Analysis of Surrounding Rock Stability tunnel factor Based on Rough Set Theory

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Abstract: We collected from the literature and analyzed 19 groups tunnel rock classification data, combined with data mining functions of rough set theory and attribute reduction capability, factor analysis model was established based on rough set theory. After 19 sets of data attribute reduction, extraction equivalence classes, calculated the attribute importance and weight, got the order of the stability factor of the tunnel, to provide data for the reference when the tunnel design and construction.

Introduction

Our country is a country of many complex terrain of the population, with the rapid economical and social development, the ground space has been insufficient to meet the needs of people's lives, the use of the tunnel gradually gains people's attention. However, due to the frequent geological disasters, resulting in the tunnel wall rock collapses and other accidents, causing huge economic losses and casualties. The experts analyzed the factor of impacting surround rock stability are so many, complex relationship between them, there is a certain link with each other. For example Zhao Yanhui etc, used the rough set theory to the metro space rock tunnel go fuzzy comprehensive evaluation, obtained factor weights, also incorporates the southeastern Ganzi Tibetan Autonomous Prefecture in Sichuan Province examples riverside station, obtained the method of evaluation results and the actual situation are the same; Liu Gang’s master thesis is the analysis of rock stability BP neural network, using BP neural network on highway tunnel surrounding rock stability classification, then choose from the variety of complex factors relative importance of surrounding rock stability factors, and then targeted to develop countermeasures.

Rough Set Theory

As a theoretical of data analyzing and data processing, rough set theory was founded in 1982 by a Polish scientist Z. Pawlak. Rough set theory is a new mathematical tool of dealing with fuzzy and uncertain knowledge,the main idea is to keep the same classification capability, reduced by the knowledge everywhere in the decision or classification rules. Currently, the rough set theory has been successfully applied to machine learning, decision analyzing, process controling, pattern recognition, data mining and other fields.

It has a unique advantage is that it can tap the uncertain data hidden information, the missing information database can automatically add, this feature is gradually being used by some experts and scholars, and most people think that rough set theory will be a great space for development in the large-scale complex field.

Calculating the impact of objective factors of weight which based the rough set theory is feasible.

Sloping stability based on rough theory analysis

Rough set theory is not required to provide any other a priori information other than historical data, that it can be given an objective description of information systems, rough set theory can therefore be used as front-end data processor, on the one hand it can reduce redundancy and improve the effectiveness of information, on the other hand it also reduces noise interference, to prevent over-training and non-convergence phenomenon. Using rough set theory to analyze the properties that affect the stability of the tunnel importance and weight, the first is to complete the original data table and check compatibility, repairing dataset missing data, removing duplicate information dataset, and discrete processing; rough set of software reuse discrete data after attribute reduction, get equivalence classes of different factors, and finally the sample set performed after reduction attribute weight calculation. Rough set theory reduction process shown in Figure 1:

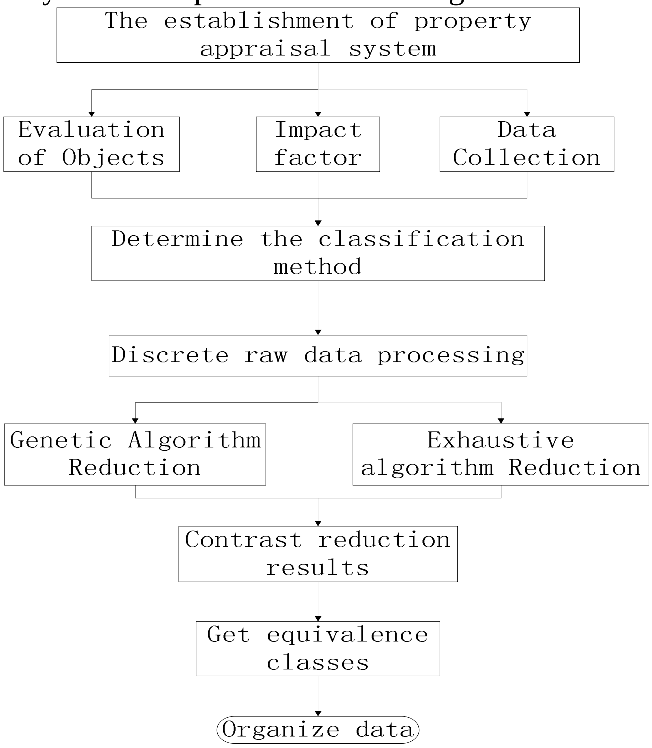

Fig 1 Evaluation of rough set theory flowchart

Examples of Application Engineering and Analysis

Source of raw data

The stability of surrounding rock tunnel directly related to the design, construction, use and maintenance. Many scholars are closely related through various experiments to prove the stability and mechanical properties of rock surrounding rock, rock structure and natural stress state, groundwater, excavation, support method, but play a major role in affecting is the integrity of the rock, groundwater seepage, natural stress state of rock, rock quality indicators, geological structure. These five factors have not yet been analyzed, it can not be targeted to strengthen and consolidate the design and construction process.

