Advances in Computational Design, *Vol. 2, No. 2 (2017) 121-131*
DOI: https://doi.org/10.12989/acd.2017.2.2.121

Collapse risk evaluation method on Bayesian network prediction model and engineering application

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(Received October 12, 2016, Revised January 9, 2017, Accepted January 10, 2017)

Abstract. Collapse was one of the typical common geological hazards during the construction of tunnels. The risk assessment of collapse was an effective way to ensure the safety of tunnels. We established a prediction model of collapse based on Bayesian Network. 76 large or medium collapses in China were analyzed. The variable set and range of the model were determined according to the statistics. A collapse prediction software was developed and its veracity was also evaluated. At last the software was used to predict tunnel collapses. It effectively evaded the disaster. Establishing the platform can be subsequent perfect. The platform can also be applied to the risk assessment of other tunnel engineering.

Keywords: 76 large or medium collapses; Bayesian network; prediction model of collapse; collapse prediction software; engineering application

1. Introduction

At present, China has become one of the countries with the most serious tunnel collapse disasters in the world. The poor geological condition of tunnel was the main cause of the collapse, especially in water-rich weak and broken strata (Chen and Zhao 2009). The tunnel engineering in Hurongxi expressway, Chengdu Chongqing Expressway, Yuanjiang Mohei expressway, Zhuyong highway, Guangxi Binyang New South Railway, Lan Xin railway have occurred serious collapse disasters, most of which located in water-rich and soft or broken stratum. For example, there were five large-scale collapse during the construction of the Jinyun Mountain tunnel of Chengdu Chongqing Expressway. Among them, the 4th was the biggest one which scale was 22 m long, 10-14 m wide and 18-25 m high, and 4000-5000 m^3 collapse volume. Another example was Hurongxi Expressway Longtan Tunnel had three large scale of collapse during construction. Collapse volume exceeded 9000 m^3. Construction period delayed over 1 years.

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http://www.techno-press.org/?journal=acd&subpage=7 ISSN: 2283-8477 (Print), 2466-0523 (Online)

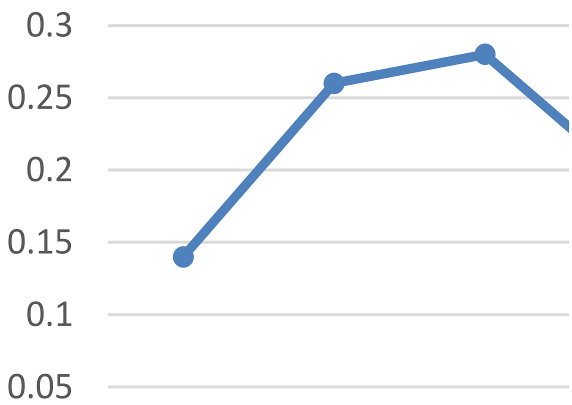

Fig. 1 Collapse probability under the condition of different tunnel buried depth

Most of the collapse occurred in the tunnel through the poor geological condition such as water-rich, weak and fractured formation. The collapse disaster not only caused heavy casualties and economic losses, but also brought about the non-repairable destruction to the surface water resources and ecological environment.

Bias network can be applied to the analysis of the uncertainty matters as a directed graphical description of the probability relation which used a variety of control factors to make decisions, making reasoning from incomplete, imprecise or uncertain information. Bias formula has been successfully applied in medical diagnosis, market prediction, signal estimation and product inspection which all have achieved good results, but it has not been applied in the prediction of tunnel engineering disaster risk (Qin and Liu 2005). This was the first time Bias network used to the risk assessment of the tunnel collapse disasters in this paper. Considering the multiple factors of tunnel depth, surrounding rock grade, unfavorable geology, excavation span, groundwater, rainfall, the collapse accident prediction model was established (Qian and Rong 2008).

