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Research Article

A Dynamic Risk Assessment Method for Deep-Buried Tunnels Based on a Bayesian Network

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In view of the shortcomings in the risk assessment of deep-buried tunnels, a dynamic risk assessment method based on a Bayesian network is proposed. According to case statistics, a total of 12 specific risk rating factors are obtained and divided into three types: objective factors, subjective factors, and monitoring factors. The grading criteria of the risk rating factors are determined, and a dynamic risk rating system is established. A Bayesian network based on this system is constructed by expert knowledge and historical data. The nodes in the Bayesian network are in one-to-one correspondence with the three types of influencing factors, and the probability distribution is determined. Posterior probabilistic and sensitivity analyses are carried out, and the results show that the main influencing factors obtained by the two methods are basically the same. The constructed dynamic risk assessment model is most affected by the objective factor rating and monitoring factor rating, followed by the subjective factor rating. The dynamic risk rating is mainly affected by the surrounding rock level among the objective factors, construction management among the subjective factors, and arch crown convergence and side wall displacement among the monitoring factors. The dynamic risk assessment method based on the Bayesian network is applied to the No. 3 inclined shaft of the Humaling tunnel. According to the adjustment of the monitoring data and geological conditions, the dynamic risk rating probability of level I greatly decreased from 81.7% to 33.8%, the probability of level II significantly increased from 12.3% to 34.0%, and the probability of level III increased from 5.95% to 32.2%, which indicates that the risk level has risen sharply. The results show that this method can effectively predict the risk level during tunnel construction.

1. Introduction

With the growth of China's economy, the demand for infrastructure such as railways is increasing, especially in western China. According to statistics, at the end of 2019, 16084 railway tunnels were in operation, with a total length of 18041 km, and 2950 tunnels were under construction with a total length of 6374 km [1]. Due to the growth in the scale of construction, an increasing number of deep-buried tunnels have been excavated in western China. The construction of a deep-buried tunnel is a systematic project with complex process, multifactor, and multirisk characteristics. Frequent accidents occur during the construction process. Therefore, it is necessary to carry out risk management in the construction stage of deep-buried tunnels.

Scholars worldwide have carried out many studies of risk assessments in tunnel and underground engineering. Common risk assessment methods include fault tree analysis (FTA) [2–5], event tree analysis (ETA) [6], Monte Carlo (MC) simulation [7, 8], the analytic hierarchy process (AHP) [4], the analytic network process (ANP) [9], fuzzy sets [10, 11], and numerical simulation [12, 13]. However, most risk assessment methods are based on static data calculations, and a few dynamic assessment methods are based only on regularly checking risk analysis results, modifying controls according to different risk situations, or tracking by risk event registration, and these methods are essentially static risk analyses.

Many scholars have made various attempts to perform dynamic risk analysis in tunnel construction. Spackova

et al. [14] introduced a new quantitative model for the prediction of a tunnel construction risk rate. The model takes into account the variability of the failure rate in different sections of the tunnel, depending on changes in geotechnical conditions. The accuracy of the prediction depends on the accuracy of the geological survey report, so this model is often not accurate enough in field applications. Zhang et al. [15] proposed a new assessment method based on case-based reasoning, advanced geological prediction, and rough set theory. In this method, a geological prediction based on the surrounding rock ahead of the tunnel face is analyzed. However, attribute reduction is needed to obtain the prediction, and the attribute reduction is obtained manually from similar cases and is therefore highly subjective. In contrast to previous risk assessment methods using the two parameters of consequence and likelihood, Fouladgar et al. [16] proposed a three-parameter method that takes into account the influence parameters. However, some of the parameters conflict with each other. Although fuzzy sets are adopted, vague and uncertain problems still cannot be solved well. Nyvlt et al. [17] introduced the concept of risk analysis in the scope of risk management and employed methods well known in the aeronautics and aircraft industry. In fact, this method is still an improvement of fault tree analysis and is mainly applied to choose sound and cost-effective solutions.

Since most risk assessment methods can only be used for qualitative or semiquantitative risk estimation, it is difficult to accurately reflect the risk level. A Bayesian network probability model has great advantages for solving events caused by event uncertainty and correlation [18, 19]. In recent years, with the development of tunnel engineering risk management, many scholars have introduced Bayesian networks into risk assessment and conducted a large amount of research. A method for systematically assessing and managing the risks associated with tunnel construction was described by Sousa and Einstein [20]. The method includes a combination of a geological prediction model that allows prediction of geology before tunnel construction and a construction strategy decision model that allows selection of the construction strategy that leads to the least risk. Both models are based on Bayesian networks. However, this method was only applied during the verification process after a case accident happened. Spackova and Straub [21], Wu et al. [22, 23], and Sun et al. [24] introduced a dynamic Bayesian network to quantify uncertainty in a tunnel construction process. A fuzzy Bayesian network-based approach for safety risk analysis was developed by Zhang et al. [25] to perform safety analysis of underground-buried pipelines adjacent to the construction of an underwater tunnel. Feng and Jimenez [26] presented a novel application of Bayesian networks to predict tunnel squeezing caused by creep. However, only five design indicators were considered in this method, and site construction was not considered. Gerassis et al. [27] presented a methodology for safety prioritization in tunnel construction based on Bayesian analysis of data from occupational accidents recorded in recent years. However, this method has not been verified by engineering.

Although some scholars have carried out research on the application of Bayesian networks in tunnel construction risk assessment, many shortcomings remain in prior probability acquisition, model construction, and engineering verification. In addition, the current literature does not have a Bayesian network estimation model to assess the risks of constructing deep-buried tunnels. In view of the shortcomings of dynamic risk analysis, this paper proposes a dynamic risk rating method based on a Bayesian network for deep-buried tunnel construction and constructs a dynamic risk rating system. This method divides the dynamic risk level of tunnel construction into three parts: objective factor level, subjective factor level, and monitoring factor level. By classifying the three types of risk factors of deep-buried tunnel construction, different types of risk factors can be considered in detail. In the past, tunnel construction risk assessment usually regarded each risk factor as a separate factor variable, and this approach not only did not take into account the complex uncertainties and interactions between risk factors but could also not achieve true quantitative and dynamic ratings. According to the specific conditions of tunnel construction, the specific parameters of the three types of factors are graded according to certain rules, and a dynamic risk rating system structure is constructed; then, the Bayesian network structure is obtained. The nodes of the Bayesian network are determined according to the selection of various factors. The node ranges are determined according to factor grading standards. The probability distribution of a node range is determined by historical statistical data and expert experience. Finally, the comprehensive risk rating is calculated based on the three factor levels by the Bayesian network. Dynamic risk ratings are achieved based on feedback from monitoring data as construction progresses.

2. Establishment of Dynamic Risk Rating System

According to the incomplete statistics of tunnel construction accident data, a large number of accident risk sources are obtained [28, 29]. The risk sources include subway factors and natural factors, including construction management, survey, design, construction quality, geological conditions, and other risk sources. According to the risk sources obtained from the accident statistics, there are 12 risk indicators for deep-buried tunnels: section size, construction method, tunnel depth, surrounding rock level, groundwater, mud inrush, prereinforcement effects, support timing, support strength, construction quality, construction experience, and construction management. Therefore, according to the attributes of the different risk sources, the risk rating factors are divided into three categories, namely, objective factors, subjective factors, and monitoring factors, according to the risk level of the three factors, and the final risk level is determined.

