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Safety Risk Assessment of a Pb-Zn Mine Based on Fuzzy-Grey Correlation Analysis

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Abstract: Improving safety management and risk evaluation methods is important for the global mining industry, which is the backbone of the industrial development of our society. To prevent any accidental loss or harm to human life and property, a safety risk assessment method is needed to perform the continuous risk assessment of mines. Based on the requirements of mine safety evaluation, this paper proposes the Pb-Zn mine safety risk evaluation model based on the fuzzy-grey correlation analysis method. The model is compared with the risk assessment model based on the fuzzy TOPSIS method. Through the experiments, our results demonstrate that the proposed fuzzy-grey correlation model is more sensitive to risk and has less effect on the evaluation results under different scoring attitudes (cautious, rational, and relaxed).

Keywords: system modelling; safety control; risk evaluation; decision support; expert evaluation; fuzzy logic; grey theory

1. Introduction

Mining ensures the supply of the required material as the foundation for the industrial development of our society, but also is the cause of many accidents and deaths worldwide [1]. Therefore, mine safety is very important to ensure the sustainable development of the global economy [2]. To prevent mine accidents, mine safety risk should be assessed and properly managed. Safety risk management [3], the evaluation and mitigation of the safety risks of the consequences of hazards, has gradually developed into an independent research discipline, because of the continuous development of risk analysis and control theory. Improving the level of safety management has become an urgent real requirement for business enterprises since the emergence of globalization and the introduction of corporate social responsibility. Researchers have done many experiments using fuzzy logic [4] in the field of risk assessment, including hazardous industrial installations [5,6], the aluminum industry [7], hydropower stations [8], shipping routes [9], supply chains [10], railway transportation systems [11], construction projects and green buildings [12,13], and occupational health and safety [14,15].

There are many risk assessment methods specifically dedicated to evaluating industrial or mining safety, for example fuzzy logic [16–18], nature inspired intelligence [19], neural networks [20,21], set pair analysis [22,23], the cloud model [24,25], grey system theory [26], and the analytic hierarchy process (AHP) [27]. Shi et al. [28] suggested grey-fuzzy evaluation integrated with grey statistics, AHP, grey correlation analysis (GCA), and fuzzy judgment for assessing the eco-environment vulnerability. Shi [29] adopted the grey-fuzzy evaluation method for vulnerability evaluation of teaching quality. Wang et al. [30] proposed the hybrid method based on GCA and fuzzy comprehensive judgment (FCJ) to evaluate the quality of passenger train service. In 2014, the order of preference by similarity to ideal solution (TOPSIS), a multi-criteria decision support method, was proposed to assess the risks of underground coal mines associated with human health and safety [31]. Verma and Chaudhri integrated the fuzzy reasoning technique and fuzzy AHP approaches for the assessment of the risk levels related to the risk factors in the mining industry [32]. Petrović et al. proposed a model of the risk evaluation of mining equipment failure based on the fuzzy sets and analyzed the detectability, occurrence, and severity of the risk indicators [33]. Wang et al. estimated and ranked all risk factors to support the safety managers in the mining industry by using the fuzzy AHP [34]. Nawrocki and Jonek-Kowalska provided a framework for joint internal and industrial assessment of operational risk using fuzzy sets [35]. Verma and Chaudhri presented a review of risk evaluation methods used in the global mining industry [36]. By using AHP, Yang et al. suggested a fuzzy evaluation model for mine water and sand inrush caused by underground mining [37]. By using fuzzy AHP to prioritize risk factors, Ghasemi et al. presented a methodology to evaluate the roof fall susceptibility during retreat mining [38]. Wang et al. suggested a fuzzy fault tree analysis method to evaluate the risk of coal dust explosions [39]. Samantra et al. described a risk based decision-support methodology to select an appropriate safety indicator system for the underground coal mining industry by using interval valued fuzzy rules to model subjectivity and vagueness [40]. Bao et al. presented a safety and occupational health management system for the mining industry by choosing gas, noise, and dust risk factors [41]. Samantra et al. presented a hierarchical structure of occupational health hazards in an underground coal mine by using fuzzy rules for translating linguistic data into digital risk ratings [42]. Qiu et al. combined fuzzy Delphi AHP and grey relational analysis to assess the risk of water inrush in mines [43]. Han et al. used the mixed center-point triangular whitening weight function to assess coal mine industry safety in China [44].

Grey theory, originally introduced by Deng [45,46], is a decision-making method to address the systems described by incomplete information. The grey relational analysis is an analytical method for the evaluation of alternatives and addressing complex relations between multiple factors and variables. It allows for studying problems where only partial information is known, for example for uncertain systems with few data available. Grey theory has been adopted for data modelling and forecasting, systems' analysis, as well as for decision-support and control [47–49].

Based on the previous studies and considering the actual situation of the Pb-Zn mine, we propose the safety risk ranking and classification evaluation model of the Pb-Zn mine based on the fuzzy-grey correlation method. We compare our method with the fuzzy TOPSIS risk assessment model under the same index to verify the proposed method and present the results.

The structural organization of the remaining parts of the paper is as follows. We describe the proposed methods based on fuzzy-grey theory in Section 2. We describe the comprehensive risk evaluation model based on fuzzy-grey correlation in Section 3. We present the results of fuzzy-grey correlation risk rating assessment in Section 4. We discuss the results in Section 5. Finally, we present conclusions in Section 6.

2. Methods

2.1. Preliminaries

In the following, we provide the definition of the related concepts of fuzzy numbers.

Definition 1 ([50])**.** *The normal convex fuzzy sets on the real number field R are called the fuzzy numbers; the regular closed convex fuzzy sets are called the closed fuzzy numbers; the regular bounded closed convex fuzzy sets are called the bounded closed fuzzy numbers. If $\tilde{A}$ is the fuzzy number and $A_1 = 1 - cut$ is a single point set, that is $A_1 = \{x_0\}$, then $\tilde{A}$ is a strictly fuzzy number.*

Definition 2 ([51])**.** *Let $\tilde{A}$ be a fuzzy number; $\tilde{A}$ is set $Supp\tilde{A} = (a_1, a_2), a_1 > a_2$; if:*

- $a_1 \geq 0$, *set* $\tilde{A}$ *to a positive fuzzy number, indicated by* $\widetilde{A} > 0$;
- $a_2 \leq 0$, *set* $\tilde{A}$ *to a negative fuzzy number, indicated by* $\widetilde{A} < 0$;
- $a_1 < 0, a_2 > 0$, *set* $\tilde{A}$ *to a zero fuzzy number, indicated by* $\tilde{A} \geq 0$ *or* $\tilde{A} \leq 0$;
- $a_1 < 0, a_2 > 0$ *and* $\mu_{\tilde{A}}(0) = 1$, *set* $\tilde{A}$ *to a zero fuzzy number, indicated by* $\tilde{A} = 0$.