2. Collapse statistics and analysis of several factors

Based on the statistics of the 76 large and medium-sized collapses in China, the hydrogeological environment was analyzed before the collapse of tunnel happened. Then the tunnel environment and reasons of collapse were analyzed during collapse happened and after tunnel collapse. Six main controlling factors of the tunnel collapse were selected which were shown on bellows (Zhou and Li 2013).

The factor of groundwater and rainfall were mainly divided into: Groundwater erosion fault collapse caused; the weight of surrounding rock increased by the rain, seepage instability of surrounding rock; surrounding rock soften, the self-stabilization ability reduced and so on.

The depth of tunnel: depth of the tunnel was related to the initial geo stress of surrounding rock and many factors, the greater the depth, the greater the geo stress and the more unfavorable the stability of surrounding rock. When the buried depth was large, the arched collapse was easy to happen. When the buried depth was small, it was easy to penetrating collapse. Collapse probability under the condition of different tunnel buried depth was shown on Fig. 1.

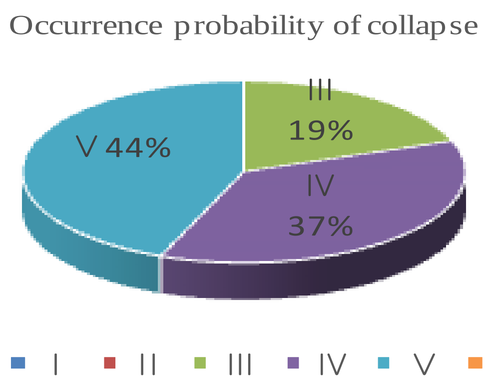

Fig. 2 Collapse probability under the condition of different surrounding rock grade

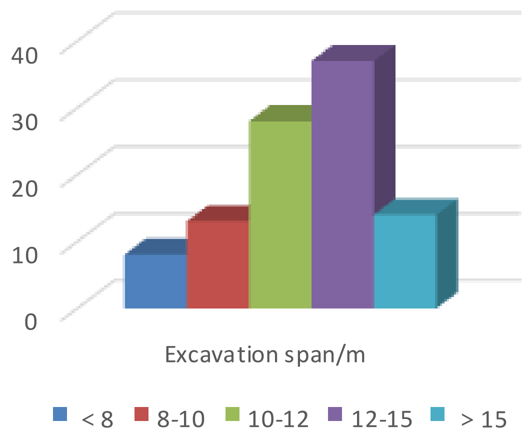

Fig. 3 Collapse probability under the condition of different excavation span

Surrounding rock grade: the higher the surrounding grade is, the poorer the stability of the surrounding rock is, the more prone collapse to occur. Collapse probability under the condition of different surrounding rock grade was shown on Fig. 2. Collapses were mainly concentrated on the grade four and grade five surrounding rock area. The amount of tunnels in the six grade of surrounding rock little, and often was taken good reinforcement measures. So the probability of collapse was relatively low and the scale of collapse were small.

The larger the excavation span, the greater the disturbance of the mountain, and the greater the probability of collapse the tunnel has. The redistribution of internal stress was the key factor which leads to the collapse of the tunnel, and the span of the excavation plays an important actor on the redistribution of the stress in the tunnel. With the increase of the excavation span, the probability of collapse was gradually increasing, especially in the range of 10-15 m. However, as there were fewer tunnels with the span over 15 m in China. So less statistics showed that the probability of collapse was also lower (shown in Fig. 3).

The adverse geological conditions were mainly included fault zone, bad ground (loose, water-rich and swelling). When the tunnel was in the bad geological conditions, the collapse was easy to occur for the poor stability of surrounding rock mass. In particular, fault fracture with low strength, easy deformation, strong permeability, poor water resistance and other shortcomings, it was more likely to lead to the collapsing. The fault zone played an important role on 36 collapses from the collapse statistics. In addition, the fault zone was more likely to result in small-scale collapse than other factors and has more threatening.

3. Basic theory of Bayesian network and the construction of Bayesian collapse prediction network

3.1 Basic theory of Bayesian networks

Based on the probability theory, Bias network has broad application prospects in the field of fault diagnosis, accident statistical analysis and prediction as a new method to deal with uncertain knowledge.

