

## Research Article

# Risk Early Warning Evaluation of Coal Mine Water Inrush Based on Complex Network and Its Application

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As one of the five major coal mine disasters, the water inrush disaster poses a serious threat to the safety of the country and people, so the prevention work for that becomes very important. However, there is no perfect assessment system that can better solve the complex dependence relationships among disaster-causing factors of water inrush disasters. This study applied the knowledge of Complex Networks to research water inrush disaster, and based on that, the early warning evaluation system that combined ANP and Cloud model was established in order to solve the complex dependence problem and prevent the occurrence of water inrush. Moreover, this evaluation model was applied to the example Y coal mine to verify its superiority and feasibility. The results showed that the main cloud of goal was located at the yellow-strong warning level, and the first-level indicators were, respectively, at that the yellow-strong level of mining conditions, the yellow-strong warning level of hydrological factors, between the yellow-strong warning level and purple-general level of the geological structure, and among the blue-slightly weak warning level, purple-general level, and yellow-strong level of the human factor. The prediction results were consistent with the actual situation of the coal water inrush disaster in Y mine, which further proved that this early warning evaluation model is reliable. In response to the forecast results, the authors put forward relative improvements necessary to strengthen the prevention ability to disaster-causing factors among hydrological factors, mining conditions, and geological structure, which should comprehensively increase knowledge, technology, and management of workers to avoid leaving out disaster-causing factors. Meanwhile, the warning evaluation model also provides the relevant experience basis for other types of early warning assessment networks.

## 1. Introduction

With the rapid development of the Chinese market economy, the utilization rate of primary energy has generally increased. For example, the reserves of coal are about 90% [1–4]. Moreover, the usage amount of coal can still occupy an important position in future modern production. The most important mining method in China is underground mining [5–8]. Its advantages are large mining volume and wide mining range [9–11]. There are also many unsafe

factors, such as water inrush disasters. It is one of the most important five disasters in a coal mine. It is a water accident that occurred suddenly during the production process. The characteristics of water inrush disasters are rapid development and wide coverage [12]. Since the 1980s, more than 250 mines across the country have been flooded with more than 1700 deaths and economic losses of over 35 billion yuan [13, 14].

Therefore, the early warning work of coal mine water inrush is very important. Since the early 20th century,

scholars at home and abroad have already started exploring and researching this area. With the rapid development of computer technology, the different scientific systems have been merged to form many prediction methods for water inrush disasters. Yang et al. established the risk assessment model of floor water inrush through the GA-BP network model [15]. Wang used MATLAB to build a model for predicting the depth of floor damage [16]. Wang et al. proposed the risk assessment model of coal mine water inrush disaster based on a dynamic tree [17]. Qin et al. used D-S theory to evaluate the risk degree of coal mine water inrush disaster [18]. Wang et al. proposed the evaluation method of the accident tree model in coal mine water inrush disaster [19].

Water inrush disaster is a complex nonlinear problem [20, 21]. Its disaster-causing factors can interact with each other. Only by determining the relationship between disaster-causing factors can we better prepare for early warning assessment. The research status at home and abroad is still in the blank research stage on a complex relationship between disaster-causing factors. In addition, there is no study on using the Complex Network method combined with ANP and Cloud model to measure the important influencing factors of water inrush disaster. This study uses Complex Network model for the first time to deal with complex relationship problems between disaster-causing factors of water inrush to prevent the occurrence of water inrush disaster in coal mine. We also used ANP combined with Cloud model to calculate the early warning level of each factor accurately. Moreover, this study also offers a theoretical basis and practical guiding significance for other coal mines on the early warning work to water inrush disaster.

## 2. Theoretical Basis

### 2.1. Complex Network

**2.1.1. Composition of the Complex Network Model.** The Complex Network model is composed of nodes and connected edges [22, 23]. Each independent node in the network represents a disaster-causing factor. The impact of nodes on the occurrence, development, and results of disasters are clarified. The connected edges can reflect the connection relationship between all nodes in the network. If a certain factor can cause a new disaster to occur, a connected edge will be formed.

The connected edges include a single route and multiple route [24]. Single disaster route refers to factor A causing factor B to change, and thus, factor B can cause factor C to change. On the other hand, a multiple disaster route refers to factors A and B together causing factor C to change catastrophically. When the disaster-causing factors interact and feed back each other leading to the occurrence of disaster results, a multiple disaster route will be formed. It can produce a catastrophe that is quite complex and difficult to prevent. Moreover, combining all multiple disaster routes can form a Complex Network model.

**2.1.2. Expression of the Complex Network Model.** The Complex Network model is defined in the form of graph theory [25]. We can set up  $G = (V, E)$ , where  $V$  is the set of all nodes ( $V = \{v_1, v_2, \dots, v_n\}$ );  $E$  is the set of all connected edges ( $E = \{e_1, e_2, \dots, e_n\}$ ). Moreover, each edge can connect two different nodes expressed as  $e_{ij} = \{v_i, v_j\}$ . If  $e_{ij} = e_{ji}$ , it will mean that this network is undirected. Otherwise, the network is directed.

The method of recording a Complex Network is by constructing an adjacent matrix. If a connected edge between any two nodes exists, it will be recorded as 1 in an adjacent matrix; otherwise, it will be recorded as 0. The adjacent list is one of the most common ways to store the content of a Complex Network. It consists of many sets of numbers. There are two numbers in each row in the adjacent list, which represent two different numbered nodes. Moreover, the space between two numbers indicates that a connected relationship exists. Therefore, the adjacent matrix and adjacent list are interdependent, as shown in Figure 1.