Definition 3 ([52]). *Let any fuzzy numbers be represented by a pair of functions and any fuzzy number be set* $\tilde{b} = (b^L(r), b^R(r))$ *to satisfy for* $\forall r, 0 < r < 1$: *(1)* $b^L(r)$ *is a bounded left continuous non-decreasing function; (2)* $b^R(r)$ *is a bounded right continuous non-increasing function; (3)* $b^L(r) \leq b^R(r)$. *Then, the fuzzy number* $\tilde{b} = (b^L(r), b^R(r))$ *is a function pair.*

Definition 4. *Let fuzzy number* $\tilde{A}$ *have membership degree:*

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{x-c}{b-c}, & b \leq x \leq c \\ 0, & x > c \end{cases} \tag{1}$$

Let us call $\tilde{A}$ *the triangular fuzzy number denoted by* $\tilde{A} = (a, b, c)$.

Definition 5 ([53]). *Let* E *be a fuzzy set on* R; *the membership function denoted by* $E(x)$, $x \in R$. *If* $E(x)$, *satisfies these properties: (1)* $E(0) = 1$; *(2)* $E(x)$ *is a monotonically increasing left continuous function in the interval* $-1,0)$ *and in the interval* $0,1$ *is a monotonically decreasing right continuous function; (3) when* $-\infty < x < -1$ *or* $1 < x < +\infty$, $E(x) = 0$. *Then, the fuzzy set* E *is a fuzzy structured element on* R.

Definition 6 ([53]). *Let* E *be a fuzzy element on* R; *if (1)* $\forall\, x \in (-1,1)$, $E(x) > 0$; *(2)* $E(x)$ *is continuous and strictly monotonically increasing in the interval* $-1,0)$ *and continuous and strictly monotonically decreasing in the interval* $0,1$, *then call* E *the regular fuzzy structure element. If* $E(x) = E(-x)$, *then* E *is a symmetric structured element.*

Definition 7. *Let fuzzy sets* E *have membership functions:*

$$E(x) = \begin{cases} 1+x, x \in [-1,0] \\ 1-x, x \in [0,1] \\ 0, \ other \end{cases} \tag{2}$$

Call it a triangular fuzzy structured element.

2.2. Fuzzy-Grey Relation Ranking Method Based on the Structured Element Method

The fuzzy-grey relation ranking method based on the structured element method is described as follows:

Step 1: Fuzzy structure meta-representation of the fuzzy decision matrix.

The original data fuzzy matrix $\tilde{X}$ is constructed by the known risk values.

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{pmatrix} \tag{3}$$

where $\tilde{x}_{ij}$ $(i = 1,2,\cdots,m, j = 1,2,\cdots,n)$ represents the risk value RM_{ij} (fuzzy number) of the evaluation object i in the evaluation index j. Let E be a regular fuzzy structured element, and use the structured element to represent the fuzzy number:

$$\tilde{x}_{ij} = f_{ij}^{x}(E) \tag{4}$$

where $f_{ij}^{x}(x), x \in [-1,1]$ is a monotonically increasing function.

Step 2: Assign weight to the fuzzy decision matrix, then the fuzzy decision matrix would be:

$$\tilde{V}=\begin{pmatrix}\tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n}\\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn}\end{pmatrix} \tag{5}$$

Among them $\tilde{v}_{ij}=\tilde{w}_j\tilde{x}_{ij}=g_j(E)f_{ij}^{x}(E), i=1,2,\cdots,m,\ j=1,2,\cdots,n$. $\tilde{w}_j=g_j(E)$ is the fuzzy weight, and $g_j(x),\ x\in[-1,1]$ is a monotonically increasing function. For the convenience of description, let $\tilde{v}_{ij}=f_{ij}(E)$, $f_{ij}=g_jf_{ij}^{x}$.

Step 3: Determine the ideal object $\tilde{v}_0$ that is the optimal index set; denoted by $\tilde{v}_0=(\tilde{v}_{01},\tilde{v}_{02},\cdots,\tilde{v}_{0n})$. Usually, the optimal value of the j^{th} index in all the subjects is taken as the value of $\tilde{v}_{0j}$.

$$b\tilde{v}_{0j}=\begin{cases}\max\limits_i \tilde{v}_{ij}, \text{the } j\text{th index has a positive impact}\\ \min\limits_i \tilde{v}_{ij}, \text{the } j\text{th index has a negative impact}\end{cases} \tag{6}$$

Correspondingly, define the ideal function of each index:

$$\mathrm{f}_{\mathrm{j}}^{1}=\begin{cases}\max\limits_i f_{ij}, \text{the } j\text{th index has a positive impact}\\ \min\limits_i f_{ij}, \text{the } j\text{th index has a negative impact}\end{cases} \tag{7}$$

Here, $x\in[-1,1],\ \ j=1,2,\cdots,n$.

When RM selects the $[0-1]$ fuzzy scale, the range of RM is $[0,3]$, and the optimal index is defined as $\tilde{v}_0=(\tilde{v}_{01},\tilde{v}_{02},\cdots,\tilde{v}_{0n})=(0,0,\cdots,0)$. At this time, $f_j^1=0, j=1,2,\cdots,n$.

When RM selects the $[\frac{1}{9}-9]$ fuzzy scale, the range of RM is $[\frac{1}{9}^3, 9^3]$, and the optimal index is defined as $\tilde{v}_0=(\tilde{v}_{01},\tilde{v}_{02},\cdots,\tilde{v}_{0n})=(\frac{1}{9}^3,\frac{1}{9}^3,\cdots,\frac{1}{9}^3)$. At this time $f_j^1=\frac{1}{9}^3, j=1,2,\cdots,n$.

Step 4: Calculate the distance between fuzzy numbers based on structured elements.

Let $E(x), x\in[-1,1]$ be a membership function of structured element E. The fuzzy number represented by the structure element is: $\tilde{A}=f(E)$ and $\tilde{B}=g(E)$. The fuzzy distance $D(\tilde{A},\tilde{B})$ [54] between $\tilde{A}$ and $\tilde{B}$ is:

$$D(\tilde{A},\tilde{B})=\sqrt{\int_{-1}^{1}E(x)(f(x)-g(x))^2\,dx} \tag{8}$$

According to the definition of the fuzzy distance, the distance between the j^{th} index of the evaluation object i and the j^{th} index of the ideal object is:

$$D(\tilde{v}_{ij},\tilde{v}_{0j})=\sqrt{\int_{-1}^{1}E(x)(f_{ij}(x)-f_j^1(x))^2\,dx} \tag{9}$$

When $\tilde{v}_{ij}=f_{ij}(E)$ is the triangular fuzzy number, it is represented by (a,b,c). E is the triangular fuzzy element structure. Its linear function of the structured elements is:

$$f_{ij}(x)=\begin{cases}(b-a)x+b, x\in[-1,0]\\ (c-b)x+b, x\in[0,1]\end{cases} \tag{10}$$

The distance between the j^{th} index of the evaluation object i and and the j^{th} index of the ideal object is:

$$D(\tilde{v}_{ij},\tilde{v}_{0j})=\sqrt{\begin{array}{l}\int_{-1}^{0}(1+x)((b-a)x+b-f_j^1(x))^2\,dx+\\ \int_{0}^{1}(1-x)((c-b)x+b-f_j^1(x))^2\,dx\end{array}} \tag{11}$$

