A Deformation Forecasting Model of High and Steep Slope Based on Fuzzy Time Series and Entire Distribution Optimization

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ABSTRACT Because the deformation of the slope is affected by the stability of the underground structure, natural factors, and human factors, it is difficult for the traditional prediction model of the slope to accurately predict sudden changes. This paper proposes a method to predict the deformation of high and steep slopes based on the fuzzy time series and Entire Distribution Optimization. The division of the domain is optimized by the Entire Distribution Optimization, and the deformation of high and steep slopes is predicted by the fuzzy time series. The experimental results show that the fuzzy time series has a good predictive effect on the number of mutations, and the Entire Distribution Optimization avoids the one-sidedness of dividing the domain by mean, which improves the accuracy of the deformation forecasting model of the high and steep slope.

INDEX TERMS Deformation of the slope, entire distribution optimization, fuzzy time series, mine.

I. INTRODUCTION

With the rapid development of the economy, the demand for mineral resources continues to increase. Among them, rare earth, coal, metals, and other mineral resources have played a huge role in the development of the economy. Since the mining time of a mine refers to the period time from the start of production to the completion of mining, the slope of mine is usually in a dynamic process of continuous excavation. Among them, in the mining operations of some open-pit mine, it is necessary to carry out blasting work or use large-scale equipment to advance the progress of the project, so many high and steep slopes are formed around the open-pit mine. Moreover, the internal structure of the high and steep slope has been destroyed, and undergoes the comprehensive impact of the external environment and blasting, so the stability of the slope will be seriously affected.

The traditional method of obtaining deformation data of mine slopes is mainly through multi-period deformation monitoring [1]. With the development of technologies such as GPS and InSAR, real-time and dynamic deformation monitoring technology has emerged. The current theories and methods of deformation prediction mainly include time series analysis, regression analysis, gray theory, and neural network models [2]. Among them, time series analysis highlights the time series and does not consider the influence of external factors. However, because the complex and changeable environment of mine has many uncertain factors, time series analysis often has large deviations. Due to the numerous influencing factors of mine slopes, the accuracy of regression analysis with the unreasonable selection of modeling factors will have large deviations. Because of the complex source of...
the original monitoring data of mine slopes, the gray model that requires strict original monitoring data will have lower accuracy. The prediction result of the BP neural network model is related to the selection of the initial value, and it is difficult to determine the most reasonable initial value under the complicated environment of mine slope. Therefore, it is urgent to find an effective model for predicting mine slopes.

Since the fuzzy time series has a better predictive effect on the sudden change factors, a deformation forecasting model of high and steep slope based on the fuzzy time series can be established [3]. Fuzzy time series (FTS), was proposed by Song and Chissom [4]–[6] in 1993 and introduced the concept of the fuzzy set to time series. Chen [7] proposed the basic architecture of the FTS model in 1996, which is simple to calculate and has high accuracy. The models of fuzzy time series can be divided into four categories. The first method is the early methods represented by Song [4], [5], Chen [6]. Based on the minimum and maximum values of historical data, this type of method rounds down and rounds up to determine the domain of the model [7]. Then, according to the size of the domain, this type of method divides the domain equally. This kind of method is simple and fast. When calculating the degree of membership, the setting of the membership function is very simple and the speed of calculation is faster. However, the shortcomings of the first method are also significant [8]. At first, the accuracy is not high enough. Secondly, the fuzzy set corresponding to the interval obtained by the first method is somewhat far-fetched in semantic interpretation and not easy to understand and accept. The second method is proposed by Huang [9], Jilani [10], and Yu [11] to divide the interval according to the distribution of historical data. The second method usually divides the concentrated distribution interval of historical data in detail and extends the relatively scattered interval of historical data. At the same time, the second method can also design a new distance formula and divides the interval according to the distribution of the distance between the samples. And the distance of the second method determines the number of intervals based on the statistical peak value of the sample, and so on. The second method has obvious statistical significance, strong self-interpretability, and can obtain higher accuracy of prediction than the first method. The third method is proposed by scholars represented by Aladag [12], [13], Egrioglu, and Yolcu [14]–[16], which uses neural networks and optimization algorithms to find the optimal fuzzy subset. The third method takes the error of prediction result as the target variable, and the division of interval as the variable. And it finds the minimum value of the prediction error according to the search method. The division of intervals at this time is regarded as the optimal division scheme of the model universe. The accuracy of the third method is higher than that of the first method, but the natural meaning of the division of intervals is not as intuitive as the first two types of methods. The fourth methods are Least Squares Support Vector Machine [17], genetic algorithm [18], [19], Fibonacci sequence [20], clustering algorithm [21]–[23], quantum optimization algorithm [24], particle swarm optimization [25], [26], granular computing and bio-inspired computing [27]. The basic idea of the fourth method adopts a suitable algorithm for cluster analysis of the sample data and determine the division of each sub-interval. The fourth method is still relatively good in terms of predicting results. Due to the use of clustering algorithms and machine learning methods, the accuracy of the distinction of sample data can be improved, and the fourth methods are more illustrative. In recent years, new ideas have emerged for the improvement of time series. Neutrosophic set (NS) is used to represent time series, artificial neural network (ANN) is used for prediction, and the gradient descent algorithm is used to optimize accuracy [28].