### 2.2. ANP and the Cloud Model

**2.2.1. ANP.** Analytic Network Hierarchy Process (ANP) is a comprehensive and multiple objective decision-making method based on AHP, proposed by T. L. Saaty in 1996 [26, 27]. Its application range is very wide. It not only inherits the hierarchical characteristics from AHP but also considers nonindependent relationships such as feedback and dependence among internal elements [28, 29]. Therefore, ANP is more realistic than AHP.

Water inrush disaster is a Complex Network problem. There are many interdependent and feedback decision elements. Therefore, using ANP to calculate the weights of all elements in a water inrush disaster network can better solve the actual prevention problems.

**2.2.2. Cloud Model.** In 1995, academician D. Y. Li proposed the Cloud model concept based on the limitations of probability theory and fuzzy mathematics on the analysis of uncertainty problems [30], using three feature numbers to represent the ambiguity and randomness of the Cloud model. It can intuitively reflect the mathematical mapping of qualitative language [31, 32]. So far, it has been widely used in data analysis, decision judgment, intelligent control, and other fields [33, 34].

The three characteristic numbers of the Cloud model are Ex (Expected Value), En (Entropy), and He (Hyperentropy), which are expressed as C (Ex, En, He). Ex is the expectation of cloud drop  $x$  distributed in the domain  $U$ , which can reflect the central location of the Cloud model. En is the entropy of Ex that can represent the span and dispersed degree of Cloud model. He is the entropy of En, which can determine the thickness of cloud. The larger He indicates that the cloud image is more dispersed and larger in thickness.

$U$  is set to be the precise quantitative domain.  $C$  is a qualitative language in  $U$ . If the quantitative value  $x \in U$  and  $x$  is a random quantitative realization of  $C$ , then  $\mu(x)$  will be

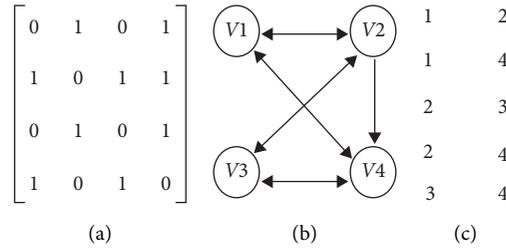


FIGURE 1: The nodes relationship of Complex Network for (a) adjacent matrix; (b) connected relationship; (c) adjacent list.

the certainty of  $x$  to  $C$ , which is a stable random number in  $[0, 1]$ . That is expressed as  $\mu:U \rightarrow [0, 1]$ . There are  $x \in U$  and  $x \rightarrow \mu(x)$ . All distribution forms of  $x$  on  $U$  are called clouds. Each  $x$  is a cloud drop [35].

The Cloud Generator is an algorithm to realize the mutual conversion between qualitative and quantitative in Cloud model [36]. It is also one of the most important steps in the uncertainty reasoning process in the entire Cloud model. It includes two types: Forward Cloud Generator and

Backward Cloud Generator. Forward Cloud Generator is the process of converting qualitative indicators into quantitative data. It is based on cloud numbers to form a cloud image, as shown in Figure 2(a). Backward Cloud Generator is to convert quantitative data into qualitative indicators, which can convert precise numerical values into cloud numbers, as shown in Figure 2(b). The calculation formulas of cloud numbers are as in

$$\left\{ \begin{aligned} Ex &= \bar{x} = \frac{1}{n} \sum_{i=1}^n xi, En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n} \sum_{i=1}^n |xi - Ex|, He = \sqrt{S^2 - En^2} = \left[ \frac{1}{n-1} \sum (xi - \bar{x})^2 - En^2 \right]^{1/2}. \end{aligned} \right. \quad (1)$$

### 3. Constructing the Complex Network Model

**3.1. Structural Analysis.** Through collecting a large amount of data of water inrush disaster from related papers and websites, we drew the network relationship of water inrush disaster, as shown in Figure 3. We can get the most important disaster-causing factors of coal mine water inrush disasters from all countries. It can provide a corresponding experience basis for the analysis of a specific coal mine water inrush disaster. There are 161 nodes and 149 connected edges in Figure 3. Nodes represent the disaster-causing factors and a connected edge indicates that there is a mutually influential relationship between two nodes.

The nodes with fewer connection relationships to other nodes in Figure 3 are all distributed on the outermost side of network. However, the nodes frequently influence other nodes that are located in the center of the network. In addition, all connected edges are directional. If the arrow points from node  $x$  to  $y$ , then it will mean that node  $x$  can cause catastrophe to node  $y$ , which is recorded as  $e_{xy}$ .

**3.2. Analysis of Topological Characteristics.** Topological characteristics are unique attributes of the Complex Network model [37]. By analyzing them, we can better understand the structure of the Complex Network model.

**3.2.1. Degree Centrality.** Degree centrality is a measured method to the importance of nodes, which includes in-degree and out-degree. Out-degree is from a certain node pointing to other nodes. The nodes with larger out-degree values are the

main factors leading to water inrush disasters. For example, the out-degree value of dynamic water pressure is 9, which indicates the dynamic water pressure can cause 9 nodes to be catastrophic. In-degree is directed by other nodes to a certain node. The factors with a larger in-degree value are the root cause of water inrush disaster.

However, there is not exiting any relationship between out-degree and in-degree. A node with a larger out-degree value may not necessarily have a larger in-degree value. Therefore, when considering the degree centrality of the node, the out-degree and in-degree should be comprehensively analyzed.

**3.2.2. Closeness Centrality.** The closeness centrality of a node represents the distance to other nodes. The greater the closeness centrality of a node, the closer the distance to other nodes. For example, in shipping logistics network, if you need to select a transit center that is closer to all logistics points, you should select the node with the greatest closeness centrality [38, 39].

In the network of water inrush disaster, there are 102 nodes with closeness centrality not less than 1. It shows that the distances between nodes in the entire network are relatively closer. Moreover, it is more convenient for each node to influence others. In the network, the closeness centrality of coal body cementation degree is the largest, which is 2.125. It indicates that the coal body cementation degree is closest to other nodes in the entire network and it is easiest to activate other disaster-causing nodes.

