that data fusion under uncertain conditions becomes smoother and more reliable. Simultaneously, the validity factor that is introduced dynamically adjusts the weight of each evidence source based on its confidence level, which in turn prevents unreliable information from impacting the overall assessment. These two mechanisms combined allow the improved D-S framework to have more consistent fusion results and thus to considerably increase the accuracy and reliability of the tunnel monitoring system's intelligent risk alerts and supporting decision-making processes.

3 Results

3.1 Three features of software

Figure 2 shows the software functional module structure of the whole process management system of tunnel construction based on digital twin, which is clearly divided into seven functional modules from the top layer to the functional layer, namely, system management, construction management, tube tracking, environment monitoring, personnel tracking, shield monitoring and material management, which embodies the core design idea of the intelligent monitoring system proposed in this paper. Each module relies on the digital twin BIM platform to realize data visualization, risk assessment, and intelligent warning, and is closely integrated with the multi-source information fusion and risk assessment formula proposed in the previous section.

System Management Module – Global Control and Configuration Optimization Module contains five subfunctions: report management, user management, model management, data management, and system settings, which are used for the global control and maintenance of the platform operating environment [21,22].

Its mathematical modeling can be described by the system operation optimization objective function:

$$min_{\theta} J_s(\theta) = \lambda_1 \cdot C_{sys}(\theta) + \lambda_2 \cdot E_{fail}(\theta) \tag{6}$$

Where θ is the system configuration parameter, C_{sys} Is the operation cost, E_{fail} is the failure risk, and λ_1,λ_2 Are the weights.

Construction Management Module – Dynamic Progress Control and Quality Early Warning Module realizes dynamic monitoring of the construction process through three-dimensional progress, two-dimensional display, advancement synchronization, schedule management, and quality early warning.

Its warning trigger depends on the risk assessment threshold determination formula:

$$R(t) = \sum_{i=1}^{n} w_i r_i(t), R(t) > R_{\text{th}} \Rightarrow \text{Trigger, alarm} \tag{7}$$

where $r_i(t)$ represents the value of each risk indicator at time t, w_i Is the weight, and R_{th} Is the risk threshold.

Pipe Tracking Module – Condition Monitoring and Abnormality Detection Module monitors the quality status of the pipe sheet through 3D display, inspection management, quality monitoring, maintenance management, and status warning. The D-S evidence theory of multi-source information fusion is adopted to categorize and warn of the condition of pipe sheets:

$$m(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K} \tag{8}$$

Where K is the conflict factor and the fusion result $m(A)$ Determines the risk level of the pipe sheet.

Environmental Monitoring Module – Multi-dimensional environmental dynamic visualization, environmental monitoring to achieve a Three-dimensional environment, two-dimensional display, monitoring synchronization, environmental evolution, environmental warning, real-time sensing using GIS and IoT sensing network.

The early warning mechanism adopts a risk model based on time series prediction:

$$E_t = f(E_{t-1}, \Delta t, \beta), P(E_t > E_{\text{limit}}) \rightarrow \text{Alarm} \tag{9}$$

Where E_t Is the current environmental risk value, and f is the prediction function.

Personnel tracking module – trajectory tracking and area warning. Personnel tracking realizes dynamic management of underground workers through personnel information, 3D trajectory, personnel positioning, and area warning.

The optimization of the positioning trajectory can be modeled as a shortest path constraint problem:

$$min_{p(t)} \int_0^T \| v(t) \|^2 dt, s.t. p(t) \in \Omega_{\text{safe}} \tag{10}$$

Where $p(t)$ Is the personnel position trajectory, $v(t)$ Is the velocity vector, and Ω_{safe} Is the set of safe areas.

Shield Monitoring Module – Shield Parameter Diagnosis and Intelligent Early Warning Includes Virtual propulsion, 2D display, shield data, and fault analysis, which realizes state diagnosis by monitoring key parameters of the shield machine.

Shield machine failure warning can be based on a Bayesian a posteriori probability model:

$$P(F|X) = \frac{P(X|F)P(F)}{P(X)}. \tag{11}$$

Among them, F denotes the failure event, X is the monitoring data feature, and the failure risk is judged by the maximum a posteriori probability (MAP).

Material Management Module – The equipment and material full life cycle management module realizes material management, equipment management, statistical analysis, and ensures the integrity of the material supply chain through data retrospection and predictive maintenance.

Its optimization model is a multi-objective inventory optimization:

$$min_{I_t} (C_h(I_t) + C_s(I_t)), s.t. I_t \geq I_{min} \tag{12}$$

where I_t Is the inventory quantity at time t, C_h Is the inventory holding cost, and C_s Is the stock-out cost.

4 Discussion

4.1 Model for evaluating the security of multi-source information fusion

4.1.1 Multi-scale and multi-dimensional evaluation metrics

Disconnection of Evaluation Scales and Limitations of Information Sources

Current tunnel construction safety evaluations often exhibit discontinuity across different evaluation scales. Typically, they focus separately on macro-level assessments during the investigation and design phases and micro-level risk evaluations at the tunnel face during construction. This significant gap between scales results in a lack of coordination between global and localized assessments, making it difficult to establish a dynamic and coherent evaluation framework. Moreover, the data used in these evaluations primarily rely on previously disclosed geological information and construction design documents, neglecting multi-source heterogeneous data generated during the construction process [23]. As a result, the limited dimensionality and adaptability of the information hinder the ability to achieve comprehensive, real-time safety perception and integrated risk assessment throughout the construction lifecycle.

As shown in Figure 3, in the process of conventional drill-and-blast tunnel construction, the spatial scale presents a gradual convergence process from large to small, which can be summarized into three typical scale evolution paths: the first is the whole tunnel scale based on the design stage, focusing on the overall direction and structural design; the second is the scale for the construction of overpassing exploration used to supplement the geologic information, and the specific scope is closely

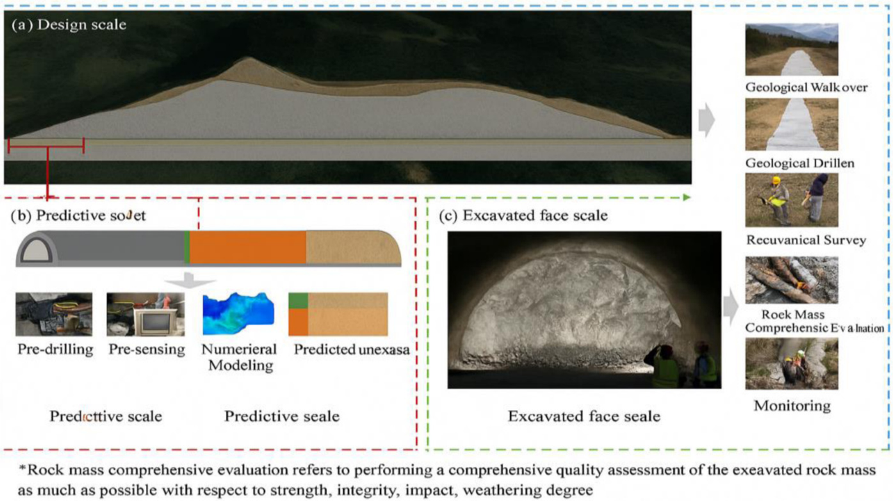


Fig. 3. Typical scale variation of tunnel construction and the structure of the evaluation index dimension.

related to the ability of the detection technology used; the third is the local scale of the palm face formed by the excavation revelation, which is the key area for in situ rock evaluation and dynamic monitoring [24]. The second is the scale of advanced exploration used to supplement geological information during construction, the specific scope of which is closely related to the capability of the exploration technology used; the third is the local scale of the palm face formed by excavation, which is the key area for in-situ rock evaluation and dynamic monitoring.