When $f_j^1(x)$ is constant, then:

$$D(\tilde{v}_{ij}, \tilde{v}_{0j}) = \sqrt{\frac{(c-b)^2 + (b-a)^2 + 4(b-f^1)(c-a) + 12(b-f^1)^2}{12}} \tag{12}$$

Step 5: Calculate the elements in the correlation coefficient matrix β between the evaluation object i and the ideal object:

$$\beta_{ij} = \frac{\underset{i}{min}\underset{j}{min} D(\tilde{v}_{ij}, \tilde{v}_{0j}) + \rho \underset{i}{max}\underset{j}{max} D(\tilde{v}_{ij}, \tilde{v}_{0j})}{D(\tilde{v}_{ij}, \tilde{v}_{0j}) + \rho \underset{i}{max}\underset{j}{max} D(\tilde{v}_{ij}, \tilde{v}_{0j})} \tag{13}$$

Similarly, ρ is the resolution coefficient, and its specific value can be selected according to the principle of "fully reflecting the integrity of the correlation and having the anti-interference effect" [55]. Take $\rho = 0.5$ for calculation.

Each element in the matrix C of the correlation coefficient between the object i and the ideal object is evaluated:

$$C_i = \sum_{j=1}^{n} \tilde{w}_j \beta_{ij} \tag{14}$$

Here, $\tilde{w}_j$ is the fuzzy weight of the j^{th} index.

Sorted by the degree of relevance, the larger the C_i value, the higher the corresponding mine safety.

2.3. Fuzzy-Grey Correlation Ranking Method Based on the Structured Element Method

The traditional grey relation analyzes the similarity between the evaluation object and the reference object. In the following, the reference object is exchanged with the evaluated object to achieve the level division of the evaluation object based on the fuzzy structure meta distance. The specific steps are as follows:

Step 1: Fuzzy structure meta-representation of fuzzy decision matrix.

The original data fuzzy matrix $\tilde{X}$ is constructed by the known risk values as follows:

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{pmatrix} \tag{15}$$

where $\tilde{x}_{ij}$ $(i = 1,2,\cdots,m, j = 1,2,\cdots,n)$ represents the risk value RM_{ij} (fuzzy number) of the evaluation object i in the evaluation index j.

Let E be a regular fuzzy structured element, and use the structured element to represent the fuzzy number:

$$\tilde{x}_{ij} = f_{ij}^{x}(E) \tag{16}$$

where $f_{ij}^{x}(x)$, $x \in [-1, 1]$ is a monotonically increasing function.

Step 2: Assign the weight to the fuzzy decision matrix, then the matrix would be:

$$\tilde{V} = \begin{pmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn} \end{pmatrix} \tag{17}$$

Among them, $\tilde{v}_{ij} = \tilde{w}_j \tilde{x}_{ij} = g_j(E) f_{ij}^{x}(E)$, $i = 1,2,\cdots,m$, $j = 1,2,\cdots,n$. $\tilde{w}_j = g_j(E)$ is the fuzzy weight, and $g_j(x)$, $x \in [-1, 1]$ is a monotonically increasing function. For the convenience of description, let $\tilde{v}_{ij} = f_{ij}(E)$ $f_{ij} = g_j f_{ij}^{x}$.

Step 3: Determine the p level standard matrix corresponding to n indicators:

$$\tilde{T}=\begin{pmatrix}\tilde{t}_{11} & \tilde{t}_{12} & \cdots & \tilde{t}_{1n}\\ \tilde{t}_{21} & \tilde{t}_{22} & \cdots & \tilde{t}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{t}_{p1} & \tilde{t}_{p2} & \cdots & \tilde{t}_{pn}\end{pmatrix} \tag{18}$$

$\widetilde{T}=(\tilde{T}_1,\tilde{T}_2,\cdots,\tilde{T}_p)$ is the j^{th} index of the k level evaluation of the standard value ($k=1,2,\cdots,p$, $j=1,2,\cdots,n$) and is also expressed by a fuzzy number. If the RM evaluation selects the $[0-1]$ fuzzy scale, the range of RM is $[0,3]$, and the standard value of the k^{th} stage may be:

$$T_k^*=\{t_{k1}^*,t_{k2}^*,\cdots,t_{kn}^*\}=\{3\frac{(k-1)}{(p-1)},3\frac{(k-1)}{(p-1)},\cdots,3\frac{(k-1)}{(p-1)}\} \tag{19}$$

here $k=1,2,\cdots,p$, is the standard value of the evaluation level and is the value with the largest degree of membership.

Step 4: Calculate the elements in the weighted p level standard matrix $\tilde{t}^*{}_{kj}=\widetilde{w}_j\tilde{t}_{kj}$, $j=1,2,\cdots,n$, $k=1,2,\cdots,p$.

Step 5: Calculate the distance between the j^{th} index of the evaluation object i and the j^{th} index of each level in the standard matrix:

$$D_i(\tilde{v}_{ij},t^*{}_{kj}), j=1,2,\cdots,n, k=1,2,\cdots,p \tag{20}$$

$$D_i(\tilde{v}_{ij},t_{kj}^*)=\sqrt{\int_{-1}^{1}E(x)(f_{ij}(x)-t_{kj}^*)^2\,dx} \tag{21}$$

Here, $D_i(\tilde{v}_{ij},t_{kj}^*)$ is a definite number.

When $\tilde{v}_{ij}=f_{ij}(E)$ is the triangular fuzzy number (here, it is represented by (a,b,c)), take E as the triangular fuzzy element structure; the linear function of its structured element is:

$$f_{ij}(x)=\begin{cases}(b-a)x+b, x\in[-1,0]\\ (c-b)x+b, x\in[0,1]\end{cases} \tag{22}$$

The distance between the j^{th} index of the evaluation object i and the j^{th} index of the ideal object is:

$$D_i(\tilde{v}_{ij},t_{kj}^*)=\sqrt{\int_{-1}^{0}(1+x)((b-a)x+b-t_{kj}^*)^2\,dx+\int_{0}^{1}(1-x)((c-b)x+b-t_{kj}^*)^2\,dx} \tag{23}$$

When t_{kj}^* is constant, then:

$$D(\tilde{v}_{ij},t_{kj}^*)=\sqrt{\frac{(c-b)^2+(b-a)^2+4(b-t_{kj}^*)(c-a)+12(b-t_{kj}^*)^2}{12}} \tag{24}$$

is constant $k=1,2,\cdots,p$.

Step 6: Calculate the correlation coefficient matrix β_i between each index of evaluation object i and the standard value of each level of evaluation:

$$\beta_i=\begin{pmatrix}\beta_{i11} & \beta_{i12} & \cdots & \beta_{i1n}\\ \beta_{i21} & \beta_{i22} & \cdots & \beta_{i2n}\\ \vdots & \vdots & \ddots & \vdots\\ \beta_{ip1} & \beta_{ip2} & \cdots & \beta_{ipn}\end{pmatrix} \tag{25}$$

Each of these elements:

$$\beta_{ijk}=\frac{\min_k\min_j D(\tilde{v}_{ij},t_{kj}^*)+\rho\max_k\max_j D(\tilde{v}_{ij},t_{kj}^*)}{D(\tilde{v}_{ij},t_{kj}^*)+\rho\max_k\max_j D(\tilde{v}_{ij},t_{kj}^*)} \tag{26}$$

Similarly, take $\rho=0.5$ for calculation.