2.1. Risk Rating Factors and Grading Criteria

2.1.1. Objective Factors. Objective factors refer to the influencing factors related to the tunnel itself, mainly based on natural factors and objective conditions, including section size, construction method, tunnel depth, surrounding rock level, groundwater, and mud inrush.

2.1.2. Subjective Factors. Subjective factors refer to the factors that are related to people and influenced by their subjective state in the construction of deep-buried tunnels. The subjective factors in the construction stage include many aspects, and when considering the risks to construction, we should focus on selecting the factors that have a greater impact on the degree of risk. The subjective factors are mainly reflected in the following aspects: prereinforcement effect, support timing, support strength, construction quality, construction experience, and construction management.

2.1.3. Monitoring Factors. In the construction of deep-buried tunnels, monitoring and measurement are the main basis for testing design parameters, assessing rock stability, and evaluating construction methods. In addition to geological surveys and tests during the predesign stage before the construction of deep-buried tunnels, it is also necessary to monitor the entire construction process, that is, to test the changes in the surrounding rock and ground settlement by manual observation and various instruments and to assess the appearance and mechanical changes in the supports. The monitoring factors selected in this paper include inner-tunnel observation, arch crown convergence, and side wall displacement.

Based on the above analysis, the three types of risk rating factors are selected as shown in Table 1.

According to construction experience, the different types of factors are classified, each of which is divided into 2 to 5 different levels. In particular, the allowable relative displacement and deformation management level standards of arch crown convergence and side wall displacement are determined by reference to Code for Shotcrete-Bolt Construction Method of Railway Tunnel (TB 10108-2002) [30], as shown in Tables 2 and 3, respectively. Therefore, the final grading criteria for the three types of risk rating factors are shown in Table 4.

2.2. Establishment of Risk Factor Rating System. Building a reasonable dynamic risk rating system is a prerequisite for dynamic risk rating. The objective factors, subjective factors, and monitoring factors are combined to comprehensively consider the impacts of the three types of factors on deep-buried tunnel construction. First, according to the construction process, the three types of factors are self-rated, and the final risk level is determined according to the obtained self-ratings. As construction progresses, the monitoring factor level changes as the monitoring data change. Therefore, it is possible to achieve a dynamic risk level integrated with the objective factor level and the subjective factor level through changes in the monitoring factor level. The three types of risk factor rating systems are shown in Figure 1, Figure 2, and Figure 3.

According to the three types of risk factor rating systems, a comprehensive dynamic risk rating system is constructed, as shown in Figure 4.

The comprehensive tunnel dynamic risk rating is divided into three levels: I, II, and III. The risk level description and response suggestions are shown in Table 5. As construction progresses, when the probability of a certain level

TABLE 1: Risk rating factors.

Factor category	Factor selection
Objective factors	Section size, construction method, tunnel depth, surrounding rock level, groundwater, mud inrush
Subjective factors	Prereinforcement effect, support timing, support strength, construction quality, construction experience, construction management
Monitoring factors	Inner-tunnel observation, arch crown convergence, side wall displacement

TABLE 2: Allowable relative displacement (%).

Surrounding rock level	Tunnel depth (m)		
	<50	50~300	>300
III	0.10~0.30	0.20~0.50	0.40~1.20
IV	0.15~0.50	0.40~1.20	0.80~2.00
V	0.20~0.80	0.60~1.60	1.00~3.00

The relative displacement value refers to the ratio of the measured displacement to the distance between two measuring points or the ratio of the measured value of the arch crown convergence to the height of the tunnel.

TABLE 3: Deformation management level standard.

Management level	Management of displacement	Construction status
III	$U_0 < (1/3)U_n$	Normal
II	$(1/3)U_n < U_0 < (2/3)U_n$	Monitoring strengthening
I	$U_0 > (2/3)U_n$	Take measures in time or stop work

U_0: measured deformation value; U_n: allowable deformation value.

drops sharply or increases significantly, measures including shutdown should be considered. When the probability of each level changes little, the construction risk status is relatively stable.

3. Bayesian Network Construction

3.1. Background of Bayesian Network. A Bayesian network, which is also known as a belief network, is a probabilistic graphical model that represents a set of variables $\{X_1, X_2, \cdots, X_3\}$ and their conditional probability distributions via a directed acyclic graph (DAG) [31]. Bayesian networks aim to model conditional dependence, and therefore causation, by representing conditional dependence by edges in a directed graph. With these relationships, a person can efficiently conduct inference on the random variables in the graph via the use of factors. The nodes in the directed acyclic graph of the Bayesian networks represent random variables, which can be observable variables, hidden variables, or unknown parameters. The arrows that connect the two nodes

TABLE 4: Risk rating factors grading criteria.

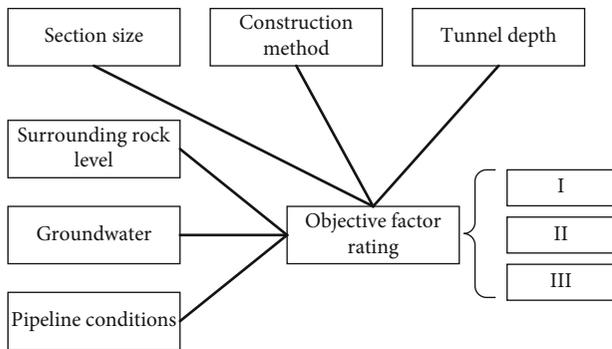| Factors		Grading			
Objective factors	Section size	Medium		Large	
	Construction method	Center diagram (CD) method	Bench cut method (BCM)	Ring cut method (RCM)	Full face excavation method (FFEM)	Center cross diagram (CRD) method
	Tunnel depth	<15 m		15~25 m	>25 m
	Surrounding rock level	IV		V	VI
	Groundwater	No water		Water leaking	Water gushing
	Mud inrush	No mud		Mud leaking	Mud inrush
Subjective factors	Prereinforcement effects	Good		Medium	Poor
	Support timing	In time			Late
	Construction quality	Good		Medium	Poor
	Construction experience	Well experienced		Medium	Inexperienced
	Construction management	Strict		Medium	Poor
	Support strength	High		Medium	Low
Monitoring factors	Inner-tunnel observation	Normal		Slight cracks	Slip off
	Arch crown convergence	III		II	I
	Side wall displacement	III		II	I

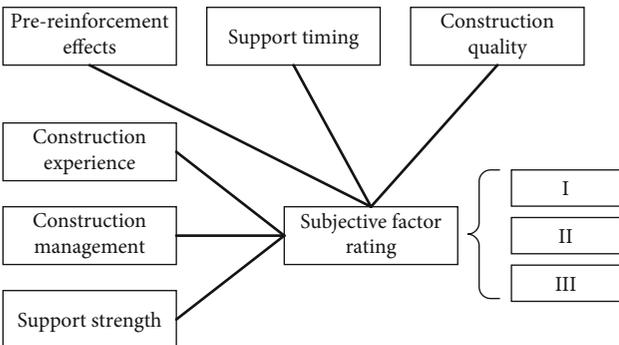FIGURE 1: Objective factor rating system.