In terms of indicator dimensions, based on different data sources, the evaluation indicator system can be summarized into the following three core dimensions: one is the geological dimension, which focuses on reflecting the natural attributes of the engineering geological environment, such as the depth of burial, geostress and other basic conditions; the second is the construction dimension, which focuses on the design parameters and the control variables of the construction process, such as the diameter of the excavation and the length of the cycle; and the third is the prediction dimension, which is based on the data deduction made by the existing information. The third dimension is the prediction dimension, which mainly includes the data deduction and trend judgment based on the existing information, including the prediction of the mechanical properties of the surrounding rock, the prediction of the rock quality indexes obtained from the over detection, the results of the numerical simulation analysis, and the dynamic trend of the monitoring data, etc. This unit is often present in practical assessments, which is a very common practice. Despite being sometimes ignored, this aspect of practical assessment is very important from the standpoint of safety regulations and early risk warning.

4.1.2 Integrated safety evaluation index system across construction stages

The complete process of tunnel construction can, as per the earlier mentioned multi-dimensional and multi-scale framework, be divided into three major phases: excavation monitoring, advanced prediction, and inquiry and design. For the purpose of having risk detection and safety control that can adapt easily to these stages, it is necessary to create an assessment index system that can support different typical danger situations at the same time [25]. This paper presents an integrated safety evaluation index system focusing on three typical tunnel construction safety issues: collapse, mud/water inrush, and large deformation. The construction of the system, which is in accordance with relevant technical principles and engineering practices, is detailed in Table 1.

4.2 Basic probability assignment construction in the presence of interval uncertainty

The main condition to be satisfied by the probability assignment technique is its flexibility to deal with the different data types coming from the tunnel engineering assessment, especially the combination of interval and point values. This research employs an interval-based Euclidean distance model to compute Basic Probability Assignment (BPA) and to give strong quantification under uncertainty.

More specifically, the reference interval j^{th} The safety level is denoted by, and the observed value of the evaluation indicator is marked by the interval $[x_j^L, x_j^U]$. The next statement describes how i^{th} the Euclidean distance $[s_i^L, s_i^U]$ is defined between them:

$$d_{ij} = \sqrt{(x_j^L - s_i^L)^2 + (x_j^U - s_i^U)^2}. \tag{13}$$

The distance depicts how alike the observed indicator value is to the established safety levels. Dempster–Shafer (D-S) evidence theory is the very basis for the construction of proper membership functions, and those functions are then used for BPA value calculation. The method has made the model stronger in terms of handling fuzzy and uncertain situations that come from multi-source data, consequently making it ideal for complex and dynamic tunneling construction situations.

Table 1. Integrated safety evaluation index system for tunnel construction.

Stage	Index dimension	Typical evaluation indicators	Applicable hazard types
Investigation & Design	Geological Factors	Tunnel depth, in-situ stress, lithological composition, and fault development	Collapse, mud/water inrush, large deformation
	Design Parameters	Excavation section size, initial support parameters, and construction method	Collapse, large deformation
Advance Prediction	Geophysical Data	Anomalous reflections in advance detection, rock mass integrity within detection range	Mud/water inrush, collapse
	Simulation Output	Stress–strain distribution of the surrounding rock, plastic zone expansion trend	Large deformation, collapse
Excavation Monitoring	Real-Time Measurements	Convergence deformation, crown settlement, and internal force of support structures	Large deformation, collapse
	Safety Feedback	Early warning levels, abnormal response rate	Mud/water inrush, collapse, large deformation

4.2.2 Attenuation of conflict in multi-source evidence

An increase in evidence-gathering instruments (sources of evidence) will result in a simultaneous increase in the distribution of opinions among all actors wary of providing evidence in real-life cases [20]. For tunnel construction safety evaluation, which inherently involves multi-source and multi-index information, integrating a rich set of indicators is both necessary and justified. However, excessive conflict among these sources can degrade the reliability of the fusion result.

To address this issue, this study employs the Murphy average evidence method [24] to mitigate the degree of conflict between evidence bodies before fusion. This approach is based on the idea of averaging conflicting evidence to reduce the impact of inconsistency and improve the credibility of D-S fusion results.

Assume there are n highly conflicting evidence bodies denoted as m_j, where $j = 1, 2, \ldots, n$. The average evidence body $\overline{m}$ is calculated as follows:

$$\overline{m}(A) = \frac{1}{n}\sum_{j=1}^{n} m_j(A), \quad \forall A \subseteq \Theta \tag{14}$$

Where: Θ Represents the frame of discernment, A is a subset hypothesis within Θ, $m_j(A)$ Denotes the basic probability assignment (BPA) of the jth evidence on hypothesis A.

After obtaining the average BPA$\overline{m}$It is treated as a neutralized evidence body and fused again with each original evidence using the standard Dempster combination rule. This process effectively dampens extreme inconsistencies and ensures that the final fused result reflects a balanced aggregation of all evidence sources.

4.3 Validation of assessment result reliability

In the wake of the identification of the probability distribution, the maximum membership concept is applied as a method in the safety evaluation process to allocate the final safety level. But still, this technique might discard the integral distributional data and, in some instances, give rise to misleading or oversimplified conclusions. So, it becomes very important to set up a mechanism that will authenticate the reliability and the validity of the evaluation's output.

The present study provides an effective way out of this predicament by introducing a factor of effectiveness that reflects the degree of one's confidence in the outcome of the evaluation. The new metric is then more sophisticated in measuring the decisiveness of choice since it shows how much the selected class dominates the other potential categories in the probability distribution. The validity factor η is explained as follows:

$$\eta = \frac{P_{\max} - P_{\text{avg}}}{1 - P_{\text{avg}}}. \tag{15}$$

The value $P_{\max}$ The maximum probability, that is, the probability associated with the grade that was selected, P_{avg} is the average probability for each class.

So, the stronger the selected class, $\eta \in [0, 1]$ which means the better η The decision, the bigger the score, according to this equation η. However, an even or indecisive distribution suggests smaller point values, which could signal reluctance or rethinking.

In real-life situations, there is a possibility of using a limit, for example, η > 0.5, to judge to what degree the classification result is correct. The checking procedure not only reinforces but also makes the final safety grade allocation statistically and logically sound, implying that it is the overall assessment framework's reliability that is strengthened.

This new way of doing things adheres to the risk categorization criteria and the early-warning management practices that have been applied in metro tunnel engineering for quite some time to guarantee a smooth coexistence with the already existing conventional tunnel construction safety measures. The whole array of sensing devices and data transmission modules conforms to the national specifications for underground construction monitoring that are currently in place, which means that there will be a smooth integration with the old safety supervision workflow. What is more, the system uses a modular deployment architecture, which means that it becomes possible to retrofit the ongoing construction projects with IoT sensors gradually and connect them to the monitoring platform, all of this without halting construction activities.

To assess the uncertainty propagation in the fusion process quantitatively, the belief interval length is applied as an index of uncertainty measurement. Before evidence fusion, the average belief interval length of all monitoring indicators is 0.37, which signifies a very high level of uncertainty that is mainly due to the noise from the sensors and the lack of complete data. Subsequently, with the use of the improved D-S evidence theory and the correction of the effectiveness factor, the average belief interval length is now 0.14, which indicates a 62.1% reduction in the uncertainty level. This indicates that the method put forth can efficiently eliminate the conflicting evidence and, consequently, the reliability of the multi-source risk assessment result during the tunnel construction is increased.

Measurement errors in sensor data and their impact on fusion algorithm

The sensors that are part of the real-time monitoring system for tunnels generate data, but the data is not always accurate due to measurement errors, for example, temperature, pressure, and calibration changes caused by the environment, like dust, vibrations, and humidity. In case the errors are not corrected accurately through the data fusion algorithm, the end risk assessment might get severely affected.

As a counteraction to these errors, the system utilizes preprocessing methods such as outlier removal and error filtering, which help to diminish the influence of erroneous data on the fusion algorithm. Furthermore, the D-S evidence theory, which is adopted in the fusion process, allows bringing in doubtful or even conflicting data and, at the same time, limiting the adverse effect of mistakes to a minimum.

Nonetheless, even with these measures in place, the total measurement errors still may affect the end risk assessment, particularly when there is a high level of uncertainty or multiple conflicting data sources. In such cases, the effectiveness factor and conflict weakening strategy are utilized as they assist in making the fusion results stable and ensuring that the final risk assessment does not get too much influence from the unreliable measurements.

