Research Article

Risk Assessment of the Rockburst Intensity in a Hydraulic Tunnel
Using an Intuitionistic Fuzzy Sets-TOPSIS Model

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1. Introduction

Rockbursts are a complex and dynamic geological hazard phenomenon [1]. Its occurrence has brought great harm to construction safety; in particular, different rockburst has frequently occurred during the construction of hydraulic stations and tunnels in recent years [2]. For example, during the construction of diversion tunnels in the Taipingyi hydropower station in China, different types of rockbursts occurred approximately 120 times, much equipment was damaged, and the loss of life was significant. Especially the worst rockburst accident in the Qianfu coal mine in Henan Province, China, resulted in the death of 8 workers, 20 days’ loss of construction periods [3], and 75 workers were buried in the mine shaft [4]. Therefore, the prediction and analysis of the rockburst phenomenon are helpful to the rational design and construction of engineering. The prediction and assessment of rockburst intensity have currently become an important issue [5].

The intensity of rockburst is defined as the fractured degree of rockburst [6]. Due to the randomness and complexity of rockburst occurrence, a complex nonlinear relationship exists among the different influential factors. They resulted in the applicable limitation of classical mechanics on predicting the rockburst phenomenon. Therefore, investigations on the assessment and prediction of rockburst intensity have been performed by many researchers [7]. The current method to assess the rockburst intensity is mainly divided into the following three types [8]:

(i) Theoretical methods include the Russians criterion [9], Turchaninov criterion [10], Barton criterion [11], and Hoek criterion. For example, the theory of intelligent rock mechanics is suggested by Feng [12] based on the artificial intelligence methods combined with the rock mechanics to systematically investigate the rockburst phenomenons.
(ii) Field surveys include the electromagnetic radiation method, theological method, rebound method, and resistance method [13].

(iii) Applied mathematical methods [14] include the artificial neural network [15], ambiguity and mathematical evaluation [16], gray relational theory [17], cloud model [18], and catastrophe relational theory method. For example, the optimal support vector machine is provided by Zhou et al. [9] to prove the higher accuracy of SVM on the prediction of rockburst intensity.

These methods have been applied to determine the rockburst intensity successfully. But shortcomings remain, e.g., their assessment process is very complex, the loss of information is great, and the uncertainty and fuzziness of occurrence of the rockburst intensity are not considered in these methods.

To overcome the above-given shortcomings, the intuitionistic fuzzy sets-TOPSIS model is applied to assess the rockburst intensity in the paper. Relatively to the traditional fuzzy mathematical method, the nonmembership function is added in the intuitionistic fuzzy sets [9], so the vague concept can be expressed definitively. And, it is characterized as the sufficient usage of original datum, minor information loss, and wide application [19], so it is an efficient multiple attribute decision-making method [2, 20]; a new model is constructed when the intuitionistic fuzzy sets theory is combined with the TOPSIS model. The study of [2] estimates the risk level of landslide hazards in Shiwangmiao using the intuitionistic fuzzy sets-TOPSIS model, the good results are obtained. However, the exponential type of membership degree function is adopted in the proposed model in the paper, and the hesitate degree is considered, so the new model has higher efficiency in comparison with the fuzzy sets theory and Gu et al. [2]. And the proposed model is applied to evaluate the risk level of rockburst intensity for the first time.

The paper is organized as follows: In Section 1, the engineering overview in the study area is introduced first. In Section 2, a new risk assessment method of rockburst intensity is presented based on the Intuitionistic Fuzzy Sets-TOPSIS model. In Section 3, the Intuitionistic Fuzzy Sets-TOPSIS model is established for the rockburst intensity in Jiangbian hydropower, and the assessment results of the proposed model are discussed. In Section 4, the establishment of a level assessment model of the rockburst intensity in hydraulic tunnels is described. Section 5 describes the discussions and comparative analysis. In Section 6, conclusions are drawn.