This paper proposes a method based on fuzzy time series and Entire Distribution Optimization to predict the deformation of high and steep slopes. The slope variables are zenith distance, azimuth angle, and skew distance, and 104 sets of data are taken respectively. Then, according to the interval of variable, the domain is reasonably divided into 14 continuous intervals by using the Entire Distribution Optimization. And the membership function of each interval of the domain is defined by the triangular fuzzy membership function. Among them, Entire Distribution Optimization takes an error as fitness and obtains the division of fuzzy interval under the minimum error value. Then the historical data is fuzzified, and the measurement data is allocated to each fuzzy interval for fuzzification. After establishing the fuzzy relationship, the paper puts all the fuzzy relationships with the same initial state into the same fuzzy relationship group to establish the fuzzy matrix. Finally, defuzzification prediction is carried out according to the established fuzzy matrix. Through the comparison of the error, it can be seen that the prediction error of the model is the smallest, and the prediction effect of sudden changes is also the best. Therefore, this model is a new method and idea for predicting the deformation of high and steep slopes in mines.

II. BACKGROUND KNOWLEDGE
A. VARIABLES OF SLOPE
In this paper, the slope variables are selected as zenith distance, azimuth angle, and skew distance. The zenith distance (Fig. 1) refers to the angular distance between the celestial body and the zenith on the celestial circle. It is calculated from the top of the line directly connecting the station and the center of gravity of the earth, and the range is from 0° to 180°. The azimuth angle (Fig. 2) refers to the horizontal angle from the north direction of a certain point along the clockwise direction to the target direction line, and the unit is “degree” and “close position”. The skew distance (Fig. 3) refers to the distance between two points that are not at the same height.

After obtaining the three basic variables of zenith distance, azimuth angle, and skew distance, three-dimensional coordinates (X, Y, Z) and displacement can be calculated. This paper focuses on the study of the three basic variables. For the measurement point and the target point,
Figure 1. The schematic diagram of the zenith distance.

Figure 2. The schematic diagram of the azimuth angle.

Figure 3. The schematic diagram of skew distance.

The vertical displacement between the measuring point and target point is related to the zenith distance, azimuth angle, and skew distance. Here, the plumb line is the x-axis, and the direction perpendicular to the plumb line is the y-axis. The z-axis coordinate of the target point is as follows:

\[ Z_2 = Z_1 + \Delta Z = Z_1 + g \times \cos \beta \]  

(3)

The three-dimensional displacement of the measuring point and target point is related to zenith distance, azimuth angle, and skew distance. The three-dimensional coordinates of the target point are as follows:

\[ X_2 = X_1 + \Delta X = X_1 + g \times \cos \alpha \times \cos \beta \]  

(4)

\[ Y_2 = Y_1 + \Delta Y = Y_1 + g \times \sin \alpha \times \cos \beta \]  

(5)

Among them, \( \Delta X \), \( \Delta Y \), and \( \Delta Z \) are the displacements of the x-axis, y-axis, and z-axis respectively.

B. FUZZY TIME SERIES

Song and Chissom [4]–[6] proposed a fuzzy time series model in 1993. Time series refers to the data series produced by phenomena that change with time.