The system, thus, by dealing with measurement errors in an explicit manner, guarantees more stable and trustworthy risk forecasts and also positively influences the decision-making process related to the safety of tunnel construction.

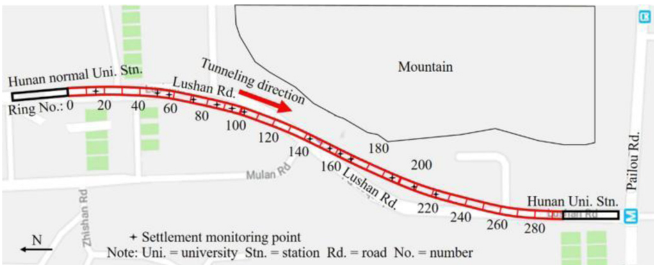


Fig. 4. Shield tunnel line layout.

The parameters of the digital twin model and the weights of the risk assessment are modified automatically in the course of construction. The system is always up-to-date with the current situation because it is using the data from the IoT sensors that are installed all over the construction site. The model changes its characteristics as the new data comes in; thus, the risk assessments are always accurate, reflecting the state of the tunnel and the surrounding rock conditions. This entire adjustment process is carried out automatically, allowing no manual labor to be involved and making it possible for risk assessments to be changed throughout the construction period.

Nonetheless, certain primary limit values or parameters, such as alarm thresholds or risk categorization, may be established by hand at the time of the setup so as to guarantee that the system follows the standard safety practices in this field.

4.4 Application example

4.4.1 Project overview

In this paper, a shield tunnel interval of XX urban rail transit is selected as the verification scene for the experiment, and the study section is the tunnel line between Hunan Normal University Station and XX University Station. The total length of the line is about 280 meters, laid along Lushan Road, and the direction of shield propulsion is from west to east. During the construction process, settlement monitoring points are set up at each ring number along the tunnel, realizing real-time monitoring of settlement, deformation, and construction status of the whole line. The tunnel passes through many urban buildings and transportation facilities, and the construction environment is complicated, which puts forward higher requirements for real-time monitoring and risk control [26,27].

The geological conditions of this section are diverse, crossing backfill, clay, marl, mudstone, sandstone, limestone, and other lithologies, with weak interlayers and lithological mutations in local areas and neighboring mountains, with significant differences in the stability of the surrounding rock. The complex stratigraphic structure brings uncertainty risk for shield construction. In this study, multi-source monitoring equipment is deployed in the interval, collecting surface and underground data through IOT, and combining with the BIM digital twin model to carry out real-time dynamic simulation and visualization monitoring, which provides high-precision data support for risk warning and construction decision-making (see Figs. 4 and 5).

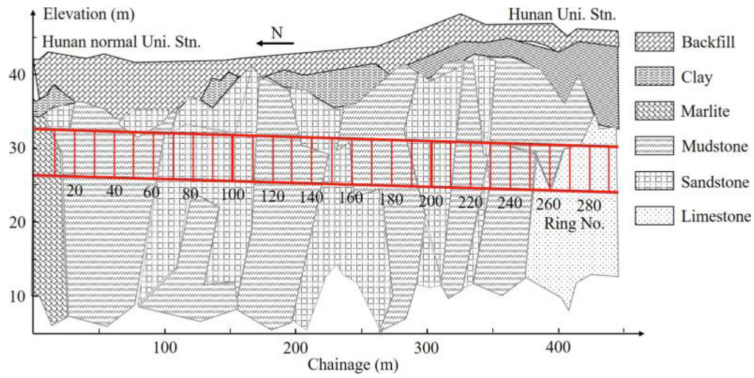


Fig. 5. The shield tunnel's geological longitudinal section.

Table 2. Re-instantiating surveillance devices in the jinan high-speed railway depot tunnel underpass area.

Monitoring point ID	Location description	Measurement method	Monitoring objective	Frequency (times/day)
MP-01	Subgrade near track #3	Intelligent Total Station	Horizontal displacement	4
MP-02	Contact network pole #12	Inclinometer	Angular deformation	2
MP-03	Deep soil layer (depth 15 m)	Tilt meter	Deep soil mass movement	Continuous
MP-04	Track bed near the main entrance	Static leveling	Vertical settlement	4
MP-05	Groundwater monitoring well	Water level sensor	Water table fluctuation	Continuous

4.5 Monitoring scheme

During the tunnel construction in the project section, the tunnel will pass underneath the Jinan High-Speed Train Depot, which includes multiple tracks. Due to the depot's intensive operational activities, frequent train parking, and complex traffic conditions occur. Therefore, monitoring the tunnel segment beneath this critical infrastructure is of paramount importance.

To ensure that the tunnel excavation and construction activities do not adversely affect the depot's normal operation and the safety of the tracks, a multi-dimensional and comprehensive monitoring system is deployed. This system integrates the following measurement techniques: Intelligent Total Station (ITS) surveying for precise displacement monitoring, Static leveling for vertical settlement measurements, Inclinometer and tilt meter measurements for angular deformation monitoring, and Water level sensors to monitor groundwater fluctuations.

Considering the specific characteristics of this monitoring project, the system is implemented on the basis of the Railway Deformation Monitoring Intelligent Management Platform. The platform facilitates real-time deformation monitoring of key structural and geotechnical elements within the influence zone of the tunnel excavation, including: Subgrade deformation, Contact network pole displacement, Deep soil mass movements, and Water table fluctuations.

The layout of monitoring points is detailed in Table 2, which specifies the measurement types, locations, and their functional roles.

To minimize any possible adverse effects of the tunnel construction and excavation operations on depot operation normalcy and track safety, a monitoring system of several aspects and dimensions has been installed. The system comprises the following measurement techniques: installation of groundwater level sensors for monitoring the groundwater fluctuation; readings from inclinometers and tilt meters for monitoring the angular deformation; application of Intelligent Total Station (ITS) surveying for precise displacement monitoring; and static leveling for vertical settlement measurements.

The Railway Deformation Monitoring Intelligent Management platform acts as the basis of the system's realization, considering the special characteristics of this monitoring project. In the tunnel excavation zone, continuous monitoring of deformations is carried out using the system in crucial structures and geotechnical elements, such as subgrade deformation, displacement of contact network poles, deep soil mass movements and water table level changes.

A comprehensive map of the monitoring points is given in Table 2, where the different types of measurements, locations, and their respective functions are all indicated.

Our multi-sensor integrated monitoring system, by timely detecting any unusual ground or structural movements, secures the opportunity of deploying preventive mitigation measures to safeguard depot operations and stability monitoring.

Sensor reliability and maintenance

As a construction site is a very harsh environment with high humidity, dust, vibrations, and other factors, the sensors must be very dependable. The entire system has been incorporating periodic intervals for calibration and maintenance of sensors to eliminate data inaccuracies and degradation due to long usage, and thus, to ensure sensor dependability. The sensors actually had some

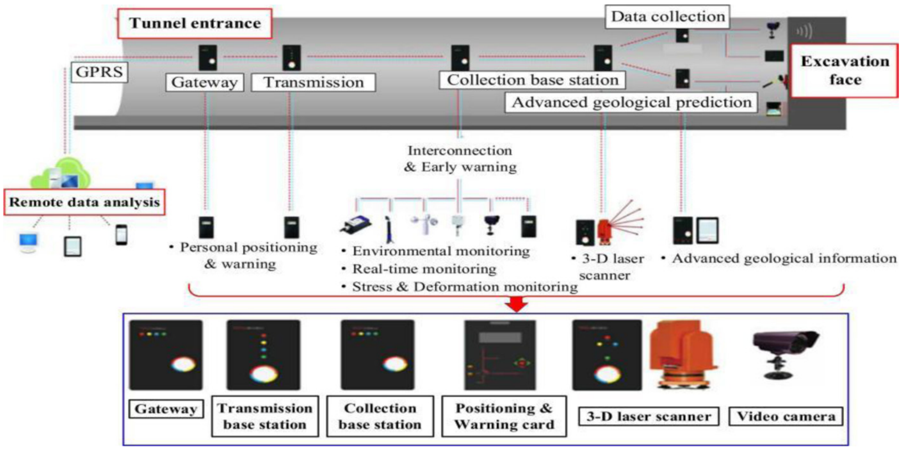


Fig. 6. Intelligent monitoring system schematic plan for tunnel construction.

environmental safeguards or protections, like fog-free lenses, moisture-proof sealing, and dust-proof cabinets, that were provided to them so that they would not be impacted by their environment. In the event of a sensor failure, automatic takeover by the backup systems and failure detection will thus facilitate data integrity and monitoring without interruptions.