The correlation coefficient matrix C_i between the evaluation object i and the evaluation level:

$$C_i = \left(C_{i1}, C_{i2}, \cdots, C_{ip}\right) \tag{27}$$

Each of these elements:

$$C_{ik} = \sum_{j=1}^{n} \widetilde{w}_j \beta_{ijk} \tag{28}$$

Similarly, $\widetilde{w}_j$ is the fuzzy weight of the j^{th} index. Sorted by the degree of correlation, the maximum value of C_{ik}, the corresponding mine i has a safety level of k. This completes the mine safety assessment.

3. Comprehensive Risk Evaluation Model Based on Fuzzy-Grey Correlation

3.1. Index and Weight Data for Application Analysis of the Comprehensive Risk Evaluation Model

Referring to the mine safety risk assessment index given in [56], the Pb-Zn mine safety indicators are given in Table 1. In the design of the simulation experiment, the evaluation results are compared with the method used in [36].

Table 1. Pb-Zn mine safety indicators' evaluation system.

Primary Indicator	Secondary Indicators	Three Level Indicators
Natural conditions A1	Safe production capacity B1	Satisfaction of safety production capacity C1
	Hydrogeological conditions B2	Water rich C2 of the formation
		Rock mass water rich C3
		Fold, fracture structure of the water rich C4
	Rock top floor conditions B3	Rock formation management ease C5
	Engineering geological conditions B4	Soil thickness C6
		Rock mass hardness C7
	Dust explosion conditions B6	Probability of dust explosion C8
	Mining situation B7	Mining depth C9
Personnel quality A2	Cultural quality B8	The average level of education C10
	Professional quality B9	Senior technician ratio C11
		Senior management ratio C12
		Certified staff ratio C13
	Physical fitness B10	Medical examination pass rate C14
	Safety awareness B11	Safety training attendance C15
	Personnel insecure behavior B12	"Three violations" incidence of C16
Equipment Situation A3	Equipment advanced level B13	Million tons Pb-Zn mine production equipment total value C17
	Equipment mechanization B14	Tons of Pb-Zn ore production equipment total value C18
	Equipment failure B15	Production equipment failure rate C19
	Equipment maintenance B16	Production equipment maintenance rate C20
	Equipment renovation B17	Production equipment update rate C21
Production process A4	Temperature B18	General face temperature conditions C22
	Wind speed B19	Average wind speed C23
	Noise B20	Average noise decibel C24
	Harmful gases B21	The average concentration of harmful gases C25
	Dust B22	The average dust concentration C26
	Lighting B23	The average illuminance C27
	Workplace B24	Roadway pass rate C28

Safety Management A5	Safety management system B25	Safety management system improvement rate C29
	Safety risk management B26	Hidden rectification pass rate C30
	Safety and quality standardization management B27	The average score of safety and quality standardization examination C31
	Safety information management B28	Per capita information management input ratio C32
		Security information office rate C33
	Security input B29	Security input ratio C34
	Safety education and training B30	Training funding ratio C35
		Staff training rate C36
		Certified growth ratio training C37
	Safety incident management B31	Pb-Zn mine million tons mortality rate C38
		The number of serious injuries throughout the year C39
		Percentage of minor injuries C40
	Major disaster management B32	Million tons of ore explosion alarm rate C41
		Million tons of ore production flood alarm rate C42
		Million tons of ore fire alarm rate C43
		Tons of ore hit the ground pressure alarm rate C44
	Occupational health management B33	The proportion of occupational patients C45
	Emergency management B34	“Safe hedging six systems” complete rate C46

In this paper, three groups of the Pb-Zn mines are scored by a group of experts. The numbers a, b, and c are the three elements of the triangular fuzzy number. The data quality control here is mainly conducted by manual identification. The original data of fuzzy risk values assessed by the experts are shown in Table 2.

Table 2. Risk values scored by experts represented as triangular fuzzy numbers.

Three Level Indicator	Mine 1			Mine 2			Mine 3		
	a	b	c	a	b	c	a	b	c
C1	0.9867	1.32	1.6533	1.91	2.2433	2.5767	1.2233	1.5567	1.89
C2	0.8413	1.008	1.3413	1.0953	1.262	1.5953	1.0593	1.226	1.5593
C3	0.8111	1.1445	1.4778	0.3778	0.5444	0.8778	0.1	0.1	0.4333
C4	0.66	0.9933	1.3267	1.0733	1.4067	1.74	0.68	1.0133	1.3467
C5	2	2.5	2.8333	2	2.5	2.8333	1.3333	1.8333	2.3333
C6	0.039	0.2057	0.539	1.4523	1.7857	1.9523	0.587	0.9203	1.2537
C7	0.3333	0.8333	1.3333	1.6667	2.1667	2.6667	1.8333	2.3333	2.6667
C8	1.3333	1.8333	2.3333	1	1.5	2	1.1667	1.6667	2.1667
C9	1.356	1.6893	2.0227	0.5593	0.8927	1.226	1.523	1.8563	2.1897
C10	0.4517	0.6183	0.9517	0.6405	0.8072	1.1405	0.5799	0.7465	1.0799
C11	0.74	0.74	1.0733	1.35	1.5167	1.85	1.1433	1.31	1.6433
C12	0.82	0.82	1.1533	1.5867	1.7533	2.0867	1.5967	1.7633	2.0967
C13	0	0	0.3333	0.02	0.1867	0.52	0.02	0.1867	0.52
C14	0.02	0.1867	0.52	0.1967	0.53	0.8633	0.2067	0.54	0.8733
C15	0.2767	0.61	0.9433	0.8867	1.22	1.5533	1.1233	1.4567	1.79
C16	0.6983	1.0317	1.365	1.065	1.3983	1.7317	1.365	1.6983	2.0317
C17	0.8543	1.021	1.3543	1.488	1.8213	2.1547	1.5097	1.8431	2.1764
C18	0.0461	0.2127	0.5461	0.7599	1.0933	1.4266	0.4055	0.7388	1.0721
C19	0.5033	0.8367	1.17	0.71	1.0433	1.3767	0.5233	0.8567	1.19
C20	0.02	0.3533	0.6867	0.03	0.3633	0.6967	0.03	0.3633	0.6967
C21	1.5967	1.93	2.2633	1.97	2.3033	2.6367	1.98	2.3133	2.6467
C22	0.5	0.6667	1	1.0417	1.375	1.7083	0.75	1.0833	1.4167
C23	0.8658	1.1992	1.5325	1.2242	1.5575	1.8908	1.0825	1.4158	1.7492
C24	0.5167	0.85	1.1833	0.7833	1.1167	1.45	0.7583	1.0917	1.425
C25	1.2708	1.6042	1.9375	1.5833	1.9167	2.25	1.2917	1.625	1.9583
C26	0.998	1.3313	1.6647	1.7527	2.086	2.4193	1.3033	1.6967	2.03
C27	0.5733	0.74	1.0733	0.9733	1.3067	1.64	0.5133	0.8467	1.18
C28	0.06	0.3933	0.7267	0.62	0.9533	1.2867	0.61	0.9433	1.2767
C29	0.02	0.1867	0.52	0.7167	1.05	1.3833	1.07	1.4033	1.7367
C30	0.03	0.3633	0.6967	0.8367	1.17	1.5033	1.24	1.5733	1.9067
C31	0.0266	0.1933	0.5266	0.4177	0.7511	1.0844	0.6088	0.9421	1.2755
C32	0.11	0.2767	0.61	1.4433	1.7767	2.11	1.6033	1.9367	2.27
C33	0.15	0.4833	0.8167	1.3267	1.66	1.9933	1.71	2.0433	2.3767
C34	0.72	0.8867	1.22	1.1033	1.4967	1.83	1.39	1.7233	2.0567
C35	0.63	0.63	0.9633	1.5267	1.86	2.1933	1.7633	2.0967	2.2633
C36	0.01	0.01	0.3433	0.77	1.1033	1.4367	1.4133	1.7467	1.9133
C37	0.89	0.89	1.2233	1.1367	1.3033	1.6367	1.48	1.6467	1.98
C38	0	0	0.3333	0.6677	1.001	1.3343	0.6667	1	1.3333
C39	0.2027	0.3693	0.7027	1.2593	1.5927	1.926	0.9627	1.296	1.6293
C40	0.686	1.0193	1.3527	1.986	2.3193	2.6527	2.3527	2.686	2.8527
C41	0.2967	0.63	0.9633	1.21	1.5433	1.8767	0.67	1.0033	1.3367
C42	0.03	0.3633	0.6967	0.55	0.8833	1.2167	1.3567	1.69	2.0233
C43	0.5133	0.8467	1.18	1.7133	2.0467	2.2133	0.2767	0.61	0.9433
C44	1.3603	1.6937	2.027	1.1997	1.533	1.8663	0.3423	0.6757	1.009
C45	0.005	0.1717	0.505	0.1727	0.506	0.8393	0.004	0.3373	0.6707
C46	0.1867	0.3533	0.6867	0.4633	0.7967	1.13	0.8367	1.17	1.5033
C47	0.1767	0.51	0.8433	1.07	1.4033	1.7367	0.7167	1.05	1.3833
C48	0.01	0.1767	0.51	0.9167	1.25	1.5833	1.1433	1.4767	1.81