2. Engineering Overview

The Jiangbian hydropower station is located in the southeastern direction of Garze Tibetan Autonomous Prefecture, Sichuan Province, China. It is the fifth stage power station in the downstream river section of the mainstream of the Kowloon River, and it is the last level hydraulic power station in the river section. The dam diversion scheme is adopted in the power station. The building sections are composed of the underground power plant, water diversion systems, and head hub [4], and the head hub is composed of the water inlet of the hydropower station, barrage, and brake. Its installed capacity is 330 MW, and its total storage capacity is $133 \times 10^4 m^3$. It belongs to a large-scale second-class hydropower project, and its specific location is plotted in Figure 1.

The diversion tunnel goes through the mountain ridge downstream of the rock mass in the Bailong temple, and it is located on the left side of the Jiulong River. Its length is approximately 8.6 km, the excavation path is about 8.4 m, and the burial depth is 300–600 m. The length of depth $\geq 300$ m in the hydraulic tunnel is around 4824 m, which accounts for 54% of the total length. It belongs to a deep tunnel; the probability of rockburst occurrence is excellent in the deepest tunnels. When the burial depth of the hydraulic tunnel is beyond 550 m, its depth arrives at the middle depth of the rockburst zones, rockbursts frequently occur, and the excavation progress is greatly affected. The probability of intense rockbursts in local tunnels under high in situ stress conditions is also significant. The locations of hydraulic tunnels are plotted in Figure 2.

3. Methodology

3.1. Determination of the Assessment Index about the Rockburst

Many factors influence the occurrences of rockbursts, so the construction of scientific and practical index systems is essential to correctly assess the level of rockburst intensity. According to the requirements for systematicness, scientificness, and representativeness, and the relevant documents [21], the lithological conditions, stress conditions, and surrounding rock conditions are considered.

3.1.1. Correlated Index considering the Lithological Conditions

(1) Elastic Strain Energy Index $W_{et}$. Based on the viewpoint of energy, the occurrences of rockbursts are determined by the stress magnitudes of the rock mass and the storage and release of energy in the rock mass. The gathering ability of elastic strain energy can be determined quantitatively using the elastic strain energy index. Its magnitude is obtained by the uniaxial compressive experiment of the rock mass. When the magnitudes of loading arrive at 70–80% of the peak intensity, loading is canceled and its stress and strain curve is plotted in Figure 3.

(2) Uniaxial Compressive Strength $\sigma_c$. Because rockburst often occurs in high-strength elastic-brittle rock masses, the effects of external loading can be effectively transformed into elastic energy and stored in the rock mass. When the energy storage conditions are good in the rock mass, the probability of rockburst occurrence is excellent, so the uniaxial compressive strength $\sigma_c$ of rock is used to represent the hardness degree of the rock mass.

3.1.2. Correlated Index considering the Stress Conditions

(1) Strength Stress Ratio $\sigma_c/\sigma_t$. The sources of energy in the rock mass also depend on the magnitudes of the initial stress. Especially for areas with inequalities in three-dimensional stress or high stress, the occurrence probability of
rockburst is more significant. So the ratio of the uniaxial compressive strength and maximum principal stress in the stress field is applied to determine the conditions of rockburst occurrence.

(2) Ratio of Shear Stress and Uniaxial Compressive Strength $\sigma_\theta/\sigma_c$. The shear stress in the tunnel and the uniaxial compressive strength of rocks are often applied together to describe a rockburst in the experiment. The ratio of the
maximum shear stress and uniaxial compressive strength of rocks is considered the basis of rockburst occurrence.