Failure handling procedures

In case of a sensor failing, the system's backup sensors go on automatically so as not to interrupt the data-gathering process. Moreover, the system has real-time failure notifications to inform operators and initiate corrective action, thereby reducing downtime. The monitoring at the construction site, even under tough conditions, will be uninterrupted due to the automated reaction system.

The intelligent monitoring system, which was designed for the tunnel construction in this study, is depicted in Figure 6 with its total layout. The system allows the whole construction process at the excavation face and tunnel entrance to be monitored in real-time, with data collection and remote analysis done with the assistance of intelligent analysis. The IoT technology-based system integrates several sensors that are interconnected through gateways, transmission stations, and data-gathering stations to form a powerful and efficient data communication network that assures real-time information sharing and exchange.

To enhance operational safety, the early warning systems and the people positioning are installed inside the tunnel for the dynamic tracking of underground workers and sending alerts for the occurrence of dangerous conditions.

Moreover, 3D laser scanners can elaborate the spatial as well as the temporal accuracy of monitoring by executing very precise dynamic scans of the excavation face and tunnel cross-sections. Therefore, this process makes it possible to have instantaneous updates and to simulate the digital twin model. The continuous recording of the construction site by high-definition video cameras is also part of the system. This feature gives visual support in the areas of risk assessment and construction management.

The monitoring data is sent in real-time over a GPRS network to a distant data analysis platform, which creates a closed-loop control system of "data acquisition – wireless transmission – intelligent analysis – early warning feedback." The technology manages to carry out risk control very accurately and in such a way that it can even break down the construction safety and emergency response capabilities. It does so by alerting the constructors very quickly and thus supporting decision-making when any abnormal signs are detected.

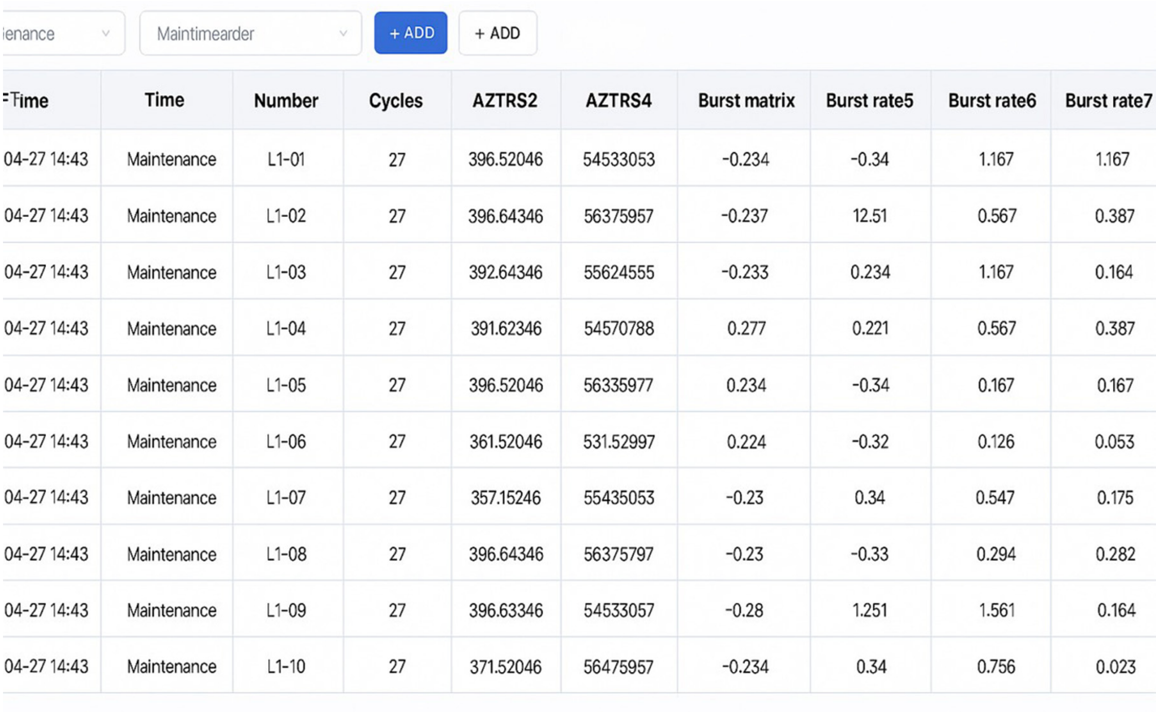
4.6 Deformation monitoring platform

This module offers users a full view of each monitoring point by presenting the monitoring data in different formats, such as data tables, statistical charts, and trend graphs. The deformation trends are very easily picked up, and the correct and timely decisions are made during the construction process thanks to the attractive and easy-to-use interfaces of the platform.

The monitoring data is analyzed statistically in detail, and such an analysis is depicted in Figure 7 and includes some key metrics like the amount of displacement, settlement, and deformation rates at different places of measurement. At the same time, trend graphs in Figure 8 show the changes in monitored parameters over time, pointing out the periods of high-rate deformation or possible anomalies.

A deformation monitoring platform is one that supports continuous data updating and remote access, which means that all the concerned people will be able to monitor the changes and respond to new risks very quickly. Furthermore, the system's performance in guaranteeing the safety of construction and the soundness of structures is tremendously enhanced by the advanced functionalities such as the threshold alerts and the automatic reporting.

The operational status of monitoring points is shown completely through the combination of a variety of rich charts and visualization tools by the railway monitoring platform. The visualization tools consist of early warning notifications, problem management statistics, total alterations at every site, largest movements recorded, and the location mapping of monitoring points. These representations are made on large screens so that users can easily know the situation around them and then take action. The data interface of the monitoring platform, which is



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Time	Time	Number	Cycles	AZTRS2	AZTRS4	Burst matrix	Burst rate5	Burst rate6	Burst rate7
04-27 14:43	Maintenance	L1-01	27	396.52046	54533053	-0.234	-0.34	1.167	1.167
04-27 14:43	Maintenance	L1-02	27	396.64346	56375957	-0.237	12.51	0.567	0.387
04-27 14:43	Maintenance	L1-03	27	392.64346	55624555	-0.233	0.234	1.167	0.164
04-27 14:43	Maintenance	L1-04	27	391.62346	54570788	0.277	0.221	0.567	0.387
04-27 14:43	Maintenance	L1-05	27	396.52046	56335977	0.234	-0.34	0.167	0.167
04-27 14:43	Maintenance	L1-06	27	361.52046	531.52997	0.224	-0.32	0.126	0.053
04-27 14:43	Maintenance	L1-07	27	357.15246	55435053	-0.23	0.34	0.547	0.175
04-27 14:43	Maintenance	L1-08	27	396.64346	56375797	-0.23	-0.33	0.294	0.282
04-27 14:43	Maintenance	L1-09	27	396.63346	54533057	-0.28	1.251	1.561	0.164
04-27 14:43	Maintenance	L1-10	27	371.52046	56475957	-0.234	0.34	0.756	0.023

Fig. 7. Monitoring data-dependent statistical subjects.

