Uncertainty Prediction of Mining Safety Production Situation

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1 **Uncertainty prediction of mining safety production situation**

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Abstract:

In order to explore the occurrence and development law of mining safety production accidents, analyze its future change trends, and aim at the ambiguity, non-stationarity, and randomness of mining safety production accidents, an uncertainty prediction model for mining safety production situation is proposed. Firstly, the time series effect evaluation function is introduced to determine the optimal time granularity, which is used as the window width of fuzzy information granulation (FIG), and the time series of mining safety production situation is mapped to *Low*, *R* and *Up* three granular parameter sequences, according to the triangular fuzzy number; Then, the mean value of the intrinsic mode function (IMF) is maintained in the normal dynamic filtering range. After the ensemble empirical mode decomposition (EEMD), the three non-stationary granulation parameter sequences of *Low*, *R* and *Up* are decomposed into the intrinsic mode function components representing the detail information and the trend components representing the overall change, and then the sub-sequences are reconstructed according to the sample entropy to highlight the correlation among the sub-sequences; Finally, the cloud model language rules of mining safety production situation prediction are created. Through time series discretization, cloud transformation, concept jump, time series set division, association rule mining and uncertain reasoning, the reconstructed component sequence is modeled and predicted by uncertainty information extraction. The accuracy of the uncertainty prediction model was verified by 21 sets of test samples. The average relative errors of *Low*, *R* and *Up* sequences were 9.472 %, 16.671 % and 3.625 %, respectively. The research shows that the uncertainty prediction model of mining safety production situation overcomes the fuzziness, non-stationarity and uncertainty of safety production accidents, and provides theoretical reference and practical guidance for mining safety management and decision-making.

Keywords: Mining safety prediction; Uncertainty; Time granularity; Fuzzy information granulation; Ensemble empirical mode decomposition; Cloud model

0 Introduction

Mining is an important basic industry of the national economy, supporting the rapid development of social economy, but mining is also an industry with high casualty rate in industrial production process (Fernando et al., 2017). At present, China is in the process of rapid development of modernization. In general, it is still in a special period of prone and frequent production safety accidents. “Safety first, prevention first and comprehensive management” are the general guidelines for safety production management in China. Accurate prediction of mining safety production situation is the premise of providing mining safety decision-making and ensuring mining safety production, which has become one of the core contents of modern mining safety management. According to the development trend of mining safety production situation, corresponding measures can be taken to promote the development of mining system in the direction of safety and achieve the purpose of safe production and management (Grant et al., 2018). Therefore, it is of great practical significance to carry out research on the occurrence and development laws of the mining safety production situation and analyze its future change trends.

The mining safety system is a complex circulatory system, which is affected by many factors such as natural conditions, laws and regulations, social environment, enterprise environment and operating environment, and has the characteristics of non-linearity, non-stationarity and uncertainty (Emily et al., 2016). The existence of accidental factors, sudden factors and random factors in the mining system has brought difficulties and challenges to the safety accident prediction. At present, domestic and foreign scholars have carried out a lot of research on mining system accident prediction.

Li et al. (2016) comprehensive early warning index is calculated by multi-objective linear weighting function, and the accident early warning index model is established according to grey system theory GM (1, 1). Meng et al. (2017) predicted mine safety accidents based on principal component method and neural network. Wang et al. (2017) used the RS method as the characteristic parameter of pre-processor reduction, and then carried out classification modeling based on SVM method. They established the early warning index system of mining safety production from four aspects of personnel, environment, equipment and management, used genetic algorithm for RS rough set attribute reduction, and used rough set support vector machine combination forecasting model for coal mine risk prediction. Barman et al. (2019) optimized the parameter selection of SVM by Firefly algorithm (FA) to improve the prediction accuracy of SVM model. Huang et al. (2019) carried out the modeling and simulation of large mine accident data analysis and prediction based on decision tree-BP neural network. Luo et al. (2020) based on Cusp mutation model and DS fusion evidence theory, the instability warning of underground rock mass in mining area was carried out. These methods often require a large amount of historical data and clear risk indicators. However, the development of China's mining safety accident database is not perfect, the accurate statistical data can be obtained is limited, and some data are greatly affected by random factors, there is a certain statistical error, unable to correctly identify its distribution.

Although the occurrence of accidents is disorderly and irregular, the surface phenomenon of contingency of mining safety accident system is always dominated by its internal laws. A large number of statistical data show that, the accident situation and its influencing factors are a closely linked whole, and this whole has relative stability and sustainability, and is essentially causal and inevitable (Eric et al., 2019). And although individual accidents have random uncertainty, but in a large sample of the overall still show some regularity, still can understand and grasp the future law and trend of the accident to a certain extent. Therefore, the detailed analysis of various influencing factors can be abandoned, and the trend of mining accidents can be predicted on the basis of scientific statistical data. As the situation of mine casualties changes over time, there will be a certain statistical law (Dan et al., 2011). Therefore, time series prediction method can be used to predict mining accidents.

For the time series prediction of mining accidents, Xu et al. (2012) proposed a dynamic unbiased grey Markov prediction model to predict the situation of mining safety production. Jiang et al. (2014) realized mine accident prediction based on grey theory. Mohseni et al. (2016) used time series seasonal decomposition method to predict the accident in Tazareh coal mine. Chen et al. (2017) proposed a new coal mine accident prediction method: the fusion of set pair analysis and fault tree. Wang et al. (2017) combined ARMA model with Markov prediction model to construct an ARMA-Markov combined prediction model that can take into account the randomness and trend of mining safety production accidents. Shikha et al. (2017) developed a system based on accident prediction fuzzy inference method (FRA) to predict the possibility of mine accidents in India. Lu et al. (2018) found the approximate algebraic fitting relationship between the number of accidents and the time change according to the variation law and characteristics of mining accidents, and realized the intelligent prediction of the number of accidents. Kumar et al. (2020) realized underground mine accident prediction based on binary logistic regression model. However, these methods are subject to their own inherent defects, and the robustness of the prediction results is poor. Therefore, many scholars have made corresponding improvements and improvements on the basis of these models. Liu et al. (2014) used GM (1, 1) to predict the data trend, and used support vector machine to predict the residual sequence. Finally, the results of the two models were fused to establish a combined prediction model of grey support vector machine GM (1, 1)-SVM. Erasmo et al. (2016) constructed ARIMA-NARX model by combining ARIMA model with nonlinear autoregressive exogenous model (NARX). Wu et al. (2018) processed the original data based on fuzzy information granulation, and established the mine accident prediction model by using support vector machine (SVM) and differential evolution algorithm (DE). Novri et al. (2018) Aiming at the problem of low prediction accuracy of ARMA model for nonlinear factors, an ARMA-ANN prediction model is established by introducing artificial neural network. Ma et al. (2019) realized the adaptive optimization selection of penalty parameters and kernel function parameters of support vector machine by using genetic algorithm (GA), trained SVM model and nonlinear prediction of time series. Wu et al. (2020) smoothed the time series of mining safety production situation through empirical mode decomposition, and then modeled and