**Definition 1:** Divide the domain \( U \) into a limited number of ordered subsets, that is, \( U = \{u_1, u_2, \ldots, u_n\} \), so define a fuzzy set \( A \) on the domain \( U \):

\[ A = \frac{f_A(u_1)}{u_1} + \frac{f_A(u_2)}{u_2} + \ldots + \frac{f_A(u_n)}{u_n} \]  

(6)

In the formula, \( f_A(u_i) \in [0, 1] \) represents the membership degree of element \( u_i \) to the fuzzy set \( A \).

**Definition 2:** Suppose \( f_i(t)(t = 1, 2, \ldots) \) is a set of fuzzy sets defined on the domain \( Y(t)(t = \ldots, 0, 1, 2, \ldots) \) of real number sets. If \( F(t) = \{f_1(t), f_2(t), \ldots\} \), then \( F(t) \) is a fuzzy time series on the domain \( Y(t) \).

C. ENTIRE DISTRIBUTION OPTIMIZATION

Entire Distribution Optimization (EDO) is derived from the Particle Swarm Optimization (PSO). EDO is a high abstraction of the population distribution law of PSO and does not need to be restricted to the highly fitting of the population distribution form of PSO. EDO has the advantages of simple implementation, fast convergence, strong robustness, etc. Compared with PSO, EDO optimizes from the overall perspective. The iterative process is carried out between a point and a population. There is only one operator and the Cauchy distribution is generated with the best point as the center.

EDO is an algorithm that iterates over the optimal position in the population. EDO finds the best point in the new population by generating a population that conforms to the Cauchy
Set the initial parameters of EDO and randomly select the initial population. When $\beta > \beta_{\text{max}}$ or $\theta < \theta_{\text{min}}$

Calculate fitness and the most significant position in this population (Pnew).

If Pnew > P (the most significant position in the previous population)

Pnew replaces P, and r remains unchanged.

else

P remains unchanged, and M = M – 1.

If M = 0

M is restored to its original value and $r = r \times \alpha$.

else

M = M – 1, and $r = r$.

end

Take P as the center and use Cauchy distribution to generate a new population.

end

Output the most significant position (P)

distribution around the best point of the population. Then, EDO finds the optimal position of the population by changing the scale parameter of Cauchy distribution and the number of stagnations. When the maximum number of iterations or the minimum population diameter is met, EDO ends and outputs the optimal position of the population. The initial parameters of EDO include the size of the population (N), the radius of the Cauchy distribution (r), the scale parameters of the Cauchy distribution ($\alpha$), the number of stagnations (M), the maximum number of iterations ($\beta_{\text{max}}$), and the minimum diameter of the population ($\theta_{\text{min}}$), and the initial population is randomly selected. The implementation process of the Entire Distribution Optimization is as follows:

1) Initialize, and set 0.5 times of the defined domain as the radius of the Cauchy distribution, then randomly generate a population in the defined domain.

2) Find the optimal solution and determine the best individual by calculating the fitness value in the population. If the calculated current individual is better than the best individual last time, replace, otherwise keep the best individual.

3) Taking the best individual calculated in step 2) as the center, use Cauchy distribution to generate a new population.

4) Determine whether the end requirement is met. If the preset maximum number of iterations is not reached, go to step 2) to continue the calculation. If the requirement is met, stop the iteration and output the result.

The parameter settings are as follows: the symbol for the number of iterations is $\beta$, and the symbol for the diameter of the population is $\theta$. The pseudo-code of EDO is as follows:

D. EVALUATION INDEX OF MODEL

The accuracy of the algorithm in this paper is described by error. A lower error represents a better algorithm and a higher accuracy. The calculation formula of error is as follows:

$$MSE = \frac{\sum_{i=1}^{m} |F(i) - D(i)|}{m - 1}$$

(7)

In the formula, $m$ is the number of variables, $F(i)$ is the expected output, $D(i)$ is the actual output.