3.1.3. Correlated Index considering the Surrounding Rock Conditions. The occurrence of rockbursts is determined by the degree of integrity of the rock mass, and the rockburst phenomenon often occurs in fresh and intact rock masses because there are few cracks in hard intact rock masses. However, rockbursts cannot occur near the rupture zone of faults or in the development site of joints. The integrity of the rock mass is defined as the distance between adjacent cracks in the rock mass, and the cracks do not go through from macroscopic observations. According to the energy’s viewpoint, the rock mass’s integrity index can be represented by the integrity coefficients $K_v$ of the rock mass, which are calculated using the velocity of the longitudinal wave in the rock mass.

According to the above-mentioned discussions, the elastic strain energy index of rocks ($W_{et}$), uniaxial compressive strength ($\sigma_c$), strength stress ratio $\sigma_c/\sigma_1$, the ratio of shear stress and uniaxial compressive strength $\sigma_\theta/\sigma_c$, and integrity coefficients of the rock mass ($K_v$) are selected as the level assessment indices of the rockburst intensity in this paper. All of these indices are qualitative indices. The five-level assessment indices are divided into four types of rockburst intensity: strong rockburst tendency (I), medium rockburst tendency (II), weak rockburst tendency (III), and no rockburst tendency (IV). Their classification standards are shown in Table 1.

3.2. Construction of the Model Frame. The level assessment of rockburst intensity in hydraulic tunnels has essential significance for predicting the occurrence of rockbursts and the determination of the supporting mode.

A new model is provided based on the combination of intuitionistic fuzzy sets and the TOPSIS model to assess the level of rockburst intensity. Its calculation model is plotted in Figure 4.

In Figure 4, the assessment indices are firstly determined for the rockburst intensity. Then, the original data from the study area are conducted. For example, their parameters of membership degree function and nonmembership degree function are solved, and the decisive matrix about the original data is calculated. And, the weight coefficients based on the entropy method are determined. Secondly, the weighted decisive matrix is obtained. Finally, ranking sequences of the degree of membership are determined. The levels of rockburst intensity are judged according to the maximum degree of membership criterion, and the conclusions are drawn.

3.3. Entropy Weight Theory

(1) Normalization of different indices, they are shown as follows:

\[
\begin{align*}
    r_{ij} &= \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}} \\
    r_{ij} &= \frac{x_{i\max} - x_{ij}}{x_{i\max} - x_{i\min}} \\
\end{align*}
\]

where $x_{ij}$ is the corresponding magnitude of the $j$th assessment index in the $i$th scheme ($i = 1, 2, 3, ..., m$; $j = 1, 2, 3, ..., n$)

(2) The determination of index weights

Based on the normalized index matrix, the index weights can be calculated as follows:

\[
\omega_j = \frac{1 - s_j}{n - \sum_{j=1}^{n} s_j}
\]

where

\[
\begin{align*}
    s_j &= -k \sum_{i=1}^{n} b_{ij} \ln(b_{ij}) \\
    b_{ij} &= \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}
\end{align*}
\]

3.4. Establishment of a Decisive Matrix for Intuitionistic Fuzzy Sets. The intuitionistic fuzzy sets model originated from the
fuzzy sets theory. It is provided by Atanassov [22] first. In the suggested model, two scales [23, 24] are applied to define the fuzziness (membership degree and nonmembership degree), and three states (support, opposition, and neutrality) can be described.

$x$ is assumed as a nonempty set, and $X$ is a given domain, an intuitionistic fuzzy set in $X$ can be expressed as follows [2]:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle | x \in X \},$$

(4)

where $\mu_A$ and $\nu_A$ represent, respectively, the membership degree and nonmembership degree of the element $x \in A$ in $X$, and the conditions can be confirmed: $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \leq 1, \ x \in X$, where $\pi_A(x)$ is called as the degree of hesitation of $x \in A$.