115 predicted the stationary series separately according to ARMA. The prediction accuracy of
116 these improved methods is improved. However, these models still have the following two
117 problems. One is that only point prediction of time series can be obtained without
118 considering the fuzziness of time series. There are many uncertain factors and statistical
119 errors in mining safety production situation. If the statistical error of mining accidents and
120 some random factors of mining accidents can be considered, the quantitative time series of
121 mining safety production situation will be internalized, and the prediction results will be
122 more reliable. Therefore, it is of more important value in practical application to accurately
123 predict the change trend and change space of mining safety production situation and master
124 its fluctuation range. Second, most of these methods do not consider the important factor in
125 time series data — time granularity. If the granularity is too large, it is easy to lose important
126 or even decisive information. On the contrary, if the particle size is too small, the prediction
127 will fall into details, resulting in too large data changes and unpredictable. Different
128 granularity of time data plays different roles in time series prediction (Lin et al., 2020).
129 Appropriate granularity is a necessary condition for correctly understanding knowledge and
130 rules.

131 Although in the past few decades, scholars have done a lot of research and exploration
132 on the safety accident prediction of mining system, but the summary and analysis of the
133 relevant literature of the accident prediction model for a long time shows that in the
134 prediction of mining safety accident system, there are still the following difficulties: in the
135 process of mining safety production situation prediction, less consideration of time
136 granularity leads to the prediction into details or unpredictable; smooth processing is easy to
137 lose the original sequence feature information or feature performance is not obvious; mining
138 safety production situation is fuzzy and uncertain. In order to carry out the mining safety
139 management work in a targeted and targeted manner, it is necessary to further explore the
140 relevant factors and characteristics of the occurrence and development of the accident,
141 excavate the internal information of the mining safety production situation time series,
142 establish the most suitable system prediction model combined with the characteristics of the
143 mining safety accident system, scientifically and accurately predict the occurrence and
144 development trend of mining accidents, and reduce the probability of accidents, and conduct
145 targeted research on these three problems.

146 In order to better excavate the regularity of mining safety production situation and
147 reveal the characteristics of mining safety production situation, the best time granularity of
148 mining safety production situation should be determined firstly, take the best time granularity
149 as the window width. The mining safety production situation is granulated according to the
150 best time granularity, and the information granules that can reflect the characteristics of the
151 original data are obtained. Some statistical errors and uncertainty factors of non-coal mine
152 safety production situation are reflected in the granulation interval. The error of mining safety
153 production situation is mapped in three windowed time series of *Low*, *R* and *Up*, highlighting
154 the inherent characteristics of mining safety production situation time series.

155 The time series of mining safety production situation is a dynamic stochastic process,

which has non-stationary characteristics and is difficult to accurately identify its distribution. The ensemble empirical mode decomposition can discrete the random non-stationary time series into the high-frequency signal sequence that represents the overall trend and the low-frequency signal sequence that represents the random disturbance. It can decompose the hidden information of the original time series, characterize the characteristics of the original time series more clearly, and preserve its dynamic characteristics. Then, the characteristics of the original sequence can be revealed by studying these components. Compared with differential operation and empirical mode decomposition, aggregated empirical mode decomposition can completely preserve the information of the original time series, and can well suppress the phenomenon of modal aliasing. For the stationary sequence after ensemble empirical mode decomposition, the sample entropy is used to reconstruct it, which can take into account the correlation in the sub-sequence and better reflect the original characteristics of the non-coal mine safety production situation time series.

Qualitative concepts and uncertainty reasoning reflect human intelligence and are one of the most significant differences between human and machine at the same time. Cloud model is a model that combines randomness and fuzziness to realize the uncertain transformation between qualitative and quantitative through uncertainty reasoning (Wu et al., 2019). Since it was proposed, it has been a hot topic for researchers from all walks of life to explore applications. Cloud models have been successfully applied in financial markets, data mining, artificial intelligence, image processing, decision analysis and many other fields (Ye et al., 2011). Time series prediction based on cloud model is to use cloud theory as the theoretical basis of knowledge representation, propose prediction knowledge, and integrate knowledge of different time granularity for time series prediction. The prediction knowledge to be expressed by the system should be fuzzy and uncertain. Time series prediction based on cloud model can not only compress time granularity, but also compress information granularity. In recent years, the application of cloud model in time series prediction has become increasingly widespread. The theoretical advantages of cloud model are clearly reflected in the study of knowledge representation and uncertainty reasoning (Hassen et al., 2020). Although machine learning and deep learning methods such as support vector machine and neural network can better extract the deterministic information in the stationary component sequence, they lack the consideration of the uncertain information of the stationary sequence, and use the conceptual method to grasp the uncertainty of the quantity, which is more realistic and universal than the mathematical expression (Bauer et al., 2020). Then, how to express the qualitative knowledge expressed in natural language? How to reflect uncertainty in natural language, especially fuzziness and randomness? How to realize the conversion between qualitative and quantitative knowledge? How to embody the soft reasoning ability in language thinking? Therefore, we propose a qualitative and quantitative uncertainty conversion model which called cloud model, to realize the uncertainty conversion between qualitative concepts and quantitative values based on cloud model.