The Bias formula was as follows

$$P(a\mid B)=\frac{P(B\mid a)P(a)}{P(B)} \tag{1}$$

Where, *B* was training data; *a* was candidate hypotheses in the hypothesis space *A*; *P*(*a*) represents the prior probability of *a*. If without the prior probability of *a*, it could be simply given each candidate hypothesis with the same a priori probability; *P*(*B*) represents the prior probability of the training data *B*; *P*(*a*|*B*) represents the probability of *a* when *B* was established, which called Posterior probability of *B* and reflects the confidence in the *a* after seeing the training data *B*.

The maximum probability of training data *B*, which was called maximal posterior hypothesis, was given

$$a_{map}=\mathrm{argmaxP(a\mid B)}=\mathrm{argmax}\frac{\mathrm{p(B\mid a)\,P(a)}}{\mathrm{P(B)}}=\mathrm{argmaxP(B\mid a)\,P(a)} \tag{2}$$

((*a* belongs to set *A*))

In the last step, *P*(*B*) was removed because it was not associated with *a* constant.

In some cases, assuming that the candidate has the same prior probability and simplifying the formula, the maximum possible hypothesis was found through considering *P*(*a*|*B*). The *P*(*a*|*B*) hypothesis maximum likelihood was expressed as

$$a_{ML}=\arg\max P(B\mid \mathrm{a})\ \text{((a belongs to set A))} \tag{3}$$

3.2 The range of the bias network construction and the probability distribution of different factors

The influence factors of tunnel collapse were too many and complex. The groundwater (W), Bad geology (G), Surrounding rock grade (L), Tunnel buried depth (D), Excavation span (S), Rainfall (R) 6 factors were selected as the main prediction index of tunnel collapse (C) risk in this paper. The corresponding variable set was *X*=(*W*, *G*, *L*, *D*, *S*, *R*).

The corresponding range was shown in Table 1.

The relationship between main controls factors of collapse was shown on Fig. 4. The network

Table 1 Domain of different variables on tunnel collapse

Groundwater (*W*)	Defective geology (*G*)	Classification of surrounding rock (*L*)	Tunnel depth (*D*)	Excavation span (*S*)	Rain (*R*)	Tunnel collapse
1.Not very developed 2. Moderate development 3. Well development	1. Can be ignored 2. Medium 3. Serious	1. I-III 2. IV 3. V	1. <15 m 2. 15-20 m 3. 20-50 m 4. 50-70 m 5. >70 m	1. <8 m 2. 8-10 m 3. 10-12 m 4. 12-15 m 5. >15 m	1. No rain or less 2. Moderate rainfall 3. Heavy rainfall	1. Happened 2. Not happened

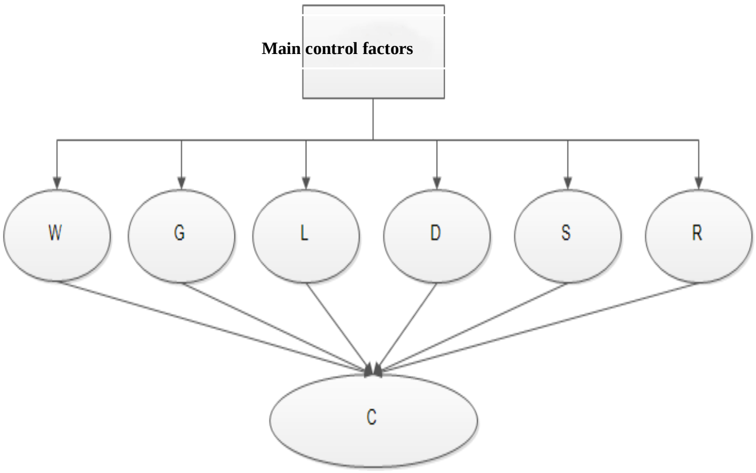

Fig. 4 Bayesian network structure on collapse prediction

Table 2 Collapse probability distribution under the condition of different excavation span