In the calculation of the fuzzy weights, we used the comprehensive fuzzy weight based on the scoring attitude as in [56]. In the simulation experiment, we combined the fuzzy weight calculated by different weighting methods with different scoring attitudes to evaluate the safety risk assessment. The model was verified by simulation; the comprehensive weight of the maximum eigenvalue method and entropy weight, the comprehensive weight of the least squares method and the entropy weight, the comprehensive weight of the sum method and the entropy weight, the comprehensive weight of the product method and the entropy weight were the four comprehensive weights CW1–CW4, which are shown in Table 3.

Table 3. Comprehensive weights of expert group for Pb-Zn mine safety indicators.

Three-Level Indicator	Comprehensive Weight 1			Comprehensive Weight 2			Comprehensive Weight 3			Comprehensive Weight 4		
	Cautious Attitude	Rational Attitude	Relaxed Attitude	Cautious Attitude	Rational Attitude	Relaxed Attitude	Cautious Attitude	Rational Attitude	Relaxed Attitude	Cautious Attitude	Rational Attitude	Relaxed Attitude
C1	0.005	0.004	0.001	0.005	0.004	0.002	0.005	0.004	0.001	0.005	0.004	0.001
C2	0.007	0.006	0.001	0.006	0.006	0.002	0.006	0.006	0.001	0.006	0.006	0.001
C3	0.02	0.056	0.004	0.017	0.055	0.005	0.017	0.056	0.005	0.018	0.056	0.005
C4	0.014	0.006	0.003	0.012	0.005	0.005	0.012	0.006	0.004	0.012	0.006	0.004
C5	0.009	0.005	0.004	0.007	0.005	0.007	0.007	0.005	0.005	0.008	0.005	0.005
C6	0.024	0.043	0.008	0.023	0.043	0.012	0.021	0.044	0.01	0.023	0.043	0.009
C7	0.012	0.014	0.002	0.011	0.014	0.005	0.011	0.014	0.003	0.011	0.014	0.003
C8	0.014	0.004	0.005	0.012	0.004	0.008	0.012	0.004	0.006	0.012	0.004	0.006
C9	0.011	0.009	0.004	0.009	0.009	0.007	0.009	0.009	0.005	0.01	0.009	0.005
C10	0.016	0.013	0.007	0.016	0.016	0.012	0.013	0.013	0.009	0.013	0.013	0.009
C11	0.008	0.006	0.005	0.006	0.006	0.006	0.007	0.007	0.006	0.007	0.007	0.007
C12	0.014	0.017	0.011	0.016	0.017	0.009	0.012	0.017	0.013	0.013	0.017	0.013
C13	0.046	0.077	0.285	0.043	0.076	0.335	0.042	0.077	0.33	0.042	0.077	0.33
C14	0.033	0.014	0.02	0.031	0.015	0.023	0.028	0.015	0.024	0.029	0.014	0.024
C15	0.047	0.042	0.036	0.046	0.04	0.035	0.04	0.042	0.046	0.041	0.043	0.047
C16	0.082	0.085	0.065	0.112	0.098	0.055	0.072	0.083	0.082	0.077	0.086	0.075
C17	0.031	0.021	0.018	0.017	0.012	0.022	0.03	0.022	0.02	0.026	0.021	0.023
C18	0.058	0.042	0.034	0.041	0.031	0.035	0.057	0.044	0.038	0.053	0.041	0.037
C19	0.015	0.005	0.005	0.011	0.003	0.008	0.014	0.005	0.006	0.013	0.004	0.007
C20	0.019	0.002	0.007	0.017	0.002	0.002	0.018	0.002	0.007	0.018	0.002	0.008
C21	0.015	0.01	0.009	0.008	0.006	0.012	0.015	0.011	0.01	0.013	0.01	0.011
C22	0.013	0.005	0.005	0.01	0.005	0.01	0.011	0.006	0.006	0.012	0.006	0.007
C23	0.007	0.002	0.002	0.006	0.002	0.005	0.006	0.002	0.003	0.006	0.002	0.003
C24	0.007	0.001	0.001	0.006	0.001	0.004	0.006	0.001	0.002	0.006	0.001	0.002
C25	0.017	0.009	0.008	0.014	0.01	0.017	0.014	0.01	0.009	0.015	0.01	0.01
C26	0.022	0.013	0.012	0.024	0.019	0.025	0.018	0.014	0.014	0.02	0.014	0.014
C27	0.008	0.002	0.002	0.008	0.002	0.004	0.007	0.002	0.002	0.007	0.002	0.002
C28	0.022	0.008	0.008	0.021	0.009	0.011	0.02	0.008	0.009	0.02	0.008	0.009
C29	0.027	0.014	0.02	0.027	0.013	0.016	0.031	0.015	0.015	0.031	0.015	0.015
C30	0.024	0.029	0.043	0.031	0.028	0.026	0.043	0.039	0.031	0.04	0.035	0.028
C31	0.028	0.033	0.027	0.029	0.032	0.019	0.034	0.037	0.019	0.034	0.036	0.019
C32	0.019	0.046	0.014	0.021	0.045	0.008	0.018	0.043	0.004	0.018	0.043	0.004
C33	0.012	0.018	0.006	0.012	0.018	0.006	0.011	0.017	0.002	0.011	0.017	0.002
C34	0.026	0.034	0.041	0.036	0.033	0.025	0.033	0.034	0.032	0.036	0.038	0.033
C35	0.008	0.013	0.012	0.009	0.022	0.003	0.012	0.016	0.006	0.011	0.015	0.006
C36	0.019	0.039	0.025	0.015	0.039	0.003	0.03	0.041	0.013	0.027	0.04	0.013
C37	0.005	0.004	0.005	0.009	0.012	0.004	0.007	0.005	0.002	0.007	0.005	0.002
C38	0.017	0.015	0.026	0.021	0.015	0.014	0.029	0.017	0.013	0.025	0.016	0.013
C39	0.015	0.027	0.013	0.015	0.026	0.01	0.019	0.028	0.007	0.018	0.027	0.008
C40	0.005	0.007	0.005	0.005	0.008	0.004	0.007	0.008	0.002	0.006	0.008	0.002
C41	0.024	0.027	0.025	0.035	0.028	0.014	0.025	0.019	0.019	0.027	0.021	0.019
C42	0.014	0.014	0.009	0.014	0.012	0.006	0.014	0.012	0.007	0.014	0.012	0.007
C43	0.016	0.025	0.009	0.016	0.024	0.006	0.016	0.023	0.007	0.016	0.024	0.007
C44	0.009	0.006	0.003	0.01	0.006	0.003	0.009	0.005	0.002	0.009	0.005	0.002
C45	0.042	0.03	0.075	0.04	0.029	0.084	0.04	0.029	0.081	0.041	0.029	0.081
C46	0.028	0.046	0.026	0.038	0.046	0.014	0.029	0.038	0.02	0.03	0.041	0.02
C47	0.025	0.013	0.017	0.026	0.012	0.014	0.023	0.01	0.016	0.024	0.011	0.016
C48	0.017	0.016	0.007	0.017	0.017	0.006	0.016	0.015	0.005	0.016	0.015	0.006