Based on this, the analysis of time series characteristics based on mining safety production situation is studied. Firstly, the optimal time granularity of mining safety

production situation is determined, and it is used as a window width. Then, the triangular fuzzy number is used to granulate the fuzzy information of mining safety production situation time series. Then, the windowed time series are smoothed by ensemble empirical mode decomposition and sample entropy reconstruction, which highlights the characteristics of the original sequence. According to the characteristics of the reconstructed sequence, the uncertainty prediction of the reconstructed sequence is carried out based on cloud theory, and the uncertainty prediction model of mining safety production situation is constructed. The development trend of mining safety production situation is predicted, which provides a novel idea for the prediction of mining safety production situation.

The rest of this paper is organized as follows: Section 1 provides a detailed introduction to the modeling principle and process of the uncertainty prediction model. Section 2 explains the source of the data and validates the model. The comparison of prediction accuracy of the models is performed in Section 3. Section 4 discusses and elaborates the future research directions while the conclusions drawn from this research are summarized in Section 5.

1 Establishment of the model

1.1 Fuzzy information granulation of time series

The accuracy of time series prediction is closely related to the inherent law of the original time series. Since there is a certain statistical error in the statistics of accidents, the inherent law of time series will be weakened and the accuracy of the model will be affected. Therefore, considering the fuzzification of statistical accident information and the granulation of fuzzy information, the time series of mining safety production situation is mapped to triangular fuzzy information particles including low boundary value *Low*, median value *R* and high boundary value *Up*, and the statistical error is reflected in the original time series of mining safety production situation.

The triangular fuzzy information particle is used to granulate the time series of mining safety production situation. Firstly, the original time series is divided into some sub-sequences according to a certain window *w*. The original time series window takes one season as a unit, namely, the window size is 3. Then fuzzy granulation is performed on each window to obtain three time series after windowing. The membership function of fuzzy particles after granulation is (Akram et al., 2020):

$$A(x, a, m, b) = \begin{cases} 0 & x < a \\ \frac{x-a}{m-a} & a \leq x \leq m \\ \frac{b-x}{b-m} & m \leq x \leq b \\ 0 & x > b \end{cases} \quad (1)$$

where *x* is a variable in the domain. *a*, *m*, *b* is a parameter, corresponding to the three variables *Low*, *R*, *Up* after window fuzzification. *Low* describes the minimum change of the fuzzy granulation window; *R* describes the general average level of the fuzzy granulation window change, and *Up* describes the maximum value of the fuzzy granulation window change.

1.2 Decomposition and Recombination of Granulated Sequences

The time series of mining safety production situation is a dynamic stochastic process, which has non-stationary characteristics and is difficult to accurately identify its law of distribution. Aggregated empirical mode decomposition can discrete random non-stationary time series into high-frequency signal series that represent the overall trend and low-frequency signal series that represent random disturbance. Compared with differential operation Aggregated empirical mode decomposition, it can completely retain the information of the original time series, and it can well suppress modal aliasing compared with empirical mode decomposition.

1.2.1 Empirical mode decomposition

Empirical mode decomposition (EMD) is based on the local characteristic time scale of the signal itself, which decomposes the fluctuations or trends in different scales of the signal step by step, and produces a series of data sequences with different characteristic scales, namely, the Intrinsic Mode Function (IMF) (Stallone et al., 2020). IMF signals are based on the following three assumptions:

- 1) The original time series has at least one maximum point and one minimum point;
- 2) The characteristic time scale is defined as the time interval between adjacent extreme points;
- 3) If the original time series has no extreme points and only inflection points, it is necessary to differentiate it one or more times to obtain the extreme points before decomposing it, and then integrate the results to obtain the corresponding components.

EMD realizes the decomposition of the original signal through the process of "sieving", and shows the changing trend of the original signal more clearly through transformation. The algorithm process is as follows:

Step 1: For a given signal, determine all extreme points. The upper and lower envelopes are obtained by connecting all the maximum and minimum points with cubic spline curves. Order:

$$h_t = X(t) - ([E^+(t) + E^-(t)]/2) \quad (2)$$

Step 2: Separate it and get a difference time series that removes the IMF1 component:

$$RES_1 = X(t) - IMF_1 \quad (3)$$

Repeat the screening process of Step 1 for the new time series until the residual sequence of the n th order becomes a monotonic sequence and cannot continue to decompose the IMF components.

$$RES_n = RES_{n-1} - IMF_n \quad (4)$$

Step 3: The original signal in mathematics can be expressed as the sum of n IMF components and the last residual RES:

$$X(t) = \sum_{i=1}^n IMF_i + RES_i \quad (5)$$

Where IMF_i represents the detail component. RES_i represents the approximate component.

1.2.2 Empirical mode decomposition

In the practical application of EMD, the characteristic components of different time scales are decomposed into a characteristic modal function component, or the same time scale component appears in different characteristic modal functions, that is, modal aliasing. Ensemble empirical mode decomposition can effectively make up for the deficiency of EMD. It defines the mean value of a whole test as the real IMF component, and each component contains signal and white noise with limited amplitude, which can clearly separate each time scale. The process of EEMD is as follows:

- (1) Adding white noise signals to the target data;
- (2) Decompose the added white noise signal into IMF;
- (3) Each time adding different white noise sequence, repeated steps (1), (2);
- (4) Take the mean value of each IMF as the final result.

1.2.3 Sample entropy recombination component

For multiple sub-sequences obtained by ensemble empirical mode decomposition, if they are separately built to predict, not only the calculation amount is greatly increased, but the correlation between the sub-sequences is ignored. The sample entropy algorithm is used to reconstruct the sub-sequences, which can better highlight the typical characteristics of similar sequences. Sample entropy reflects the complexity of time series. The more obvious the periodicity of time series is, the smaller the signal noise interference is, the smaller the sample entropy value is. On the contrary, the greater the signal noise interference is, the greater the sample entropy value is. This algorithm contains the characteristics of approximate entropy and does not need its own template matching, which makes up for the deficiency of approximate entropy (Mourenas et al., 2020). Considering that the sample entropy has the advantages of independent calculation of data length and good consistency, it is combined with the ensemble empirical mode decomposition to propose the feature extraction method of time series based on ensemble empirical mode decomposition and sample entropy.