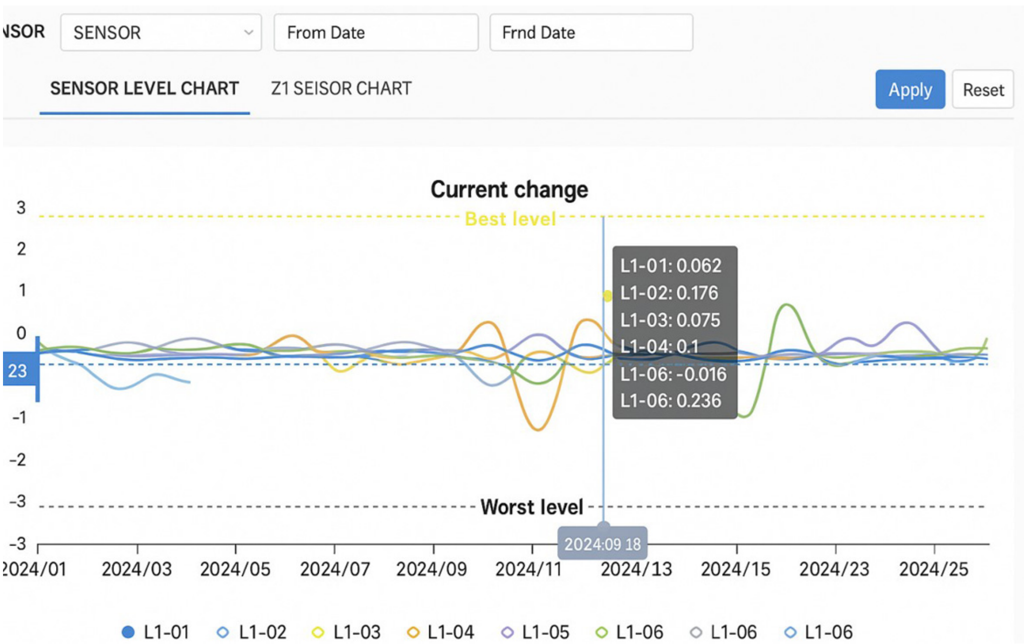

Fig. 8. Examining data tendencies.

illustrated in Figure 9, has interactive components and real-time updates that are aimed at enhancing the response time and monitoring efficiency.

Stakeholders will be able to observe and monitor the changes in ground and structural behaviors over the course of the monitoring period, thus allowing them to identify potential hazards quickly, due to this combined visualization system. The software definitely facilitates the effective monitoring of safety concerns and planning of maintenance within the entire railway operation by combining data collection, along with easy-to-understand graphical representation.

A Geographic Information System (GIS) module that is incorporated into the monitoring platform provides an overview of the project area. The module indicates on a map that can be interacted with the precise locations of all

Fig. 9. Data interface for the monitoring platform.

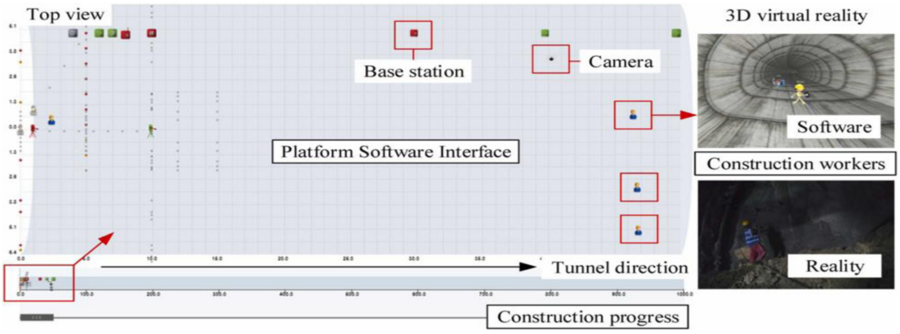

Fig. 10. The monitoring platform's GIS map view.

the monitoring devices that have been installed at the designated work points. Users can access all information related to the monitoring device, including its model specifications, installation dates, operational status, and names and categories of the monitoring points.

The GIS platform combines geographical with attribute data, thereby greatly enhancing the users' situational awareness of the monitored area and allowing for more efficient navigation and management of the monitoring assets. The spatial distribution and monitoring points relationships are better understood thanks to this geospatial representation, which leads to efficient maintenance planning and well-informed decision-making.

This research works on a positive response mechanism whereby alerts from the system are turned into options. The technology alerts the supervisors instantly via both console and mobile devices once the early warning signal hits Level III or more. Heavy machinery is booked to alter the support traits and reduce the rate of excavation. Safety personnel are already performing field inspections and taking action to strengthen the safety of the site by adjusting the shield's push and torque or erecting temporary supports. Employees in the hazardous ground are removed if the risk situation keeps escalating, and the construction is stopped until the monitoring signals indicate that it is safe to continue.

The GIS map browsing interface of the monitoring platform is depicted in Figure 10, showcasing its intuitive design and interactive features that enable comprehensive project management support.

4.7 Quantification of multi-scale indicator data collection

A detailed geological survey and design documentation have been used as the basis for the systematic collection and computation of evaluation indicators to aid in the safety assessment process. Several different scales, which portray different aspects of the environment in which the operation and tunnel construction take place, are included in the quantification.

A summary of the specific findings of data collection and quantification is provided in Table 3, showing the indicators grouped by their respective measurement scales. This gives a multi-faceted database that facilitates a thorough safety evaluation and includes parameters that are influenced by geological conditions, construction standards, and the outcomes of predictive modeling.

The processing of diverse data sources through the use of consistent metrics, such as structured quantification, assures that the safety state of the tunnel assessment yields more accurate, reliable, and often very useful insights [28].

4.8 Experimental results

Figure 11 shows the comparison between the measured and predicted results of the key parameters of this paper's system during shield tunnel construction, including thrust (a), torque (b), soil pressure (c), boring speed (d), cutter rotation speed (e), and surface settlement (f). The black solid line is the measured data collected by the system, and

Table 3. Quantification results of multi-scale indicator collection.

Indicator category	Indicator name	Data source	Quantification method / range	Applicable section
Geological Dimension	Surrounding Rock Classification	Geological Radar Forecast	Class IV; Lateral variation approx. 12%	ZK19+100 ~ ZK19+180
Geological Dimension	Stratigraphic Structure Trend	Geotechnical Survey Report	Analyzed by radar image reflection layers	Entire tunnel section
Predictive Dimension	Ground Settlement Value	Numerical Simulation (FLAC3D)	Maximum settlement approx. 8.7 mm	ZK19+100 ~ ZK19+180
Predictive Dimension	Surface Displacement Trend	Numerical Simulation (FLAC3D)	Deformation trend matches monitoring data	Simulation area
Construction Dimension	Excavation Sequence	Design File / On-site Construction	Three-step method (upper, middle, lower benches)	Entire construction zone
Construction Dimension	Initial Support Parameters	Design Documentation	Steel arch + shotcrete, K30 reinforcement	Entire tunnel section
Monitoring Dimension	Deep Displacement Monitoring	Inclinometer / Tiltmeter Data	Peak displacement approx. 5.2 mm	Junction of subgrade and face
Environmental Dimension	Water Level Variation	Water Level Sensor	Water table drop approx. 0.6 m	Adjacent influence zone

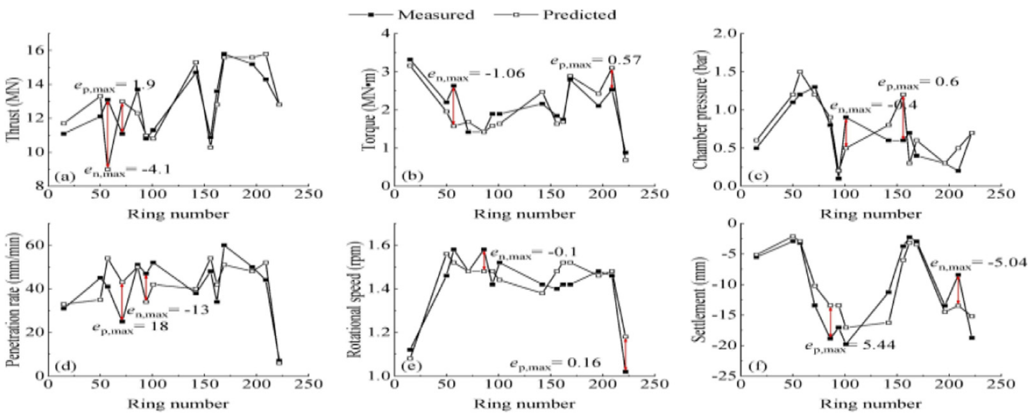

Fig. 11. Predicted and measured monitoring parameters for shield assembly.