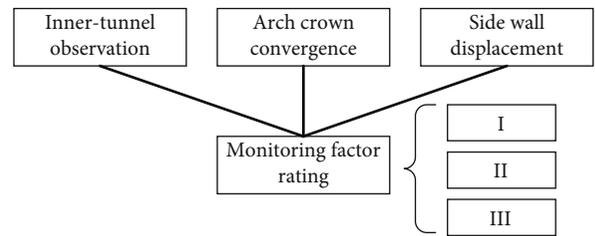FIGURE 2: Subjective factor rating system.
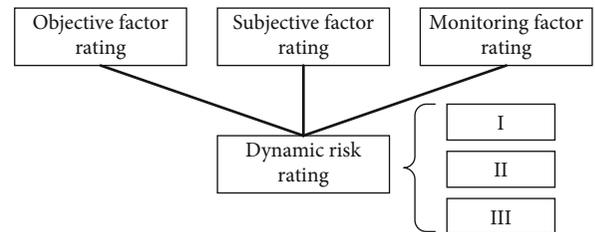

FIGURE 3: Monitoring factor rating system.

FIGURE 4: Dynamic risk rating system.

represent whether the two random variables are causally or unconditionally independent, and if no arrows are connected between the two nodes, the random variables are considered conditionally independent. If two nodes are connected by a single arrow, it means that one of the nodes represents the "parents," the other node represents the "descendants or children," and the two nodes will produce a conditional

TABLE 5: Dynamic risk rating description.

	Risk rating		
	I	II	III
Risk description	Low	Medium	High
Suggestions	Normal construction is allowable	Monitoring and support should be strengthened in time	Should stop work immediately and take measures

probability value. In a directed acyclic graph, node A points to node B, that is, A → B means that node B is affected by node A. Node A is referred to as the parent node and node B is referred to as the Child node. All parent and child nodes related to a same node are collectively called the neighbor nodes. In particular, if a node has only a child node and no parent node, the node is referred to as the root node. The value of each node in the Bayesian network is based on its neighbor node and is independent of other nonneighbor nodes. Since the probability of the root node is independent of other nodes, the probability distribution of the root node is referred to as a priori probability, and the probability distribution of other nodes is based on the probability of the root node. Figure 5 shows a typical Bayesian network structure, where X_i represents the i-th node, and X_i's cause as P_i, and X_i's result as C_i. According to this definition, we can obtain $P_2 = \{X_4, X_5\}$, $C_4 = \{X_2, X_5\}$, $P_5 = \{X_4, X_5\}$, and $C_5 = \{X_2\}$. Typically, a conditional probability table is written according to the conditional probability, and the total probability of each row of the conditional probability table is equal to 1.

Let $G = (I, E)$ represent a directed acyclic graph, where I represents the set of all nodes in the graph, and E represents the set of all directed connected segments. Let $X = (X_i)_{i \in I}$ be a random variable represented by node i in the directed acyclic graph. If the probability distribution of node X can be expressed as

$$p(x) = \prod_{i \in I} p\left(x_i \mid x_{pa(i)}\right), \tag{1}$$

then X is referred to as the Bayesian network relative to the directed acyclic graph G, where $pa(i)$ represents the cause of the node. According to Equation (1), the joint probability distribution of the Bayesian network can be written as follows:

$$P(X_1 = x_1, \cdots, X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i \mid X_j = x_j). \tag{2}$$

Bayesian networks are applied in the field of uncertainty analysis because of their strong mathematical reasoning and computational abilities and the use of graphics to visually express the characteristics of model calculation results. The construction of a Bayesian network is a systematic and complex process in which the selection of nodes and node ranges and the probability distribution of nodes are keys to whether Bayesian network construction is reasonable.

3.2. Steps to Construct a Bayesian Network. There are three ways to build a Bayesian network [32]: (i) based on expert knowledge, (ii) data self-learning, and (iii) combining the above two approaches. Overreliance on expert knowledge leads to excessive subjectivity, and a Bayesian network that is built entirely by self-learning from a database requires very large amounts of data, which are not often readily available or well qualified. By combining these two ways to build a Bayesian network, the advantages of the two ways can be used. The network structure is built based on expert knowledge, and the probability distribution is constructed according to data; this approach not only utilizes the efficiency of data self-learning but also avoids the redundancy of nodes and structural confusion. Data self-learning mainly comes from previous case statistics. The Bayesian network construction process is shown in Figure 6.

3.3. Determining the Nodes and Node Ranges of the Bayesian Network. According to the dynamic risk rating system of urban subway tunnel construction established above, the three types of influencing factors in the system are in one-to-one correspondence with the nodes of the Bayesian network structure. The root nodes represent each risk factor, including (A1) section size, (A2) construction method, (A3) tunnel depth, (A4) surrounding rock level, (A5) groundwater, (A6) mud inrush, (A7) prereinforcement effects, (A8) support timing, (A9) construction quality, (A10) construction experience, (A11) construction management, (A12) support strength, (A13) inner-tunnel observation, (A14) arch crown convergence, and (A15) side wall displacement. The three types of factor ratings are used as middle nodes, namely, (B1) objective factor rating, (B2) subjective factor rating, and (B3) monitoring factor rating. The target node is the final dynamic risk rating (C1). Each node range corresponds to the factor grading in the risk factor rating system. The specific nodes and node ranges are shown in Table 6.

3.4. Determining the Probability Distribution. There are two main methods to determine the probability distribution, namely, through historical data statistics and through expert experience. Both methods have shortcomings. The approach based on historical data and statistics requires large amounts of data as a prerequisite. Due to limited conditions, there may be incomplete data or deviations. In addition, it is heavy work to perform data processing, classification, and collation. Some probabilities are difficult to quantify and cannot be fully used. However, according to expert experience, the probability distribution is determined by the length of time and authority of experts in the field. Due to the varying experience and conservatism of different experts, this method is prone to greater subjectivity. Even if expert experience is

X_4	0	1
Prob.	0.4	0.6

X_5		
	0	1
X_4 0	0.32	0.68
1	0.54	0.46

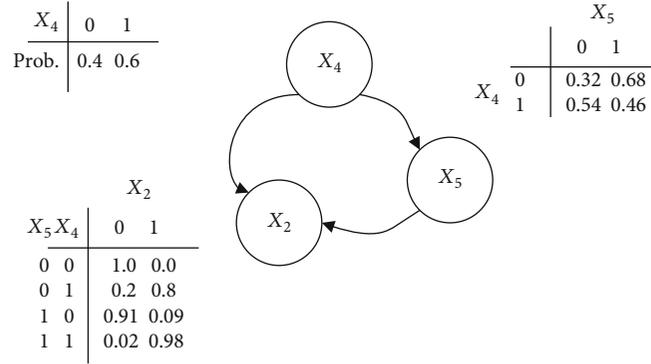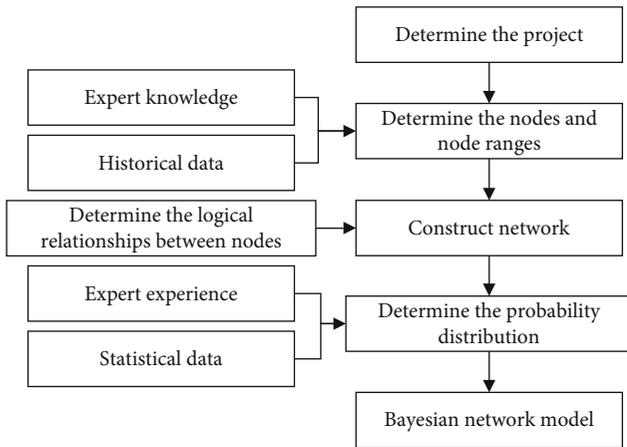| X_2		
X_5 X_4	0	1
0 0	1.0	0.0
0 1	0.2	0.8
1 0	0.91	0.09
1 1	0.02	0.98

FIGURE 5: Bayesian network.