The calculation process of sample entropy is as follows:

(1) For the sequence after aggregated empirical mode decomposition, an n -dimensional vector group $X_m(1), \dots, X_m(N-m+1)$ is formed according to the sequence number, where $X_m(i) = \{x(i), x(i+1), \dots, x(i+m-1)\}$, $1 \leq i \leq N-m+1$.

(2) For a given $X_m(i)$, calculate the number of distances between $X_m(i)$ and $X_m(j)$ less than or equal to r , which is the number of template matching B_i , and calculate the ratio of B_i to the total distance $N-m+1$, $B_i^m(r)$:

$$B_i^m(r) = \frac{1}{N-m+1} B_i \quad (6)$$

(3) Define $B^{(m)}(r)$ as:

$$B^{(m)}(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r) \quad (7)$$

(4) Increase the dimension m to $m+1$ dimension, repeat steps (1)~(3) for the $m+1$

dimension vector to obtain $B^{(m+1)}(r)$.

(5) The sample entropy of this sequence is:

$$SampEn(m, r, N) = -\ln\left[\frac{B^{(m+1)}(r)}{B^{(m)}(r)}\right] \quad (8)$$

Where m is the reconstruction dimension, generally $m=2$. N is the data length. r is similar tolerance, generally 0.1~0.25 times of standard deviation.

1.3 Prediction of granulation time series based on cloud theory

Time series prediction based on cloud theory is mainly based on the following two principles (Gu et al., 2021):

(1) Fourier transform in physics can often deal with complex situations in one space simply in another.

(2) Any probability distribution can be decomposed into several normal distribution combinations.

Time series analysis mainly studies the random dynamic data from the perspective of frequency domain and time domain, and conducts uncertain data modeling for dynamic data. There are few studies on the prediction of time series based on cloud model. In this paper, the method of time series prediction based on cloud theory is mainly based on the normal cloud model generator. The prediction of granulation time series based on cloud theory is as follows:

1.3.1 Discretization of time series

The purpose of discretization of time series data is automatic generation of concept level. The common methods for discretization of time series data are mainly the equal-distance interval method and the equal-frequency interval method, that is, dividing the time series into several subintervals subjectively with equal width (or according to the frequency of data value, equal frequency). Both methods have strong subjective factors, which cannot reflect the uncertainty of extracting concepts from continuous time series data. Moreover, the concept tree generated by these methods is rigid, and the membership relationship between hierarchical concepts cannot be reflected, and the actual data distribution is not considered.

Fourier transform in physics can transform the time-domain space and frequency-domain space, and often simply handle the complex situation of one space in another space. Any probability distribution can be decomposed into several normal distribution combinations. Based on the above two points, the cloud transform algorithm is used to discretize the time series data.

Given the frequency distribution function $f(x)$ of time series, it is converted into the superposition of multiple normal cloud models according to a specific algorithm. The mathematical expression is:

$$F(x) \rightarrow \sum_{i=1}^n c_i * C(c_i * C(Ex_i, En_i, He_i)) \quad (9)$$

Where c_i is the coefficient, n is the number of discrete qualitative concepts generated.

1.3.2 Concept hierarchy

The cloud transformation method automatically generates a series of basic concepts represented by the cloud model according to the distribution of data values in the attribute domain, and realizes the soft partition of the domain. In the process of knowledge discovery, these basic concepts can be regarded as the leaf nodes of the pan-concept tree for concept jump. The so-called concept leap is to raise the concept directly to the required concept granularity or concept level on the basis of the concept leaf node. Common types are: user-defined jump, intelligent jump and interactive jump. According to human cognitive psychological characteristics, generally 7 ± 2 concepts are the most appropriate.

Set two adjacent cloud models $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2)$, and $Ex_1 < Ex_2$. Let the merged cloud model be $C(Ex, En, He)$, then:

$$C = C_1 \cup C_2 \Leftrightarrow \quad (10)$$

$$\begin{cases} Ex = \frac{Ex_1 + Ex_2}{2} + \frac{En_2 + En_1}{4} \\ En = \frac{Ex_2 - Ex_1}{4} + \frac{En_2 + En_1}{4} \\ He = \max(He_1, He_2) \end{cases} \quad (11)$$

Through the above methods, the basic concepts of mining safety production situation can be upgraded to the required conceptual level.

1.3.3 Time series set partitioning

When the concept is jumped to the appropriate granularity or level, the maximum value judgment method is used to determine the values of each time in the time series.

Given a time series X_t , $t \in N$, the concept set of a concept granularity corresponding to X_t is :

$$C = C\{C_1(Ex_1, Ex_2, Ex_3), C_2(Ex_1, Ex_2, Ex_3), \dots, C_n(Ex_n, Ex_n, Ex_n)\} \quad (12)$$

Then each x_t as the corresponding value to be determined, the idea of maximum determination method is shown in Fig.1. The antecedent cloud generator $CG_1, CG_2, \dots, CG_n$ corresponds to each concept in C , and the membership degree of x_t to each concept is calculated as $\mu_1, \mu_2, \dots, \mu_n$, respectively. If $\mu_i = \max(\mu_k)$, $k = 1, 2, \dots, n$, then the concept C_i is the subordinate concept of x_t . If there are two or more maximum membership degrees, one of them is randomly selected as the membership concept of x_t . According to the definition of cloud, $\mu_1, \mu_2, \dots, \mu_n$ are a set of random variables with stable tendency. Therefore, x_t may belong to different concepts in overlapping regions under different conditions, which is consistent with people's psychological cognitive characteristics.