**3.2.3. Intermediary Centrality.** The greater the intermediary centrality of a node, the larger the possibility of being a



TABLE 1: The most important multiple nodes.

Nodes	Degree centrality	Closeness centrality	Intermediary centrality	Eigenvector centrality
Coal seam thickness	14	1	1	0.333150175
Depth of mining floor failure	12	0	3	0.285557293
Coal seam burial depth	9	1	2	0.21416797
Working surface length	6	1	0	0.630880426
Key position of the water barrier	8	0	1	0.190371529
Karst collapse column	5	0	6	0.320266341
Water inrush volume	1	0	1	1
Fault	5	0	3	0.231522494
Aquifer	3	0	2	0.559491103
Mining depth	3	1.333	0	0.183929612
Water barrier thickness	4	1	0	0.095185764
Karst fissure development degree	1	1.9	1	0.511898221
Dynamic water pressure	10	1	9	0.023796441
Collapse column	3	1	6	0.071389323
Ordovician water channel	2	0	1	0.160133171
Mining methods and processes	3	1.2	0	0.071389323
Reduce the strength of fractured rock mass	1	0	2	0.13633673
Complex geological conditions	2	1	1	0.047592882
Folds	3	1.6	5	0.023796441
Hidden troubles are not in place	1	1	0	0
Illegal production	1	1	1	0
Production organization management chaos	1	1	0	0
Production technology management chaos	1	1	2	0

indicators: geological structure, hydrological factors, mining conditions, and human factors. Then, the first-level indicators are correspondingly divided into the second-level indicators. According to the research requirements, the top 23 important second-level indicators are selected, as shown in Figure 4.

#### 4.2. Index Weights Based on ANP

**4.2.1. Constructing the ANP Model.** The ANP model is consists of a control layer and a network layer [40]. The control layer includes goal and dimensions and the control layer is a decision-making system for coal mine water inrush disaster. The goal is the final purpose of the system decision and dimensions are the first-level indicators whose numbers need to be set according to the specific model. It is affected by the next layer of factors. The four dimensions of mining conditions, hydrological factors, geological structure, and human factors are set as U1, U2, U3, and U4, respectively.

Factors of network layer contain the second-level indicators from Complex Network. The relationships of mutual feedback and dependence between the second-level indicators form a network system, as in Figure 5. The second-level indicators were, respectively, expressed as U1i ( $i = 1, 2, 3, 4, 5, 6$ ), U2i ( $i = 1, 2, 3, 4, 5, 6$ ), U3i ( $i = 1, 2, 3, 4, 5, 6$ ), and U4i ( $i = 1, 2, 3, 4, 5$ ).

**4.2.2. Calculating Weights.** The weights calculated process in ANP are extremely complicated. Thus, it is based on Super Decisions (SD) software for scientific weights calculation in this article [41]. It can clearly show the coupling relationship between various indicators. The calculation steps are as follows.

First of all, we need to build a network relationship model. It is very important to clarify the dependence and feedback relationship between indicators in the ANP model, which has a certain influence on the correctness of the decision. The connected relationship of all elements is entered, consulting related literature to the SD.

Secondly, it is necessary to collect expert evaluation data. There are connected relationships between elements in the same and different dimensions. The important influence degree of other elements that have a connection relationship with the certain element is judged. Ten experts in the relevant field were consulted by 1 ~ 9 scale scoring method [42]. The score rules are shown in Table 2. It is particularly important to note that the ANP model also requires consistency testing, which must be less than 0.1.

Then, unweighted matrix and weighted matrix of elements are obtained by inputting all scored data from 10 experts into SD. If the values of the unweighted matrix and weighted matrix are 0, then there is no dependent and feedback relationship between the two elements.

Finally, the comprehensive weights are calculated. We can obtain the normalized matrix from the unweighted matrix and weighted matrix in SD. Moreover, according to the academical abilities and experiences of 10 experts, we set weighted coefficients as shown in Table 3. Combining the normalized matrix and weighted coefficient to get the final comprehensive weights of elements, we obtain the following calculation formula as

$$\overline{\text{limiting}} = \sum_{k=1}^{10} (S_k \times P_k), \quad (2)$$

where  $P_k$  is the elements' normalized weights from 10 experts and  $S_k$  is the weighted coefficient of each expert.

4.3. *Building Cloud Models of Comment Sets.* Before constructing a risk early warning assessment model of water inrush disaster, the corresponding comment sets should be established. Moreover, the comment sets classified of early warning model should be based on the past examples of many coal mines water inrush disasters.

In this article, the influence degrees of disaster-causing factors in water inrush disaster are divided into five comment sets: weak, slightly weak, general, strong, and stronger. It is expressed as  $V = \{V_1, V_2, V_3, V_4, V_5\} = \{\text{weak, slightly weak, general, strong, stronger}\}$ .

The golden section method is used to generate a corresponding closed comment set as  $(C_{\min}, C_{\max})$ . In the golden section model, the closer the score to the center of domain, the smaller En and He. In addition, the cloud model parameters between two adjacent evaluation intervals are 0.618 times [43]. It can be represented by the corresponding cloud characteristic numbers, as follows:

$$\begin{cases} Ex = \frac{(C_{\max} + C_{\min})}{2}, \\ En = \frac{(C_{\max} - C_{\min})}{6}, \\ He = k. \end{cases} \quad (3)$$

In Equation (3),  $k$  is a constant that needs to be determined according to the ambiguity of comment.