FIGURE 6: Bayesian network construction process.

obtained, it should be corrected according to the actual situation. This method is often used when data acquisition is difficult or when the amount of data is small. Therefore, this paper adopts a combination of two methods: the learning and entry functions of Netica software are used to help complete the determination of the probability distribution based on previous statistical data combined with expert experience.

3.5. Determining the Bayesian Network.

The dynamic risk rating Bayesian network is constructed according to the nodes, node ranges, and dynamic risk rating system determined above. The risk factors (A1, A2, A3…A15) are root nodes, the three types of risk ratings (B1, B2, B3) are middle nodes, and the comprehensive dynamic risk rating (C1) is the target node. Using the Bayesian network, the comprehensive dynamic risk rating under different risk factors is visually displayed in the form of graphs and data.

First, according to the dynamic risk rating system, the three types of risk factors are taken as the parent nodes, and the three types of risk factor ratings are taken as child nodes to construct their own risk rating networks. Second, the three types of risk ratings are taken as the parent nodes, and the dynamic risk rating is taken as the child node. The three types of risk rating networks are integrated to build a comprehensive dynamic risk rating network structure as shown in Figure 7.

Netica is a graphical Bayesian network software that can quickly realize the construction of a Bayesian network and can determine the probability distribution according to the case data. This software also allows input of the probability distribution by expert knowledge [26]. This paper uses Netica to determine the probability distribution based on the established dynamic risk rating network structure combined with historical data and expert knowledge. The dynamic risk rating Bayesian network structure model is shown in Figure 8. The numbers in the figure are probabilities, and the black bars indicate the magnitudes of the probabilities.

As shown in Figure 7, under the current conditions and probability distribution, the objective factor rating probabilities of levels I, II, and III are 81.3%, 12.2%, and 6.43%, respectively; the subjective factor rating probabilities of levels I, II, and III are 78.2%, 13.8%, and 7.93%, respectively; the monitoring factor rating probabilities of levels I, II, and III are 71.2%, 21.0%, and 7.76%, respectively; and the dynamic risk rating probabilities of levels I, II, and III are 80.6%, 12.8%, and 6.57%, respectively. The descriptions and response recommendations for levels I, II, and III of the dynamic risk rating are described in Table 5.

3.6. Model Application.

According to the established Bayesian network structure model, the logical relationships between nodes can be explored, and logical reasoning can be carried out. There are many data analysis tools in Netica, including posterior probabilistic analysis and sensitivity analysis. Using these tools, the probability results under different node states can be calculated.

3.6.1. Posterior Probabilistic Analysis.

The posterior probability calculation can be performed using the Bayesian network. The so-called posterior probability refers to the recorrection probability after obtaining result information and is the result of the cause-seeking problem. In other words, it is the probability of a certain situation when an event actually occurred under the original probability distribution. Both results and reasons can be predicted through the constructed model.

(1) Result Prediction. The objective factor, subjective factor, and monitoring factor ratings are changed separately, and the dynamic risk rating is calculated.

TABLE 6: Nodes and node ranges.

| Nodes	Node range				
A1 section size	Medium			Large	
A2 construction method	Center diagram method (CD)	Bench cut method (BCM)	Ring cut method (RCM)	Full face excavation method (FFEM)	Center cross diagram method (CRD)
A3 tunnel depth	<15 m		15~25 m	>25 m	
A4 surrounding rock level	IV		V	VI	
A5 groundwater	No water		Water leaking	Water gushing	
A6 mud inrush	No mud		Mud leaking	Mud inrush	
A7 prereinforcement effects	Good		Medium	Poor	
A8 support timing	In time			Late	
A9 construction quality	Good		Medium	Poor	
A10 construction experience	Well experienced		Medium	Inexperienced	
A11 construction management	Strict		Medium	Poor	
A12 support strength	High		Medium	Low	
A13 inner-tunnel observation	Normal		Slight cracks	Slip off	
A14 arch crown convergence	III		II	I	
A15 side wall displacement	III		II	I	
B1 objective factor rating	I		II	III	
B2 subjective factor rating	I		II	III	
B3 monitoring factor rating	I		II	III	
C1 dynamic risk rating	I		II	III	
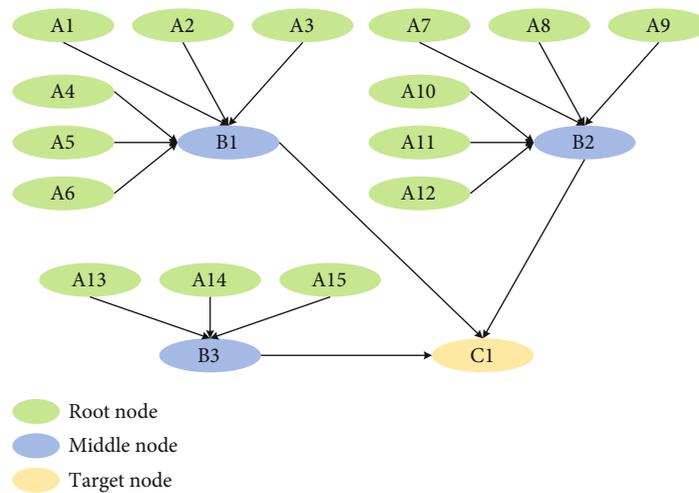
FIGURE 7: Dynamic risk rating network structure for tunnel construction.

(1) Different objective factor ratings

When the objective factor rating is fixed at level I, the level I probability of the dynamic risk rating increases from 80.6% to 86.7%, the level II probability decreases from 12.8% to 9.30%, and the level III probability decreases from 6.57% to 3.95%. When the objective factor rating is fixed at level II, the level I probability of the dynamic risk rating decreases from 80.6% to 62.4%, the level II probability increases from 12.8% to 24.9%, and the level III probability increases from 6.57% to 12.7%. When the objective factor rating is fixed at level III, the level I probability of the dynamic risk rating sharply decreases from 80.6% to 37.8%, the level II probability increases from 12.8% to 34.1%, and the level III probability significantly increases from 6.57% to 28.1%. These probability changes are shown in Figure 9.

