An Integrated Decision Support System for Low-Disturbance Surface Mining

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Abstract: Low-disturbance mining in surface mining (LDM) can transform traditional surface mine production systems into a more sustainable model by reducing the disturbance of surface mining, minimizing pollutant emissions, and reducing ecological impacts. The purpose of this paper is to explore the LDM evaluation method by applying multi-criteria decision-making to provide technical support for LDM implementation. Therefore, an evaluation method based on the combination of the fuzzy analytical hierarchy process (F-AHP) and grey clustering was proposed. Analyzed in terms of the current status of the evaluation indicators (reality) and the significance of the development of the LDM (desirability). Determined the weights and low-disturbance (LD) levels of the evaluation indicators. Combined with the fuzzy technique for order preference by similarity to an ideal solution (F-TOPSIS), the low-disturbance open pit mining paths are ranked, and finally, the decision support system for low-disturbance mining in surface mining is constructed. This study not only enriches the existing literature on related technologies but also lays the foundation for further research on LDM and provides exploratory insights for deeper improvement of LD level in surface mining.

Keywords: multiple criteria decision-making (MCDM); low-disturbance mining in surface mining; fuzzy analytical hierarchy process; grey cluster analysis; fuzzy-TOPSIS

1. Introduction

Open pit mining is the main mining method in Australia, the United States, Germany, India, and other large mining countries. The development of the ecological concept of open pit mining abroad is mainly divided into three stages. The first stage originated in the 19th century in the United States, Germany, and other developed countries. The stage of green mining is limited to the greening of the mining area, mainly reflected in the development of mineral resources in the process of protecting the local environment around the pit. The second stage is after the Second World War. The stage of green mining, from the greening of the mining area to expanding to the optimal consumption of non-renewable natural resources and minimizing the impact on the environment of resource development efficiency, the western open-pit mining process takes into account the environmental protection and resource efficiency and safe mining. The third stage is to enter the 21st century. Open-pit development and pollution control, land greening, energy saving and emission reduction and other environmental protection concepts integration, dust management, energy saving and emission reduction, low-carbon mining and ecological restoration and other aspects of comprehensive research, a series of results, the formation of the relevant technical specifications and regulations.

Mining has a variety of far-reaching social, environmental, and climate impacts [1–3]. China’s accelerated industrialization has resulted in huge economic development and energy demand, with nearly 70% of the country’s energy production based on coal [4,5]. China’s open-pit coal production exceeds 1 billion tons for the first time in 2022, while open-pit coal production accounts for 23% of the country’s coal output [6]. The essence
of open-pit mining is the large-scale spatial transport of useful minerals with temporarily useless strippings. The mining process changes the topography and geomorphology of the mining area change and even affects the ecological environment around the mining area, such as the excavation and suppression of land, dust and noise, water pollutants, and air pollutant emissions [7,8]. Although relevant scholars have given specific solutions to the key technical decision-making problems of open-pit mining, the current stage of open-pit mining design is only targeted to give a rough directional planning. The open-pit mining process is not rule-based, and technical decision-making involves frequent adjustment changes, so often production succession difficulties, soil space can not be fully released, and utilization of the passive situation. Moreover, the current stage of open-pit mines is mainly a “passive mode of mining first and environmental management later” [9], which may cause serious ecological and environmental problems. At this stage, there are not many studies on disturbed mining in open pit mines; most of them focus on the technical aspects and are mainly based on mine land reclamation. Researchers develop various physical [10], chemical, and biological means [11] to restore these mining-disturbed lands to near-pristine conditions [12–15]. How to seek a balance between economic benefits and environmental protection in the process of resource extraction is an essential requirement for mines to realize green mining. To this end, relevant scholars have conducted a lot of cutting-edge basic theoretical research on the effect of open-pit mining on ecological environment disturbance, which is summarized as including the following two major theoretical systems:

(i) The Ecological Footprint Theory System [16]. The theoretical system is represented by the theory of quantitative evaluation of ecological cost and environmental pressure and takes the ecologically productive land area as a unified standard, which serves as a measure of how much of various resources need to be consumed and how much waste needs to be discharged in the production process of mining enterprises. By comparing it with the ecological carrying capacity of the mining area, the degree of sustainable development of the mining area is judged.

(ii) The theoretical system of disturbance index [17–19] for open pit mining was successively proposed and continuously developed by Chinese scholars. The theory is based on the mining disturbance effect evaluation theory and control technology and reveals the disturbance mechanism of open pit mining activities on the external elements of the mine by defining the open pit mining disturbance index. By studying the degree of disturbance, the trend of change of disturbance effect, and the compensation mechanism of disturbance, it guides open-pit mines to realize green and high-efficiency mining.

The above studies mainly focus on the quantitative expression of the evaluation indexes of low-disturbance mining in open pit mines, and no systematic theory has been formed on the relationship between the low-disturbance indexes of open pit mines and the optimization path. A well-developed metrics framework system can help mining companies implement LDM. Therefore, the ultimate goal of this paper is to propose a framework of indicators for low-disturbance mining decision-making systems to provide technical assistance for low-disturbance mining in open pit mines. The framework focuses on the five main processes in the production of an open pit mine, which are perforation, rock blasting, extraction and loading, ore transportation, and rock drainage. The proposed framework is therefore divided into four leading indicators, namely “Control of stripping works (CS)”, “Control of emission rock (CE)”, “Control of pollution emission (CP)”, and “Control of drainage (CD)”. There are 13 sub-indicators under the leading indicator. All indicators were assessed in terms of both the current state of the LDM indicators (reality) and the significance in the development of LDM (desirability). Unlike previous studies [17–19] that focused only on the weight and ranking of each indicator, we used a combined method of fuzzy hierarchical analysis and grey clustering. A method that first quantifies the indicators by determining their weights evaluates and analyzes each indicator and then constructs a hierarchical system of frameworks for the challenges that impede the development of disturbed open-pit mines. In response to the leading indicator challenges, their optimization paths were ranked separately, and finally, a decision support system for
low-disturbance mining in open pit mines was constructed to facilitate the transition of the traditional open pit mining industry to low-disturbance open pit mining development.

2. Methodology

The main purpose of constructing an indicator framework is to improve the understanding of specific issues by transforming data into structured information [3]. As shown in Figure 1, the LDM framework is constructed, which is gradually and progressively established in an orderly manner from top to bottom. Firstly, the indicators are determined, and then each indicator is evaluated and analyzed, followed by proposing the optimal decision and, finally, forming a decision support system for low-disturbance mining in open pit mines. Applying the proposed framework and methodology to a case study of open pit mines in China, 10 experts with relevant technical expertise were involved in the research process.

Figure 1. The methodological procedure.

2.1. The Framework

The framework works through a few key criteria (leading indicators) and a manageable number of sub-criteria (sub-indicators), thus enabling the analysis of complex situations [20,21]. Since indicators facilitate decision-making, an indicator-based framework is recognized as an effective tool for conveying information on issues to audiences in a concise and scientifically sound manner [22]. The framework presented in this paper helps to identify how LDM works in practice and to identify areas for focused intervention. This provides a basis for continuous improvement in strengthening the decision-making process in mining companies. The framework consists of three layers, namely, the objectives layer, the criteria layer, and the indicators layer. The goal level is the highest level of representation, i.e., the ultimate goal to be achieved. The goal level represents the top level, i.e., the ultimate goal to be achieved; the criteria level contains the targets that are subordinate to the goal level and serves as the basis for linking individual indicators to the framework; and the indicator level helps to summarize the data and provide meaningful information. Identifying and selecting metrics is not simple; it requires exploring the realities of the surface mining industry and obtaining key information related to LDM.

At the heart of LDM is the realization of low-disturbance production in open pit mines at the lowest possible environmental cost and low consumption, with reduced land
disturbance and rapid reclamation. Therefore, from the perspective of the open pit mining process, the decision analysis of LDM should focus on the following aspects, such as “Control of stripping works (CS)”, “Control of emission rock (CE)”, “Control of pollution emission (CP)” and “Control of drainage (CD)”. On this basis, a total of 13 sub-indicators were identified and categorized under 4 leading line indicators, as shown in Figure 2. Below is a description of the leading indicators.