the hollow box is the predicted value calculated by the digital twin model proposed in this paper, which are highly coincident, verifying the effectiveness of the monitoring platform of this study in dynamic data fitting and risk warning. As can be seen in the Figure 11, all six types of parameters show obvious fluctuations in different ring number segments, especially in the vicinity of rings 50 to 100 and 180 to 200. The thrust, torque, and earth pressure show more substantial changes, which potentially affect the construction stability. In this paper, the system realizes the synchronization between the prediction curve and the measured curve through multi-source monitoring and real-time calculation of the BIM model, and the maximum prediction deviation. $e_{p,\max}$ and the maximum negative deviation $e_{n,\max}$ Are within the acceptable range, e.g., the maximum prediction error for thrust is only 1.9 MN, and the maximum prediction error for torque is 1.9 MN for thrust, 0.57 MN-m for torque, and 5.44 mm for settlement, the prediction accuracy of digging speed and cutter rotation speed is especially high, and the fluctuation changes are completely captured by the model with a very small error. In addition, the settlement curve (f) shows a significant drop near the 200 ring, and both the measured and predicted values reflect the existence of this risk point, and the system triggers the warning function in time, which verifies the practicality of the risk intelligent warning module Sitaraman (2023) talks about the use of masked AI with edge computing in the IoT security system, where through the combination of homomorphic encryption and federated learning, privacy is not a problem and even

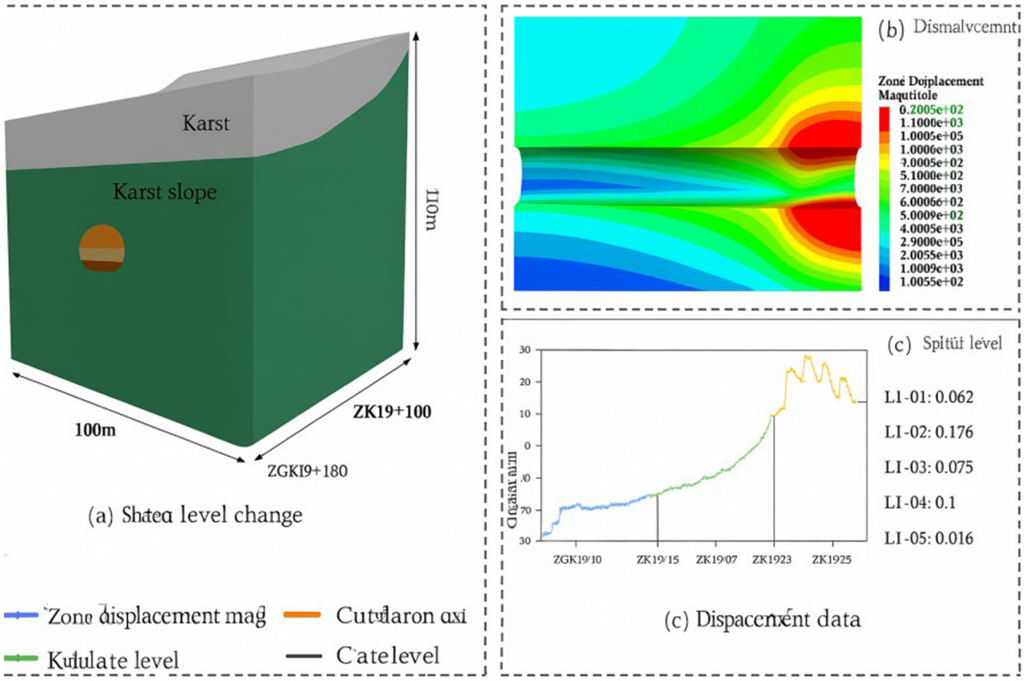

Fig. 12. ZK19+100 ~ ZK19+180 numerical simulation results.

decentralized systems perform well. So, the suggested approach developed a tunnel monitoring system that conveyed all these privacy-protection methods, AI included, which not only improved the security of sensor data but also made the risk assessment real-time and reliable without affecting the performance and security [29,30].

As shown in Table 3, under this scale of analysis, two specific indicators were selected for data collection and quantification: geological radar forecasting results and numerical simulation-based settlement predictions. These indicators are very important to indicate the geotechnical conditions of the tunnel and to predict its possible failure.

The application of FLAC 3D software allowed for the finite difference analysis of the numerical simulation of the 80-meter-long segment, which is located between ZK19 +100 and ZK19+180. The topographic contour of the tunnel face, the boundaries of geological stratification, and soil-rock parameters, which were obtained from the design documents and geotechnical study reports, were all considered during the model development. The excavation process in the simulation was a rigorous following of the actual construction sequence and used the three-step excavation method.

The 3D model arrangement, consisting of geological layers, excavation phases, and terrain geometry, is illustrated in Figure 12a. The related displacement cloud map after excavation is presented in Figure 12b, and the simulated deformation trend curve across monitoring sections is shown in Figure 12c. The simulation result was subsequently integrated into the quantitative evaluation system as a significant part of the predictive dimension within the multi-scale safety assessment framework. This approach allows for quicker engineering decisions and better forecasting of settlement problems.

Under this scale, a set of evaluation indicators with modifications has been selected and quantified through the combination of the geological forecasting data that was gathered while tunneling and the latter analysis. These parameters are very important for risk assessment and structural reaction forecasting in the context of the excavation face.

Data used for prediction, mostly obtained through advanced borehole logging, geological drilling, and ground-penetrating radar (GPR), are extremely important because they indicate the geographic position of fracture zones, less strong zones, and aquifers. Basically, it is necessary that some pre-excavation conditions be present in order to support real-time decision-making and to change excavation methods if needed.

The comprehensive list of the prognostic markers along with their quantifiable values is provided in Table 4 below. The data presented is important for evaluating construction safety codes and predicting risks that may arise in front of the tunnel face.

The field investigations of professionals, precise on-site monitoring, and permanent supervision at the four selected tunnel faces (including ZK19+104) together produced a sophisticated database of field-scale safety indicators. These data, representing the real geological response and structural behavior, are of utmost importance for estimation evaluations, validation, and updating of risk control measures.

Table 5 presents a summary of the specific field-measured indicators and their corresponding values at the scale of this excavation face. These values are based on the indicator framework established in Table 2. The data collected includes measurements of displacement, stress reactions, and the status of support structures;

Table 4. New finding-based estimands from ancient sources.

Indicator name	Measurement method	Value range or category	Engineering implication
Fracture Zone Width	Ground-Penetrating Radar	2.5–5.0 m	Indicates potential risk zones for collapse
Surrounding Rock Weathering Degree	Advanced Borehole Logging	Moderate to severe	Affects support structure design
Groundwater Enrichment Level	Forecast Borehole Water Test	Moderate (localized strong)	Risk of water inflow or gushing
Rock Mass Integrity (RQD)	Core Drilling (Forecast Hole)	40%–60%	Determines stability and excavation difficulty
Anomalous Reflection Zone Depth	GPR Longitudinal Section	8–12 m ahead of the tunnel face	Used to pre-locate weak rock layers or voids
Karst or Cavity Signal Strength	Electromagnetic Scanning	High intensity signal zone	Indicates possible hidden cavities or erosion areas

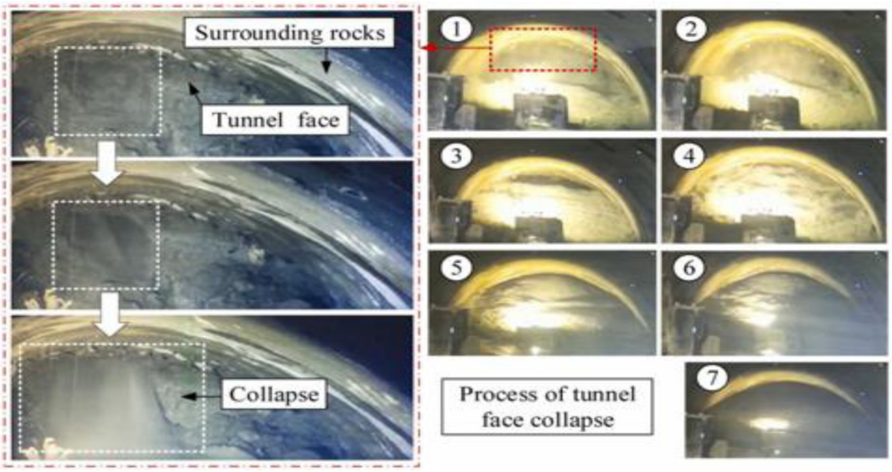

Fig. 13. Collapse process and monitoring effect of the tunnel palm face.

all these factors are considered and monitored in the safety assurance and real-time construction adjustment process.