III. METHOD

Classical fuzzy time series use the mean to divide the domain. The structure is simple, but the processing of data is one-sided and the prediction error is large. This paper uses the Entire Distribution Optimization to optimize the interval division of the fuzzy time series and takes the error as the fitness degree to obtain the fuzzy interval division under the minimum error value. The detailed steps of deformation prediction of high and steep slope based on the Entire Distribution Optimization to improve the classic fuzzy time series are as follows:

A. DEFINITION OF DOMAIN

Assuming that $y(t)$ is the data of zenith distance, azimuth angle, and skew distance at the historical time $t$, and the range is [$U_{\text{min}}, U_{\text{max}}$]. To ensure that the predicted value is within the bounded universe, the starting point of the universe U is defined as $U_{\text{min}} - D_{\text{min}}$, and the end of U is $U_{\text{max}} + D_{\text{max}}$, where $D_{\text{min}}$ and $D_{\text{max}}$ are two positive integers and are used to adjust the limit. Therefore the domain of discourse is defined as:

$$U = [U_{\text{min}} - D_{\text{min}}, U_{\text{max}} + D_{\text{max}}]$$

(8)

B. DIVISION OF FUZZY INTERVAL

Through Entire Distribution Optimization, U is reasonably divided into $i$ continuous intervals, and the corresponding fuzzy concepts are listed. At the same time, this paper also uses the mean to divide the domain, which is compared with the model that uses the EDO to divide the domain.

1) Initialization: The initial population is randomly selected in the entire defined domain, that is, different division points in the interval. The initial parameters of EDO are as follows: $N = 70$, the radius of the Cauchy distribution (r) is set to 0.5 times the defined domain, $\alpha = 0.93$, $M = 9$, $\beta_{\text{max}} = 500$, $\theta_{\text{min}} = 0.000001$.

2) Calculate the fitness value of each individual in the population, where the fitness function is defined as for formula (7). And find the best individual this time, and compare it with the best individual last time. If it is better than the best individual last time, let it replace the best individual last time, and the population diameter remains unchanged.

3) If the best individual this time is worse than the best individual last time, keep the best individual last time as the best individual, and reduce the number of stagnations (M) by 1. If M is 0, the diameter of the population will be reduced to 0.93 of the original diameter, and the number of stagnations (M) becomes 9. If the number of stagnations (M) is not 0, keep the original diameter of the population (r) unchanged, and reduce the number of stagnations (M) by 1. Take the most significant position in the previous population (P) as
D. THE CREATION OF FUZZY RELATIONSHIP

Create fuzzy logic relationships, and create fuzzy logic relationship groups. A fuzzy relationship is established through a fuzzy set of continuous time series. In the training phase, the current state and the next state of all language values are known and used as training data. Once the semantic meaning is determined, all the fuzzy relations of each order can be established. Search all fuzzy sets from the time series according to the mode \( F(t-1) \rightarrow F(t) \). Firstly, find out all the first-order fuzzy relations, where \( F(t-1) \) is the current state and \( F(t) \) is the next state, until the \( n \)-th order fuzzy relations are found, replace the fuzzy sets with the corresponding semantic values respectively. And create all fuzzy relations. According to the above fuzzy relations created on the research data, the fuzzy relations of the same left operand (LHS) are grouped into a group to establish the fuzzy logic relation matrix.

E. DEFUZZIFICATION

The methods of defuzzification include the barycenter method, maximum membership method, and the weighted average method. This paper uses the following function to calculate the predicted output at the time \( t \):

\[
FV(t) = \frac{n \times FV1(t) + FV2(t)}{n + k \times n1 - (k - 1) \times n2}
\]  

(9)

In the formula, \( k(k > 0) \) is the order of a fuzzy relationship \( F(t-k), F(t-k+1), \ldots, F(t-2), F(t-1) \rightarrow F(1) \).

And \( FV1(t) \) represents the mean value of the middle points \( m_{il}(i = 1, 2, \ldots, l) \) of the semantic values of all fuzzy relation groups generated by the training data at the time \( t \), namely

\[
FV1(t) = \frac{m_{1l} + m_{2l} + \ldots + m_{ll}}{l}
\]  

(10)

If this fuzzy relationship does not exist, then \( FV1(t) = m_{l-1} \), where \( m_{l-1} \) is the midpoint of the semantic values of all fuzzy relation groups generated from the training data at the time \( t-1 \). In this paper, the number of fuzzy relation groups is 15, that is \( l = 15 \). The formula of the function \( FV2(t) \) is

\[
FV2(t) = n1 \times m_{l-1} + (n1 - n2) \times m_{l-2} + \ldots + (n1 - n2) \times m_{l-k}
\]  

(11)

In the formula, \( m_{l-1}, \ldots, m_{l-k}(k > 0) \) is the middle point of the semantic value of all fuzzy relationship groups generated from the training data at the time \( t-1, \ldots, t-k \). And \( n, n1, n2 \) is the undetermined parameter generated after training with training data, that is, the training data is substituted into the formula (9) to calculate the predicted value and the actual value as the mean square error to obtain the minimum mean square error value and assign it to \( n, n1, n2 \).