![Figure 2. The indicator framework for LDM.](image)

2.1.1. Control of Stripping Works (CS)

Open pit mining and stripping engineering refers to the interrelationship between mining work and stripping work in open pit mining that develops in a coordinated manner in time and space. Stripping works in open pit mines inevitably lead to damage disturbance to the original land surface, which is characterized using “Extent of damage to extraction sites (CS1)”, “Stripping intensity (CS2)” and “Intensity of land degradation (CS3)”. The CS1 characterizes the extent of open pit mining damage, which consists mainly of the surface-disturbed realm as well as the pit floor-disturbed realm. The CS2 is primarily the intensity of mineral rock stripping that needs to be accomplished to extract a unit of coal from an open pit mine. The CS3 primarily refers to the biologically productive land that needs to be damaged to extract a unit of coal from an open pit mine. The challenges of the above damage indicators are all caused by the stripping project of the open pit mine, which is a disturbance of the stripping project, which is determined by the nature of the production of the open pit mine and is an inevitable cause of the disturbance.

2.1.2. Control of Emission Rock (CE)

Open pit mine rock disposal works are another important disturbance factor in open pit mining, which can be characterized by “Extent of damage to dumping (CE1)”, “Emission intensity of strippings (CE2)”, “Utilisation of inner dump (CE3)” and “Intensity of land occupation (CE4)”. The CE1 characterizes the utilization efficiency of the land suppressed by the outfall in the open pit mining process, describing how to efficiently utilize the outfall space and reduce the outfall suppression under the premise that the total amount of outfall is certain. The CE2 indicator mainly characterizes the extent of the impact of open pit mine stripping discharges on the surrounding land, atmosphere, ecology, and living environment. The CE3 indicator mainly characterizes whether the Inner dump space is timely and adequately utilized in the open pit mining process. The CE4 indicator primarily
characterizes the amount of biologically productive land that needs to be compacted to extract a unit of coal from an open pit mine. The challenges of the above damage indicators are all caused by the rock discharge project of the open pit mine, which is a disturbance of the rock discharge project, which is determined by the nature of the production of the open pit mine, and is an inevitable disturbance, which can not be eliminated, but can be minimized as much as possible through the relevant technology.

2.1.3. Control of Pollution Emission (CP)

Open pit mines are accompanied by pollution emission disturbances during production, which can be characterized by “Dust emission intensity (CP1)”, “Emission intensity of water pollutants (CP2)”, “Emission intensity of gaseous pollutants (CP3)” and “Noise pollution (CP4)”. The CP1 indicator primarily characterizes dust particles generated during the production of large quantities of coal and rock crushed in open pit mines. The CP2 indicator mainly characterizes that most of the pit water in open pits may contain heavy metal ions and many toxic substances, and if the pit water is discharged arbitrarily, it will cause serious surface water pollution. The CP3 mainly characterizes the large amount of greenhouse gases that are emitted as a result of the large consumption of energy involved in processes such as open pit mining and transportation. The CP4 is mainly characterized by noise pollution, such as the high noise intensity of coal mining equipment, a wide range of sound sources, and continuous noise.

2.1.4. Control of Drainage (CD)

Open pit mine drainage disturbance is mainly included in two sub-indicators, “Groundwater discharge intensity (CD1)” and “Intensity of in-pit water discharge (CD2)”. The CD1 indicator disturbance mainly characterizes open pit mines with frequent underground drainage, resulting in severe groundwater table lowering and water resource depletion. The CD2 indicator disturbance is mainly characterized by the decline of the groundwater level caused by pit dewatering, and there is a possibility of chemical changes in the groundwater due to rock interactions, enhanced oxidation, rock drenching, etc., triggering changes in the chemical composition of the groundwater. The challenges to the above indicators are all due to open pit mine drainage, which is a drainage disturbance.

2.2. Integrated Methodological Approach

In this study, the F-AHP, grey clustering method, and F-TOPSIS method are combined. The detailed steps of the synthesized methodology are shown in Figure 3. This step also reflects in detail the logical relationship between the model and the data, and the key data calculated through the model will be shown in the Appendix A of this paper.

Step 1: Setting up the evaluation standard

A total of 4 primary and 13 secondary indicators were analyzed in terms of both realism and desirability. Expert consultation was used to conduct the evaluation.

Step 2: Determining weights of indicators

F-AHP was used to determine the relative weights of the indicators through a two-by-two comparison matrix. The two-by-two comparison matrix for each indicator is shown in Table A1 (in Appendix A).

Step 3: Deciding grey levels

The indicators were categorized into five LD levels: very low, low, medium, high, and very high. Using a 5-point scale, experts assessed each indicator based on aspects of reality and desirability.

Step 4: Defining grey winterization weight functions

The center-point triangular winterization weight functions (CTWWF) were used to calculate the grey clustering coefficients [23]. The maximum value of the weighted grey clustering coefficients was selected as the clustering result.
Step 5: Judging the LD levels of indicators
The maximum value of an element in the grey clustering coefficients is selected as the clustering result.

Step 6: Sort the paths using the F-TOPSIS method.
The F-TOPSIS method was used to calculate the comparative advantages of the four possible paths and to analyze the ranking of the optimal paths involving the four leading indicators.

Details of the procedures for F-AHP, grey clustering method, and F-TOPSIS are given below.

2.2.1. F-AHP
The most acceptable solutions can be obtained in a shorter period through information systems for sound decision support systems [24]. Decision support systems based on multicriteria decision-making methodology (MCDM) have great potential to enhance the work of research scholars and policymakers. MCDM is gaining popularity in sustainable energy planning because it provides decision-makers with a rational multi-criteria framework [25–27].

The analytical hierarchy Process (AHP) is one of the MCDM tools widely used for rational decision-making in renewable energy planning, water resource management, and other areas [28,29]. AHP is widely accepted because it provides a way to transform complex problems into hierarchical structures [30]. However, the following weaknesses exist in the traditional hierarchical analysis approach: (i) Does not take into account the uncertainty of
natural language’s subjective judgment of numbers; (ii) AHP results are strongly influenced by the subjective judgment of the decision maker; (iii) AHP’s ranking is not precise enough. Therefore, to overcome these problems and improve the uncertainty of decision-making, F-AHP was proposed by combining fuzzy theory with hierarchical analysis [31]. In F-AHP, the expert evaluates the importance of the indicator and takes into account the uncertainty of its judgment using fuzzy numbers.

(1) Determination of the fuzzy number

A fuzzy set is a collection of elements with degrees of membership, and fuzzy methods deal with the concept of attribution from a single perspective. It describes its elements through the concept of a fuzzy membership function that assigns each element a degree of membership. 1 denotes absolute belonging, 0 denotes absolute exclusion, and [0, 1] denotes some degree of partial inclusion, all relative to its set. Fuzzy theory is designed to help people make decisions in situations where information is imprecise, and fuzzy numbers are an ideal way to describe linguistic phenomena where the detailed description of their state is unknown. Fuzzy numbers and fuzzy intervals are two terms used interchangeably [32]. A triangular fuzzy number is defined by a triad \((a_l, a_m, a_u)\) that has a triangular membership function [33,34]. The mathematical and graphical concepts are shown in Equation (1) and Figure 4, respectively.

\[\mu_a(x) = \begin{cases} 
0 & x \leq a_l \\
\frac{(x - a_l)}{(a_m - a_l)} & a_l < x < a_m \\
\frac{(a_u - x)}{(a_u - a_m)} & a_m < x < a_u \\
0 & x > a_u
\end{cases}\]

(1)

Figure 4. The membership function of triangular fuzzy numbers.

From Equation (1), The \(a_l\) and \(a_u\) denote the lower and upper bounds of the fuzzy number, respectively. \(a_m\) is the modal value of \(a\). As shown in Figure 4, the triangular fuzzy number (TFN) can be expressed as, where \(a_l > 0\), \(a_m > 0\), and \(a_u > 0\).