Span	<8	8-10	10-12	12-15	>15	Σ
Probability	0.08	0.13	0.28	0.37	0.14	1

Table 3 Collapse probability distribution under the condition of different tunnel buried depth

Depth	<15	15-20	20-50	50-70	>70	Σ
Probability	0.14	0.26	0.28	0.19	0.13	1

Table 4 Collapse probability distribution under the condition of different tunnel buried depth

Geology	ignored	common	serious	Σ
Probability	0.184	0.382	0.434	1

descripted the relationship between collapse and various influencing factors. The state of each variable had a certain influence on the collapse accident.

Through the analysis of the statistics of all the large and medium-sized collapse accidents in China, the relevant probability distribution was obtained, as shown in Tables 2-7.

3.3 The construction of Bias network prediction model

Table 5 Collapse probability distribution under the condition of different surrounding rock grade

Rock grade	I	II	III	IV	V	Σ
Probability	0	0	0.195	0.366	0.439	1

Table 6 Collapse probability distribution under the condition of different groundwater development situation

Underground water	Not very developed	Moderate developed	developed	Σ
Probability	0.2	0.343	0.457	1

Table 7 Collapse probability distribution under the condition of different rainfall conditions

Rain	No rain	Rained	Heavy rain	Σ
Probability	0.197	0.421	0.382	1

Suppose *D* was a database of *M* cases and each candidate network only contained *D* variables. For each structure B_s, the posterior probability of $P(B_s|D, \zeta)$ was calculated. The structure with the maximum posterior probability was chosen. The formula was as follows

$$P\left(B_S \mid D, z\right)=\frac{P\left(D, B_S \mid z\right)}{P\left(D \mid z\right)} \tag{4}$$

$P(D|\zeta)$ was a structure independent constant which only need to calculate the $P(D|B_s, \zeta)$ (*BD* criteria)

$$\mathrm{P}(\mathrm{D}, \mathrm{B_S} \mid \mathrm{z}) = \mathrm{P}(\mathrm{B_S} \mid \mathrm{z})\,\mathrm{P}(\mathrm{D} \mid \mathrm{B_S}, \mathrm{z}) \tag{5}$$

As $P(D, B_S \mid \zeta) \propto P(B_S \mid D, \zeta)$, so

$$\max_{B_S}\left\{P(D, B_S \mid z)\right\} \Leftrightarrow \max_{B_S}\left\{P(B_S \mid D, z)\right\} \tag{6}$$

It was assumed that the variable group A combine with probability distribution can be encoded in a network structure η, then,

$$P(x \mid \theta_\eta, \eta^{\mathrm{h}}) = \prod_{i=1}^{n} P(x_i \mid \mu(\mathrm{x_i}), \theta_{\mathrm{i}}, \eta^{\mathrm{h}}) \tag{7}$$

θ_i was the parameter vector of $P(x_i|\mu(x_i),\theta_n,\eta^h)$, and θ_n was the vector of the parameter group $(\theta_1, \theta_2 \ldots \theta_n)\cdot\eta^h$ indicates the physical joint distribution which can be decomposed according to the hypothesis of η.

Assuming that $D=(X_1, X_2 \ldots X_n)$ was a random sample of the joint distribution of X. Bayesian network can be simplified as: a random sample D was given and the calculation of the posterior distribution $P(\theta_n|D,\eta^h)$.

The local distribution function was given, two assumptions should be met.

(1) Random sample D was not missing data; (2) The parameter vector θ_{ij} independent of each other.