To establish the intuitionistic fuzzy matrix, the corresponding parameters can be expressed as follows [25, 26]:

$$\mu_{nk} = \exp \left[ -\frac{(x_n - c_{nk})^2}{2\sigma_{nk}^2} \right],$$

(5)

$$\nu_{nk} = 1 - \exp \left[ -\frac{(x_n - c_{nk})^2}{2\sigma_{nk}^2} \right].$$

(6)

where $c_{nk}, c_{nk}, \sigma_{nk},$ and $\sigma_{nk}$ are corresponding parameters; $\alpha$ is the hesitating degree, its magnitude is 0.2 in the paper.

According to the fuzzy number $A_{nk} = \langle \mu_{nk}, \nu_{nk} \rangle$, the decisive matrix can be obtained as follows [27, 28]:

$$F_p = \begin{bmatrix}
(\mu_{11}, \nu_{11}) & (\mu_{12}, \nu_{12}) & \cdots & (\mu_{1K}, \nu_{1K}) \\
(\mu_{21}, \nu_{21}) & (\mu_{22}, \nu_{22}) & \cdots & (\mu_{2K}, \nu_{2K}) \\
\vdots & \vdots & \ddots & \vdots \\
(\mu_{N1}, \nu_{N1}) & (\mu_{N2}, \nu_{N2}) & \cdots & (\mu_{NK}, \nu_{NK})
\end{bmatrix}.$$

(10)

3.5. The Procedure of Suggested Model. Its specific procedure is listed as follows:
(1) The assessment index of rockburst intensity is determined firstly, then the classification criterion of rockburst intensity is constructed.

(2) Determining the weight coefficients of different indices

The weight coefficients of membership degree are $\alpha = (\alpha_1, \alpha_2, ..., \alpha_n)$, ones of nonmembership degree are $\beta = (\beta_1, \beta_2, ..., \beta_n)$, then weight coefficients of assessment index can be expressed as follows [2]:

$$\omega_n = \langle x_n, y_n \rangle = \langle \min(\alpha_n, \beta_n), 1 - \max(\alpha_n, \beta_n) \rangle,$$

(11)

where $\omega_n$ is the weight coefficients of assessment indices, $x_n, y_n$ denotes the important and non-important degree, it should meet with $0 \leq x_n + y_n \leq 1$.

(3) According to equations (10) and (11), the weighted decisive matrix can be determined as follows:

$$F_p = \omega_n F = \langle x_n \mu_{nk}, y_n + v_n - y_n, y_n \rangle_{nk},$$

(12)

(4) Determining plus and negative ideal solution

They can be obtained as follows:

$$B^+ = [\langle \mu_1^+, v_1^+ \rangle, \langle \mu_2^+, v_2^+ \rangle, ..., \langle \mu_n^+, v_n^+ \rangle],$$

$$B^- = [\langle \mu_1^-, v_1^- \rangle, \langle \mu_2^-, v_2^- \rangle, ..., \langle \mu_n^-, v_n^- \rangle],$$

(13)

where $\mu_n^+ = \max\{\mu_{nk}\}$, $v_n^+ = \max\{v_{nk}\}$, $\mu_n^- = \min\{\mu_{nk}\}$, and $v_n^- = \max\{v_{nk}\}$, $n = 1, 2, ..., n$.

(5) Determining Euclidean distance

The Euclidean distance is calculated as follows [2]:

$$D(s_k, B^+) = \frac{1}{2} \sum_{n=1}^{N} \left[ (\mu_{nk} - \mu_n^+)^2 + (v_{nk} - v_n^+)^2 + (\mu_n^+ + v_n^+ - \mu_{nk} - v_{nk})^2 \right].$$

(14)

$$D(s_k, B^-) = \frac{1}{2} \sum_{n=1}^{N} \left[ (\mu_{nk} - \mu_n^-)^2 + (v_{nk} - v_n^-)^2 + (\mu_n^- + v_n^- - \mu_{nk} - v_{nk})^2 \right],$$

(15)

$$\eta_k = \frac{D^2(s_k, B^+)}{D^2(s_k, B^+) + D^2(s_k, B^-)},$$

(16)

where $D(s_k, B^+)$ and $D(s_k, B^-)$ are the expression of Euclidean distance; $\eta_k$ is the degree of membership.

