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# Unascertained measurement classifying model of goaf collapse prediction*

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**Abstract** Based on optimized forecast method of unascertained classifying, a unascertained measurement classifying model (UMC) to predict mining induced goaf collapse was established. The discriminated factors of the model are influential factors including overburden layer type, overburden layer thickness, the complex degree of geologic structure, the inclination angle of coal bed, volume rate of the cavity region, the vertical goaf depth from the surface and space superposition layer of the goaf region. Unascertained measurement (UM) function of each factor was calculated. The unascertained measurement to indicate the classification center and the grade of waiting forecast sample was determined by the UM distance between the synthesis index of waiting forecast samples and index of every classification. The training samples were tested by the established model, and the correct rate is 100%. Furthermore, the seven waiting forecast samples were predicted by the UMC model. The results show that the forecast results are fully consistent with the actual situation.

**Keywords** unascertained measurement classifying model, goaf, collapse prediction, mining engineering

## Introduction

The damage of the environment and ground construction caused by mining induced goaf collapse can not be ignored, of which destroying performances are [1-4]: causing damage to the ground, large surface movement basin where a lot of water stores in are formed in the plain areas, causing difficulties in using residents water and irrigation water, goaf collapse also may cause landslides, endangering the safety of building structures and production and life safety facilities. Therefore, goaf collapse forecast has always been an important research topic in mining engineering fields. In recent decades, tremendous progress has been made on the forecast theory and methods of goaf collapse. Upon how to predict goaf collapse, many scholars are doing an in-depth study in this area. They proposes many forecasting methods, such as, fuzzy comprehensive evaluation method [4], random media theory [5, 6], neural network prediction method [1,7], etc.. The majority of these methods focus on the definite status, while the research in the uncertainty status is still relatively few. Goaf collapse forecast is a very complex work, as a great number of uncertain factors exist. In order to solve the problems caused by surface subsidence, it is necessary to have in-depth study. In this regard, unas-

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certained classifying method provides a very good idea. This paper optimizes the unascertained classifying prediction method, applying this method to goaf collapse prediction, and then the unascertained classifying model for goaf collapse prediction is established. For application, the established model is applied to the goaf collapse of one mine in Beijing with the given facts, the correct rate is 100%, which proves a new idea in goaf collapse forecast.

## 1 The unascertained measurement classifying model

### 1.1 Classifying matrix

Suppose: (1) Sample space is $X=\{x_1, x_2, \cdots, x_n\}$, here $x_i$ is sample $i$; (2) Each classifying sample has $m$ classifying indices, so the classifying index space is $I=\{I_1, I_2, \cdots, I_m\}$; (3) The value of each classifying index has $k$ classifying grades, so the classifying space of $X$ is $U=\{C_1, C_2, \cdots, C_k\}$. Then, according to Ref. [8–10], $x_i$ can be denoted as $x_i=\{x_{i1}, x_{i2}, \cdots, x_{im}\}$, here $x_{ij}$ is the classifying value of index $I_i$ of sample $x_i$, $i=1, 2, \cdots, n$; $j=1, 2, \cdots, m$.

The grading rank $C_1, C_2, \cdots, C_k$ is orderly. Suppose $C_1>C_2>\cdots>C_k$ or $C_1<C_2<\cdots<C_k$. Then, the classifying matrix is constructed as:

$$\begin{array}{c} \\ I_1 \\ I_2 \\ \vdots \\ I_m \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_k \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mk} \end{bmatrix} \end{array},$$

where, $a_{jp}(1\leqslant j\leqslant m, 1\leqslant p\leqslant k)$ is the value of classifying criterion, which is the average value of the classifying indices in the $p$ classification [10,11], satisfying $a_{j1}>a_{j2}>\cdots a_{jk}$ or $a_{j1}<a_{j2}<\cdots<a_{jk}$.

### 1.2 Unascertained measure of single index

Denote the unascertained measure for $x_{ij}\in C_p$ as $\mu_{ijp}=\mu(x\in C_p)$, here $C_p\in U$, $p=1, 2, \cdots, k$; $\mu_{ijp}$ is the degree of $x_{ij}$ belonging to $C_p$.

If $\mu$ meet normalization rule and has additive property, i.e.:

$$0\leqslant \mu(x_{ij}\in C_p)\leqslant 1,$$

$$\mu(x_{ij}\in U)=1,$$

$$\mu\left|x_{ij}\in \bigcup_{L=1}^{p} C_L\right| = \sum_{L=1}^{p}\mu(x_{ij}\in C_L),$$

where, $i=1, 2, \cdots, n$; $j=1, 2, \cdots, m$; $p=1, 2, \cdots, k$; $\mu$ is the unascertained measure [10].