Assuming that each parameter vector θ_{ij} has a Dirichlet distribution, the posterior distribution is

$$P(\theta_{ij} \mid \mathrm{D}, \eta^{\mathrm{h}}) = Dir(\theta_{ij} \mid \alpha_{ij1} + N_{ij1}, \alpha_{ij2} + N_{ij2}, ..., \alpha_{ijr_i} + N_{ijr_i}) \tag{8}$$

Parameters were used to maintain independence for the given *D*, the mathematical expectation could be calculated as

$$P(x^{N+1} \mid \mathrm{D}, \eta^{\mathrm{h}}) = \prod_{i=1}^{n} \frac{\alpha_{ijk} + N_{ijk}}{\alpha_{ij} + N_{ij}} \tag{9}$$

Where

$$\alpha_{ij} = \sum_{k=1}^{r_i} \alpha_{ijk}, \quad N_{ij} = \sum_{k=1}^{r_i} N_{ijk} \tag{10}$$

However, *P*(*C*|*W*, *G*, *L*, *D*, *S*, *R*) could not find the appropriate statistical data and the following ways was used to transform. According to the Bias formula

$$P(C \mid W, G, L, D, S, R) = \frac{P(W, G, L, D, S, R \mid C) P(\mathrm{C})}{P(W, G, L, D, S, R)} \tag{11}$$

And

$$P(W, G, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) = P(W)P(G)P(L)P(D)P(S)P(R) \tag{12}$$

The joint probability of each variable was expressed as

$$P(\mathrm{C}, W, G, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) = P(W)P(G)P(L)P(D)P(S)P(R)\,\mathrm{P}(\mathrm{C} \mid W, G, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) \tag{13}$$

The joint probability distribution of each variable in the forecast model is

$$\begin{aligned} &P(\mathrm{C}, W, G, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) = P(W)P(G)P(L)P(D)P(S)P(R)\,\mathrm{P}(\mathrm{C} \mid W, G, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) P(W \mid C) \\ &P(G \mid C)P(L \mid C)P(D \mid C)P(S \mid C)P(R \mid C)\,\mathrm{P}(\mathrm{C}) \end{aligned} \tag{14}$$

Obtained

$$\mathrm{P}(\mathrm{C} \mid \mathrm{W}, \mathrm{G}, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R}) = \frac{\mathrm{P}(\mathrm{W}, \mathrm{G}, \mathrm{L}, \mathrm{D}, \mathrm{S}, \mathrm{R} \mid \mathrm{C})\,\mathrm{P}(\mathrm{C})}{\mathrm{P}(\mathrm{W})\,\mathrm{P}(\mathrm{G})\,\mathrm{P}(\mathrm{L})\,\mathrm{P}(\mathrm{D})\,\mathrm{P}(\mathrm{S})\,\mathrm{P}(\mathrm{R})} \tag{15}$$

As the *P*(*C*|*W*, *G*, *L*, *D*, *S*, *R*) was a multiple of *P*(*C*). After comparison, when the multiple exceeded two, the collapse was easy to happen. As the uncertainty and randomness of the collapse accident, Bayesian network was built to predict the collapse accident. Under the condition of a given set of tunnel conditions W=w_1, G=g_1, L=l_1, S=s_1, R=r_1. The probability of C=c_1 was compared with the multiple relation of *P*(*C*), and the possibility occurrence of collapse accident was judged after that.

4. Construction and accuracy evaluation of bias collapse prediction software

4.1 Construction of bias collapse prediction software

Based on the construction of Bayesian network for collapse prediction, the collapse prediction and evaluation software (Fig. 5) was established. The basic idea was as follows: Determining the