The weights for cautious, rational, and relaxed attitude are summarized in Figure 1 (only the 20 largest weights are shown for each group). The largest comprehensive weights were certified staff ratio C13 for relaxed attitude and "three violations" incidence C16 for cautious and rational attitude. This means that the factors of "certified staff" (which is related to the competences and qualifications of the personnel) and "three violations" (which is related to insecure behavior of the personnel) have the largest impact on the security assessment of the mine.

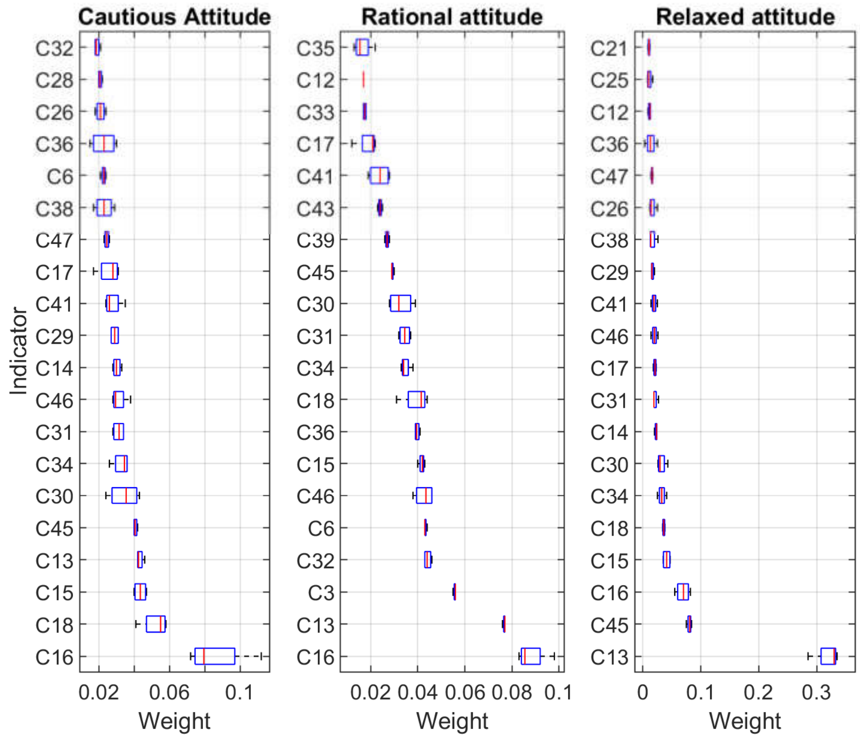

Figure 1. Comprehensive weights for cautious, rational, and relaxed attitude (only the 20 largest weights are shown for each group).

Similarly, the safety of the mine was also categorized into seven levels, as presented in Table 4, in order to conduct the contrast tests.

Table 4. Security risk rating evaluation form.

Security Risk Rating	Risk Implications	Security Management Advice
Very low	No risk	To ensure safety
Slightly low	Basically no risk	Safer
Low	Less risky	Safe, but hidden
Medium	Average risk	Basic security, need to deal with hidden dangers
Slightly high	Should pay attention to risk	As soon as possible to eliminate the risk, which is not safe to be rectified
High	Higher risk	Should stop production for rectification
Very high	High risk	After rectification and acceptance can start

4. Results of Fuzzy-Grey Correlation Risk Rating Assessment

To verify the validity of the fuzzy-grey correlation risk assessment model proposed here, the eigenvalue method based on the cautious attitude, rational attitude, and relaxed attitude for the comprehensive weight of the maximum eigenvalue method and entropy weight (CW1), the comprehensive weight of the least squares method and the entropy weight (CW2), the comprehensive weight of the sum method and the entropy weight (CW3), the comprehensive weight of the product method and the entropy weight (CW4) were used. The security risks under the four comprehensive weights were evaluated and compared with the results in [36]. The detailed experimental data are shown in Tables 5–7.

4.1. Fuzzy-Grey Correlation Risk Rating Based on Cautious Comprehensive Weight

According to the results of the simulation presented in Table 5, the fuzzy-TOPSIS model proposed in [56] was applied under the four kinds of comprehensive weights of the cautious scoring attitude. The results of the expert group assessment (represented in Figure 2) showed that the comprehensive risk level of the three mines was slightly lower, in which Mine 2 and Mine 3 had comprehensive risk ratings each of medium. By using the fuzzy-grey correlation method studied in this paper, the results of the expert group were as follows: the risk level of Mine 1 was lower, and the risk levels of Mine 2 and Mine 3 were medium. From the simulation, the results demonstrated that the proposed model was more sensitive to security risks.