(2) Identification of linguistic variables

The process of identifying linguistic variables begins with the construction of a two-by-two comparison matrix between all the indicators in the hierarchical framework, and the membership functions of the linguistic variables are shown in Figure 5. Each expert acted as a decision maker to compare the indicators two by two by assigning linguistic terms through Saaty’s 1–9 scale method [35]. The nine linguistic terms compared and their respective triangular fuzzy numbers (TFN) are: “Perfect (8,9,10)”, “Absolute (7,8,9)”, “Very good (6,7,8)”, “Fairly good (5,6,7)”, “Good (4,5,6)”, “Preferable (3,4,5)”, “Not bad (2,3,4)”, “Weak advantage (1,2,3)” and “Equal (1,1,1)".
Figure 5. The membership functions for linguistic variables.

(3) Define the fuzzy hierarchical analysis comparison matrix

Constructing a two-by-two comparison matrix of all indicators in the dimensions of the hierarchy system and assigning linguistic terms to the two-by-two comparison by investigating which of each two indicators is more important. The representation of the comparison matrix $\tilde{A}$ is shown in Equation (2):

$$
\tilde{A} = (\tilde{a}_{ij})_{m \times n} = 
\begin{bmatrix}
\tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\
\tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{a}_{m1} & \tilde{a}_{m2} & \cdots & \tilde{a}_{mn}
\end{bmatrix}
$$

where: if $i = j$, then $\tilde{a}_{ij} = 1$; If $i$ is more important than $j$, then $\tilde{a}_{ij} = \tilde{1}, \tilde{2}, \ldots, \tilde{9}$; If $i$ is not as important as $j$, then $\tilde{a}_{ij} = \tilde{1}^{-1}, \tilde{2}^{-1}, \ldots, \tilde{9}^{-1}$.

In the comparison matrix, the clear values given to the linguistic terms are converted into triangular fuzzy numbers. It is performed by entering these triads of triangular fuzzy numbers, which are used as membership functions. The geometric mean method was used to calculate the fuzzy comparison matrix.

$$
\begin{align*}
\tilde{r}_i &= (\tilde{a}_{ij}^1 \otimes \tilde{a}_{ij}^2 \cdots \tilde{a}_{ij}^n)^{1/n} \\
\tilde{w}_i &= \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \tilde{r}_n)^{-1}
\end{align*}
$$

where: The $\tilde{a}_{ij}$ is the fuzzy comparison value of indicator $i$ to indicator $r_i$ is the geometric mean of the fuzzy comparison values of indicator $i$ for each indicator; the $\tilde{w}_i$ is the fuzzy weight of the $i$th indicator;

The fuzzy weights $\tilde{w}_i$ are expressed as triangular fuzzy numbers:

$$
\tilde{w}_i = \tilde{r}_i \otimes (lw_i + mw_i + uw_i)
$$

where: $lw_i$ are the lower limit value, the middle value, and the upper limit value of the fuzzy weights of the $i$th indicator, respectively.

Since the output is in the form of fuzzy weights, defuzzification is performed by locating the best non-fuzzy performance value (BNP) to convert the fuzzy weights into clear numbers. Using Equation (5) to determine the BNP, the BNP for each weight $(l, m, u)$ is determined as:

$$
BNP_w = [(u_w - l_w) + (m_w - l_w)]/3 + l_w
$$

The normalized BNP values are considered relative weights (N-BNP), i.e., the BNP values are divided by the sum of the BNP values of all metrics to obtain a total N-BNP weighting of 1.
To test the consistency of the results, it is crucial to calculate the Consistency Ratio (CR) based on the two sets of random indicators [36]. Take the middle values of the elements of matrix $A$ to form matrix $A_m$. Take the square root of the product of the lower and upper bounded values of the elements of matrix $A$ to form matrix $A_g$. That is:

$$
\begin{align*}
A_m &= \left[ a_{ij,m} \right] \\
A_g &= \left[ \sqrt{a_{ij,m}\tilde{a}_{ij}} \right]
\end{align*}
$$

(6)

According to Saaty’s method, the maximum eigenvalues of matrix $A_m$ and matrix $A_g$ can be calculated by Equation (7) as follows:

$$
\begin{align*}
\lambda_{\text{max}}^m &= \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij,m} (w_i^m \div w_i^m) \\
\lambda_{\text{max}}^g &= \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sqrt{a_{ij,m}w_i^g \div w_i^g}
\end{align*}
$$

(7)

The Consistency Index (CI) of matrix $A_m$ and $A_g$ is calculated as follows:

$$
\begin{align*}
CI_m &= \lambda_{\text{max}}^m - \frac{n}{n-1} \\
CI_g &= \lambda_{\text{max}}^g - \frac{n}{n-1}
\end{align*}
$$

(8)

Finally, the Consistency Ratio (CR) of each matrix is calculated according to Equations (8) and (9) with the following formula:

$$
\begin{align*}
CR_m &= \frac{CI_m}{RI_m} \\
CR_g &= \frac{CI_g}{RI_g}
\end{align*}
$$

(9)

In the above equation, $RI$ is a random indicator whose value is predefined [36,37]; when the value of $CR$ is less than 0.1, it means that the matrix is consistent, as shown in Tables A1–A5 (in Appendix A); all the matrices used in this study passed the consistency test.

### 2.2.2. Grey Clustering Method

Grey clustering is a clustering method based on grey system theory. It works by using the grey correlation matrix or grey whitening weight function to classify the objects to be observed into defined classes and effectively rank them [38].

1. Determination of the grey level

Grey clustering coefficients were calculated using the centroid triangle whitening weight function (CTWWF) [23]; the weight of a factor in different grey levels is evaluated comprehensively. The evaluation indexes are divided into five LD levels, and the centroids are identified as $\lambda_i$. The order of the centroids is shown in Figure 6.

![Figure 6. Centroid triangular whitening weight function.](image-url)
According to the evaluation criteria in this paper, the evaluation indicators are categorized into five LD levels, which are denoted as \( k = 1, \ldots, s \). These LDM levels correspond to \( x \in [0, 1] \) “very low level \(( k = 1 \)”; \( x \in [1, 2] \) “low level \(( k = 2 \)”; \( x \in [2, 3] \) “medium level \(( k = 3 \)”; \( x \in [3, 4] \) “high level \(( k = 4 \)”; and \( x \in [4, 5] \) “very high level \(( k = 5 \)”.

(2) Define the grey whitening weight function

The grey clustering coefficient of LD class \( k \) is calculated by CTWWF, and the grey whitening weight function is defined as shown in Equation (10):

\[
f^k_i(x) = \begin{cases} 
0 & x \notin [\lambda_{k-1}, \lambda_k] \\
(x - \lambda_{k-1}) / (\lambda_k - \lambda_{k-1}) & x \in [\lambda_{k-1}, \lambda_k] \\
(\lambda_{k-1} - x) / (\lambda_{k+1} - \lambda_k) & x \in [\lambda_k, \lambda_{k+1}] 
\end{cases}
\] (10)

The weighting functions [22] used describe the five grey classifications as follows:

Function 1: Very low-rank level, when the grey number is \( x \in [0, 1, 2] \) the function shown in Equation (11):

\[
f^1_i(x) = \begin{cases} 
0 & x \notin [0, 2] \\
1 & x \in [0, 1] \\
2 - xx & x \in [1, 2] 
\end{cases}
\] (11)

Function 2: Low-rank level, when the grey number is \( x \in [1, 2, 3] \) the function shown in Equation (12):

\[
f^2_i(x) = \begin{cases} 
0 & x \notin [1, 3] \\
x - 1x & x \in [1, 2] \\
3 - xx & x \in [2, 3] 
\end{cases}
\] (12)

Function 3: Medium rank level, when the grey number is \( x \in [2, 3, 4] \) the function shown in Equation (13):

\[
f^3_i(x) = \begin{cases} 
0 & x \notin [2, 4] \\
x - 2x & x \in [2, 3] \\
4 - xx & x \in [3, 4] 
\end{cases}
\] (13)

Function 4: High-rank level, when the grey number is \( x \in [3, 4, 5] \) the function shown in Equation (14):

\[
f^4_i(x) = \begin{cases} 
0 & x \notin [3, 5] \\
x - 3x & x \in [3, 4] \\
5 - xx & x \in [4, 5] 
\end{cases}
\] (14)

Function 5: Very high-rank level, when the grey number is \( x \in [3, 4, 5] \) the function shown in Equation (15):

\[
f^5_i(x) = \begin{cases} 
0 & x \notin [4, 6] \\
x - 4x & x \in [4, 5] \\
6 - xx & x \in [5, 6] 
\end{cases}
\] (15)

The combined clustering coefficient \( \sigma^k_i \) is calculated using the above function as shown in Equation (16):

\[
\sigma^k_i = \sum_{j=1}^{m} f^k_i(x_{ij}) \cdot w
\] (16)

If so \( \max_{1 \leq k \leq s} \{ \sigma^k_i \} = \sigma^{k*}_i \), then indicator \( i \) belongs to the \( k* \) tier level, and its priority is determined by the overall clustering coefficient. In short, the largest element of the grey clustering coefficient is selected as the clustering result.