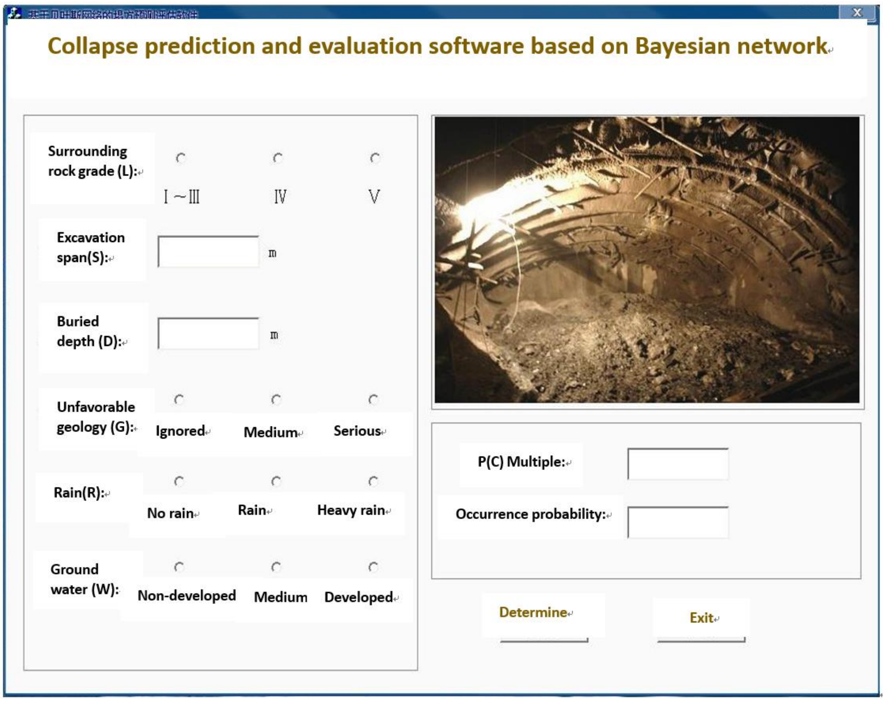

Fig. 5 Collapse prediction software based on Bayesian network

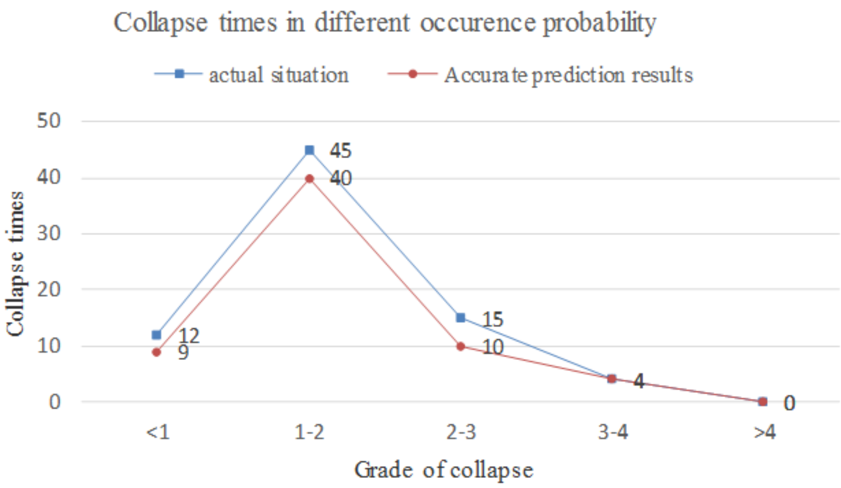

Fig. 6 Histogram of statistical results analysis

value of each factor through the actual environmental geological conditions $W=W_1$, $G=G_1$, $L=L_1$, $S=S_1$, $R=R_1$. The posterior probability of A (B multiples) was calculated. When it was greater than two times, the collapse was easy to occur. When it was less than 1 times, the collapse cannot occur.

4.2 Accuracy prediction of software

Table 8 surrounding rock subsection calculation of the right tunnel

No.	Mileage	Representative borehole	Representative lithology	Rock grade
1	YK170+195-YK170+270	SD16	Marl	V
2	YK170+270-YK170+480	SD16	Marl	IV
3	YK170+480-YK171+090	SD17	Marl	V

In order to verify the validity and accuracy of the model, the historical data of 76 collapses were tested by the software. It was found that 63 collapses were successfully predicted. The other 13 collapse were not reliably predicted. The accuracy rate can reach 83% (shown in Fig. 6). The reasons which make the prediction inaccurately were as following: 1. Bayesian network need more data to support; 2. collapse was the common result of multiple factors, and some of which were exceptions or difficult to obtains, six main control factors were selected in this paper, so that the prediction accuracy decreased. However, the overall predictions were valid.