In this article, the central cloud feature numbers are set  $Ex_3 = 0.5$  and  $He_3 = 0.005$ . The calculation formulas (4) to (6) are as follows:

$$\begin{cases} Ex_1 = 0, \\ Ex_2 = Ex_3 - \frac{(1 - 0.618)(C_{\max} + C_{\min})}{2} = 0.30, \\ Ex_3 = 0.5 \\ Ex_4 = Ex_3 + \frac{(1 - 0.618)(C_{\max} + C_{\min})}{2} = 0.69, \\ Ex_5 = 1, \end{cases} \quad (4)$$

$$\begin{cases} He_1 = \frac{He_2}{0.618} = 0.013, \\ He_2 = \frac{He_3}{0.618} = 0.008, \\ He_3 = 0.005, \\ He_4 = \frac{He_3}{0.618} = 0.008, \\ He_5 = \frac{He_4}{0.618} = 0.013, \end{cases} \quad (5)$$

$$\begin{cases} En_1 = \frac{0.618 \times (C_{\max} - C_{\min})}{6} = 0.103, \\ En_2 = \frac{(1 - 0.618)(C_{\max} - C_{\min})}{6} = 0.064, \\ En_3 = \frac{0.618 \times (1 - 0.618)(C_{\max} - C_{\min})}{6} = 0.039, \\ En_4 = \frac{(1 - 0.618)(C_{\max} - C_{\min})}{6} = 0.064, \\ En_5 = \frac{0.618 \times (C_{\max} - C_{\min})}{6} = 0.103. \end{cases} \quad (6)$$

All closed intervals  $(C_{\min}, C_{\max})$  are distributed in the theoretical domain  $[0, 1]$ . Moreover, the cover width of cloud model is  $[Ex - 3En, Ex + 3En]$ . The comment sets as shown in Table 4. We used the cloud feature numbers of different risk comment sets to generate the cloud image corresponding by MATLAB, as shown in Figure 6.

4.4. *Comprehensive Early Warning Assessment.* Ten experts in a related field were invited to conduct a questionnaire survey, which includes 2 second-level professors, 4 associate professors, 2 senior engineers, and 2 doctors. Moreover, the 23 important second-level indicators were scored reasonably, ranging from 0 to 100. The experts should give the highest and the lowest scores of indicators, respectively. Finally, the results to the domain  $[0, 1]$  are normalized.

4.4.1. *Comprehensive Cloud of First-Level Indicators.* The corresponding maximum and minimum cloud feature numbers  $C$  ( $Ex$ ,  $En$ ,  $He$ ) of indicators are obtained by a Backward Cloud Generator. According to the calculated formulas (7), the comprehensive cloud feature numbers of the second-level indicators are obtained by maximum and minimum cloud feature numbers fitted. However, the second-level indicators are used to calculate the comprehensive cloud, which is not considered as a relative influence on the first-level indicators. Therefore, it can not reflect the accurate prediction results.

Through formulas (8), we can obtain more accurate cloud characteristic numbers of the first-level indicators. We used MATLAB to generate the corresponding cloud image and compared it with the standard grades to clarify the early warning level of various first-level indicators.

4.4.2. *Comprehensive Cloud of Goal.* The comprehensive cloud feature number of goal is a summary for the evaluation model and its comprehensive degree is strongest because the correlations between the first-level indicators are much greater than those between the second-level indicators. We can use the integrated cloud algorithm to obtain the cloud feature number of goals, as in formula (9). Moreover, we compared it with standard grades to clarify disaster level of goal.

$$\begin{cases} Ex = \frac{Ex_{\max}En_{\max} + Ex_{\min}En_{\min}}{En_{\max} + En_{\min}}, \\ En = En_{\max} + En_{\min}, \\ He = \frac{He_{\max}En_{\max} + He_{\min}En_{\min}}{En_{\max} + En_{\min}}, \end{cases} \quad (7)$$

$$\begin{cases} Ex = \frac{Ex_1w_1 + Ex_2w_2 + \dots + Ex_nw_n}{w_1 + w_2 + \dots + w_n}, \\ En = \frac{w_1^2}{w_1^2 + w_2^2 + \dots + w_n^2} * En_1 + \frac{w_2^2}{w_1^2 + w_2^2 + \dots + w_n^2} * En_2 + \dots + \frac{w_n^2}{w_1^2 + w_2^2 + \dots + w_n^2} * En_n, \\ He = \frac{w_1^2}{w_1^2 + w_2^2 + \dots + w_n^2} * He_1 + \frac{w_2^2}{w_1^2 + w_2^2 + \dots + w_n^2} * He_2 + \dots + \frac{w_n^2}{w_1^2 + w_2^2 + \dots + w_n^2} * He_n, \end{cases} \quad (8)$$

$$\begin{cases} Ex = \frac{Ex_1En_1w_1 + Ex_2En_2w_2 + \dots + Ex_nEn_nw_n}{En_1w_1 + En_2w_2 + \dots + En_nw_n}, \\ En = En_1w_1 + En_2w_2 + \dots + En_nw_n, \\ He = \frac{He_1En_1w_1 + He_2En_2w_2 + \dots + He_nEn_nw_n}{En_1w_1 + En_2w_2 + \dots + En_nw_n}. \end{cases} \quad (9)$$

In Equations (7) and (8),  $w_i$  is comprehensive weights of second-level indicators;  $n$  is total number of second-level indicators;  $(Ex_i, En_i, He_i)$  are cloud characteristic numbers of second-level indicators;  $(Ex_{\max}, En_{\max}, He_{\max})$  and  $(Ex_{\min}, En_{\min}, He_{\min})$  are the corresponding maximum and minimum cloud feature numbers. In Equation (9),  $w_i$  is the comprehensive weights of first-level indicators;  $n$  is the total number of first-level indicators;  $(Ex_i, En_i, He_i)$  are the cloud characteristic numbers for first-level indicators.