Fig.1 Principle of Maximum Judgment

1.3.4 Association rule mining based on cloud

The basic idea of cloud association knowledge mining is to use cloud to represent the “soft threshold” of support and confidence in association rule mining. The positive cloud generator is used to realize the conversion from qualitative linguistic value to quantitative value. Cloud transformation is used to divide the universe of discourse of numerical attributes into multiple qualitative concepts represented by clouds, so as to realize the discretization of numerical attributes. On this basis, *Apriori* algorithm is finally used to realize the mining of different types of association rules in the database. These rules are composed of the concepts represented by the cloud model. Due to the fuzziness and randomness of the cloud model, the obtained association rules are more suitable for human thinking. The support and confidence represented by the cloud model make the threshold no longer fixed, but because of the fuzziness of its unique boundary, more uncertain mining results can be obtained in the process of mining. Furthermore, it is easier to obtain association rules at different conceptual levels by means of concept jumping strategy. According to the requirements of association mining algorithm, this kind of conceptual sequence represented by normal cloud model can be converted into Boolean data table.

1.3.5 Uncertainty prediction

Based on concept, the qualitative knowledge is constructed into rule generator according to cloud theory, which is called uncertainty reasoning based on cloud model. With the help of normal cloud model to replace the division of the universe of quantitative attributes, the concept of normal cloud association rules on quantitative attributes is proposed, and the method of mining normal cloud association rules is given. Since the normal cloud model better softens the dividing boundary of the quantitative attribute universe, it can make the mined normal cloud association rules and prediction results more easily understood.

If A then B, where A and B are concept cloud objects. This is a simple form of qualitative rules. A X-condition cloud generator and a Y-condition cloud generator are connected to a single-condition rule generator, as shown in Fig.2. When inputting a specific value x_0 , CG_A will be excited to generate a stable random membership value μ_i , which will be used as the input of CG_B . At the same time, CG_B will be excited to generate a cloud droplet x , (x, μ) is a random cloud droplet generated by the rule generator. Because of the uncertainty of

the cloud model in the algorithm, the quantitative values x and μ of this group of cloud droplets are not unique or determined. This illustrates the transmission of uncertainty in the reasoning process of cloud rule generator. Regular generator is more common: one-dimensional or multidimensional antecedent cloud (multidimensional structure usually through a number of one-dimensional antecedent cloud splicing), one-dimensional consequent cloud (Yan et al., 2019). Time series prediction based on cloud model can generate a single-condition single-rule generator through the qualitative knowledge obtained by the final mining, and then construct a prediction inference engine of multiple qualitative rules to achieve time series prediction.

Fig.2 Single condition single rule generator

2 Model application

Taking the mortality rate of 10,000 people from mining accidents in mining industry across the country from January 2005 to June 2020 as the research object. The data comes from the statistics of domestic mining safety production accidents and the statistical analysis of mining employees on the "National Data" website. 175 sets of data on the mortality rate of 10,000 people from mining accidents from January 2005 to September 2018 were used as the training set to build the model. The 21 sets of data on the death rate of 10,000 people from mining accidents from October 2018 to June 2020 are used as the test set to verify the reliability of the model. Fig.3 shows the time series of the death rate of 10,000 people from mining safety accidents across the country from 2005 to 2020.

Fig.3 Time series chart of death rate per 10,000

Fig.4 Fuzzy information granular view

The time series of mining safety production situation is the waveform of time, and the time series of mining safety production situation has the characteristics of random fluctuation. China's mining safety accident database development is not perfect, can get accurate

statistical data is limited, has certain fuzziness. In order to solve the fuzziness of mining safety production situation, the fuzzy information of the recombinant sub-sequence is first granularized according to a certain window to obtain the information granules that can reflect the characteristics of the recombinant sub-sequence, and the fuzziness is reflected in the information interval.

The selection of granulation window width has certain subjectivity, which will have different effects on the actual prediction. Previous studies often determine the window width through subjective experience. In order to reduce the subjectivity of window width selection, the best time granularity of mining safety production situation is considered as the window width. In order to evaluate the prediction effect based on different time granularity in a given time domain, the time sequence mining evaluation effect function $F(a_{ti} \in A_T)$ is introduced. This function represents the accuracy of mining safety production situation prediction based on the extraction of time granularity a_{ti} . Based on this function, the best time granularity of mining safety production situation can be found. The best time granularity determination method of mining safety production situation is as follows:

Assuming that the domain U_T and its corresponding time granularity set A_T are given, the optimal time granularity a_{ti} is defined as $\forall a_{ti} \wedge a_{tj} \neq a_{ti} \wedge F(a_{ti}) > F(a_{tj})$. The acquisition of optimal time granularity is of great significance for mining safety production situation prediction. In general, the best time granularity is neither atomic nor domain-based (Luo et al., 2019). Due to the complexity of mining accident data, the optimal time granularity is often impossible to obtain at one time, and the prediction accuracy reaches a certain degree before it has application significance. Based on the prediction accuracy threshold λ , an algorithm for solving the optimal time granularity from coarse to fine according to the time granularity is given.

Input: Time domain U_T , alternative n equivalent partition time series based on time granular, time series data mining evaluation effect function $F(a_{ti} \in A_T)$, prediction accuracy threshold λ .

Output: Optimal time granule shape OPT.

(1) From n partitions, according to $F(a_{ti} \in A_T)$, a partition is selected to get the time granular set TG_i under a_{ti} .

(2) The prediction effect under each TG_i is evaluated in turn. If the accuracy reaches the preset threshold, the algorithm ends. Otherwise, according to each time granule of the current TG_i , the time granule expression sequence with the best $F(a_{ti} \in A_T)$ effect is selected. Further, the time granule under the current granularity is tried to be divided, and the divided results are merged according to the precursor and successor relationship of the time granule.

(3) We continue to evaluate the prediction effect under the current particle size until the accuracy reaches the preset threshold or is less than a certain time particle size, and obtain the optimal time particle size and its expression, denoted as OPT.

If $n=\{n_1, n_2, n_3\}=\{1, 2, 3\}$ respectively represents three optional methods of time granularity, (1, 2, 3 represent the 1st, 2nd and 3rd fractions of the given time granularity),

then the next method for solving the optimal time granularity under a given U_T is shown in Fig.5.