(6) Determining the risk level of rockburst intensity

When the membership degrees are determined, the maximum membership degree is regarded as the assessment level of rockburst intensity.

4. Establishment of a Level Assessment Model of the Rockburst Intensity in Hydraulic Tunnels

Three tunnel sections in the Jiangbian power station are selected as the samples to verify the feasibility of level assessment of the rockburst intensity. Tunnel section #1 is selected in the upstream area of the diversion tunnel. Its burial depth is approximately 1000 m, the compressive strength of rocks in the tunnel section is high, the magnitudes of stress are significant, and the structural plane of surrounding rock is well developed. The medium and medium to weak rockburst intensities often occur during construction. Some rockburst phenomena remain in certain tunnel sections after the tunnel excavation, and the support mesh is blown up. The sabotaging scene is plotted in Figure 5.

Tunnel sections #2 and #3 are selected downstream of the diversion tunnel, and the burial depth in these tunnel sections is approximately 1200 m. The stress is very high, so the integrity is bad. Many drop blocks originating from the cutting of the construction face are found in the vaults of the structural plane, and the intensity of rockburst belongs to no rockburst and weak rockburst. The original data from three rockburst samples is shown in Table 2.

Based on Table 1, according to equations (5)–(9), for tunnel section #1, the parameters of the membership and nonmembership functions can be calculated and are shown in Table 3.

The membership function and nonmembership function are plotted in Figures 6 and 7, respectively.

Tunnel section #1 is selected as an example to assess the rockburst intensity. Based on (4) and (10), combined with Figures 6 and 7, the decisive matrix $F$ about tunnel section #1 can be shown as follows:
Figure 5: Rockburst site after shotcrete support.

Table 2: Original data in three tunnel sections at the Jiangbian hydropower station.

| Serial number | $\sigma_c$ | $\sigma_c/\sigma_t$ | $\sigma_d/\sigma_c$ | $W_{ct}$ | $K_v$ |
|---------------|------------|---------------------|---------------------|----------|-------|
| 1#            | 137.22     | 4.40                | 0.59                | 3.46     | 0.68  |
| 2#            | 140.21     | 5.33                | 0.43                | 3.14     | 0.60  |
| 3#            | 130.21     | 21.11               | 0.30                | 4.21     | 0.52  |

Table 3: Parameters of the membership and non-membership function.