The unascertained measure matrix of single index is constructed as:

$$(\mu_{ijk})_{m\times K} = \begin{bmatrix} \mu_{i11} & \mu_{i12} & \cdots & \mu_{i1k} \\ \mu_{i21} & \mu_{i22} & \cdots & \mu_{i2k} \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{im1} & \mu_{im2} & \cdots & \mu_{imk} \end{bmatrix} \quad (i=1,2,\cdots,n).$$

Suppose $a_{j1}<a_{j2}<\cdots<a_{jk}$ [10]. We take:

$$\begin{cases} \mu_{ij1}=1 \text{ and } \mu_{ij2}=\mu_{ijk}=0 & (\text{if } x_{ij}\leqslant a_{j1}), \\ \mu_{ijk}=1 \text{ and } \mu_{ij1}=\mu_{ijk\text{-}1}=0 & (\text{if } x_{ij}\geqslant a_{jk}), \\ \mu_{ijl}=\dfrac{a_{jl+1}-x_{ij}}{a_{jl+1}-a_{jl}} \text{ and } \mu_{ijl+1}=\dfrac{x_{ij}-a_{jl+1}}{a_{jl+1}-a_{jl}}, & \\ \quad (x_{ij}\geqslant a_{jk}), & \\ \mu_{ijk}=0, \ (\text{if } k<l \text{ or } k>l+1). & \end{cases}$$

### 1.3 Index weights

In the evaluating system of unascertained measure, index weights directly affect the classification result. Index weights $w_j$ is characterized by $w_j=\{w_1, w_2, \cdots, w_n\}$, $0\leqslant w_j\leqslant 1$, $\sum_{j=1}^{n} w_j=1, j=1,2,\cdots,m.$

According to the theory of information entropy, unascertained measure $\boldsymbol{\mu}_{ijk}$ can be expressed as:

$$H_j=\sum_{i=1}^{K}\mu_{ijk}\lg \boldsymbol{\mu}_{ijk},$$

$$v_j=1+\frac{1}{\lg K}\sum_{k=1}^{K}\boldsymbol{\mu}_{ijk}\lg \boldsymbol{\mu}_{ijk},$$

$$w_j=v_j\Big/\sum_{i=1}^{n}v_i.$$

Then $w_j$ reflects a degree of importance for $I_j$, and $0\leqslant w_j\leqslant 1$, $\sum_{j=1}^{n}w_j=1$, so $w_j$ is the weight of index $I_j$ [9–11].

### 1.4 Composite unascertained measure of multiple indexes

Based on the unascertained measure of single index and index weights [10,11], the composite unascertained measure of multiple indices can be worked out as follow:

$$\mu_{ik}=\sum_{j=1}^{m}w_j w_i \boldsymbol{\mu}_{ijk}$$

$$(i=1,2,\cdots,n,\ j=1,2,\cdots,m, \text{and } \ p=1,2,\cdots,k).$$

Apparently $0\leqslant\mu_{ik}\leqslant 1$, and

$$\sum_{i=1}^{k}\mu_{ik}=\sum_{i=1}^{k}\sum_{j=1}^{m}w_j\boldsymbol{\mu}_{ijk}=\sum_{j=1}^{m}\left|\sum_{i=1}^{k}\boldsymbol{\mu}_{ijk}\right|w_j=\sum_{j=1}^{m}w_j=1.$$

### 1.5 Determining the grade of samples

Suppose $d_k(k=1, 2, \cdots, K)$ is unascertained measurement vectors, then $d_k$ is called unascertained measurement distance, it can be calculated as follows:

$$d_k=\sqrt{(\mu_{i1}-0)^2+(\mu_{i2}-0)^2+(\mu_{ik}-1)^2+\cdots+(\mu_{iK}-0)^2}\,.$$

Comparing the rate of $d_k(k=1, 2, \cdots, K)$, if:

$$d_{k0}=\min(d_1,d_2,\cdots,d_K),$$

thus, $x_i$ belongs to $C_{k0}$ [8] virtual dynamic parameterized design of mechanical structure carries out under the visual computer environment.

## 2 Application and discussion

### 2.1 Effective indexes and the UMC model for predicting goaf collapse

Goaf collapse is caused by a variety of complicated factors which work together. Therefore, all the influential factors should be fully taken into account when discriminated function is established. The main influential factors include goaf volume rate, goaf vertical depth of the surface, the complexity of the geological structure, etc.. Referring to relevant research findings and information on the comprehensive analysis of this paper identified the following seven indicators: The cover layer type, cover layer thickness, the complexity of the geological structure, coal seam dip angle, goaf volume rate, goaf vertical depth of the surface, goaf space overlay layers as the factors of goaf collapse.

This paper takes the data of one mine ground subsidence provided by the Reference [7] as an example, the former 17 groups measured data are selected as training samples, the later 7 groups as the forecast samples. The forecast categories are divided into two kinds, which are stabilization and stability. Among the 17 groups' data, 9 groups are collapse samples and 8 groups are stable samples. The cover layer type, cover layer thickness, The complexity of the geological structure, coal seam dip angle, goaf volume rate, goaf vertical depth of the surface, goaf space overlay layers are chose as the influencing factors of discriminated function.