(2) Different subjective factor ratings

When the subjective factor rating is fixed at level I, the level I probability of the dynamic risk rating increases from 80.6% to 87.1%, the level II probability decreases from 12.8% to 8.87%, and the level III probability decreases from
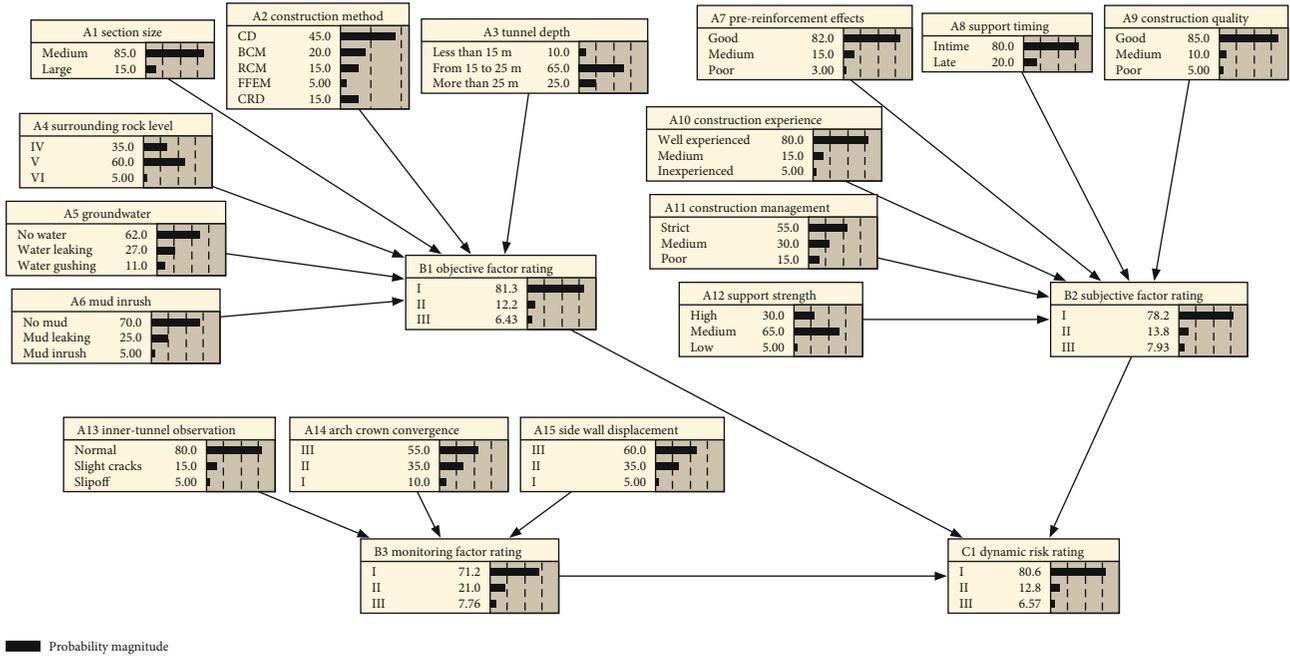
Figure 8: Dynamic risk rating Bayesian network structure model for tunnel construction.
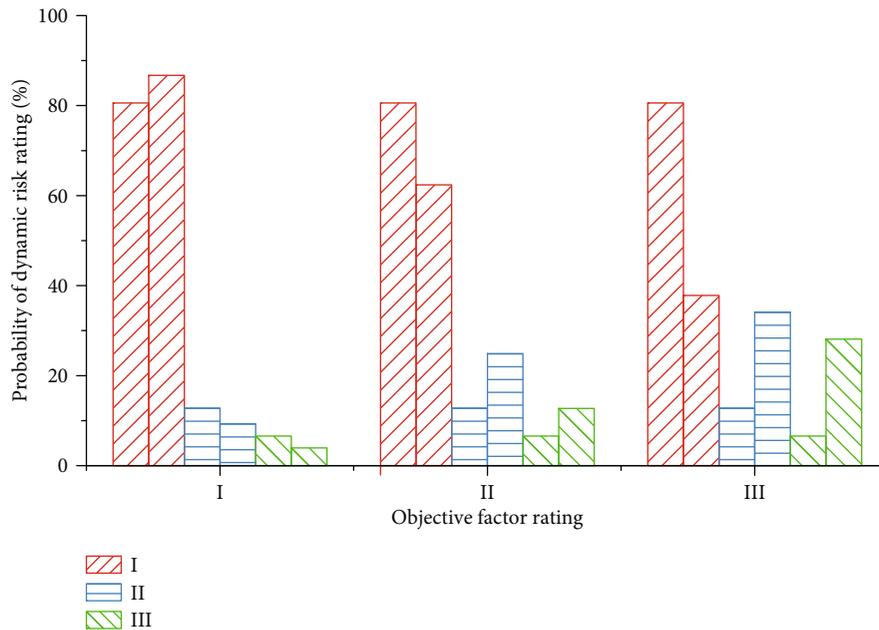

Figure 9: Probability changes with different objective factor ratings.

6.57% to 4.04%. When the subjective factor rating is fixed at level II, the level I probability of the dynamic risk rating decreases from 80.6% to 63.1%, the level II probability increases from 12.8% to 24.2%, and the level III probability increases from 6.57% to 12.7%. When the subjective factor rating is fixed at level III, the level I probability of the dynamic risk rating sharply decreases from 80.6% to 47.4%, the level II probability increases from 12.8% to 31.8%, and the level III probability increases from 6.57% to 20.8%. These probability changes are shown in Figure 10.

(3) Different monitoring factor ratings

When the monitoring factor rating is fixed at level I, the level I probability of the dynamic risk rating increases from 80.6% to 88.6%, the level II probability decreases from 12.8% to 7.81%, and the level III probability decreases from 6.57% to 3.57%. When the monitoring factor rating is fixed at level II, the level I probability of the dynamic risk rating decreases from 80.6% to 65.1%, the level II probability increases from 12.8% to 23.1%, and the level III probability
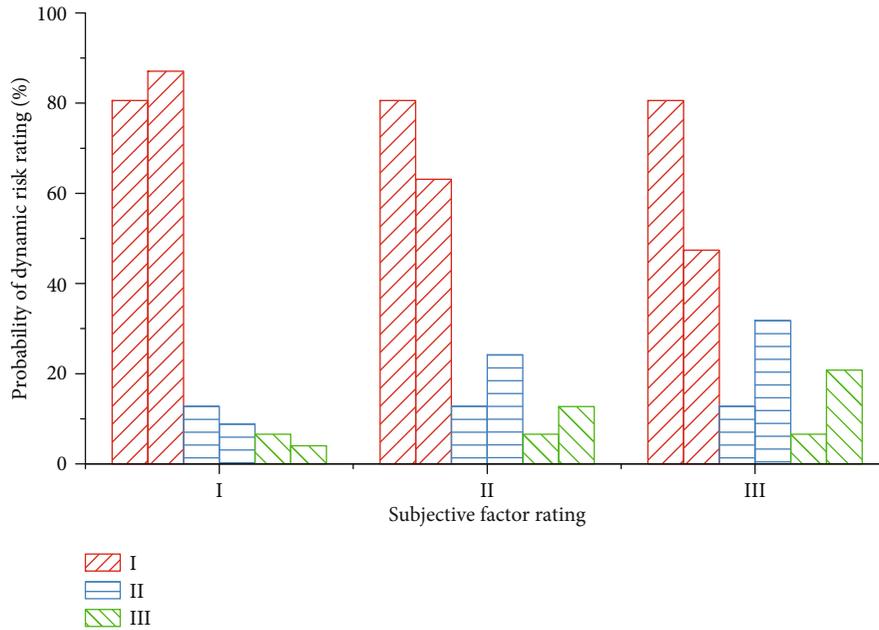
FIGURE 10: Probability changes with different subjective factor ratings.

increases from 6.57% to 11.8%. When the monitoring factor rating is fixed at level III, the level I probability of the dynamic risk rating sharply decreases from 80.6% to 49.3%, the level II probability increases from 12.8% to 30.7%, and the level III probability increases from 6.57% to 19.9%. These probability changes are shown in Figure 11.