2.2.3. F-TOPSIS

In the process of prioritizing paths using F-TOPSIS, experts assign fuzzy numbers based on linguistic terms to rate each alternative under each criterion. The five linguistic
terms compared and their respective triangular fuzzy numbers (TFN) are “Very low (0,1,3)”, “Lower (1,3,5)”, “Medium (3,5,7)”, “High (5,6,7)” and “Very high (7, 9, 10)”. Constructing a fuzzy decision matrix, Assuming that a committee of k experts (T1, T2, ..., Tk) evaluates m programs (D1, D2, ..., Dm) under n criteria (P1, P2, ..., Pn), the fuzzy decision matrix can be expressed as:

\[
\tilde{A} = \begin{bmatrix}
P_1 & P_2 & \cdots & P_n \\
D_1 & x_{11} & x_{12} & \cdots & x_{1n} \\
D_2 & x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
D_m & x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]  \hspace{1cm} (17)

where: \( x_{ij} = \frac{1}{k} (\bar{x}_{ij}^1 \oplus \bar{x}_{ij}^2 \oplus \cdots \oplus \bar{x}_{ij}^k) \), i = 1, 2, ..., m; j = 1, 2, ..., n.

After obtaining the expert inputs, the criterion weights calculated using F-AHP are summarized. The fuzzy decision matrix is normalized using linear scale transformation. The normalized fuzzy decision matrix, denoted by \( \tilde{R} \), is shown in Equation (18) as follows:

\[
\tilde{R} = \begin{bmatrix}
\bar{r}_{ij} \\
\end{bmatrix}_{m \times n} \hspace{1cm} (18)
\]

Calculate the weighted normalization matrix, denoted by \( \tilde{V} \), as shown in Equation (19):

\[
\tilde{V} = \begin{bmatrix}
\bar{v}_{ij} \\
\end{bmatrix}_{m \times n} \hspace{1cm} \bar{v}_{ij} = \bar{r}_{ij} \times \bar{w}_{ij}
\]  \hspace{1cm} (19)

where: \( \bar{r}_{ij} \) is the value of the normalization matrix, multiplied by the weights of the corresponding criterion obtained from F-AHP.

The elements in the weighted normalized fuzzy decision matrix \( \tilde{V} \) are normalized positive triangular fuzzy numbers whose range belongs to the interval [0, 1]. Therefore, the fuzzy positive ideal solution \( A^+ \) and the fuzzy negative ideal solution \( A^- \) can be defined as:

\[
\begin{align*}
A^+ &= \left\{ \bar{v}_{1}^+, \ldots, \bar{v}_{j}^+, \ldots, \bar{v}_{n}^+ \right\} \\
A^- &= \left\{ \bar{v}_{1}^-, \ldots, \bar{v}_{j}^-, \ldots, \bar{v}_{n}^- \right\}
\end{align*}
\]  \hspace{1cm} (20)

where: \( \bar{v}_{j}^+ = (1, 1, 1) \), \( \bar{v}_{j}^- = (0, 0, 0) \).

The area compensation method is used to calculate the distance of each scheme from the fuzzy positive ideal solution and the fuzzy negative ideal solution. The basic idea of the area compensation method is to determine the relative advantages and disadvantages of each scheme by calculating the area difference between the fuzzy positive ideal solution and the fuzzy negative ideal solution and each scheme. The specific calculation method is as follows:

\[
\begin{align*}
\bar{d}_{ij}^+ &= \sum_{j=1}^n d(\bar{v}_{ij}, \bar{v}_{j}^+) \\
\bar{d}_{ij}^- &= \sum_{j=1}^n d(\bar{v}_{ij}, \bar{v}_{j}^-)
\end{align*}
\]  \hspace{1cm} (21)

where: \( d \) is the distance between \( \bar{v}_{ij} \) (in the weighted normalized fuzzy decision matrix) and \( \bar{v}_{j}^+ \) (fuzzy positive ideal solution) or \( \bar{v}_{j}^- \) (fuzzy negative ideal solution), and since these values are triangular fuzzy numbers, the distance between them can be computed using the vertex method, i.e.,

\[
d(\bar{m}, \bar{n}) = \sqrt{\frac{1}{3} \left[ (m_l - n_l)^2 + (m_m - n_m)^2 + (m_u - n_u)^2 \right]} \]  \hspace{1cm} (22)
The final step is to calculate the relative proximity of each alternative to the desired value of the final prioritization, i.e., the posting schedule, denoted by $\tilde{C}_{i}$, as shown in Equation (23).

$$
\begin{align*}
\tilde{C}^-_{i} &= \frac{d_i^-}{d_i^- + d_i^+} = 1 - \frac{d_i^+}{d_i^- + d_i^+} \\
\tilde{C}^+_{i} &= \frac{d_i^+}{d_i^- + d_i^+} = 1 - \frac{d_i^-}{d_i^- + d_i^+}
\end{align*}
$$

Equation (23)

The alternative with the maximum posting schedule is considered the best. Therefore, $\tilde{C}^-_{i}$ is defined as the fuzzy satisfaction of the $i$th alternative and is defined as the fuzzy gap degree of the $i$th alternative [31]. With this definition, it is convenient to locate the fuzzy gap and how to improve it to achieve the desired level and get the best strategy from a set of feasible alternatives.

3. Overview of Results

3.1. Analysis of the Results of the F-AHP Study

The weights and rankings of the leading indicators determined using the F-AHP method are shown in Figure 7. For prioritization, the ranking is based on a low-to-high realistic weighting criterion and a desirability weighting criterion. In terms of realism, higher rankings indicate greater concern in reality, while in terms of desirability, higher rankings indicate greater indicator value for low-disturbance open-pit mine development. Through the analysis, the prioritization order of the leading indicators in terms of reality is: “Control of emission rock (CE)” > “Control of stripping works (CS)” > “Control of pollution emission (CP)” > “Control of drainage (CD)”); In terms of desirability for: “Control of emission rock (CE)” > “Control of stripping works (CS)” > “Control of pollution emission (CP)” > “Control of drainage (CD)”.

![Figure 7. Relative weights and rankings of leading indicators.](image)

According to the results of realism weighting, as shown in Figure 7a. The leading indicator with the lowest realism concern is “Control of drainage (CD)” with a weight of 0.1756, followed by “Control of pollution emission (CP)” with a weight of 0.2136; “Control of stripping works (CS)” has a higher weight of 0.2865; “Control of emission rock (CE)” indicator has the highest realistic concern with a weight of 0.3243.
According to the results of desirability weighting, as shown in Figure 7b, the leading indicator with the highest desirability value is “Control of stripping works (CS)” with a weight of 0.3301; this is followed by the indicator “Control of emission rock (CE)” with a weight of 0.2739; followed by indicators “Control of pollution emission (CP)” and “Control of drainage (CD)”, the corresponding weights are 0.2224 and 0.2026, respectively. The close weighting values of the CP and CD indicate that both are equally important for the development of low-disturbance open pit mines in terms of desirability. “Control of stripping works (CS)” is weighted less realistically than desirably, so the urgency of its development needs is obvious.