F. CALCULATION OF PREDICTION ACCURACY

Here, the error is used to describe the accuracy of the algorithm in this paper. The lower error means that the algorithm is better and the accuracy is higher. The calculation formula of error is as formula (7).

IV. EXPERIMENTS AND RESULTS

A. ACQUISITION OF DATA

The deformation of the slope is monitored by the measuring robot (TCA2003). TCA2003 is a portable intelligent electronic total station, which has a CCD image sensor and other...
sensors, a driving system, and a distance measuring system. After the development and configuration of corresponding software, it can replace the manual search, track and identify the target automatically, and obtain the spatial coordinate information of the target. TCA2003 locates and recognizes the target point in a certain project through the cooperation between various internal sensors. And TCA2003 realizes automatic control according to the set various measurement parameters and completes functions such as positioning, tracking, and ranging. In the collection of data, the time interval of time series data is set to be about half a month. In single monitoring, the duration is 0.5 hours, and multiple measurements are taken and averaged. In the end, 104 raw data of azimuth, zenith distance, and skew distance were obtained.

To obtain a higher accuracy of measurement, the higher accuracy can be achieved by performing multiple measurements in single monitoring. It is understood that the angle measurement accuracy of the measuring robot TCA2003 is $\pm 0.00014^\circ$, the distance measurement accuracy can reach 1mm $\pm 1$ppm, and the ranging error under the automatic tracking mode is $\pm 0.005m$. The target can be monitored at a skew distance within 1000m. Let the number of measurements for single monitoring is $n(n \geq 10)$, and the ranging error is $\pm 0.005/\sqrt{n}m$, and the accuracy of angle measurement is $\pm 0.00014/\sqrt{n}^\circ$.

**B. APPLICATION OF DEFORMATION PREDICTION MODEL OF MINE HIGH AND STEEP SLOPE**

For the deformation model of a high and steep slope in mine based on fuzzy time series, Entire Distribution Optimization is used to replace the mean in order to divide the domain, and the accuracy of the model is improved. According to the mean and Entire Distribution Optimiz-ation, 104 sets of zenith distance, azimuth angle, and slope distance data measured by the measuring robot are divided into 14 fuzzy intervals. Then the semantic value is given and the fuzzy time series model is used for predictions. This paper establishes the training model through data of zenith distance and verifies the accuracy of the model through data of azimuth angle and slant distance.

The output of the model is shown in Figure 8 to Figure 13. The performance evaluation index is the formula (7), which is the error. In Figures 8 to 13, the abscissa represents time, and the ordinate represents the expected output and predicted output of the slope variable at a certain moment, where blue represents the expected output and red represents the predicted output. It can be seen from the figure that the model has a predictive effect. The 104 sets of data are completely predicted. The overall effect is good, but the error of individual mutation data points is relatively large. The methods include dividing the domain by mean and dividing the domain by the Entire Distribution Optimization, which is used to divide the domain to predict the zenith distance, azimuth difference, and skew distance. The errors are shown in Table 4 and Figures 7. In this paper, dividing the domain by EDO is referred to as DEDO, and dividing the domain by mean is referred to as MEAN. For the zenith distance, the error of the model using DEDO is better than the error of the model using MEAN, and the error is reduced by 6.14%. Similarly, for the azimuth angle and the slope distance, the errors are reduced by 4.88% and 23.84% respectively. In general, dividing the domain by
TABLE 2. The comparison of different methods of domain division. This table is the same as Table 1, but the content is about azimuth angle.

| Number of interval boundary values | dividing the domain by mean | dividing the domain by EDO |
|-----------------------------------|-----------------------------|---------------------------|
| 1                                 | 272.09099                   | 272.09099                 |
| 2                                 | 272.09110                   | 272.09127                 |
| 3                                 | 272.09121                   | 272.09152                 |
| 4                                 | 272.09132                   | 272.09161                 |
| 5                                 | 272.09144                   | 272.09171                 |
| 6                                 | 272.09155                   | 272.09180                 |
| 7                                 | 272.09166                   | 272.09186                 |
| 8                                 | 272.09178                   | 272.09194                 |
| 9                                 | 272.09189                   | 272.09199                 |
| 10                                | 272.09200                   | 272.09208                 |
| 11                                | 272.09211                   | 272.09215                 |
| 12                                | 272.09223                   | 272.09222                 |
| 13                                | 272.09234                   | 272.09238                 |
| 14                                | 272.09245                   | 272.09243                 |
| 15                                | 272.09257                   | 272.09257                 |