| Index          | I                | II               | III              | IV               |
|----------------|------------------|------------------|------------------|------------------|
| $\sigma_c$     | $\mu_1 = \sigma_1 = 210$ | $\mu_2 = \sigma_2 = 150$ | $\mu_3 = \sigma_3 = 100$ | $\mu_4 = \sigma_4 = 40$ |
| $\sigma_t$     | $\sigma_1 = 491.11$ | $\sigma_2 = 491.11$ | $\sigma_3 = 218.27$ | $\sigma_4 = 873.05$ |
| $\sigma_d$     | $\sigma_1 = 880.93$ | $\sigma_2 = 880.93$ | $\sigma_3 = 391.52$ | $\sigma_4 = 1566.1$ |
| $\sigma_c/\sigma_t$ | $\mu_1 = \sigma_1 = 1.25$ | $\mu_2 = \sigma_2 = 4$ | $\mu_3 = \sigma_3 = 10$ | $\mu_4 = \sigma_4 = 19$ |
| $\sigma_d/\sigma_c$ | $\sigma_1 = 0.8526$ | $\sigma_2 = 1.228$ | $\sigma_3 = 11.05$ | $\sigma_4 = 11.05$ |
| $W_{ct}$       | $\sigma_1 = 1.5294$ | $\sigma_2 = 2.2$ | $\sigma_3 = 19.82$ | $\sigma_4 = 19.82$ |
| $K_v$          | $\sigma_1 = 0.675$ | $\sigma_2 = 0.425$ | $\sigma_3 = 0.1$ | $\sigma_4 = 0.0098$ |
|                | $\sigma_1 = 0.0085$ | $\sigma_2 = 0.0085$ | $\sigma_3 = 0.0014$ | $\sigma_4 = 0.0005$ |
|                | $\sigma_1 = 0.0153$ | $\sigma_2 = 0.0153$ | $\sigma_3 = 0.0024$ | $\sigma_4 = 0.0004$ |
| $W_{ct}$       | $\sigma_1 = 3.41$ | $\sigma_2 = 3.41$ | $\sigma_3 = 1.23$ | $\sigma_4 = 0.5457$ |
|                | $\sigma_1 = 6.12$ | $\sigma_2 = 6.12$ | $\sigma_3 = 2.20$ | $\sigma_4 = 0.9788$ |
| $K_v$          | $\sigma_1 = 0.8$ | $\sigma_2 = 0.7$ | $\sigma_3 = 0.6$ | $\sigma_4 = 0.275$ |
|                | $\sigma_1 = 0.0014$ | $\sigma_2 = 0.0014$ | $\sigma_3 = 0.0014$ | $\sigma_4 = 0.0413$ |
|                | $\sigma_1 = 0.0024$ | $\sigma_2 = 0.0024$ | $\sigma_3 = 0.0024$ | $\sigma_4 = 0.074$ |
The uniaxial compressive strength $\sigma_c$

strong rock burst tendency (I)
medium rock burst tendency (II)
weak rock burst tendency (III)
no rock burst tendency (IV)

Figure 6: Continued.
According to equation (11), the weight coefficients can be calculated based on the following intuitionistic fuzzy numbers:

\[
\omega = \begin{bmatrix}
(0.1743, 0.7528) & (0.1878, 0.7537) & (0.1212, 0.819) & (0.2343, 0.7216) & (0.1498, 0.8203)
\end{bmatrix}.
\]
The uniaxial compressive strengthen $\sigma_c$

- strong rock burst tendency (I)
- medium rock burst tendency (II)
- weak rock burst tendency (III)
- no rock burst tendency (IV)

(b) strength stress ratio $\sigma_c/\sigma_1$

- strong rock burst tendency (I)
- medium rock burst tendency (II)
- weak rock burst tendency (III)
- no rock burst tendency (IV)

(c) the ratio of shear stress and uniaxial compressive strength $\sigma_\theta/\sigma_c$

- strong rock burst tendency (I)
- medium rock burst tendency (II)
- weak rock burst tendency (III)
- no rock burst tendency (IV)

Figure 7: Continued.
Substituting matrix $F$ and $\overline{F}$ into $\omega$, the weighted intuitionistic fuzzy sets can be obtained as follows:

$$\overline{F}_P = \omega F = \begin{bmatrix}
(0.0008, 0.9878) & (0.1476, 0.7755) & (0.0073, 0.957) & (0.0008, 0.9879) \\
(0.0006, 0.9904) & (0.1759, 0.7625) & (0.0454, 0.8884) & (0.0098, 0.9989) \\
(0.0792, 0.8507) & (0.0244, 0.9256) & (0.1) & (0) \\
(0.9996) & (0.0214, 0.9266) & (0.2341, 0.7217) & (0.0009, 0.9874) \\
(0.0009, 0.9911) & (0.1299, 0.8347) & (0.0152, 0.9526) & (0.0206, 0.9407)
\end{bmatrix}.$$  

According to equation (13), the minus and plus ideal solutions in tunnel section #1 are calculated as follows:
the GRNN model and the improved SVM method [29]. But suggested model, and its accuracy is identical to the results from different sample sections. Its accuracy is 100% in the sug-

Table 4: Intensity assessment of rockburst and comparison.