(2) Reason Prediction. A node status can be calculated by the Bayesian network under different dynamic risk ratings according to the original model when the target node of the dynamic risk rating is fixed. When the dynamic risk rating is fixed at level I, the ratings of the three types of factors do not change much, and this effect is related to the original model node state. When the dynamic risk rating is fixed at level II, the level I probability of the objective factor rating decreases from 81.3% to 59.1%, the level II probability increases from 12.2% to 23.8%, and the level III probability increases from 6.43% to 17.1%; the level I probability of the subjective factor rating decreases from 78.2% to 54.2%, the level II probability increases from 13.8% to 26.1%, and the level III probability increases from 7.93% to 19.7%; and the level I probability of the monitoring factor rating decreases from 71.2% to 43.4%, the level II probability increases from 21.0% to 37.9%, and the level III probability increases from 7.76% to 18.6%. When the dynamic risk rating is fixed at level III, the level I probability of the objective factor rating decreases from 81.3% to 48.9%, the level II probability increases from 12.2% to 23.5%, and the level III probability increases from 6.43% to 27.5%; the level I probability of the subjective factor rating decreases from 78.2% to 48.1%, the level II probability increases from 13.8% to 26.8%, and the level III probability increases from 7.93% to 25.1%; and the level I probability of the monitoring factor rating decreases from 71.2% to 38.7%, the level II probability increases from 21.0% to 37.8%, and the level III probability increases from

7.76% to 23.5%. These specific factor rating changes are shown in Table 7 and Figure 12.

According to the analysis, when the dynamic risk rating is fixed at level I, the three types of factors exhibit little change. When the dynamic risk rating is fixed at level II, all three types of factors exhibit a certain range of increase or decrease, and these increase or decrease ranges are not very different. When the dynamic risk rating is fixed at level III, the objective factor rating changes the most, followed by the monitoring factor rating, and the subjective factor rating changes the least. It can be inferred according to the changes in the Bayesian network that the dynamic risk rating is mainly affected by A4 surrounding rock level, A3 tunnel depth, and A5 groundwater among the objective factors; A11 construction management, A12 support strength, and A8 support timing among the subjective factors; and A14 arch crown convergence and A15 side wall displacement among the monitoring factors. The dynamic risk rating is most affected by B1 objective factor rating and B3 monitoring factor rating, followed by B2 subjective factor rating.

3.6.2. Sensitivity Analysis. A sensitivity analysis refers to an analysis of the influences of different nodes on the results. The sensitivity influence of each node in the Bayesian network to the dynamic risk rating node can be obtained by the sensitivity analysis tool in Netica. The calculation results are shown in Table 8.

According to the analysis, the ranking of the dynamic risk rating results affected by the three types of factors follows the order of objective factor rating, monitoring factor rating, and subjective factor rating. The main influencing factors are arch crown convergence, side wall displacement, inner-tunnel observation, support strength, surrounding rock level, support timing, groundwater, tunnel depth, and construction
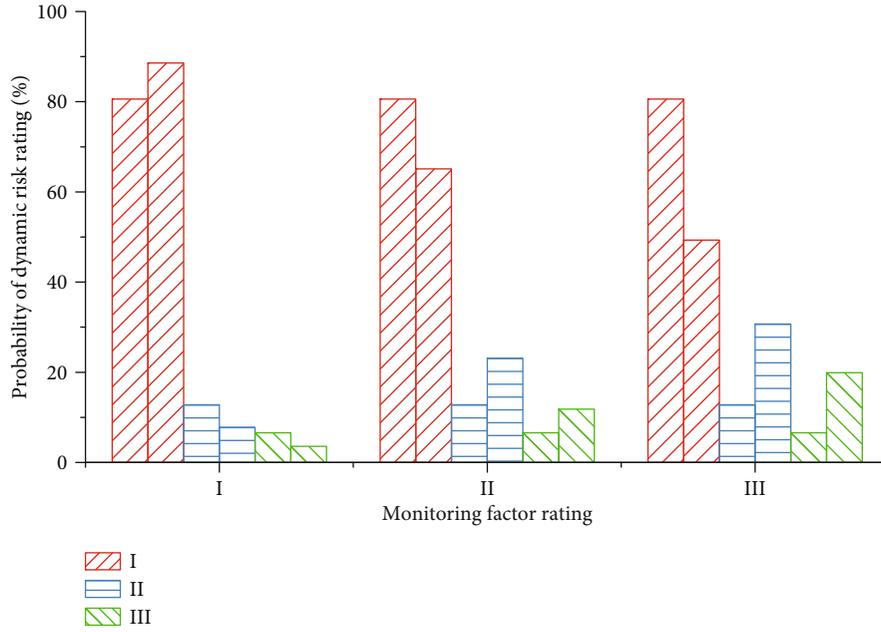
Figure 11: Probability changes with different monitoring factor ratings.

Table 7: Rating changes in the three types of factor ratings with different dynamic risk ratings.

Dynamic risk rating	Ratings of the three types of factors	Rating probability of objective factors (%)	Difference (%)	Rating probability of subjective factors (%)	Difference (%)	Rating probability of monitoring factors (%)	Difference (%)
	I	87.5	+6.2	84.5	+6.3	78.3	+7.1
I	II	9.46	-2.74	10.8	-3	17.0	-4
	III	3.02	-3.41	4.67	-3.26	4.75	-3.01
	I	59.1	-22.2	54.2	-24	43.4	-27.8
II	II	23.8	+11.6	26.1	+12.3	37.9	+16.9
	III	17.1	+10.67	19.7	+11.77	18.6	+10.84
	I	48.9	-32.4	48.1	-30.1	38.7	-32.5
III	II	23.5	+11.3	26.8	+13	37.8	+16.8
	III	27.5	+21.07	25.1	+17.17	23.5	+15.74

management, which are basically consistent with the results inferred in the previous section. This result indicates that the constructed dynamic risk rating Bayesian network model is scientific and reasonable, and changes in the risk level during deep-buried tunnel construction can be effectively and dynamically predicted.

4. Engineering Application

Humaling tunnel, one of the extralong tunnels of the Chongqing-Lanzhou railway, is situated in Lanzhou City, Gansu, China, with a maximum burial depth of 295 m. Several inclined shafts are set during the tunnel construction. The originally designed surrounding rock of the No. 3 inclined shaft was mainly IV-level sandstone, with a low water content. The inclined shaft, which was a horseshoe-shaped section with a width and height of 6.2 m and 6.5 m,

respectively, was designed to be excavated by the center diagram (CD) method.