Figure 13 records the effect of this paper's system in monitoring the whole process of tunnel palm face collapse during shield construction. The three figures on the left side show the continuous state of the tunnel's palm face before and after the collapse occurred, from the initial intact surrounding rock to the appearance of localized fissures, and then to the spalling and collapse of large pieces of surrounding rock. The system captures the subtle morphological changes in real time through video monitoring and 3D laser scanning. The seven figures on the right side clearly present the collapse process in a time sequence, with the whole process being fully recorded from the appearance of anomalies at the top of the surrounding rock (1) to the gradual expansion of the fissures (27). This event fully verifies the effectiveness of the intelligent monitoring system for tunnel construction based on IoT and digital twin proposed in this paper under extreme working conditions. The system obtains real-time signals of changes in the surrounding rock condition through the video monitoring module and stress deformation monitoring, and provides intelligent warnings through the remote data analysis platform, enabling the managers to detect the risks and take measures before the collapse occurs.

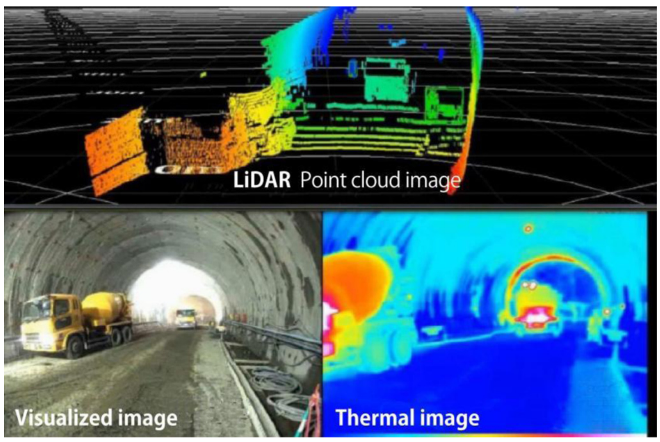

Fig. 14. Effect of multi-source sensing and monitoring of tunnel construction.

Figure 14 shows the multi-source sensing results of this paper's intelligent monitoring system at the tunnel construction site, including LiDAR point cloud images,

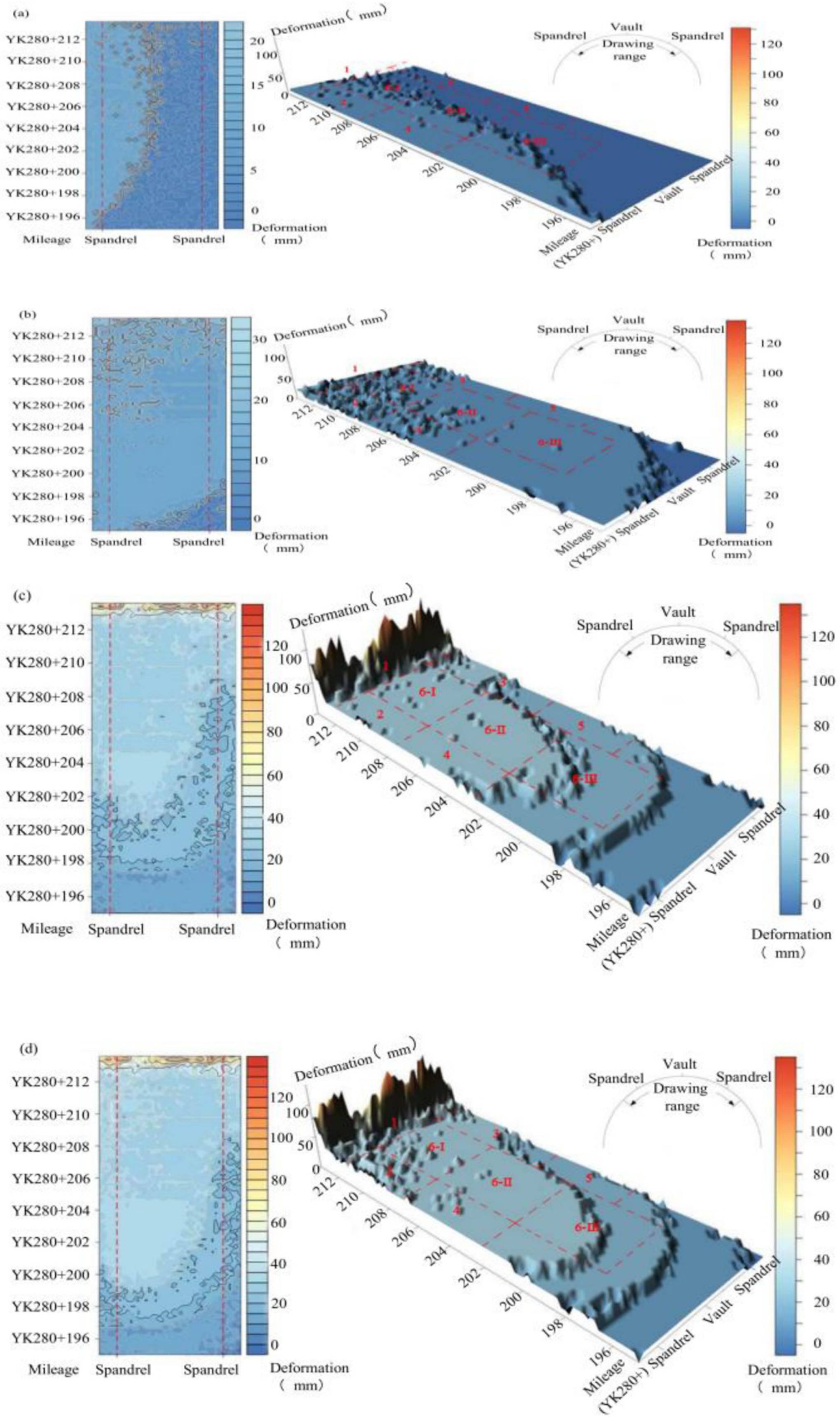

Fig. 15. 2D and 3D visualization of the deformation of the tunnel surrounding rock monitoring.

visualization images, and thermal imaging images. These three types of sensing results are obtained by the 3D LiDAR, HD visualization camera, and thermal infrared sensor integrated in the system, respectively, reflecting the advantages of the application of multi-sensor fusion monitoring in complex construction environments. The LiDAR point cloud at the top accurately captures the 3D coordinate information of the internal spatial structure of the tunnel and the construction equipment, which can generate the geometric contours of the tunnel section and construction vehicles in real time, and provide high-precision spatial data for the dynamic updating of the BIM digital twin model. The visualization image on the left side of the lower part visually reflects the real situation of the construction site, which supports the remote management to know the construction status and work progress in real time. The thermal imaging image on the right side shows the temperature distribution of the construction equipment and the surrounding environment, which can identify thermal anomalies, such as overheating of equipment or abnormal heating of local surrounding rocks, and provide an important basis for the prevention of risks such as fires and mechanical failures.