| Sample number | The assessment level | The text method | Actual investigation | GRNN   | Improved SVM |
|---------------|----------------------|-----------------|---------------------|--------|--------------|
|               | I        | II      | III     | IV      | I        | II      | III     | III      | I        | II      | III     | III      | I        | II      | III     | III      |
| 1#            | 0.2191  | 0.607  | 0.2823  | 0.2573  | II      | II      | II      | II      | 100%    | 100%    | 100%    | 100%    |
| 2#            | 0.2722  | 0.4036 | 0.4145  | 0.2366  | III     | III     | III     | III     | 100%    | 100%    | 100%    | 100%    |
| 3#            | 0.2602  | 0.284  | 0.2768  | 0.3032  | IV      | IV      | IV      | IV      | 100%    | 100%    | 100%    | 100%    |

Based on equations (14)–(16), the Euclidean distance of different levels can be calculated as follows:

\[ D(t_1; \eta_1=0.607, B^+) = 0.2458, \]

\[ D(t_1, B^-) = 0.1304, \]

\[ \eta_1 = 0.2191, \]

\[ D(t_2, B^+) = 0.2343, \]

\[ \eta_2 = 0.2912, \]

\[ D(t_3, B^+) = 0.607, \]

\[ D(t_4, B^+) = 0.4507, \]

\[ \eta_3 = 0.2827, \]

\[ D(t_5, B^-) = 0.093, \]

\[ \eta_4 = 0.0548, \]

\[ \eta_5 = 0.2575. \]

It can be found that \( \eta_3 > \eta_2 > \eta_4 > \eta_1. \) According to the maximum distance criterion, the assessment level of tunnel section #1 is II. This level demonstrates that tunnel section #1 has a medium rockburst tendency, which is consistent with that of the actual investigation [29].

Similar to tunnel section #1, the Euclidean distance that corresponds to the assessment level of tunnel sections #2 and #3 are shown in Table 4.

Table 4 shows that each sample can be generally divided into four levels. The final intensity level of tunnel section #1 is II. One of tunnel section #2 is III, and one of tunnel section #3 is IV. These results demonstrate that the surrounding rocks of tunnel section #1 have a medium rockburst tendency. So for the surrounding rocks of tunnel section #1, the corresponding measures should be adopted to prevent rockburst from occurring. The surrounding rocks of tunnel section #2 have a medium rockburst tendency, but the correlated safety sense should be established. The surrounding rocks of tunnel section #3 have no rockburst tendency. So conclusions are drawn that they are relatively safe, and the assessment results provide the basis to prevent rockburst occurrence in hydraulic tunnels in the future.

The comparative analysis in Table 4 shows that the outcomes obtained by four models are entirely consistent in different sample sections. Its accuracy is 100% in the suggested model, and its accuracy is identical to the results from the GRNN model and the improved SVM method [29]. But in comparison with the other two methods, the proposed model can convey inherent uncertainty. Large amounts of data need not be provided, its information loss is less, and high-dimensional calculation can be avoided. So the complexity of model construction and computation time are more minor. Finally, it is concluded that to assess the level of rockburst intensity using the suggested model is feasible. Its calculation process is convenient and straightforward. So the technique has excellent application prospects.

Table 4 also shows that the model achieves accurate results more details about the assessment levels of rockburst intensity can be obtained. For example, the strength stress ratio \( \sigma_1/\sigma_3 \) of tunnel section #2 is 5.33, which should belong to level II, according to Table 1. Besides, the degree of membership of the other indices falls into level III, and the intensity level probability of tunnel section #2 at level II is more significant than those of levels I, IV, and III. Therefore, it only falls into level II and almost impossibly to levels I, IV, and III. Furthermore, tunnel section #1 is more likely level II than tunnels #2 and #3 because the maximum degree of membership of tunnel section #1 for level II (0.607) is higher than those of tunnels #2 (0.607) and #3 (0.284). The results based on the suggested method accurately mirror the intensity level of rockburst and tell the intensity ranking of rockburst at the same level.