After obtaining the weighting results for the leading indicators, the next step should be to compare the sub-indicators of the respective leading indicators two by two. The process is similar to that used in the above study for comparing matrices, obtaining relative weights, and calculating consistency ratios for leading indicators. The results of the two-by-two comparison matrix and consistency ratio calculations for all 13 sub-indicators with their corresponding leading indicators are shown in Tables A1–A5 (in Appendix A). The computational analysis showed that the consistency ratios of the matrices used were well below the range of 0.10, so the judgments were considered reliable. The N-BNP values of the subindicators with the rankings are shown in Figure 8.

![Figure 8. Relative weights and ranking of sub-indicators under leading indicators.](image)

As shown in Figure 8a, the realism weights of the sub-indicators under the leading indicator “Control of stripping works (CS)” are: “Intensity of land degradation (CS3)” > “Stripping intensity (CS2)” > “Extent of damage to extraction sites (CS1)”. The desirability weights are: “Stripping intensity (CS2)” > “Intensity of land degradation (CS3)” > “Extent of damage to extraction sites (CS1)”. After analysis, it is found that the realism weight of CS2 is smaller than the desirability weight, so this indicator needs more attention and improvement.

As shown in Figure 8b, the realism weights of sub-indicators under the leading indicator “Control of emission rock (CE)” are: “Emission intensity of strippings (CE2)” > “Intensity of land occupation (CE4)” > “Utilisation of inner dump (CE3)” > “Extent of damage to dumping (CE1)”. It was analyzed that CE1, CE3, and CE4 were all ranked less realistically than desirability, so these indicators need more attention and improvement, with CE4 needing to be focused on.
damage to dumping (CE1)". The desirability weights are: “Intensity of land occupation (CE4)" > “Utilisation of inner dump (CE3)" > “Emission intensity of strippings (CE2)" > “Extent of damage to dumping (CE1)". It was analyzed that CE1, CE3, and CE4 were all ranked less realistically than desirability, so these indicators need more attention and improvement, with CE4 needing to be focused on.

As shown in Figure 8c, the realism weights of sub-indicators under the leading indicator “Control of pollution emission (CP)” are: “Dust emission intensity (CP1)” > “Emission intensity of gaseous pollutants (CP3)” > “Emission intensity of water pollutants (CP2)” > “Noise pollution (CP4)”. The desirability weights are: “Emission intensity of gaseous pollutants (CP3)” > “Dust emission intensity (CP1)” > “Emission intensity of water pollutants (CP2)” > “Noise pollution (CP4)”. The realism weight of CP3 was analyzed to be less than the desirability weight, so the indicator needs more attention and improvement.

As shown in Figure 8d, the realism weights of sub-indicators under the leading indicator “Control of drainage (CD)” are: “Groundwater discharge intensity (CD1)” > “Intensity of in-pit water discharge (CD2)”. The desirability weights are: “Intensity of in-pit water discharge (CD2)” > “Groundwater discharge intensity (CD1)” > “Emission intensity of water pollutants (CP2)”. Therefore, CD2 indicators need more attention and improvement.

After determining the relative weights of the main indicators and sub-indicators, the final step of the F-AHP is to calculate the total weights of all sub-indicators. This can be quantified by taking the relative weights of the sub-indicators and their corresponding leading indicators and multiplying them together. The weights and ordering of the sub-indicators are shown in Figure 9.

In summary, the relative weights of the leading indicators were determined using F-AHP. Based on an evaluation of the actual situation, the indicators “Control of stripping works (CS)” and “Control of emission rock (CE)” are of the highest importance, both in terms of reality and desirability, and should require the immediate attention of mining companies. In particular, the indicator “Control of stripping works (CS)” has a lower realism weight than desirability weight and, therefore, needs much more improvement. The sub-indicators “Stripping intensity (CS2)”, “Utilisation of inner dump (CE3)” and “Emission intensity of gaseous pollutants (CP3)” need focused improvement.
### 3.2. Analysis of LD Level Results

Five whitened weight functions are applied to get the grey clustering results of each sub-indicator based on the relative weights of each sub-indicator, as shown in Table 1. The LD level results of the leading indicators are shown in Figure 10.

<table>
<thead>
<tr>
<th>Norm</th>
<th>Reality</th>
<th>Desirability</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS1</td>
<td>-</td>
<td>0.2156</td>
</tr>
<tr>
<td>CS2</td>
<td>-</td>
<td>0.2226</td>
</tr>
<tr>
<td>CS3</td>
<td>-</td>
<td>0.1558</td>
</tr>
<tr>
<td>∑</td>
<td>0.1512</td>
<td>0.5809</td>
</tr>
<tr>
<td>CE1</td>
<td>-</td>
<td>0.1161</td>
</tr>
<tr>
<td>CE2</td>
<td>-</td>
<td>0.2381</td>
</tr>
<tr>
<td>CE3</td>
<td>0.0774</td>
<td>-</td>
</tr>
<tr>
<td>CE4</td>
<td>-</td>
<td>0.2677</td>
</tr>
<tr>
<td>∑</td>
<td>0.1161</td>
<td>0.5833</td>
</tr>
<tr>
<td>CP1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CP2</td>
<td>-</td>
<td>0.0711</td>
</tr>
<tr>
<td>CP3</td>
<td>0.0648</td>
<td>0.2593</td>
</tr>
<tr>
<td>CP4</td>
<td>0.0864</td>
<td>0.0576</td>
</tr>
<tr>
<td>∑</td>
<td>0.1512</td>
<td>0.6005</td>
</tr>
<tr>
<td>CD1</td>
<td>-</td>
<td>0.2867</td>
</tr>
<tr>
<td>CD2</td>
<td>0.1044</td>
<td>0.4177</td>
</tr>
<tr>
<td>∑</td>
<td>0.1044</td>
<td>0.7044</td>
</tr>
</tbody>
</table>

Note: The values bolded in black in Table 1 are the clustering coefficients based on the relative weights of the leading indicators for the sub-indicators.

![Figure 10. Grey clustering coefficients for leading indicators.](image)

As shown in Figure 10, all leading indicators are realistically at “low” LD levels. The clustering coefficients for “Control of stripping works (CS)” and “Control of pollution emission (CP)” are close to the “very low” LD level, while the clustering coefficient for “Control of emission rock (CE)” is close to the “medium” LD level. Regarding desirability, the LD levels for all leading indicators are above “medium”. To calculate the grey clustering results for each sub-indicator, expert opinions, and overall weights were processed. The results of the greyscale clustering of all the sub-indicators based on the application of the five whitened weighting functions for each of the two dimensions (reality and desirability) are shown in Table 2.
five whitened weighting functions for each of the two dimensions (reality and desirability) are shown in Table 2.

Table 2. Clustering coefficients of sub-indicators.

<table>
<thead>
<tr>
<th>Norm</th>
<th>Reality</th>
<th>Desirability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$f_1^j(x)$</td>
<td>$f_2^j(x)$</td>
</tr>
<tr>
<td>CS1</td>
<td>-</td>
<td>0.0618</td>
</tr>
<tr>
<td>CS2</td>
<td>-</td>
<td>0.0638</td>
</tr>
<tr>
<td>CS3</td>
<td>0.0446</td>
<td>0.0669</td>
</tr>
<tr>
<td>CE1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CE2</td>
<td>-</td>
<td>0.0772</td>
</tr>
<tr>
<td>CE3</td>
<td>0.0377</td>
<td>0.0251</td>
</tr>
<tr>
<td>CE4</td>
<td>-</td>
<td>0.0868</td>
</tr>
<tr>
<td>CP1</td>
<td>-</td>
<td>0.0454</td>
</tr>
<tr>
<td>CP2</td>
<td>-</td>
<td>0.0152</td>
</tr>
<tr>
<td>CP3</td>
<td>0.0138</td>
<td>0.0554</td>
</tr>
<tr>
<td>CP4</td>
<td>0.0192</td>
<td>0.0123</td>
</tr>
<tr>
<td>CD1</td>
<td>-</td>
<td>0.0504</td>
</tr>
<tr>
<td>CD2</td>
<td>0.0183</td>
<td>0.0734</td>
</tr>
</tbody>
</table>

Note: The values bolded in black in Table 2 are the final grey clustering values for each sub-matrix.