TABLE 3. The comparison of different methods of domain division. This table is the same as Table 1, but the content is about skew distance.

| Number of interval boundary values | dividing the domain by mean | dividing the domain by EDO |
|-----------------------------------|-----------------------------|---------------------------|
| 1                                 | 867.94615                   | 867.94615                 |
| 2                                 | 867.94656                   | 867.94619                 |
| 3                                 | 867.94657                   | 867.94642                 |
| 4                                 | 867.94679                   | 867.94664                 |
| 5                                 | 867.94701                   | 867.94670                 |
| 6                                 | 867.94722                   | 867.94690                 |
| 7                                 | 867.94743                   | 867.94719                 |
| 8                                 | 867.94765                   | 867.94753                 |
| 9                                 | 867.94786                   | 867.94778                 |
| 10                                | 867.94807                   | 867.94822                 |
| 11                                | 867.94829                   | 867.94825                 |
| 12                                | 867.94850                   | 867.94855                 |
| 13                                | 867.94872                   | 867.94879                 |
| 14                                | 867.94893                   | 867.94890                 |
| 15                                | 867.94915                   | 867.94915                 |

The warning of slope instability can be carried out through the deformation prediction of the slope. The slope instability includes avalanches, landslides, and lateral expansion, which are dominated by internal factors and induced by external factors. At present, there are much researches on the warning of slope instability based on displacement and displacement rate. The displacement can be obtained through zenith distance, azimuth angle, and skew distance, and the warning of slope instability can be performed by setting the threshold of difference between adjacent displacement values. Generally, the warning threshold of the soil slope is 2 cm, and the warning threshold of rock slope is less than 1 cm. The research object of this paper is rock slope.

Before the slope instability, it is necessary to protect the slope according to the results of the slope prediction. The slope protection is to ensure the stability of the slope, that is, to prevent slope instability, including engineering protection, greening protection, grid protection, and comprehensive treatment. The engineering protection is suitable for rock slope to prevent weathering. Generally, lime plastering is used to build walls to resist landslides. Greening protection refers to the selection of suitable vegetation for greening the slope. Generally, the vegetation with developed root systems and high survival rate is selected, such as green grass. The grid protection refers to the use of grids to cover a large area of the slope to prevent the danger of falling rocks. The grid protection can choose active protection net, passive protection net, steel wire rope net, ring protection net, and so on. The comprehensive treatment refers to the comprehensive use of engineering protection, greening protection, grid protection, and other measures to suit local conditions.
C. DISCUSSION

The error values are shown in Table 4 and the prediction maps (Fig. 7 to Fig. 12) can indicate the accuracy. The image can intuitively show the accuracy, and the error can accurately describe the accuracy. The zenith distance, azimuth difference, and skew distance are the three interacting variables that can predict the deformation of slope in mine. We effectively obtained the accuracy of the deformation variables of high and steep mine slopes through the prediction model based on fuzzy time series, which verified that the prediction model of high and steep slope obtained by applying the fuzzy time series model to the prediction modeling of deformation of slope in mine was feasible. Then, through the Entire Distribution Optimization to optimize the interval division of domain, and the comparison of Table 4 and the prediction graph (Fig. 7 to Fig. 12), it is shown that the optimized fuzzy interval model can significantly reduce the error, and it is verified that the Entire Distribution Optimization to optimize the division of fuzzy intervals can effectively improve the accuracy of the model.

V. CONCLUSION

This paper uses the Entire Distribution Optimization to optimize the division of domain and uses the fuzzy time series to
predict the deformation of high and steep slopes. Compared with dividing the domain by mean, this paper divides the domain by EDO, and the prediction errors of zenith distance, azimuth angle, and slope distance are reduced by 6.14%, 4.88%, and 23.84% respectively. It verifies that it is feasible to use the Entire Distribution Optimization to optimize the division of the fuzzy interval, which is a new method and idea to predict the deformation of high and steep slopes in mines.

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