According to the project, the engineering parameters are input into the constructed dynamic risk rating Bayesian network structure by Netica according to the rating system. The subjective factors are not available, so the default level is medium. The arch crown convergence and side wall displacement are monitored in tunnel section DK77+400. According to the monitoring data, the arch crown convergence is approximately 16.63 mm, and the side wall displacement is approximately 22.58 mm. The monitoring values are calculated to obtain the deformation management level according to Tables 2 and 3, at which point, the arch crown convergence level is calculated to be level III, and the side wall displacement level is level II. The comprehensive dynamic risk rating in this state can be obtained, and the rating result is shown in Figure 13.
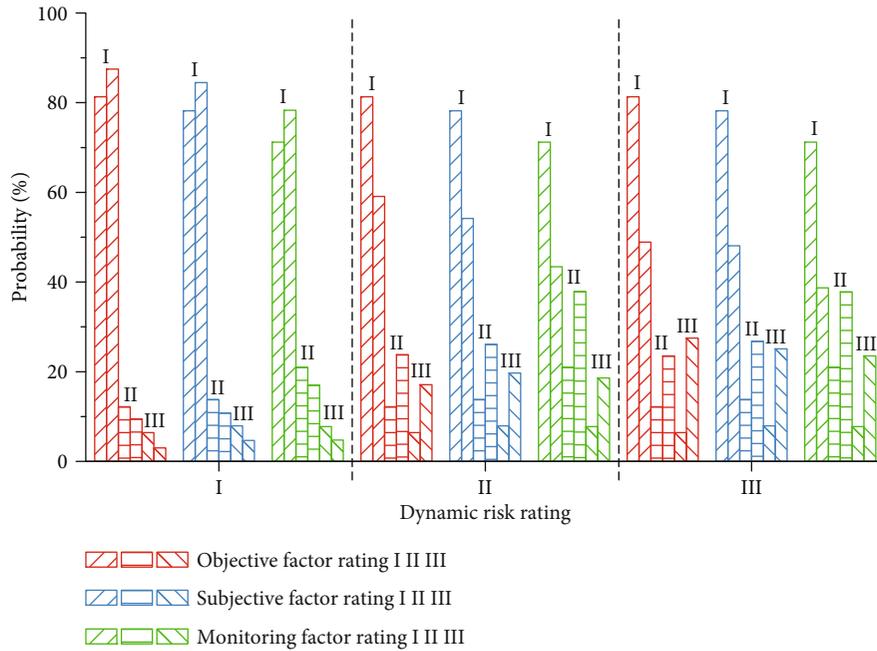
FIGURE 12: Probability changes with different dynamic risk ratings.

TABLE 8: Dynamic risk rating node sensitivities.

Node	Sensitivity	Variance in beliefs
B1 objective factor rating	0.07405	0.0120759
B3 monitoring factor rating	0.0719	0.0128749
B2 subjective factor rating	0.06513	0.0115407
A14 arch crown convergence	0.01006	0.001872
A15 side wall displacement	0.00644	0.0012051
A13 inner-tunnel observation	0.0059	0.0011156
A12 support strength	0.00165	0.0003034
A4 surrounding rock level	0.00082	0.0001496
A8 support timing	0.00064	0.0001154
A5 groundwater	0.00062	0.0001131
A3 tunnel depth	0.00059	0.0001074
A11 construction management	0.00059	0.0001078
A9 construction quality	0.00045	0.0000832
A6 mud inrush	0.00035	0.0000625
A2 construction method	0.00035	0.0000645
A7 prereinforcement effects	0.00025	0.0000466
A10 construction experience	0.00021	0.000039
A1 section size	0.00005	0.0000088

According to the calculation results, in this state, the dynamic risk rating probabilities are 81.7% for level I, 12.3% for level II, and 5.95% for level III. Compared with the dynamic risk rating description table, the risk rating is low, and normal construction is allowable.

As the inclined shaft excavation progressed, water gushing and mud inrush occurred on the tunnel face, and liquefaction occurred in the surrounding rock. A void appeared behind the primary support, which causes large deformations and collapse. After adjusting the Bayesian network, the dynamic risk rating calculation results are shown in Figure 14. According to the calculation results, the dynamic risk rating probability of level I greatly decreased from 81.7% to 33.8%, the probability of level II significantly increased from 12.3% to 34.0%, and the probability of level III increased from 5.95% to 32.2%. These changes indicate that the risk level has risen sharply at this point, and measures should be taken to stop the work. Temporary reinforcement measures were taken and water and mud were drained by the construction team. After the analysis, it was determined that the construction encountered tertiary water-rich weak sandstone. When the water content of the sandstone was low or there was no seepage, the stability of the surrounding rock was good. When the water content of the sandstone was too high to cause water seepage, the engineering properties of the sandstone deteriorated rapidly under the effect of the water. After excavation, most of the surrounding rock was in the form of fine sand, which led to extremely poor stability. After several rounds of expert demonstrations, the construction plan was changed to the six-part center cross diagram (CRD) method, and the advanced support of horizontal jet grouting was used. According to the changes in the geological conditions, after modifying the model parameters and adjusting the construction and advanced support methods, the dynamic risk rating probabilities were 73.2% for level I, 17.2% for level II, and 9.57% for level III at this time, which means that the risk level was greatly reduced.