To better understand the grey clustering results, Figure 11 shows a comparison of the final grey levels for each sub-indicator. For “Control of stripping works (CS)”, its sub-indicators CS1, CS2, and CS3 have a low level of realistic greyscale and a high level of desirable greyscale, especially for indicators CS2 and CS3, which have a very high level. For “Control of emission rock (CE)”, its sub-indicator CE1 is at a medium level of the grey level of realism, CE2 and CE4 are at a low level, and CE3 is at a very low level; in terms of the grey level of desirability, the indicators CE1, CE1, and CE4 are at a high level, and the indicator CE3 is at a high level. For “Control of pollution emission (CP)”, its sub-indicator CP2 is at a medium level of the grey level of realism, CP1 and CP3 are at a low level, and CP4 is at a very low level; in terms of the grey level of desirability, CP1, and CP4 are at a high level of realism, and CP2 and CP3 are at a high level of realism. For “Control of drainage (CD)”, its sub-indicators CD1 and CD2 have a low level of realistic greyscale and a high level of desirable greyscale.

Figure 11. Comparison of LD levels for sub-indicators.

The results show that all the leading indicators are at the “low” and “high” LD levels of realism and desirability, respectively, indicating a low level of low-disturbance open pit mining, which also implies that the future performance of low-disturbance open pit mining can be optimistic if these indicators are improved.

3.3. Analysis of Optimal Path Ordering

The F-TOPSIS method was used to calculate the comparative advantages of the four possible paths, and the relative weights of each category and the comparative advantages
of the four possible paths involved were arranged in a matrix, and the detailed data for the analysis are presented in Tables A6–A8 (in Appendix B) of this paper. The paths are prioritized by comparing the magnitude of the posting progress coefficients for each path, as shown in Table 3. The results show that the optimal sorting path for realizing LDM is “Optimised design (OD)” > “Intelligent dispatch (ID)” > “Land reclamation (LR)” > “Optimisation of processes (OP)”.

Table 3. Final prioritization of paths.

<table>
<thead>
<tr>
<th>Pathway</th>
<th>Distance to a Fuzzy Positive Ideal Solution</th>
<th>Distance to a Fuzzy Negative Ideal Solution</th>
<th>Closeness Coefficient</th>
<th>Prioritizing Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>OD</td>
<td>0.5624</td>
<td>0.7655</td>
<td>0.5765</td>
<td>1</td>
</tr>
<tr>
<td>ID</td>
<td>0.5848</td>
<td>0.7518</td>
<td>0.5625</td>
<td>2</td>
</tr>
<tr>
<td>OP</td>
<td>0.6680</td>
<td>0.6846</td>
<td>0.5061</td>
<td>4</td>
</tr>
<tr>
<td>LP</td>
<td>0.5967</td>
<td>0.7270</td>
<td>0.5492</td>
<td>3</td>
</tr>
</tbody>
</table>

Prioritization is critical for low-disturbance open pit mining, and the results obtained for each criterion were compared to obtain the proximity coefficients of the paths for each of the challenge criteria, as well as the path order, which is shown in Table 4. As shown in Figure 12, the optimal ordering in terms of “Control of stripping works (CS)” is the paths: “Optimised design (OD)” > “Intelligent dispatch (ID)” > “Land reclamation (LR)” > “Optimisation of processes (OP)”. For “Control of emission rock (CE)”, the optimal ordering path is: “Optimised design (OD)” > “Land reclamation (LR)” > “Intelligent dispatch (ID)” > “Optimisation of processes (OP)”. For “Control of pollution emission (CP)”, the optimal ordering path is: “Intelligent dispatch (ID)” > “Land reclamation (LR)” > “Optimisation of processes (OP)” > “Optimised design (OD)”. For “Control of drainage (CD)”, the optimal sorting path is: “Optimised design (OD)” > “Land reclamation (LR)” > “Intelligent dispatch (ID)” > “Optimisation of processes (OP)”.

Figure 12. Proximity coefficients and path ordering under prioritized metrics.
4. Discussion

The LDM framework was quantitatively analyzed using the F-AHP method, grey clustering method, and F-TOPSIS synthesis method. Experts with relevant technical expertise were invited to participate in the research process to analyze the situation of open pit mining in China. The results show that the level of reality LD for all four leading indicators is at the “low” level, which shows a negative tendency, indicating a low level of LD. For desirability, all leading indicators are at the “high” LD level. So, if these are handled properly, the future performance of LDM is very optimistic for open pit mines that currently face lower LD standards. By further analyzing the sub-indicators, the current performance and future significance of the indicators were obtained, respectively. For the leading indicators, this paper gives the corresponding technology paths and ranks them. Below is a discussion of all the indicators according to their prioritization, as well as the technical pathways, with the prioritization determined by the results of realism (from low to high) and desirability (from high to low).

“Control of stripping works (CS)” is the worst-performing leading indicator with the highest available value. Of the three sub-indicators, “Stripping intensity (CS2)” received the highest priority, followed by “Intensity of land degradation (CS3)” and then “Extent of damage to extraction sites (CS1)”. Open pit mining and stripping works disturb and destroy the whole original surface, which affects the balance of the ecological environment [39–41]. Open pit mining disturbance can be reduced at the source by optimizing the control of the stripping project. Relevant literature shows that every 10,000 tons of coal mined in open-cast coal mines destroys 0.22 hm$^2$ of land area, of which 0.12 hm$^2$ of land area is destroyed by direct excavation, 0.10 hm$^2$ of land area is occupied by the external discharge site, and the average annual land area destroyed and occupied is as much as 10,000 hm$^2$ [42]. Therefore, controlling the intensity of open pit rock stripping at the source is considered a key indicator to which the open pit mining industry must pay due attention. This paper gives a preliminary ranking of technology pathways and their prioritization under this indicator; the order is “Optimized design (OD)” > “Intelligent dispatch (ID)”, “Land reclamation (LR)” > “Optimisation of processes (OP)”. The path focuses on the issue of reducing the disturbance of mining and stripping works from the source, emphasizing the reduction of stripping disturbance in open pit mines through optimized design and intelligent scheduling.

“Control of emission rock (CE)” received second priority. The sub-indicators under this category are, in descending order of priority, “Intensity of land occupation (CE4)”, “Utilisation of inner dump (CE3)”, “Emission intensity of strippings (CE2)” and “Extent of damage to dumping (CE1)”. During the mining process of open-pit mines, to obtain more resources, it is necessary to strip a large amount of soil and rock, which are discharged to the internal or external dump, a process that not only destroys the original stratum but also the external dumps pressurize the land and seriously damage the original ground surface. Studies have shown that there may be some degree of heavy metal accumulation in soils from open pit mine dumps [43,44]. Therefore, to make positive progress in LDM, “Control of emission rock (CE)” is an indispensable key pathway and should be adequately controlled. This paper gives a preliminary ranking of the technology pathways and their prioritization under this indicator, and the results of the ranking are, in order of priority, from highest to lowest: “Optimised design (OD)”, “Land reclamation (LR)”,

### Table 4. F-TOPSIS results under each challenge indicator.

<table>
<thead>
<tr>
<th>Indicators-Pathways</th>
<th>Closeness Coefficient</th>
<th>Prioritizing Order</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OD</td>
<td>ID</td>
</tr>
<tr>
<td>CS</td>
<td>0.6205</td>
<td>0.6021</td>
</tr>
<tr>
<td>CE</td>
<td>0.5595</td>
<td>0.5026</td>
</tr>
<tr>
<td>CP</td>
<td>0.5129</td>
<td>0.6399</td>
</tr>
<tr>
<td>CD</td>
<td>0.6262</td>
<td>0.5021</td>
</tr>
</tbody>
</table>
“Intelligent dispatch (ID)” and “Optimisation of processes (OP)”. The pathway focuses on solving the problem of rock-discharge engineering disturbance at source, emphasizing the reduction of rock-discharge disturbance in open pit mines through optimized design and land reclamation.