5. Discussions and Comparative Analysis

5.1. Comparison with Existing Techniques

(1) GRNN method presented a technique for the risk estimation of rockburst intensity. Many factors of rockburst intensity and interaction of different indexes are considered in the GRNN model; however, uncertainty and fuzziness of risk level about the rockburst intensity are omitted, so the GRNN model requires a vast data and many investigations, and the workload is tremendous. While our proposed model overcomes these drawbacks of the GRNN model, relatively to the GRNN model, the proposed model in the paper not only deals with fuzzy information but also eases our workload. The proposed method improves the efficiency enormously.

(2) Improved SVM model has also been applied to assess the risk level of rockburst intensity. But it can not precisely express which indices require more to be supported; the proposed model can solve the issue.
The maximum membership degree that is closest to the positive ideal solution and most far from the negative ideal solution is regarded as the most appropriate basis of risk level in the rockburst intensity to cover the level ranges.

5.2. Advantages of the Proposed Model. By comparing this approach with conventional MCDM techniques, the advantages of the suggested model can be summarized as follows:

(1) Their judgments under inherent uncertainty in the proposed model can be conveyed. More significantly, the degree of indeterminacy can be handled adequately in the evaluation.

(2) Compared with the traditional assessment method, the proposed model has sufficient usage of original datum, minor information loss, and broader application. And, it can precisely determine which indexes require more to be supported.

(3) Relatively to other assessment methods, the proposed method not only can deal with vague information but also ease our workload, and the efficiency and accuracy can be improved.

6. Conclusions and Future Directions

Taking into consideration that the lithological conditions, stress conditions, and surrounding rock conditions, a new assessment method is introduced to evaluate the level of rockburst intensity in hydraulic tunnels in Jiangbian power stations. First, the decisive matrix of the rockburst intensity is constructed. Then, the weighting coefficients of different stations. First, the decisive matrix of the rockburst intensity is constructed. Then, the weighting coefficients of different stations. First, the decisive matrix of the rockburst intensity is constructed. Then, the weighting coefficients of different stations. First, the decisive matrix of the rockburst intensity is constructed. Then, the weighting coefficients of different stations. First, the decisive matrix of the rockburst intensity is constructed. Then, the weighting coefficients of different stations.

Finally, the level of rockburst intensity is judged. The proposed method is applied to assess the intensity of rockbursts in surrounding rocks in hydraulic tunnels. Its results are compared with ones of actual investigation, the GRNN model, and the improved SVM method. The outcomes obtained by four models are entirely identical; the predicting accuracy is 100%. The final intensity levels of tunnel sections #1, #2, and #3 are II, III, and IV. The tunnel section #1 has the highest level ranking of rockburst intensity, so tunnel section #1 should be considered to emphasise on prevention. Overall, the results obtained from the proposed model are highly consistent with one of the current specifications. It accurately mirrors the intensity level of rockburst and determines the intensity ranking of rockburst for different sample sections at the same level, and the proposed method can provide a new thought for the intensity assessment of rockburst in the future.

Although the Intuitionistic Fuzzy Sets-TOPSIS model improves the development of assessment theory, the model still has certain limitations. For example, the determining of certain assessment indices and weight coefficients has a specific subjectivity. Due to the comprehensiveness of influencing indexes, the assessment method strongly depends on actual data. In future work, the concept of spherical fuzzy sets can be applied [30, 31]. It is the development of intuitionistic fuzzy sets theory and provides a larger preference volume in 3D space for decision-makers, the spherical fuzzy method is used in solving a multiple criteria selection problem, its range varies from standard fuzzy sets to spherical fuzzy sets, the space is extended from 2D to 3D, this can overcome the shortcoming of intuitionistic fuzzy sets, and spherical fuzzy method will be my future direction to assess the rockburst level.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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