Fig.5 Optimal time granularity solution process

Taking every 3 months (1 quarter) as an information granulation window, the mining safety production situation time series fuzzy granulation is converted into *Low*, *R*, *Up* three parameters. The fuzzy information granulation results are shown in Fig.4. where *Low* represents the minimum monthly change of the mortality rate per 10,000 people in the mining safety production situation, *R* represents the general average monthly change of the mortality rate per 10,000 people in the mining safety production situation, and *Up* represents the maximum monthly change of the mortality rate per 10,000 people in the mining safety production situation. It can be seen from Fig.4 that the three parameters of *Low*, *R* and *Up* after fuzzy information granulation are non-stationary. In order to solve this problem, the original data are decomposed by aggregated empirical mode decomposition to obtain multiple intrinsic mode functions and a monotonic sequence that can reflect the change trend of original data, which highlights the general law of mining safety production situation. The mining safety production situation curve is shown in Fig.6 after aggregated empirical mode decomposition.

It can be seen from Fig.6 that at each decomposition level, the trend sequence represents the main fluctuation/fluctuation of the mining safety production situation, and the detail sequence mainly represents the small-scale fluctuation with large frequency. With the increase of decomposition level, the details are gradually extracted. After 6-level aggregate empirical mode decomposition, the trend has lost a lot of detail information contained in the original mining safety production situation curve, and the detail part has appeared large-scale fluctuations only at low frequencies. This shows that the six decomposition levels can meet the requirements of mining safety production situation curve decomposition, and the original mining safety production situation curve can be decomposed into low frequency detail sequence and high frequency trend sequence.

(a) *Low* - value EEMD results (b) *R* - value EEMD results (c) *Up* - value EEMD results

(d) *Low*-value Hilbert Energy Spectrum (e) *R*-value Hilbert Energy Spectrum (f) *Up*-value Hilbert Energy Spectrum

Fig.6 EEMD of the time series curve of mining safety production situation

The complexity of the original time series can be reduced by decomposing the curve of the granulation parameter series into several sub-sequences. If each sub-sequence is modeled separately, not only the computation is increased, but also the correlation between each sub-sequence is ignored. Therefore, the sample entropy is used to determine the complexity of each component and reconstruct it, which highlights the characteristics of similar sequences. The sample entropy distribution of sub-sequences is shown in Fig.7. The sample entropy reflects the complexity of the sequence. The higher the auto-correlation of the sequence is, the smaller the sample entropy is. On the contrary, the sample entropy is larger. The sample entropy values of the given sequence and sub-sequence are calculated, and the sample entropy value is significantly lower than that of the sub-sequence of the given sequence, which can constitute the trend component. The sample entropy is significantly higher than the sub-sequence of a given sequence can constitute a random component. Sub-sequences whose sample entropy values are within the range of sample entropy threshold λ of a given sequence constitute the detail components. The value of λ is determined according to the sample entropy distribution of the sub-sequence, $\lambda=0.40$. The recombinant sequence is shown in Fig.8.

Fig.7 Sub-sequence sample entropy distribution

Fig.8 Sample entropy recombination sequence

Analysis of the characteristics of Fig.8 shows that trend component, detail component and random component have their own typical characteristics. The trend component roughly reflects the overall fluctuation trend of the original mining safety production situation. The detail component can represent the detail fluctuation of mining safety production situation. The random component represents the fluctuation caused by other random factors. The above classification also basically meets the composition of mining safety production situation.

Some data of mining safety production situation fluctuate greatly under the influence of random factors, which have strong randomness and cannot correctly identify its distribution law. To solve this problem, the cloud model is used to predict the reconstructed sub-sequence. The cloud model can realize the mutual transformation from qualitative concept to quantitative value, characterize the randomness and fuzziness in time series and the correlation between them, realize the qualitative concept representation of the predicted quantitative value, and reduce the influence of randomness and fuzziness of mining safety production situation.

In fact, cloud transformation is a process of concept induction and learning from the perspective of data mining, and the results are often not unique. Two points that cloud transformation need to consider frequently are: the higher the frequency is, the more concentrated the data distribution is, and it can be regarded as the convergence center of concept; Extraction concept is an iterative process. Before the next search, the data part represented by the last extracted concept is removed from the original frequency distribution. Taking the detail sequence as an example, the discrete results of the window detail sequence are shown in Fig.9. Then, according to the method in section 1.3.2, the basic concept of discrete mining safety production situation can be upgraded to the required conceptual level, as shown in Fig.10.

Fig.9 Discretization of windowing parameters

Fig.10 Cloud transformation and conceptual jump result

In Fig.10, the cloud drop represents the actual data in the database, the x -axis represents the domain of attribute i , and the y -axis represents the membership of each cloud drop to its respective concepts. In this way, through the cloud transformation, an arbitrary irregular distribution is mathematically transformed according to a certain law, so that it becomes the superposition of several clouds with different sizes. The more superimposed clouds are, the more they can reflect the actual data distribution, and the smaller the error is. It can be seen from the experiment that the definition domain of attribute i in the database can be divided into four parts: low, lower, higher and high.

The digital characteristics of cloud models in concepts after concept jump are shown in Tab.1

Tab.1 Digital characteristics of cloud models in various concepts

Windowed sequence	Digital features	Low	Lower	Higher	High
Low	E_X	-0.56020	-0.38110	-0.21360	-0.02687
	E_N	0.01897	0.01949	0.03376	0.03873
	H_E	0.012124	0.01366	0.01337	0.01426
R	E_X	-0.20260	-0.01060	0.17170	0.26650
	E_N	0.01539	0.03197	0.02037	0.01546
	H_E	0.02476	0.04614	0.02369	0.02489
Up	E_X	0.00098	0.23520	0.27125	0.38510
	E_N	0.03320	0.02494	0.03633	0.01549
	H_E	0.03487	0.03461	0.03490	0.03466

According to the obtained concept set, the original data set is softly divided by using the maximum judgment method. By taking the mortality rate of all mining safety accidents as the input value, the membership degree μ_i of each value for each concept can be obtained, from which the maximum membership degree is selected. The corresponding concept is the concept belonging to the value. After the soft division of attributes, the amount of data is greatly reduced, and the internal relationship between attributes is also highlighted.