According to "Hydraulic Tunnel Design" and the rock classification of domestic and international experience, the surrounding rock into the following five categories as shown in Table 1.

Table 1 Tunnel Rock Classification

Classification	K_V	W（L/min·10m）	Rw（MPa）	ROD(%)	K_f
I（stable）	＞0.75	＜5	＞120	＞90	＞0.8
II（Basically stable）	0.75-0.45	5-10	120-60	90-75	0.8-0.6
III（Poor stability）	0.45-0.30	10-25	60-30	75-50	0.6-0.4
IV（Unstable）	0.30-0.20	25-125	30-15	50-25	0.4-0.2
V（Very unstable）	＜0.20	＞125	＜15	＜25	＜0.2

This paper collection from the literature analyzed 19 typical set of slope data instances, detailed data in Table 2, and lists five major factors affecting the stability of surrounding rock were rock integrity, groundwater seepage, natural stress state of rock, rock quality indicators, geological structure, and later in respectively C1, C2, C3, C4, C5 indicate, F represents rock classification, as all data and information as the rough set attribute reduction of the original data.

Table 2 Group 19 typical examples of parameter data

number	K_V Rock integrity coefficient	W（L/min·10m） Groundwater seepage	Rw（MPa） Rock saturated uniaxial compressive strength	ROD(%) Rock quality index	K_f Structural plane intensity	Rock classification
1	0.22	12	25	52	0.52	III
2	0.22	12.5	25	41.5	0.35	IV
3	0.38	10.5	40.5	50	0.55	III
4	0.32	18	26	28	0.3	IV
5	0.35	5	45	51	0.5	III
6	0.78	3.2	156.5	93	0.82	I
7	0.32	10	35	50	0.35	III
8	0.65	10	63.9	76	0.62	II
9	0.15	120	13.4	23.5	0.16	V
10	0.57	10.5	58.6	78	0.55	II
11	0.56	6	65.2	81	0.65	II
12	0.13	125	12.5	24.2	0.18	V
13	0.25	15	28	26	0.3	V
14	0.36	12	64	85	0.42	IV
15	0.57	5	48	91	0.55	III
16	0.23	13	54	65	0.51	IV
17	0.58	12	42	87	0.66	III
18	0.28	6	38	46	0.32	IV
19	0.28	14	25	23	0.17	V

Discrete processing of data

The table above shows the set of data is complete, there is no missing, there is no need to repair.

Application of rough set attribute reduction software requires the raw data discrete, equidistant method generally used for processing, calculation methods, see equation (1), the step = (max-min) / 3 represents the length of each column, max represents the maximum value for each column attribute, min represents the minimum value of each column properties, by this method a range of values for each attribute Va is divided into three levels, "0, 1, 2" respectively. Due to large amount of data, the authors calculated the above Matlab programming, the results of the original discrete data after treatment was as shown in Table 3.（Due to limited space, only partial results are listed）.

$$f(x) = \begin{cases} 0, \text{when } Va \in [min, min + step]; \\ 1, \text{when } Va \in [min + step, min + 2step]; \\ 2, \text{when } Va \in [min + 2step, min + 3step]; \end{cases} \quad \text{equation (1)}$$

Table 3 After discrete data

C1	C2	C3	C4	C5	F
0	0	0	1	1	III
0	0	0	0	0	IV
1	0	0	1	1	III
...	...	...	...	...	...
2	0	0	2	2	III
0	0	0	0	0	IV
0	0	0	0	0	V

Data attribute reduction based on surrounding rock rough set theory

Attribute reduction is one of the core content of rough set theory, usually the information in knowledge expression system are not as important, but there may be a lot of redundant information, this will have a negative impact on the systems decision and information expression , and therefore attribute reduction require in ensuring the knowledge classification and decision-making capacity the same premise, delete irrelevant or unimportant attributes.

Method property in the rough set theory reduction are two kinds, one is the Genetic Algorithm, another is Exhaustive Attack method, the two algorithms were to have its own characteristics and advantages. This paper uses the exhaustive algorithm and genetic algorithm to index attribute reduction. Reduction results of the two algorithms shows in the Fig 2 and Fig 3.

Genetic Algorithm for Attribute Reduction

	Reduct	Support	Length
1	{C1, C2, C3, C4, C5}	100	5

Fig 2 GA Reduct results

Exhaustive algorithm attribute reduction

	Reduct	Support	Length
1	{C1, C2, C3, C4, C5}	100	5

Fig 3 EA Reduct results

From the above chart shows that a consistent reduction result of genetic algorithm and exhaustive algorithm, five impact factors can affect the stability of the surrounding rock, non-redundant factors, and support both 100%.

Attribute importance calculation

The total of 19 sets of data set, with U = {1,2,3 ...... 19}, said condition attribute set C = {C1, C2, C3, C4, C5}, decision attribute set D = {F} = {{I}, {II}, {III}, {IV}, {V}}.