### 2.2 Model testing and application

In order to investigate the validity and correctness of the goaf ground subsidence prediction model, the established model is used to forecast the 17 groups measured data one by one, compared with the corresponding measured data, listing the results in Table 1, the correct rate is 100%, it is completely in line with

**Table 1 The discriminant indexes and results of samples**

| Site. No. | Discriminant indexes | | | | | | | Actually results | Predicted results |
|---|---|---|---|---|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_7$ | | |
| 1 | 3 | 7.5 | 2 | 28 | 18 | 10.4 | 3 | Collapse | Collapse |
| 2 | 3 | 11.5 | 2 | 45 | 18 | 22.0 | 3 | Collapse | Collapse |
| 3 | 2 | 14.5 | 3 | 55 | 14 | 16.0 | 3 | Collapse | Collapse |
| 4 | 3 | 12.5 | 3 | 55 | 11 | 14.5 | 4 | Collapse | Collapse |
| 5 | 3 | 15.0 | 2 | 50 | 10 | 17.5 | 3 | Collapse | Collapse |
| 6 | 2 | 15.5 | 1 | 35 | 5 | 18.2 | 1 | Stabilization | Stabilization |
| 7 | 1 | 12.0 | 2 | 40 | 7 | 25.0 | 2 | Stabilization | Stabilization |
| 8 | 3 | 17.0 | 3 | 80 | 20 | 20.2 | 2 | Collapse | Collapse |
| 9 | 2 | 12.0 | 3 | 50 | 10 | 13.5 | 3 | Collapse | Collapse |
| 10 | 3 | 14.0 | 3 | 70 | 15 | 16.7 | 2 | Collapse | Collapse |
| 11 | 3 | 13.5 | 2 | 50 | 1.5 | 15.4 | 3 | Stabilization | Stabilization |
| 12 | 2 | 19.0 | 2 | 35 | 6.0 | 26.0 | 1 | Stabilization | Stabilization |
| 13 | 1 | 10.0 | 2 | 50 | 4.0 | 22.5 | 2 | Stabilization | Stabilization |
| 14 | 2 | 15.0 | 2 | 40 | 2.0 | 16.5 | 1 | Stabilization | Stabilization |
| 15 | 2 | 10.0 | 2 | 45 | 2.5 | 16.4 | 1 | Stabilization | Stabilization |
| 16 | 2 | 15.0 | 1 | 25 | 5.5 | 30.0 | 2 | Stabilization | Stabilization |
| 17 | 3 | 9.5 | 3 | 75 | 12.0 | 12.7 | 3 | Collapse | Collapse |
| 18* | 3 | 12.0 | 2 | 40 | 10 | 17.0 | 2 | Collapse | Collapse |
| 19* | 3 | 10.5 | 3 | 50 | 13 | 14.5 | 3 | Collapse | Collapse |
| 20* | 2 | 16.5 | 3 | 70 | 20 | 20.2 | 3 | Collapse | Collapse |
| 21* | 2 | 15.0 | 3 | 70 | 18 | 17.0 | 2 | Collapse | Collapse |
| 22* | 2 | 10.0 | 2 | 45 | 2.5 | 18.4 | 1 | Stabilization | Stabilization |
| 23* | 2 | 15.0 | 1 | 25 | 5 | 24.8 | 2 | Stabilization | Stabilization |
| 24* | 2 | 16.0 | 1 | 25 | 5.8 | 40.0 | 3 | Stabilization | Stabilization |

Note: The samples with * are tested ones.

the actual situation. So conclusion can be made that the established model is stable, reliable and efficient.

From the measured data of one mine subsidence samples, 7 groups are selected as testing samples and tested into the established model, the forecast results obtained and listed in Table 1. From Table 1, the misjudgment-rate is 0; forecast accuracy is 100%.The forecast result is completely correlated with the measured results. So conclusions can be made that the unascertained classifying model of goaf ground subsidence is entirely reasonable and efficient. The discriminated accuracy is very high, and has important theoretical and practical significance in goaf ground subsidence forecast. After further verification, this method can apply to practical engineering.

## 3 Conclusions

Goaf collapse is caused by the joined effects of many factors, which is a difficult and challenge problem that the mining engineers faced. It has a direct impact on the normal production of the mining area. It relates to not only the region people's lives and property but also the safety of the structures on the ground. The UMC model of goaf ground subsidence is proposed. Meanwhile the cover layer types over layer thickness, the complexity of the geological structure, coal seam dip angle, and goaf volume rate, goaf vertical depth of the surface and goaf space overlay layers are selected as the discriminated factors, which comprehensively reflect the integrated status of the goaf collapse. The established model is used to predict the goaf collapse situation of one mine, and the forecast results in good agreement with the actually results, which is theoretical and practical significance. It also provides a new way to deal with the goaf collapse forecast.

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