5. Conclusions

This paper proposes a dynamic risk rating method for deep-buried tunnels based on a Bayesian network and constructs a
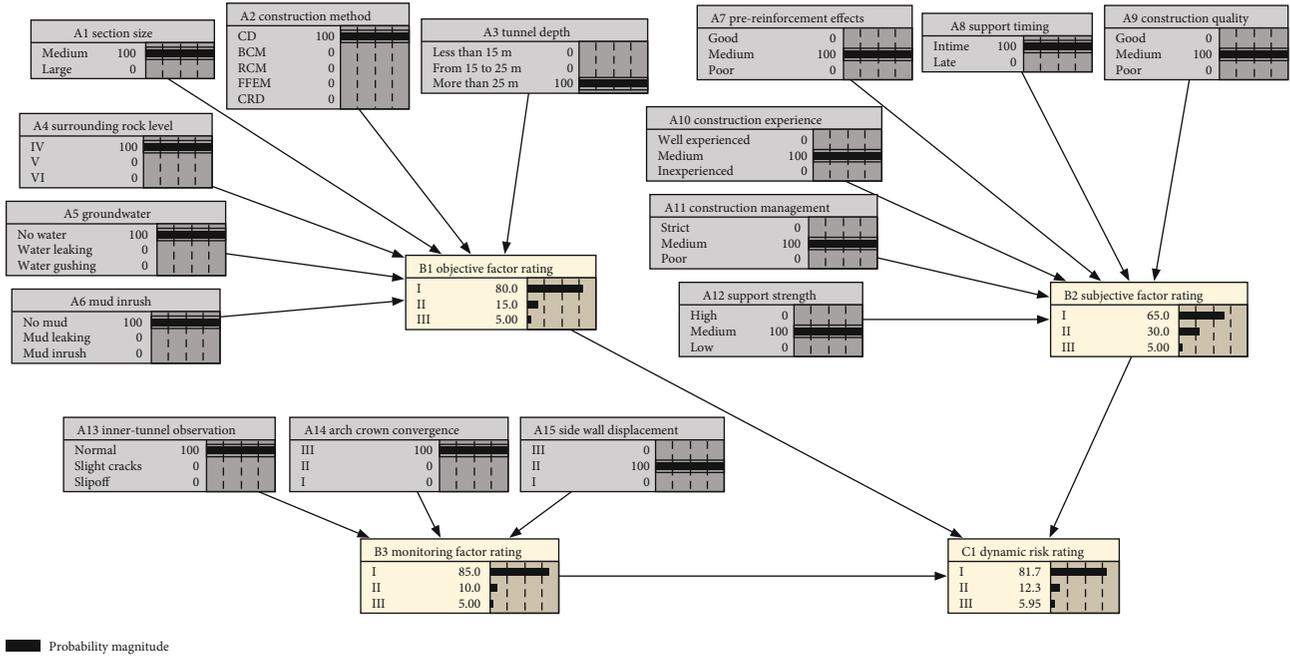
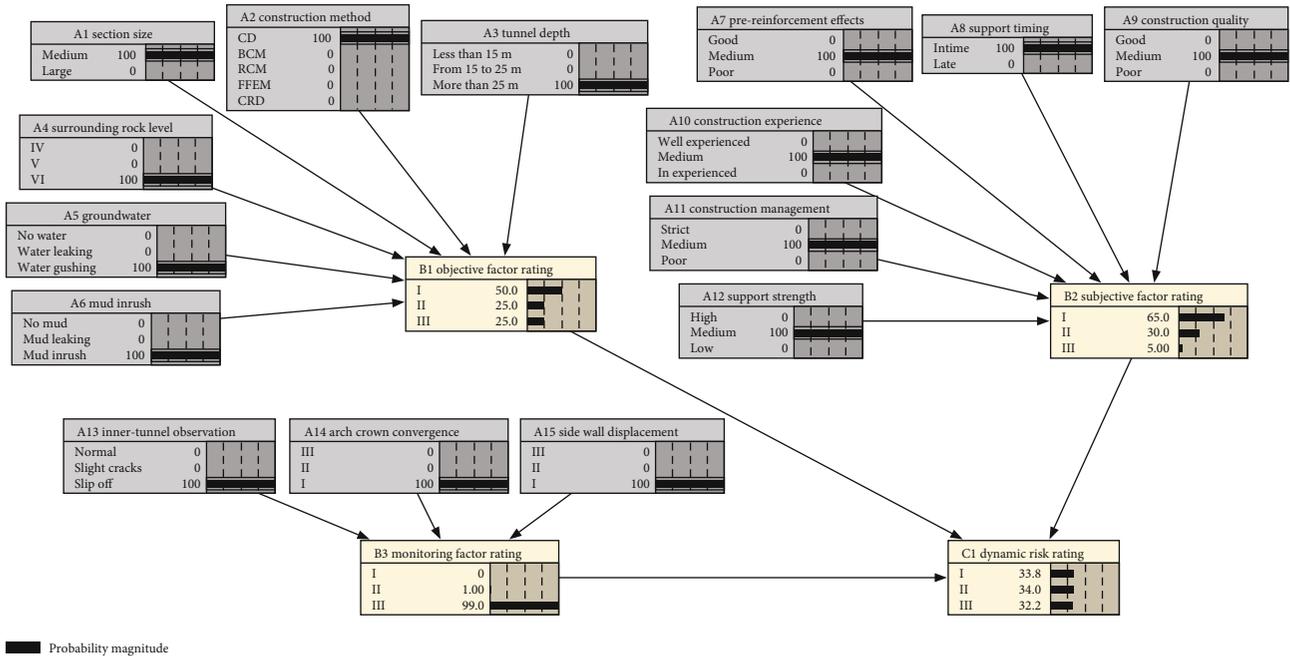Figure 13: Bayesian network calculation of the dynamic risk rating.

Figure 14: Bayesian network calculation of the adjusted dynamic risk rating.

dynamic risk rating system. The dynamic risk rating of tunnel construction is regarded as a combination of objective factors, subjective factors, and monitoring factors. According to the specific conditions of tunnel construction, the specific parameters of the three types of factors are graded according to certain rules, and a dynamic risk rating system structure is constructed; then, the Bayesian network structure is obtained. The nodes of the Bayesian network are determined according to the selection of various factors, the node ranges are determined according to factor grading standards, and the probability distribution of a node range is determined by historical statistical data and expert experience. The posterior probability and sensitivity are analyzed using Netica software. Finally, the Bayesian network is used to calculate the comprehensive risk rating based on the three types of factor ratings, and an engineering application is carried out. The following main conclusions are obtained:

(1) Three types of risk factors, subjective factors, objective factors, and monitoring factors, are comprehensively analyzed in this paper, and different grading standards of the three types of factors are determined; then, a dynamic risk rating system is established. The final risk rating is determined based on the obtained self-ratings for the three types of factors, and the dynamic risk rating integrated with the objective factor rating and the subjective factor rating is realized by changes in the monitoring factor rating using the monitoring data of construction

(2) According to the dynamic risk rating system, a dynamic risk rating Bayesian network structure is established, and the three types of risk factors in the system are in one-to-one correspondence with the nodes of the Bayesian network structure. The root nodes represent the specific risk factors, the objective factor rating, subjective factor rating, and monitoring factor rating are the middle nodes, and the target node represents the final dynamic risk rating. The node ranges are determined according to the grading of each factor. The probability distribution of the Bayesian network is determined by a combination of historical data statistics and expert experience

(3) Posterior probability analysis and sensitivity analysis of the established Bayesian network structure model were performed. When the dynamic risk rating is fixed at level I, the three types of factors exhibit little change. When the dynamic risk rating is fixed at level II, the three types of factor ratings exhibit a certain increase or decrease, and these amounts of increase or decrease in the three types of factors are not very different. When the dynamic risk rating is fixed at level III, the objective factor rating changes the most, followed by the monitoring factor rating, and the subjective factor rating changes the least. It can be inferred according to the changes in the Bayesian network that the dynamic risk rating is mainly affected by A4 surrounding rock level, A3 tunnel depth, and A5 groundwater among the objective factors; A11 construction management, A12 support strength, and A8 support timing among the subjective factors; and A14 arch crown convergence and A15 side wall displacement among the monitoring factors. The dynamic risk rating is most affected by B1 objective factor rating and B3 monitoring factor rating, followed by B2 subjective factor rating. According to the sensitivity analysis, the ranking of the dynamic risk rating results affected by the three types of factor ratings follows the order of objective factor rating, monitoring factor rating, and subjective factor rating. The main influencing factors are arch crown convergence, side wall displacement, inner-tunnel observation, support strength, surrounding rock level, support timing, groundwater, tunnel depth, and construction management, which are basically consistent with the results inferred from the changes in the Bayesian network

(4) The Bayesian network model of dynamic risk rating was applied in the No. 3 inclined shaft of Humaling tunnel. When the construction encountered tertiary water-rich weak sandstone, the dynamic risk rating probability of level I sharply decreased from 81.7% to 33.8%, the probability of level II significantly increased from 12.3% to 34.0%, and the probability of level III increased from 5.95% to 32.2%; these results indicate that the risk level had obviously increased

Data Availability

No data were used to support this study.

Additional Points

Highlights. A new dynamic risk assessment method is proposed for deep-buried tunnels. A dynamic risk rating system consisting of objective factors, subjective factors, and monitoring factors is constructed. A Bayesian network based on the dynamic risk rating system is proposed. Posterior probabilistic and sensitivity analyses are carried out. An application of the dynamic risk assessment method is carried out in the No. 3 inclined shaft of Humaling tunnel.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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