U/ind(C)equivalence class

	Eq. class	Cardinality
1	{2, 4, 18}	3
2	{13, 19}	2
3	{7}	1
4	{1}	1
5	{16}	1
6	{9, 12}	2
7	{3, 5}	2
8	{14}	1
9	{11}	1
10	{15}	1
11	{10}	1
12	{17}	1
13	{8}	1
14	{6}	1

Fig 4 Classification condition attribute set

U/(D)equivalence class

	Eq. class	Cardinality
1	{1, 3, 5, 7, 15, 17}	6
2	{2, 4, 14, 16, 18}	5
3	{6}	1
4	{8, 10, 11}	3
5	{9, 12, 13, 19}	4

Fig 5 Classification decision attribute set

U/(C-C1)equivalence class

	Eq. class	Cardinality
1	{2, 4, 18}	3
2	{13, 19}	2
3	{7}	1
4	{1, 3, 5}	3
5	{16}	1
6	{15}	1
7	{10}	1
8	{17}	1
9	{14}	1
10	{8, 11}	2
11	{6}	1
12	{9, 12}	2

Fig 6 Classification condition attribute set after remove C1

Classification condition attribute set in Fig 4, we can see Card (U / (C)) = 19; wherein the card (U / (C)) denotes the set of (U / (C)) in the number of elements;

Classification decision attribute set shown in Figure 5, can be obtained Card (U / (D)) = 19;

$POS_C(D)$= {7}U{9， 12}U{3， 5}U{14}U{11}U{17}U{8}U{6}={3， 5， 6， 7， 8， 9， 11， 12， 14， 17}， POS_C (D) represents a C positive domain, namely U/(C) within a subset of U / (D) and set within a subset, Card (POS_C (D)) = 10.

$\gamma C(D)$=Card(POS_C(D))/Card(U/(C))=, $\gamma C(D)$ represents the conditional attribute decision attribute dependence.

From the above chart we can see that after a property C1 removed, Card（U/ (C-C1)）=19; POS_{C-C1}(D)= {7}U{10}U{17}U{14}U{8,11}U{6}U{9,12}={6， 7， 8， 9， 10， 11， 12， 14， 17}， Card(POS_{C-C1}(D))=9.γ_{C-C1}(D)= Card(POS_{C-C1}(D))/Card(U/ (C-C1))=;

Using the above method, combined with the results of rough set of software, the following results can be obtained：

After removing property C2, Card（U/ (C-C2)）=19；Card(POS_{C-C2}(D))=8. γ_{C-C2}(D)= Card(POS_{C-C2}(D))/Card(U/ (C))=8/19;

After removing property C3, Card（U/ (C-C3)）=19；Card(POS$_{C-C3}$(D))=7.γ_{C-C3}(D)= Card(POS$_{C-C3}$(D))/Card(U/ (C))=7/19;

After removing property C4, Card（U/ (C-C4)）=19；Card(POS$_{C-C4}$(D))=8.γ_{C-C4}(D)= Card(POS$_{C-C4}$(D))/Card(U/ (C))=8/19;

After removing property C5, Card（U/ (C-C4)）=19；Card(POS$_{C-C5}$(D))=6. γ_{C-C5}(D)= Card(POS$_{C-C5}$(D))/Card(U/ (C))=6/19;

Attribute importance $SIG_{CD}(C1) = g_C(D) - g_{C-C1}(D) = 1 - \frac{9}{19} = \frac{10}{19}$

$$SIG_{CD}(C2) = g_C(D) - g_{C-C2}(D) = 1 - \frac{8}{19} = \frac{11}{19}$$

$$SIG_{CD}(C3) = g_C(D) - g_{C-C3}(D) = 1 - \frac{7}{19} = \frac{12}{19}$$

$$SIG_{CD}(C4) = g_C(D) - g_{C-C4}(D) = 1 - \frac{8}{19} = \frac{11}{19}$$

$$SIG_{CD}(C5) = g_C(D) - g_{C-C5}(D) = 1 - \frac{6}{19} = \frac{13}{19}$$

Visible, the most important attribute is C5, followed by property C3, the next are C2 and C4, property C1 is the lowest important factor in five.

Objective attribute weights calculation

The paper above has been calculated impact factor of five extremely attribute importance order, the importance of each attribute will be normalized to obtain the different attributes objective weight, the calculate method like equation (2).

$$W_{c_i} = \frac{SIG_{CD}(C_i)}{\sum_{i=1}^{5} SIG_{(Ci)}} \qquad \text{eqation(2)}$$

Therefore, you can get $W_{C_1} = \frac{10}{57}$、$W_{C_2} = \frac{11}{57}$、$W_{C_3} = \frac{12}{57}$、$W_{C_4} = \frac{11}{57}$、$W_{C_5} = \frac{13}{57}$.

Conclusion

Under normal circumstances, the attribute weights are mostly determined by the method of a priori knowledge of the decision makers themselves, such as expert scoring method, but this method is too subjective.

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