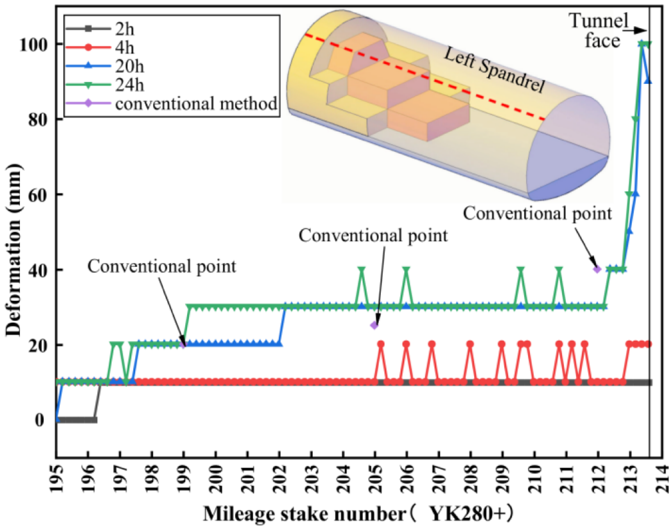

Fig. 16. Deformation of tunnel arch wall under different monitoring methods and time intervals.

Figure 15 shows the distribution of perimeter rock and lining deformation in the tunnel interval YK280+196 to YK280+212 at different monitoring stages, which is presented as a combination of a 2D planar contour map and a 3D visualization map. The color gradient in the graph increases from blue (0 mm) to red (>120 mm), reflecting the degree of deformation at different locations. With the data collected by the IoT sensing network, combined with 3D laser scanning and BIM digital twin technology, the system in this paper achieves high-precision deformation quantification and spatial modeling. From (a) and (b), it can be seen that the tunnel vault (Vault) and part of the sidewalls (Spandrel) are slightly displaced in the early stage, and the maximum deformation is controlled within 30 mm, with good overall stability. With the advancement of construction, as shown in (c) and (d), the vault area gradually shows significant displacement, with local deformation exceeding 100 mm, reducing the stability of the surrounding rock and significantly increasing the risk level. Through the three-dimensional model, it can be visually observed that the high deformation is concentrated in the location of the arch top and the two sides of the wall footing, presenting a local collapse trend. The intelligent monitoring system proposed in this paper not only accurately captures the spatial distribution characteristics of deformation development by using real-time data fusion and three-dimensional visualization, but also identifies the high-risk areas in time through the risk assessment module.

Figure 16 shows the comparison of the deformation monitoring results between this system and the traditional monitoring method at different time intervals (2 h, 4 h, 20 h, 24 h) in the area of the left arch wall (Left Spandrel) of the tunnel. The horizontal axis is the mileage pile number (YK280+), and the vertical axis is the deformation of the corresponding position (mm). The different color curves in the figure represent the data acquired by the system under 2 h, 4 h, 20 h, and 24 h cycles, respectively, while the purple markers represent the discrete point results measured by the traditional method. The results show that the traditional method can only obtain deformation data at limited mileage points, which cannot reflect the continuity of deformation and the dynamic evolution process; whereas the intelligent monitoring system in this paper realizes the continuous monitoring of the whole cross-section and the whole time scale. As can be seen from the curve changes, in the 195212-pile section, the 4 h monitoring data successfully captured multiple local deformation fluctuations, while the traditional monitoring only recorded isolated deformation points in this section, which missed the subtle risk signals. Most notably, at the location close to the palm face (pile section 213~214), the 20 h curve of this paper's system captures the high-risk point where the deformation rises sharply by more than 100 mm, which is much earlier than the hysteresis response of traditional monitoring.

Figure 17 shows the monitoring results of peripheral rock deformation from YK280+212 to YK280+248 at different dates; the curve color represents different monitoring dates, the horizontal axis is the mileage pile number, and the vertical axis is the corresponding deformation amount (mm). The monitoring direction is arranged along the digging direction, which reflects the time sequence evolution of deformation during the construction advancement. From the trend of curve changes, it can be seen that as the construction date advances (December 7 to January 9), the deformation range and amplitude gradually expand, and the high deformation zone gradually moves forward. In the early stage (12/0712/27), the high deformation area extends to the vicinity of YK280+230, and reaches 400 mm in some locations; in the late stage (12/29~01/09), there is a wide range of cumulative deformation, and the deformation of the section from YK280+236 to YK280+242 is close to or more than 500 mm, which indicates that the stability of the surrounding rock is drastically reduced.

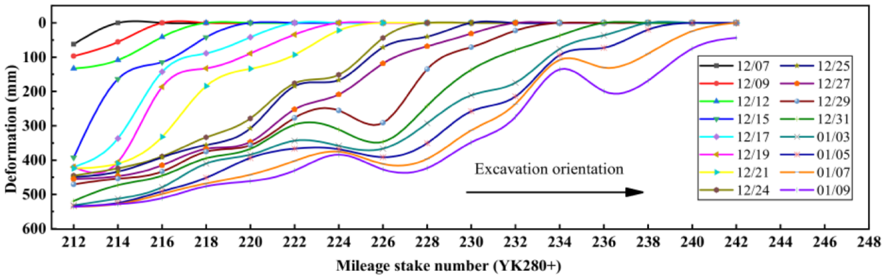

Fig. 17. Temporal evolution curve of deformation of the tunnel surrounding rock under different monitoring dates.

Table 5. Quantitative indicators collected from tunnel faces (e.g., ZK19+104).

Indicator name	Measurement method	Typical value range	Engineering implication
Vault Settlement	Automatic Leveling + Invert Monitoring	6.3–9.1 mm	Reflects vertical deformation post-excavation
Peripheral Convergence	Convergence Gauge	4.8 − 7.5 mm	Indicates lateral deformation and lining stress risk
Deep Displacement (Rock Mass)	Borehole Inclinometer	3.2 − 6.0 mm	Assesses deep structural response and slope tendency
Primary Support Load	Stress Sensor on Steel Frame	72 − 105 kN	Evaluates support system effectiveness
Face Stability Rating (Expert Review)	Field Evaluation + Classification	Stable / Moderately Weak	Used for the excavation strategy adjustment
Water Seepage Observation	Field Visual Inspection + Weep Hole Data	Localized wetting	Signals a need for drainage or waterproofing measures

5 Conclusion

The IoT+Digital Twin Tunnel Intelligent Monitoring System proposed in this paper realizes multi-source information fusion, BIM dynamic modeling, and risk intelligent early warning, which overcomes the shortcomings of traditional methods in terms of real-time, accuracy, and prediction ability. Experimental results show that the system maintains high stability and reliability under complex geological conditions, and is able to continuously track perimeter rock deformation, identify high-risk areas in advance, and capture precursors of disasters such as instability of the palm face, realizing accurate early warning and rapid response. The system significantly improves the safety control level of the whole process of tunnel construction, and has broad engineering application potential. The difficulties encountered in the actual construction of tunnels greatly affect the performance of the sensing equipment installed, which is subjected to high humidity, heavy dust, vibrations, and poor lighting conditions. The optical and electrical sensor measurements, thus, might not be so stable and reliable at a later time. Regular calibrations are necessary to correct drifts caused by hardware aging and environmental factors. In the next installations, the best industrial environmental controls, such as dust-proof cabinets, moisture-proof seals, and fog-free lenses, will be used to guarantee that the system is always available. In addition, field validation research will be performed to evaluate and measure the important factors of robustness, such as mean-time-to-failure (MTTF), accuracy decline during long-term use, and calibration intervals, which are all crucial for delivering reliable performance in true tunnel conditions. The system will provide many ways to minimize the adverse effect of the environment on sensor performance. To stop the deterioration of the optical and electrical sensors, fog-free lenses, moisture-proof seals, and dust-proof cabinets will be used. Besides, the sensors will be recalibrated periodically to eliminate any drift caused by the environment or aging. Environmental shields of industrial strength will be installed on the system, which will make it endure for a long time and will, thus, allow accurate and continuous monitoring of the system even in harsh conditions. The real-time tunnel setting will derive huge benefits in terms of sensor reliability and data accuracy from these changes. Future research will optimize the data fusion and prediction algorithms and expand their application in complex projects such as mine tunneling and urban underground space.

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The Authors do not have any conflicts.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author contribution statement

Canxin Huang, Liangpeng Wan, and Guangyi Shi are responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Huixiang Sun, Jun Wang, and Chong Zhang are responsible for collecting the information required for the framework, providing software, critical review, and administering the process.

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