Table 5. Fuzzy-grey correlation risk rating based on the cautious attitude.

Weight Categories	Evaluation Object	Correlation							Grey Related Rating	TOPSIS Rating [51]
		Very Low	Low	Slightly Low	Medium	Slightly High	High	Very High		
CW1	Mine 1	0.7305	0.8524	0.8298	0.6962	0.5715	0.4686	0.3959	Low	Slightly low
	Mine 2	0.5072	0.6429	0.7804	0.8382	0.7078	0.5556	0.4417	Medium	Slightly low
	Mine 3	0.5279	0.6577	0.7753	0.8079	0.7312	0.5639	0.4494	Medium	Slightly low
CW2	Mine 1	0.7283	0.8567	0.8393	0.6979	0.5654	0.4635	0.3921	Low	Slightly low
	Mine 2	0.5015	0.6368	0.7786	0.8494	0.7060	0.5488	0.4361	Medium	Medium
	Mine 3	0.5208	0.6497	0.7754	0.8205	0.7421	0.5661	0.4505	Medium	Medium
CW3	Mine 1	0.7425	0.8590	0.8240	0.6860	0.5632	0.4632	0.3924	Low	Slightly low
	Mine 2	0.5068	0.6439	0.7904	0.8426	0.7068	0.5537	0.4404	Medium	Slightly low
	Mine 3	0.5211	0.6502	0.7740	0.8131	0.7364	0.5671	0.4517	Medium	Slightly low
CW4	Mine 1	0.7394	0.8583	0.8267	0.6891	0.5644	0.4638	0.3928	Low	Slightly low
	Mine 2	0.5061	0.6429	0.7875	0.8433	0.7072	0.5536	0.4403	Medium	Slightly low
	Mine 3	0.5216	0.6508	0.7748	0.8143	0.7365	0.5661	0.4509	Medium	Slightly low

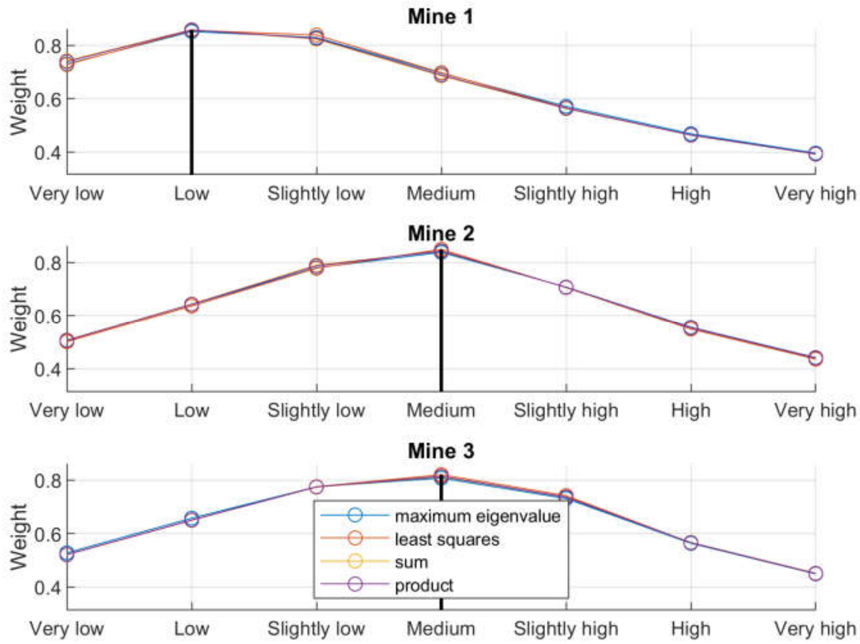

Figure 2. Fuzzy-grey correlation based on the cautious attitude.

4.2. Fuzzy TOPSIS Risk Rating Based on Rational Comprehensive Weight

According to the results of the simulation presented in Table 6, the proposed model was applied under the four kinds of comprehensive weights of the rational scoring attitude. The results (represented in Figure 3) showed that the comprehensive risk level of Mine 1 was lower, and the comprehensive risk levels of Mine 2 and Mine 3 were slightly lower.

Table 6. Fuzzy-grey correlation risk rating based on rational attitude.

Weight Categories	Evaluation Object	Correlation							Grey Related Rating	TOPSIS Rating [51]
		Very Low	Low	Slightly Low	Medium	Slightly High	High	Very High		
CW1	Mine 1	0.7501	0.8601	0.8301	0.6895	0.5559	0.4575	0.3886	Low	Low
	Mine 2	0.5189	0.6494	0.7722	0.8290	0.7212	0.5611	0.4456	Medium	Slightly low
	Mine 3	0.5433	0.5433	0.7570	0.7996	0.7417	0.5743	0.4578	Medium	Slightly low
CW2	Mine 1	0.7449	0.8575	0.8339	0.6941	0.5563	0.4572	0.3881	Low	Low
	Mine 2	0.5161	0.6460	0.7685	0.8312	0.7218	0.5603	0.4447	Medium	Slightly low
	Mine 3	0.5403	0.6487	0.7543	0.8045	0.7497	0.5784	0.4604	Medium	Slightly low
CW3	Mine 1	0.7511	0.8581	0.8273	0.6884	0.5560	0.4577	0.3887	Low	Low
	Mine 2	0.5202	0.6512	0.7753	0.8291	0.7202	0.5614	0.4461	Medium	Slightly low
	Mine 3	0.5419	0.6506	0.7537	0.7994	0.7434	0.5757	0.4586	Medium	Slightly low
CW4	Mine 1	0.7493	0.8579	0.8301	0.6898	0.5560	0.4575	0.3885	Low	Low
	Mine 2	0.5190	0.6497	0.7737	0.8308	0.7205	0.5607	0.4454	Medium	Slightly low
	Mine 3	0.5413	0.6497	0.7537	0.8014	0.7450	0.5758	0.4587	Medium	Slightly low

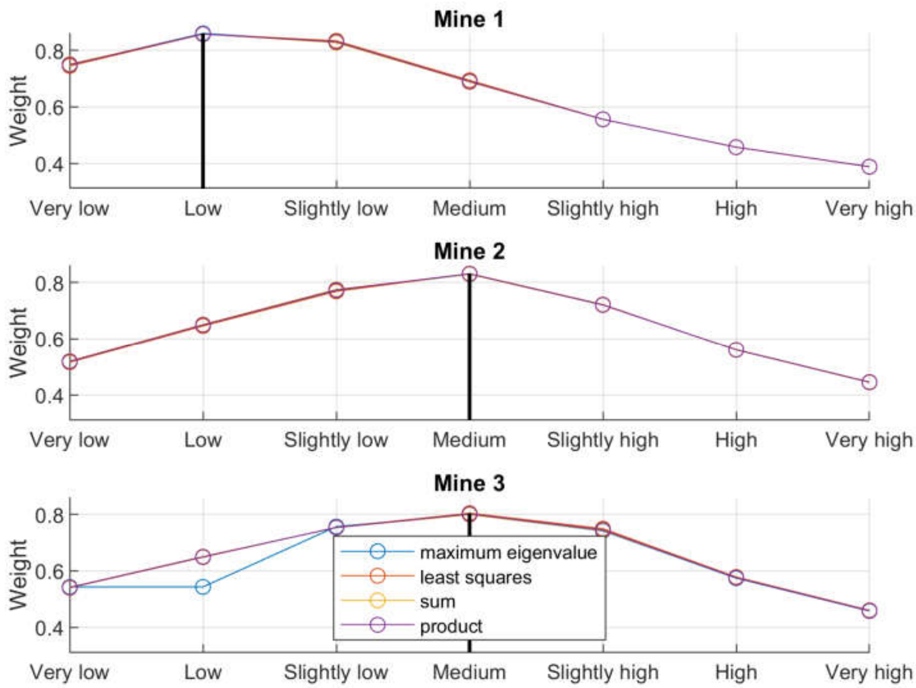

Figure 3. Fuzzy-grey correlation based on the rational attitude.