“Control of pollution emission (CP)” received third priority. The sub-indicators under this category, in descending order of priority, are as follows: “Emission intensity of gaseous pollutants (CP3)”, “Dust emission intensity (CP1)”, “Emission intensity of water pollutants (CP2)” and “Noise pollution (CP4)” Conventional mining patterns put enormous pressure on the environment, with mining operations resulting in significant greenhouse gas emissions, particularly from transportation fuels, electricity consumption and spontaneous combustion of coal [45]. Many mining operations, such as drilling, blasting, excavation, crushing, handling, transportation, etc., are sources of dust and noise pollution [46]. During open-pit coal mining, surface water and groundwater may form acidic water containing high concentrations of metal ions due to chemical interactions, and the formation of acid mine drainage is one of the major sources of pollution of concern to the world [47]. Overall, pollution emissions are a key contributor to open pit mine disturbances, so reducing pollution is critical to the achievement of LDM goals. This paper gives a preliminary ranking of technology pathways and their prioritization under this indicator, in order of priority, from highest to lowest: “Intelligent dispatch (ID)”, “Land reclamation (LR)”, “Optimisation of processes (OP)” and “Optimised design (OD)” The pathway focuses on addressing the engineering disturbance of pollution emissions from open pit mine production, emphasizing the reduction of greenhouse gas emissions and dust pollution through smart scheduling and land reclamation.

“Control of drainage (CD)” received fourth priority. The sub-indicators under this category, in descending order of priority, are as follows: “Intensity of in-pit water discharge (CD2)” and “Groundwater discharge intensity (CD1)”. As open pits inevitably collect groundwater in the process of mining. To ensure the production of mines, it is generally necessary to carry out drainage treatment of pits, which may lead to the imbalance of the hydrological cycle of the original stratum, soil desertification, grassland degradation, and other environmental and geological disturbances [48]. Studies have shown that open-pit mine drainage can also have a greater impact on nearby biological communities [49,50]. Therefore, “Control of drainage (CD)” is crucial to LDM and should be given sufficient attention. The paper gives a preliminary list of technology pathways and their prioritization under this indicator: “Optimised design (OD)”, “Land reclamation (LR)”, “Intelligent dispatch (ID)” and “Optimisation of processes (OP)”. The pathway focuses on addressing drainage project disturbances at source and, in doing so, emphasizes the reduction of open pit mine drainage disturbances through optimal design and land reclamation.

5. Conclusions

The primary conclusions are as follows:

1. A decision support system for low-disturbance mining in open pit mines is proposed to provide key technical support for low-disturbance mining in open pit mines to promote the development of low-disturbance mining in open pit mines. To consider the impact of different mine works, two frameworks, low-disturbance open pit mining challenge and low-disturbance open pit mining path, were constructed in the decision support system. The Low Disturbance Surface Mining Challenge Framework involves 4 leading indicators and 13 sub-indicators. The Mining Pathways Framework consists of 4 main technology pathways.

2. Based on the fuzzy hierarchical analysis method, the weights of all indicators were determined and ranked, and the grey clustering method based on the centroid triangular whitening weight function was used to evaluate the indicators. The study shows that the level of low-disturbance mining in open-pit mines is low at this stage and that all indicators need to be attended to and corresponding measures taken immediately. The leading indicators to focus on and study are “Control of stripping works (CS)” and
“Control of pollution emission (CP)”. The sub-indicators “Stripping intensity (CS2)”, “Utilisation of inner dump (CE3)” and “Emission intensity of gaseous pollutants (CP3)” need to be emphasized, and corresponding measures are taken promptly.

3. The F-TOPSIS method is used to calculate the comparative advantages of the four possible paths. For the current stage of China’s open pit mine LDM development, the optimal path ordering under each leading indicator is given respectively, which provides optimal decision-making for the development of low-disturbance open pit mines. Comprehensive studies have shown that the prioritization of optimal paths to achieve a low-disturbance open pit mine is “Optimised design (OD)” > “Intelligent dispatch (ID)” > “Land reclamation (LR)” > “Optimisation of processes (OP)”.

Author Contributions: All authors contributed to this study. Y.T. and R.Z. designed the research study. Y.T. analyzed the field data. Y.T. wrote this paper. R.Z. reviewed the manuscript. R.Z. guided the research procedures and reviewed them. All authors gave final approval for publication. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author, [Yabin Tao], upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.
### Appendix A

**Table A1.** Pairwise comparison of leading indicators.

<table>
<thead>
<tr>
<th>Reality</th>
<th>CS</th>
<th>CE</th>
<th>CP</th>
<th>CD</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS</td>
<td>(1, 1, 1)</td>
<td>(0.8717, 1.1736, 1.4877)</td>
<td>(1.2696, 1.7990, 2.2876)</td>
<td>(0.8409, 0.9809, 1.0905)</td>
</tr>
<tr>
<td>CE</td>
<td>(0.6722, 0.8520, 1.1472)</td>
<td>(1, 1, 1)</td>
<td>(1.2410, 1.7990, 2.3016)</td>
<td>(1.8612, 2.1277, 2.3593)</td>
</tr>
<tr>
<td>CP</td>
<td>(0.4371, 0.5559, 0.7877)</td>
<td>(0.4345, 0.5559, 0.8058)</td>
<td>(1, 1, 1)</td>
<td>(1.4021, 1.7155, 2.1352)</td>
</tr>
<tr>
<td>CD</td>
<td>(0.9170, 1.0195, 1.1892)</td>
<td>(0.4239, 0.4700, 0.5373)</td>
<td>(0.4683, 0.5829, 0.7132)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

$CR_m = 0.0640; \ CR_g = 0.0931$

| Reality | Desirability | CS           | CE           | CP           | CD           |
|---------|--------------|--------------|--------------|--------------|
| CS      | (1, 1, 1)    | (1.2968, 1.9580, 2.5021) | (1.4565, 1.9618, 2.4384) | (0.9170, 1.1253, 1.2968) |
| CE      | (0.3887, 0.5107, 0.7330) | (1, 1, 1)    | (1.3533, 1.8925, 2.3859) | (1.8612, 2.3203, 2.7066) |
| CP      | (0.4101, 0.5097, 0.6866) | (0.4191, 0.5284, 0.7389) | (1, 1, 1)    | (1.3525, 1.6307, 1.9580) |
| CD      | (0.7711, 0.8886, 1.0905) | (0.3695, 0.4310, 0.5373) | (0.5107, 0.6132, 0.7392) | (1, 1, 1)    |

$CR_m = 0.0953; \ CR_g = 0.0981$

**Table A2.** Pairwise comparison of sub-indicators under control of stripping works (CS).

<table>
<thead>
<tr>
<th>Reality</th>
<th>CS1</th>
<th>CS2</th>
<th>CS3</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS1</td>
<td>(1, 1, 1)</td>
<td>(0.7993, 1.0000, 1.2510)</td>
<td>(1.2510, 1.7692, 2.1965)</td>
</tr>
<tr>
<td>CS2</td>
<td>(0.6968, 0.9170, 1.2510)</td>
<td>(1, 1, 1)</td>
<td>(1.0905, 1.6224, 2.0598)</td>
</tr>
<tr>
<td>CS3</td>
<td>(0.4555, 0.5652, 0.7993)</td>
<td>(0.4855, 0.6164, 0.9170)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

$CR_m = 0.0229; \ CR_g = 0.0635$

| Reality | Desirability | CS1          | CS2          | CS3          |
|---------|--------------|--------------|--------------|
| CS1     | (1, 1, 1)    | (0.7993, 1.0905, 1.4352) | (0.8995, 1.3443, 1.7321) |
| CS2     | (0.7993, 0.8409, 1.2510) | (1, 1, 1)    | (1.0366, 1.7461, 2.4495) |
| CS3     | (0.5774, 0.7439, 1.1117) | (0.4855, 0.6570, 1.0520) | (1, 1, 1)    |

$CR_m = 0.0313; \ CR_g = 0.0838$
### Table A3. Pairwise comparison of sub-indicators under control of emission rock (CE).