## 5. Application

**5.1. Engineering Background.** This article takes Y coal mine as an example to verify the feasibility of the early warning assessment model; the mine position is shown in Figure 7. Y coal mine was constructed in 2005 and its reserve is 31.2 million tons. Moreover, the most mining depth is 680 m and the area of mine is 21.7 km<sup>2</sup>. The whole mining area is cut by faults with the compound fold structure. Small- and medium-sized seasonal rivers pass through the northeast of mine.

The inclination angle of the coal seam is 10~20°. The lithology of the floor is mainly medium and fine sandstone, with an average thickness of 19.80 m. There are some local vertical cracks and the sandstone fissure aquifer in the roof and floor of Y coal mine is a direct roadway water-filling source. The water-repellent layer is composed of sandy or calcareous clay with a thickness of 10–158 m, of which water blocking property is good. When encountering structures or karst collapse columns, Ordovician water directly filled roadway, which causes great harm to production.

**5.2. Constructing the Index System.** Based on the disaster-causing factors of water inrush in coal mine Y, the evaluation system was established. It includes 4 types of the first-level indicators: mining conditions, hydrological factors, geological structure, and human factors expressed as  $U = \{U1, U2, U3, U4\} = \{\text{mining conditions, hydrological factors, geological structure, human factors}\}$ . The disaster-causing factors of water inrush disasters in different coal mines may be inconsistent. Moreover, the second-level indicators of Y coal mine evaluation system are, respectively, expressed as  $U1 = \{U11, U12, U13, U14, U15, U16\}$ ,  $U2 = \{U21, U22, U23, U24, U25, U26\}$ ,  $U3 = \{U31, U32, U33, U34, U35, U36\}$ , and  $U4 = \{U41, U42, U43, U44, U45\}$ .

**5.3. Index Weights Based on ANP.** The index weights represent the contribution degree of each indicator to the entire evaluation system. Ten experts related to Y coal mine are invited to score indicators two by two according to the importance degree. The indicator's comprehensive weights are output, conforming Inconsistency <0.1," as shown in Figure 8.

**5.4. Cloud Model Early Warning Assessment.** Ten experts related to coal mine Y are invited to score 23 major second-level indicators; the rules are shown in Table 5. The highest and lowest scores are normalized to domain [0, 1]. Then, maximum and minimum cloud feature numbers are fitted to obtain comprehensive feature numbers, which are retained to three decimal places.

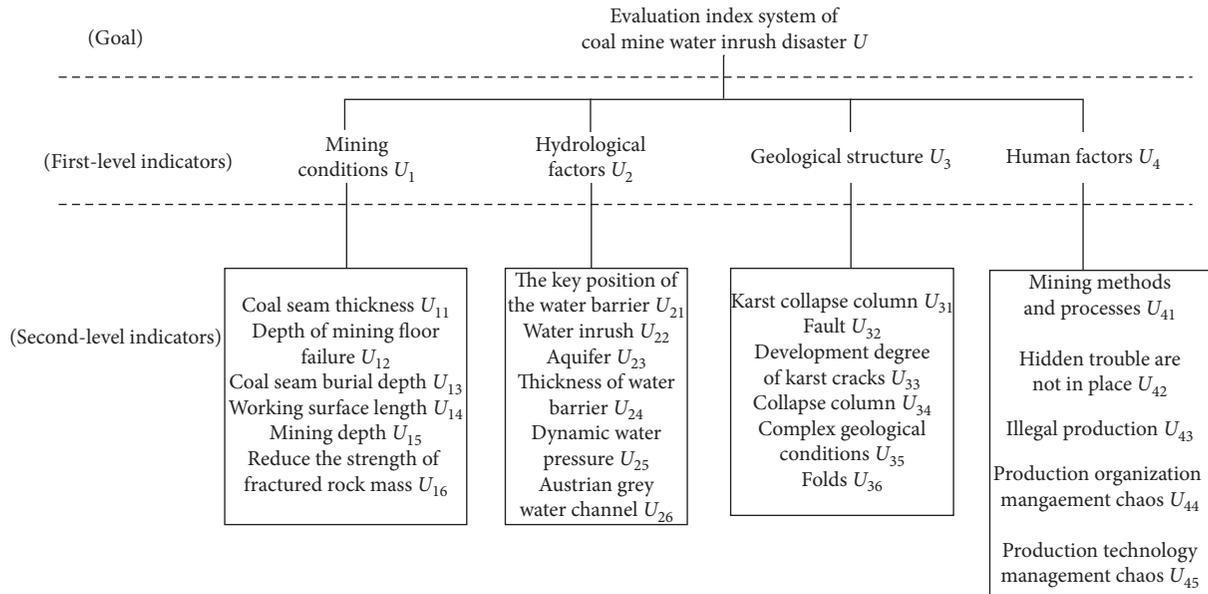


FIGURE 4: Network index system of the coal mine water inrush disaster.