By using the fuzzy-grey correlation method, the results of the expert group were as follows: the risk level of Mine 1 was lower, and the risk levels of Mine 2 and Mine 3 were medium. The simulation results showed that the proposed model was more sensitive to security risks.

4.3. Fuzzy TOPSIS Risk Rating Based on Relaxed Comprehensive Weight

According to the results of the simulation in Table 7, the proposed model was applied under the four kinds of comprehensive weights of the relaxed scoring attitude. The result (represented in Figure 4) showed that the comprehensive risk level of Mine 1 was extremely low, and the comprehensive risk levels of Mine 2 and Mine 3 were comparatively lower, for which each of mines was rated extremely low.

By using the fuzzy-grey correlation method analyzed in this paper, the results of the expert group were as follows: the risk level of Mine 1 was lower, and the risk levels of Mine 2 and Mine 3 were slightly lower. From the simulation results, we can see that the proposed model was more sensitive to security risks.

Table 7. Fuzzy-grey correlation risk rating based on relaxed attitude.

Weight Categories	Evaluation Object	Correlation							Grey Related Rating	TOPSIS Rating [51]
		Very Low	Low	Slightly Low	Medium	Slightly High	High	Very High		
CW1	Mine 1	0.827	0.8625	0.7799	0.6386	0.5263	0.4411	0.3795	Lower	Very low
	Mine 2	0.6346	0.7479	0.7883	0.7856	0.6498	0.5158	0.4210	Slightly low	Low
	Mine 3	0.6392	0.7435	0.7628	0.7637	0.6855	0.5357	0.4358	Slightly low	Low
CW2	Mine 1	0.8202	0.8433	0.7695	0.6476	0.5374	0.4485	0.3843	Low	Very low
	Mine 2	0.6606	0.7677	0.7750	0.7605	0.6423	0.5195	0.4254	Slightly low	Very low
	Mine 3	0.6726	0.7739	0.7646	0.7436	0.6612	0.5233	0.4291	Low	Very low
CW3	Mine 1	0.8246	0.8511	0.7793	0.6439	0.5309	0.4443	0.3816	Low	Very low
	Mine 2	0.6568	0.7654	0.7814	0.7737	0.6362	0.5088	0.4174	Slightly low	Low
	Mine 3	0.6662	0.7673	0.7626	0.7520	0.6704	0.5250	0.4293	Low	Low
CW4	Mine 1	0.8243	0.8511	0.7794	0.6438	0.5317	0.4447	0.3819	Low	Very low
	Mine 2	0.6569	0.7652	0.7804	0.7721	0.6379	0.5106	0.4187	Slightly low	Low
	Mine 3	0.6666	0.7677	0.7628	0.7512	0.6694	0.5254	0.4296	Low	Low

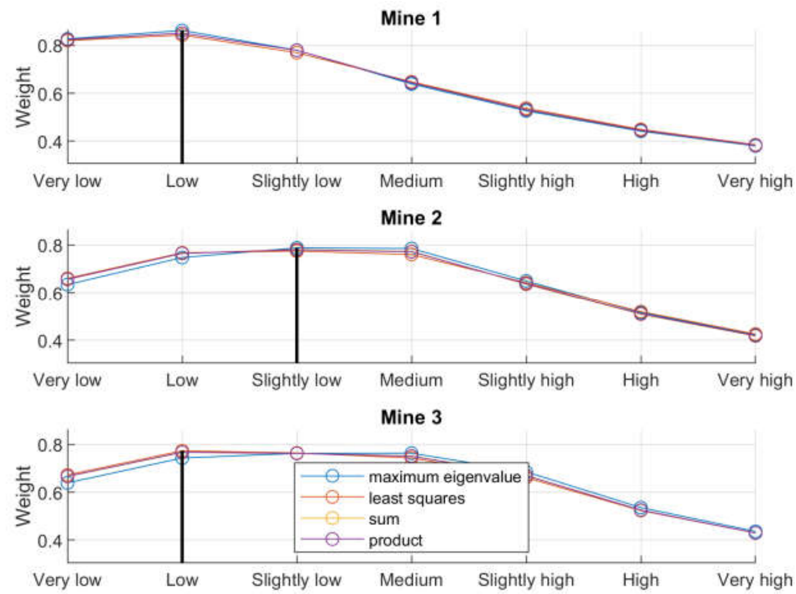

Figure 4. Fuzzy-grey correlation based on the relaxed attitude.

5. Discussion

The model proposed in this paper demonstrated three advantages following from the results of the three sets of comparative experiments.

1 The proposed model was more sensitive to risk because the overall risk rating was generally one level higher.
2 The proposed model had little change in rating results under different scoring attitudes, so different scoring attitudes had less influence on the fuzzy-grey correlation model.
3 The proposed model did not distinguish the judgment of some adjacent ranks, because there was no strict limit to the risk assessment.

In addition, the inconsistency between the indexes, such as some indexes having higher risk levels and some indexes having lower risk levels, and the results of the comprehensive analysis may have had a small degree of discrimination. Based on the analysis of the correlation value in the table, the degree of correlation between some of the adjacent level difference was very small; such as the relaxed attitude Comprehensive Weight 3 had a lower level of correlation degree of 0.7814 and a medium level of correlation degree of 0.7737.

The approach presented in this paper had similarities to other risk assessment methods based on fuzzy logic such as presented in [57–59]. However, the latter methods required a much larger number of fuzzy rules to be constructed and evaluated as compared to the method presented in this paper.

6. Conclusions

In this paper, a mine safety risk ranking and grading evaluation model that was based on the fuzzy-grey correlation method was proposed. We compared this model with the fuzzy TOPSIS risk assessment model based on the cautious, rational, and relaxed scoring attitudes. Through actual analysis, we found that the proposed model was more sensitive to risk than the fuzzy TOPSIS risk assessment model in three different situations. Our results demonstrated that the risk analysis model proposed in this paper could be successfully applied to the evaluation of mine safety. The proposed model had little change in rating results under the three different scoring attitudes, so different scoring attitudes had less impact on the results of the proposed model.

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