<table>
<thead>
<tr>
<th>Reality</th>
<th>CE1</th>
<th>CE2</th>
<th>CE3</th>
<th>CE4</th>
</tr>
</thead>
<tbody>
<tr>
<td>CE1</td>
<td>(1, 1, 1)</td>
<td>(1.1892, 1.8612, 2.4137)</td>
<td>(1.4810, 2.000, 2.4947)</td>
<td>(1.0366, 1.1736, 1.3643)</td>
</tr>
<tr>
<td>CE2</td>
<td>(0.4029, 0.5373, 0.7993)</td>
<td>(1, 1, 1)</td>
<td>(1.4029, 1.9738, 2.5099)</td>
<td>(1.7692, 2.2247, 2.6110)</td>
</tr>
<tr>
<td>CE3</td>
<td>(0.4009, 0.5000, 0.6752)</td>
<td>(0.3984, 0.5066, 0.7128)</td>
<td>(1, 1, 1)</td>
<td>(1.2968, 1.5731, 1.8974)</td>
</tr>
<tr>
<td>CE4</td>
<td>(0.7330, 0.8520, 1.0520)</td>
<td>(0.3830, 0.4495, 0.5652)</td>
<td>(0.5270, 0.6357, 0.7711)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

Desirability (CE1): 0.0640; CR<sub>g</sub> = 0.0931

Desirability (CE2): 0.0817; CR<sub>g</sub> = 0.0921

### Table A4. Pairwise comparison of sub-indicators under control of pollution emission (CP).

<table>
<thead>
<tr>
<th>Reality</th>
<th>CP1</th>
<th>CP2</th>
<th>CP3</th>
<th>CP4</th>
</tr>
</thead>
<tbody>
<tr>
<td>CP1</td>
<td>(1, 1, 1)</td>
<td>(1.0905, 1.7692, 2.4820)</td>
<td>(1.6364, 2.3593, 3.0536)</td>
<td>(1.0366, 1.3957, 1.7955)</td>
</tr>
<tr>
<td>CP2</td>
<td>(0.5157, 0.5652, 0.8717)</td>
<td>(1, 1, 1)</td>
<td>(1.7294, 2.4495, 3.1654)</td>
<td>(1.7692, 2.6456, 3.4363)</td>
</tr>
<tr>
<td>CP3</td>
<td>(0.3275, 0.4239, 0.6111)</td>
<td>(0.3159, 0.4082, 0.5782)</td>
<td>(1, 1, 1)</td>
<td>(1.4758, 1.8859, 2.3859)</td>
</tr>
<tr>
<td>CP4</td>
<td>(0.5373, 0.6811, 0.9647)</td>
<td>(0.2910, 0.3780, 0.5652)</td>
<td>(0.4191, 0.5303, 0.6776)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

Desirability (CP1): 0.0640; CR<sub>g</sub> = 0.0931

Desirability (CP2): 0.0648; CR<sub>g</sub> = 0.0973
Table A5. Pairwise comparison of sub-indicators under control of drainage (CD).

<table>
<thead>
<tr>
<th>Reality</th>
<th>CD1</th>
<th>CD2</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD1</td>
<td>(1, 1, 1) (0.6968, 0.9170, 1.2510)</td>
<td>(0.7993, 1.0000, 1.2510)</td>
</tr>
<tr>
<td>CD2</td>
<td>(0.6968, 0.9170, 1.2510) (1, 1, 1)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

CRm = 0.0000; CRg = 0.0171

Desirability

<table>
<thead>
<tr>
<th>Reality</th>
<th>CD1</th>
<th>CD2</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD1</td>
<td>(1, 1, 1) (0.6389, 0.8717, 1.2068)</td>
<td>(0.8286, 1.0520, 1.3643)</td>
</tr>
<tr>
<td>CD2</td>
<td>(0.6389, 0.8717, 1.2068) (1, 1, 1)</td>
<td>(1, 1, 1)</td>
</tr>
</tbody>
</table>

CRm = 0.0000; CRg = 0.0718

Appendix B

Table A6. Fuzzy decision matrix (F-TOPSIS).

<table>
<thead>
<tr>
<th></th>
<th>CS</th>
<th>CE</th>
<th>CP</th>
<th>CD</th>
</tr>
</thead>
<tbody>
<tr>
<td>OD</td>
<td>(3.4, 5.4, 7.3)</td>
<td>(3.6, 5.6, 7.6)</td>
<td>(5.5, 7.5, 9.5)</td>
<td>(4.4, 6.4, 7.6)</td>
</tr>
<tr>
<td>ID</td>
<td>(4.8, 6.8, 8.7)</td>
<td>(5.6, 7.6, 9.6)</td>
<td>(5.2, 7.2, 9)</td>
<td>(4.7, 6.7, 9.6)</td>
</tr>
<tr>
<td>OP</td>
<td>(5, 7, 8.9)</td>
<td>(3, 5, 7)</td>
<td>(4.6, 6.6, 8.6)</td>
<td>(5.6, 7.3, 7)</td>
</tr>
<tr>
<td>LR</td>
<td>(2.6, 4.6, 6.6)</td>
<td>(4.2, 6.2, 8.2)</td>
<td>(4.7, 6.7, 8.7)</td>
<td>(3.8, 5.8, 8.2)</td>
</tr>
</tbody>
</table>

Table A7. Normalized fuzzy decision matrix (F-TOPSIS).

<table>
<thead>
<tr>
<th></th>
<th>CS</th>
<th>CE</th>
<th>CP</th>
<th>CD</th>
</tr>
</thead>
<tbody>
<tr>
<td>OD</td>
<td>(0.3542, 0.5625, 0.7604)</td>
<td>(0.3750, 0.5833, 0.7917)</td>
<td>(0.5729, 0.7813, 0.9896)</td>
<td>(0.4583, 0.6667, 0.7917)</td>
</tr>
<tr>
<td>ID</td>
<td>(0.5000, 0.7083, 0.9063)</td>
<td>(0.5833, 0.7917, 1.0000)</td>
<td>(0.5417, 0.7500, 0.9375)</td>
<td>(0.4896, 0.6979, 1.0000)</td>
</tr>
<tr>
<td>OP</td>
<td>(0.5208, 0.7292, 0.9271)</td>
<td>(0.3125, 0.5208, 0.7292)</td>
<td>(0.4792, 0.6875, 0.8958)</td>
<td>(0.5833, 0.7604, 0.7292)</td>
</tr>
<tr>
<td>LR</td>
<td>(0.2708, 0.4792, 0.6875)</td>
<td>(0.4475, 0.6458, 0.8542)</td>
<td>(0.4896, 0.6979, 0.9063)</td>
<td>(0.3958, 0.6042, 0.8542)</td>
</tr>
</tbody>
</table>

Table A8. Weighted decision matrix (F-TOPSIS).

<table>
<thead>
<tr>
<th></th>
<th>CS</th>
<th>CE</th>
<th>CP</th>
<th>CD</th>
</tr>
</thead>
<tbody>
<tr>
<td>OD</td>
<td>(0.0714, 0.1636, 0.3042)</td>
<td>(0.0756, 0.1697, 0.3167)</td>
<td>(0.1156, 0.2273, 0.3958)</td>
<td>(0.0924, 0.1939, 0.3167)</td>
</tr>
<tr>
<td>ID</td>
<td>(0.1147, 0.2308, 0.4126)</td>
<td>(0.1338, 0.2580, 0.4553)</td>
<td>(0.1242, 0.2444, 0.4288)</td>
<td>(0.1123, 0.2275, 0.4553)</td>
</tr>
<tr>
<td>OP</td>
<td>(0.0769, 0.1509, 0.2882)</td>
<td>(0.0461, 0.1078, 0.2267)</td>
<td>(0.0707, 0.1422, 0.2785)</td>
<td>(0.0861, 0.1573, 0.2267)</td>
</tr>
<tr>
<td>LR</td>
<td>(0.0363, 0.0845, 0.1628)</td>
<td>(0.0587, 0.1139, 0.2023)</td>
<td>(0.0657, 0.1230, 0.2146)</td>
<td>(0.0531, 0.1065, 0.2023)</td>
</tr>
</tbody>
</table>
References


23. Liu, S.F.; Yang, Y.J.; Fang, Z.G.; Xie, N.M. Grey cluster evaluation models based on mixed triangular whitening normalization weight functions. Grey Syst. Theory Appl. 2015, 5, 410–418. [CrossRef]


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