For the division of time, drawing on the method of 24 solar terms in China, see Fig.11. In this paper, the 12 months of a year are divided into four cloud models: 'spring (January to March)', 'summer (April to June)', 'autumn (July to September)' and 'winter (October to December)'. Their entropy is 0.50 and their super entropy is 0.03.

Fig. 11 Time series set partition

Then, the maximum judgment method is used to determine the membership concept of each data value including time in the time series. The determined results are taken as the input data set, and the *Apriori* algorithm based on cloud model is used for association rule mining. With the concept as the basic representation, the mined qualitative knowledge is constructed into a rule generator according to the cloud theory, namely, the so-called uncertainty reasoning based on cloud model. With the help of normal cloud model to replace the division of the universe of quantitative attributes, the concept of normal cloud association rules on quantitative attributes is proposed, and the method of mining normal cloud association rules is given. Since the normal cloud model better softens the dividing boundary of the quantitative attribute universe, it can make the mined normal cloud association rules and prediction results more easily understood.

3 Model verification

3.1 Model accuracy test

The predicted values of windowed time series can be obtained by combining the predicted values of reconstructed detail series, random series and trend series. Using the model established by 165 groups of samples in the training set, 21 groups of data from October 2018 to June 2020 in the test set are used as the test set. Based on the randomness and fuzziness of cloud reasoning, 2000 cloud droplets are generated by each input, and their expected values are used as the output of the prediction results. The prediction results and relative errors of the detailed sequence and random sequence are shown in Tab.2.

Tab.2 Forecast error analysis

Time	Actual value	Forecast value range (indicated by fuzzy particles)	Low value Relative error	R value Relative error	Up value Relative error
2018.10	0.07763				
2018.11	0.03058	[0.02474,0.03362,0.08067]	0.05214	0.09937	0.03911
2018.12	0.02352				
2019.01	0.05500				
2019.02	0.05500	[0.00692,0.04676,0.05714]	0.07711	0.14988	0.07668

2019.03	0.00750				
2019.04	0.00000				
2019.05	0.00000	[0.00019,0.00166,0.05337]	--	--	0.01648
2019.06	0.05250				
2019.07	0.02250				
2019.08	0.01500	[0.01164,0.01821,0.23859]	0.16421	0.21389	0.06044
2019.09	0.01000				
2019.10	0.03000				
2019.11	0.05500	[0.03256,0.06601,0.06139]	0.08542	0.20023	0.02323
2019.12	0.06000				
2020.01	0.00000				
2020.02	0.02400	[0.00063,0.02462,0.02462]	--	0.15422	0.02598
2020.03	0.02133				
2020.04	0.00000				
2020.05	0.00533	[0.00003,0.00543,0.03238]	--	0.18266	0.01183
2020.06	0.03200				

The confidence interval is 95%, and the prediction residual of the granulation sequence is tested by normal distribution. Fig.12 shows that the prediction residual of the granulation sequence is evenly distributed in the 95% confidence interval, so the prediction residual of the granulation sequence obeys the normal distribution. The model extracts the internal information of the granulation sequence well, indicating that the prediction error is a comprehensive reflection of various random phenomena, and the model has high prediction accuracy.

Fig.12 prediction residual distribution test

3.2 Comparative analysis of models

The mining safety production situation interval prediction model based on fuzzy information granulation is compared with ARIMA, wavelet neural network and PSO-SVM prediction model. The results are shown in tab.3. The prediction n effect of each model is shown in Fig.13.

Tab.3 Model prediction result comparison

Time	Actual value	Forecast value range (indicated by fuzzy particles)	ARIMA forecast	Wavelet Neural Network Predicted Value	PSO-SVM prediction value
2018.10	0.07763		0.13743	0.04273	0.03101
2018.11	0.03058	[0.02474,0.03362,0.08067]	0.07214	0.04527	0.03295
2018.12	0.02352		0.04588	0.03977	0.03517
2019.01	0.05500		0.11772	0.03476	0.03768
2019.02	0.05500	[0.00692,0.04676,0.05714]	0.10711	0.04959	0.04045
2019.03	0.00750		0.02165	0.00734	0.04349
2019.04	0.00000		0.00342	0.00043	0.00219
2019.05	0.00000	[0.00019,0.00166,0.05337]	0.00893	0.00789	0.00038
2019.06	0.05250		0.03099	0.04089	0.04936
2019.07	0.02250		0.00444	0.00627	0.01849
2019.08	0.01500	[0.01164,0.01821,0.23859]	0.03090	0.01395	0.01648
2019.09	0.01000		0.01390	0.00801	0.01394

2019.10	0.03000		0.03542	0.02523	0.02323
2019.11	0.05500	[0.03256,0.06601,0.06139]	0.06726	0.06686	0.05777
2019.12	0.06000		0.10643	0.08065	0.05847
2020.01	0.00000		0.10352	0.01422	0.01233
2020.02	0.02400	[0.00063,0.02462,0.02462]	0.02526	0.01116	0.02598
2020.03	0.02133		0.04127	0.02066	0.01775
2020.04	0.00000		0.01112	0.0186	0.00183
2020.05	0.00533	[0.00003,0.00543,0.03238]	0.00583	0.00630	0.00447
2020.06	0.03200		0.03369	0.01745	0.03559

Fig.13 Model prediction comparison

It can be seen from Tab.3 and Fig.13 that the prediction results of ARIMA and wavelet neural network models fluctuate greatly beyond the interval range, because the ARIMA model will lose the information of the original sequence in the process of smooth processing of the original sequence by difference, and the more the difference times are, the more the information will be lost. EEMD can effectively retain the information of the original time series. Ahmadi (2020) also found a similar phenomenon in the study. Differential processing will lose the internal information of the original time series, and it is difficult to mine this part of the information lost in the prediction, resulting in a decline in the prediction accuracy. Therefore, the prediction accuracy of stationary time series after EEMD decomposition is significantly higher than that after difference processing, and the prediction stability of the model is also high. Compared with wavelet neural network, wavelet analysis is developed for the shortcomings of Fourier transform, which improves the shortcoming of Fourier transform that has no resolution ability in time domain. However, compared with EEMD, the selection of wavelet basis for wavelet neural network prediction has strong subjectivity, which affects the prediction accuracy of the model, and similar phenomena are also found in the study. Moreover, the neural network often needs a large number of training samples, and the uneven distribution of fewer training samples will lead to an increase in error, while the time series samples of mining safety production situation are limited. When the data are few, the performance of deep learning algorithm is not good. This is because deep learning algorithm requires a lot of sample data, so the prediction effect of wavelet neural network is not ideal.