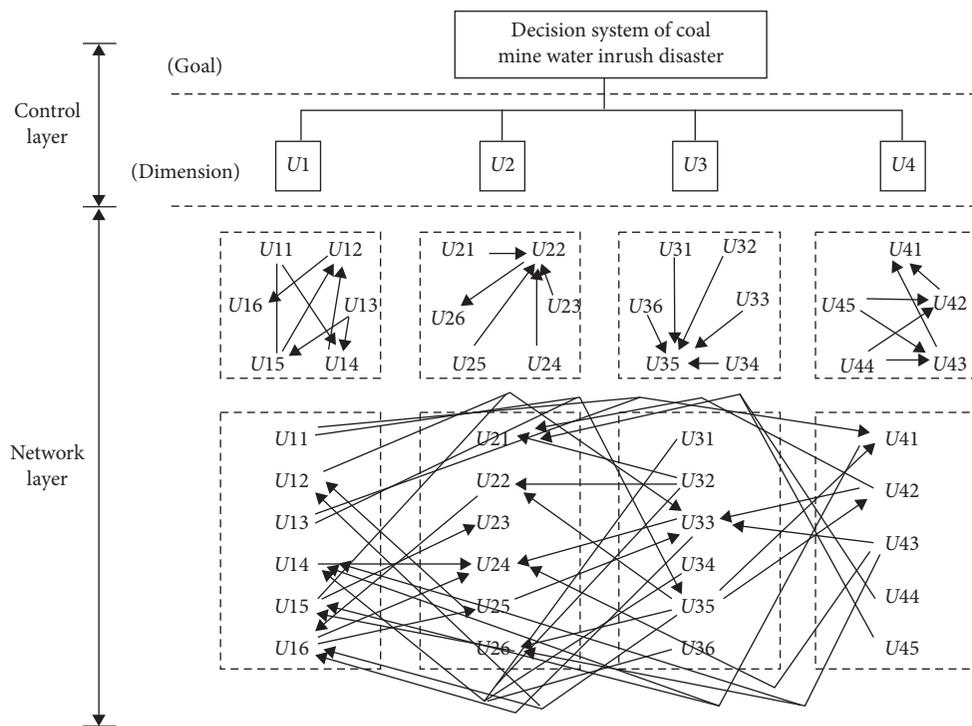


FIGURE 5: The network relationship diagram in ANP model.

TABLE 2: 1~9 scale scoring method.

Scale	Meaning
1	The two elements are of the same importance.
3	The former is slightly more important than the latter.
5	The former is significantly more important than the latter.
7	The former is more important than the latter.
9	The former is the most important than the latter.
2,4,6,8	The intermediate value of each scale.
Reciprocal (1,1/3, ..., 1/9)	The latter is more important than the former, with the same degree of importance as defined in 1~9.

TABLE 3: Expert rating weighted coefficients.

Experts	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Weighted coefficients	0.09	0.07	0.14	0.09	0.011	0.09	0.14	0.09	0.11	0.07

TABLE 4: Five standard comment sets.

Language value	Weak	Slightly weak	General	Strong	Stronger
Cloud model	(0, 0.103, 0.013)	(0.309, 0.064, 0.008)	(0.50, 0.031, 0.005)	(0.069, 0.064, 0.008)	(1, 0.103, 0.013)
x-axis value interval	[0, 0.309]	[0.117, 0.501]	[0.407, 0.593]	[0.499, 0.883]	[0.691, 1]
Warning level color	Green	Blue	Purple	Yellow	Red

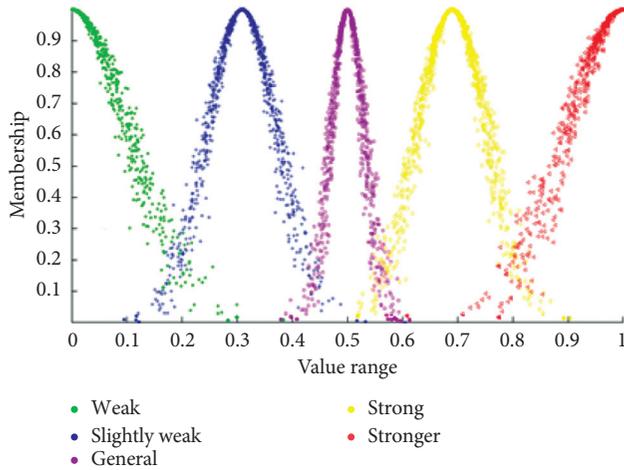


FIGURE 6: Standard evaluation cloud model.

5.4.1. *The Cloud Model Warning Results of First-Level Indicators.* Combining the cloud feature numbers and weights of second-level indicators can obtain comprehensive cloud feature numbers of first-level indicators, as shown in Table 6. They can be converted from qualitative to quantitative index through MATLAB, as shown in Figure 9. By comparing the black-circular cloud with the standard grades cloud model, we can obtain the corresponding risk level.

It can be seen from Figure 9 that the positions of four types of first-level indicators' clouds are generally at the moderate disaster level, which indicates they all can possibly cause water inrush disasters.

Figure 9(a) is the evaluation cloud map of mining conditions. It can be seen that the thickness and coverage of the main body of the black-circular cloud at the "yellow-strong" level are appropriate. It indicates that the mining conditions have strong prerequisites for disasters. So, it is necessary to strengthen the ability of prevention and control to all second-level indicators.

The evaluation cloud of hydrological factors is shown in Figure 9(b). It can be seen that the black-circular cloud image has a normal coverage and a suitable thickness, of which the main cloud basically meets with the "yellow-strong warning level." It shows that hydrological factors have a greater possibility of causing disaster. This is because hydrological factors include a series of conditions directly related to water inrush disasters, such as the aquifer and



FIGURE 7: The mine position of test Y coal mine.

hydrodynamic pressure. Thus, it should strengthen the rational prevention and control of hydrological factors.

Figure 9(c) is the evaluation cloud of geological structure. It can be seen that the black-circular cloud image has a normal coverage and thickness, of which the cloud location is between the "yellow-strong warning level" and "purple-general warning level." The geological structure can cause disaster, of which the risk rate is obviously lower than hydrological factors and mining conditions. Moreover, there are some structures with complex geological conditions and undetectable in mine, which may promote increasing the rock permeability, leading to water inrush disaster.

Figure 9(d) is the evaluation cloud of the human factor. It can be seen that the position of the black-circular cloud image is between three cloud images of "blue-slightly weak warning level," "purple-general warning level," and "yellow-strong warning level." It shows that human factors have little effect on water inrush disasters. However, its second-level indicators, such as "three violations of production," "hidden hazards can not be investigated," and other factors, will lead to inaccurate investigation on hidden dangers of water inrush disaster. It will have a certain impact on coal mine water inrush disaster. Therefore, we should focus on strengthening the quality and skills training of staff.