5. Engineering applications

A split type tunnel was located in Yangliu Village Yanduhe Town Badong Country. The entrance of the tunnel connected the Zaiziping Bridge. The export connected the Longjingzai Bridge. According to the design, the mileage of the tunnel was from ZK168+165 to ZK171+480 in the left which length and depth were 3315 m and 120 m. The right of tunnel was began in YK168+180 and ended in YK171+440. The minimum distance between left and right was 23 m. The clearance of single hole was 10.25 m×5.0 m. After the expert assessment, the rock grade was V (Table 8).

Groundwater: There were two types of water-bearing formations: One was loose rock water-bearing formation and other was fractured rock water-bearing formation. The loose rock water-bearing formation was colluvial layer, and there were two kinds of fractured rock water-bearing formations: One was weathered rock which mainly has strongly weathered rock, the other was bedrock which mainly has medium weathered rock. Based on the groundwater-bearing: the weathered rock was the most water-rich area correspondingly. After the expert assessment, the groundwater in the tunnel excavation area was medium development.

Rain: The tunnel construction was in the rainy season and the rainfall was bigger than other seasons, which belongs to the heavy rainfall.

Geological structure: The mountain that the tunnel through was consist by muddy siltstone and silty mudstone T_2b_1, marl interbedded with limestone T_2b^2 and marl T_{1j}, the yield of which was generally 132°-178°∠6°-78°. The direction of tunnel axis was 306 degrees, and the angle between the tunnel and the rock layer was 38°-84°. The rock, fold grows, were expressed as wavy extension in the horizontal and vertical directions. Two small anticlines and synclines were there from the entrance to the exit of the tunnel, both of them were wide open and secondary fold, the overall performance si southeast dipping strata. After the expert assessment, it was belongs to the serious defective geological condition.

After calculation by software, the probability of collapse occurred at the right line of the tunnel to YK170 was 1.53P(C), which was easy to collapse.

Fig. 7 Collapse situation of the right tunnel

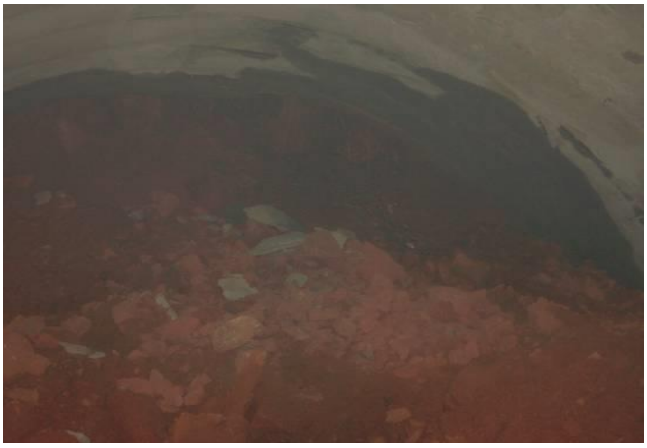

Fig. 8 Collapse body upper right's fissure water in right tunnel

In September 28th, when the right line tunnel excavated to YK170+211, the collapse happening. The most collapsing rocks were big stones, and there was fracture water flew right above the work face. The engineering example shows that the prediction software was effective (Figs. 7 and 8).

6. Conclusions

• Through the statistics of 76 large and medium-sized collapse in China, six main controlling factors, rock grade, excavation span, tunnel buried depth, bad geology, rainfall, groundwater, were determined.

• Based on the Bayesian theory, Bayesian network was constructed to predict collapse. Then the collapse prediction software was established, and 76 collapse disasters were evaluated to make sure the accuracy of the software.

• The collapse in the right line of Duanjiadian tunnel was successfully predicted by the software. The risk level and the mapping area was reduced and the risk of potential geological hazards was reduced to the risk acceptance criteria by adjusted the construction measures which makes the tunnel construction safety. The platform integrated the database environment, computer language and other content for the research required. By using this platform, the basic data was expanded for statistical analysis and the accuracy was continuously improved.

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