Compared with the support vector machine model optimized by particle swarm optimization (PSO) algorithm, the predicted value of PSO-SVM model is generally in the

interval range, but the fitting effect with the original time series is not good. It can only predict the overall trend, and the prediction accuracy of the detailed part is not high. It can be seen that the single-point prediction model is difficult to accurately predict the time series of nonlinear and non-stationary mining safety production situation. And in the short-term prediction, the average relative error of the particle swarm optimization support vector machine model is small. When the long-term prediction is carried out, the fitting effect of the particle swarm optimization support vector machine model is significantly lower than that of the uncertainty prediction model based on cloud theory. Although the machine learning method of particle swarm optimization support vector machine has good prediction effect for short-term prediction of small samples and nonlinear sequences, due to the lack of consideration of sequence timing, the prediction accuracy in medium and long-term prediction is lower than that of uncertainty prediction model based on cloud theory. And in the short-term prediction, the average relative error is small but the fluctuation is large, so the stability of the short-term prediction is not as good as the uncertainty prediction model based on cloud theory. When using Support Vector Machines (SVM) built on wavelet transform model for prediction, Dhiman (2019) also found the subjectivity of wavelet transform and the low and unstable accuracy of SVM in medium and long-term prediction.

4 Future work

The relevant research results have clearly shown that the proposed method can obtain high prediction accuracy in the prediction of mining safety production situation time series, and can effectively solve the three core problems of time granularity selection, nonstationarity and uncertainty in time series prediction. However, in order to obtain better prediction results in future prediction, the next step will continue to study in the following two aspects:

(1) It can be seen from the relevant results that the feature extraction method of time series based on ensemble empirical mode decomposition-sample entropy can better retain the information of the original time series and highlight the characteristics of the original sequence. EEMD keeps the mean value of IMF within the normal dynamic filtering range, so that the white noise is offset against each other, so as to suppress the mode mixing phenomenon and further improve the prediction accuracy. According to the chaotic prediction theory, if the maximum Lyapunov exponent of the system is λ , the maximum predictable time is about $1/\lambda$. The response frequency component reconstructed by ensemble empirical mode decomposition-sample entropy decomposition is only a part of the original signal. At this time, the maximum Lyapunov exponent of each decomposed signal is less than that of the original signal, which is of great significance to improve the maximum predictable time. Future research can be carried out in the direction of improving the maximum predictable time.

(2) The accuracy of time series prediction is closely related to the inherent law of the original time series. Due to the statistical error of accident statistics, the inherent law of time series will be weakened, which affects the accuracy of the model. In the time series

prediction based on cloud theory, a certain range can be obtained according to the $3En$ principle. The confidence interval $[Ex-3En, Ex+3En]$ can be considered as a fuzzy interval to further improve the reliability of the prediction results. Therefore, on the basis of existing research, interval prediction based on cloud theory can be carried out, and the prediction error is reflected in the prediction interval.

5 Conclusions

(1) Time series mining evaluation effect function is introduced to evaluate the prediction effect based on different time particles in a given time domain to determine the optimal time granularity. The optimal time granularity is taken as the window width of fuzzy information granulation, and then the time series of non-coal mine safety production situation are mapped into fuzzy information particle series including low boundary value *Low*, median value *R* and high boundary value *Up* by triangular fuzzy number. The fuzzy information granulation method with the best time granularity as the window width can intervalize the quantitative mining safety production situation time series, and take into account the statistical error of mining accidents and some random factors. The prediction results are more reliable and have more reference significance in practical application.

(2) Based on EEMD, the fluctuation or change trend in random non-stationary granulation time series is decomposed step by step, and a series of stationary sequences with different characteristic scales are generated. The characteristics of the original time series are characterized more clearly, and the dynamic characteristics are preserved. The stability of each sub-sequence is more obvious, and it also shows stronger regularity. Aiming at the correlation between sub-sequences, the complexity of each component after EEMD is analyzed according to the sample entropy theory, and the components after EEMD are reconstructed according to the sample entropy value. A time series feature extraction method based on ensemble empirical mode decomposition and sample entropy is proposed. The feature extraction of time series based on ensemble empirical mode decomposition-sample entropy highlights the characteristics of similar series, which is more conducive to grasping various local characteristics of mining safety production situation.

(3) According to the characteristics of each component after the feature extraction of the time series of ensemble empirical mode decomposition-sample entropy, the random dynamic data are studied from the perspective of frequency domain and time domain, and the uncertain data are modeled for the dynamic data. Through cloud transformation, concept jump, time series set partition and association rule mining, the original numerical sequence is converted into an abstract conceptual sequence represented by a certain time and information granularity. The average relative error of the predicted value of *Low* parameter based on cloud theory is 10.83457%, the average relative error of the predicted value of *R* parameter is 20.20790%, and the average relative error of the predicted value of *Up* parameter is 0.65197%. The prediction accuracy of *Low* and *Up* parameter values is significantly higher than that of *R* value, indicating that the upper and lower boundary values after fuzzy granulation can accurately describe the variation law of the time series of mining safety

production. When the actual value is higher than the high boundary value expressed by *Up* parameter, it indicates that practical measures should be taken to reduce the occurrence of mining safety accidents.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare no conflicts of interest.

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Authors' contributions

WM is the executor of the modeling design and theoretical analysis of this study, and is responsible for the writing of the first draft. YY, HN and WQ completed data analysis and guided the writing and revision of the paper; TW participates in the modeling process and results analysis. All authors read and approved the final manuscript.

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