5.4.2. *The Cloud Model Warning Results of Goal.* The cloud feature numbers of goal are the inductive summary for the entire cloud model. In the early warning evaluation system of Y coal mine water inrush disaster, the comprehensive cloud characteristic numbers of goal are C (0.679, 0.086,

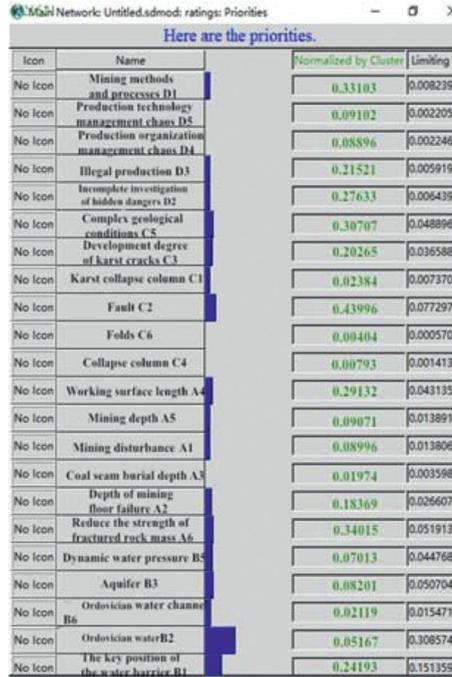


FIGURE 8: Index comprehensive weights chart.

TABLE 5: Scoring criteria for water inrush disaster indicators in Y coal mine.

Disaster level	Degree of disaster	Rating ranges
1	Weak	[0, 12.5]
2	Slightly weak	(12.5, 37.5]
3	General	(37.5, 62.5]
4	Strong	(62.5, 87.5]
5	Stronger	(87.5, 100]

TABLE 6: Comprehensive characteristic parameters and weights of each index cloud model.

First-level indicators	(Ex, En, He)	$w_i$	Second-level indicators	(Ex, En, He)	$w_i$
Mining conditions ( $U_1$ )	(0.682,0.100,0.006)	0.1707475	Mining disturbance $U_{11}$	(0.762,0.090,0.005)	0.09025
			Depth of mining floor failure $U_{12}$	(0.758,0.064,0.003)	0.17396
			Coal seam burial depth $U_{13}$	(0.730,0.044,0.003)	0.02349
			Working surface length $U_{14}$	(0.738,0.047,0.003)	0.28202
			Mining depth $U_{15}$	(0.655,0.084,0.005)	0.09082
			Reduce the strength of fractured rock mass $U_{16}$	(0.578,0.149,0.008)	0.33941
Hydrological factors ( $U_2$ )	(0.701,0.082,0.004)	0.610605	Key position of the water barrier $U_{21}$	(0.745,0.092,0.005)	0.23291
			Ordovician water $U_{22}$	(0.719,0.080,0.004)	0.47482
			Aquifer $U_{23}$	(0.654,0.075,0.004)	0.07802
			Water barrier thickness $U_{24}$	(0.669,0.073,0.004)	0.12155
			Dynamic water pressure $U_{25}$	(0.571,0.108,0.006)	0.06889
			Ordovician water channel $U_{26}$	(0.585,0.086,0.004)	0.02381
Geological structure ( $U_3$ )	(0.656,0.087,0.004)	0.1647225	Karst collapse column $U_{31}$	(0.746,0.077,0.004)	0.04282
			Fault $U_{32}$	(0.720,0.081,0.004)	0.44905
			Karst fissure development degree $U_{33}$	(0.601,0.076,0.004)	0.21256
			Collapse column $U_{34}$	(0.603,0.120,0.006)	0.00821
			Complex geological conditions $U_{35}$	(0.585,0.108,0.006)	0.28406
			Folds $U_{36}$	(0.575,0.106,0.005)	0.00331
Human factors ( $U_4$ )	(0.501,0.083,0.005)	0.05393	Mining methods and processes $U_{41}$	(0.641,0.076,0.004)	0.32893
			Incomplete investigation of hidden dangers $U_{42}$	(0.449,0.105,0.006)	0.25707
			Illegal production $U_{43}$	(0.423,0.071,0.004)	0.23631
			Production organization management chaos $U_{44}$	(0.427,0.065,0.004)	0.08967
			Production technology management chaos $U_{45}$	(0.417,0.089,0.005)	0.08803

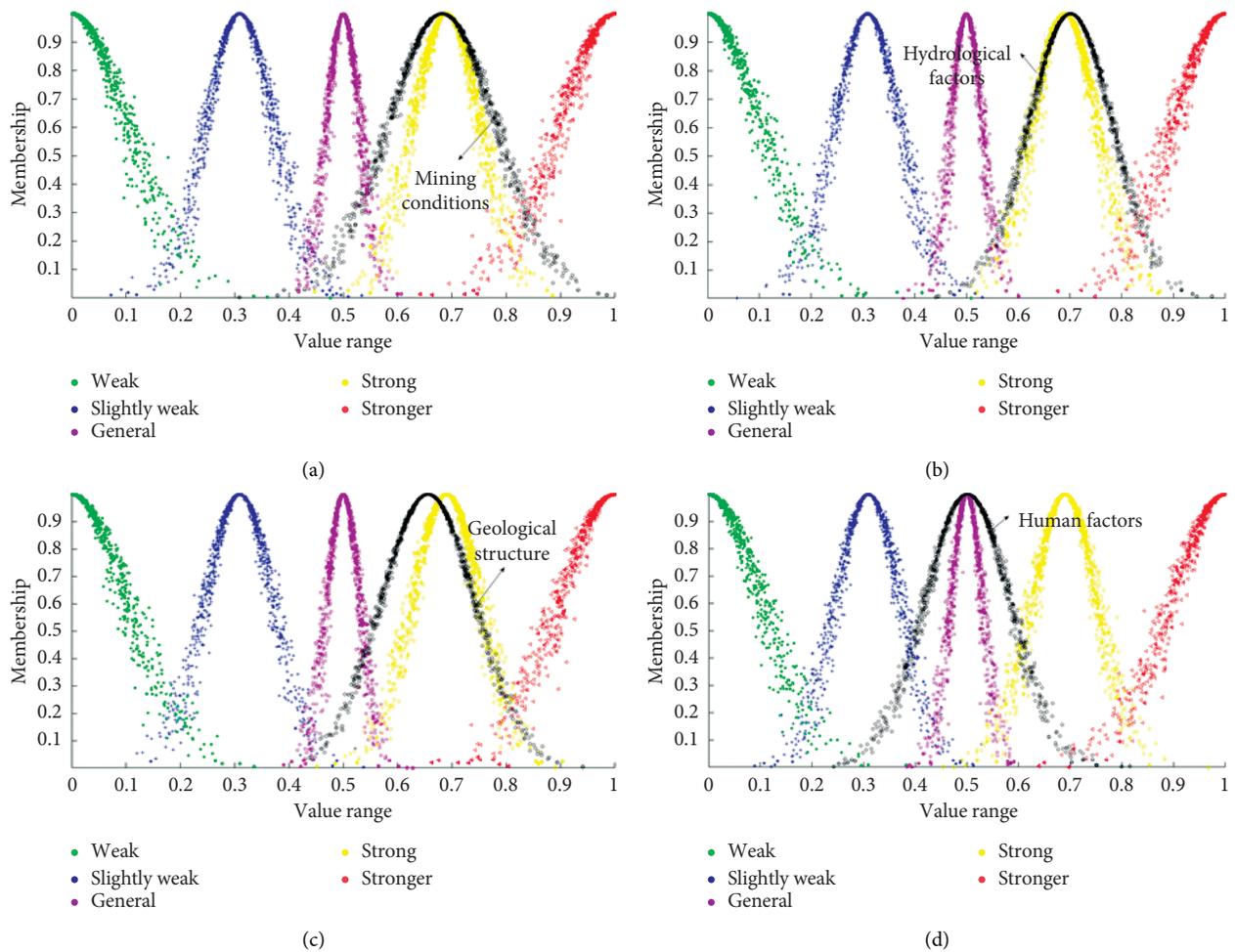


FIGURE 9: The cloud model evaluation results of first-level indicators. (a) Mining conditions evaluation cloud. (b) Hydrological factor evaluation cloud. (c) Geological structure evaluation cloud. (d) Human factors evaluation cloud.

0.004). The corresponding cloud image is shown in Figure 10.

It can be seen from Figure 10 that the cloud image of goal is a black-circular cloud, of which the coverage and thickness are appropriate. It is between three cloud images of “purple-general warning level,” “yellow-strong warning level,” and “red-strong warning level.” However, its main cloud is located at the yellow-strong warning level. It shows that there is a certain risk of water inrush in Y coal mine.

The predicted results are compared with actual disaster data of Y coal mine, which are consistent. It further proves that this early warning evaluation model of “ANP-Cloud” model based on Complex Network is reliable.

It is necessary to strengthen the prevented degree to hydrological factors, mining conditions, and geological structure. Moreover, we should comprehensively cultivate workers’ knowledge and technical capabilities. Moreover, construction technology management should be strengthened to avoid leaving out disaster-causing factors and eliminate illegal production.

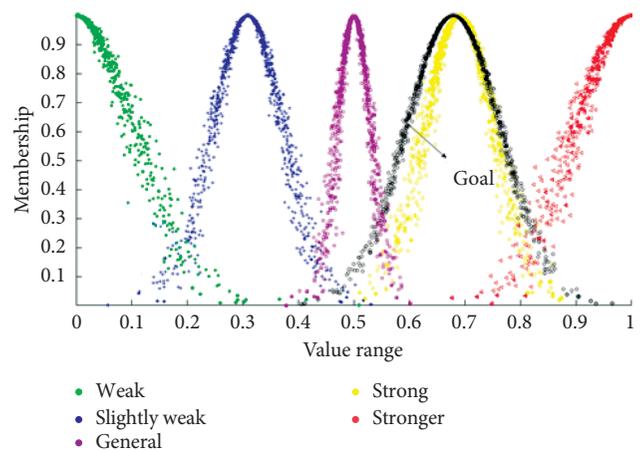


FIGURE 10: The cloud model evaluation results chart of goal.

## 6. Conclusions

In this article, the early warning evaluation system of the “ANP-Cloud” model based on Complex Network in water

inrush disaster was established to solve the problem of complex dependence relationship among disaster-causing factors and prevent water inrush disaster. Moreover, the usability and reliability of this warning evaluation model were verified in Y coal mine. The main conclusions are as follows:

- (1) The knowledge of the Complex Networks is used to establish a water inrush disaster network with 161 nodes and 149 connected edges. Through analyzing topological characteristics of the water inrush disaster network, 23 multiple importance nodes were obtained.
- (2) Based on the Complex Network model of water inrush disaster, the early warning evaluation system of the “ANP-Cloud” model was established. The main implementation steps include establishing index system, index weights based on ANP, building Cloud models of comment sets, and comprehensive early warning assessment.
- (3) Combining with the example of Y coal mine, the reliability and applicability of the evaluation model were further verified. The results show that the goal of the early warning evaluation system is a strong early warning level. Mining conditions, hydrological factors, and geological structures all belong to strong early warning levels. Moreover, human factors will have a certain effect on the other three first-level indicators. The predicted results are consistent with the actual situation of Y mine coal water inrush and the early warning evaluation system provides a base of experience for other types of network assessments.

## Data Availability

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

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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