

Article

Research on the Cutting Path Control of Coal Mining Machine Based on Dynamic Geological Models

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Abstract

Planned cutting is a core technique for intelligent coal mining, relying on high-precision geological models of fully mechanized mining faces to plan the cutting trajectory of mining equipment, with model accuracy as a prerequisite for intelligent mining. To address the limitations of traditional interpolation methods in dynamic model updating and the technical gap between geological information and equipment control parameters, this study proposes a coal mining machine cutting path control method based on dynamic geological models. An improved smooth discrete interpolation method is developed to realize dynamic updating of the geological model, effectively improving the accuracy of local geological models and ensuring safe mining operations. Meanwhile, a method for converting geological information into coal mining equipment control parameters is proposed, breaking the technical barrier between geological data and production control information and laying a foundation for unmanned and intelligent mining. Field tests conducted in a shaft coal mine in Shaanxi demonstrate that the method achieves precise control of the coal mining machine's trajectory: during a 7-day trial, the working face advanced 56 m and mined 51,000 tons of coal with minimal human intervention. Comparative analysis shows that the error between the planned cutting based on the dynamic geological model and manual cutting is within 10 cm, and the drum height curve is smoother, reducing frequent adjustments and facilitating equipment protection. Dynamic model updating ensures high accuracy, with an average absolute error of 0.029 m at 5 m from the update point and 0.101 m at 10 m, meeting the requirements for automated cutting. The successful application of this method verifies its feasibility in actual mining processes, providing a new technical approach for achieving unmanned and intelligent coal mining.



Academic Editor: Paolo Renna

Received: 26 December 2025

Revised: 29 January 2026

Accepted: 30 January 2026

Published: 25 February 2026

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Keywords: dynamic geological models; running trajectory; coal mining machine; planned cutting

1. Introduction

Coal holds an important position in China's energy structure and is the "ballast stone" of energy supply [1]. With the high-quality development of China's economy and the rapid growth of energy consumption, the stable supply of coal is crucial for ensuring the country's energy security [2]. Traditional coal mining methods have safety risks and low efficiency. Unmanned and intelligent mining can reduce the number of personnel going

underground and lower safety risks through remote control and automated equipment, thereby improving mining efficiency and resource utilization rates [3,4].

China's intelligent coal mining has experienced several stages, namely "remote control-memory cutting-planned cutting" [5]. In the "remote control" phase, coal mining mainly relies on remote control technology, achieving unmanned or minimally manned operations on underground working faces. This marks a shift from traditional manual operations to automated and remote operations, enhancing the safety and efficiency of the work. With the advancement of technology, coal mine intelligence has entered the memory cutting stage [6], where the coal mining machine can remember its previous cutting trajectory and, to a certain extent, automatically cut coal based on the remembered path. However, this method has limitations as it cannot adapt to real-time changes in the coal seam, resulting in insufficient precision in mining. To overcome the shortcomings of memory cutting, intelligent coal mining has begun to explore planned cutting technology. By establishing a 3D geological model of the working face and utilizing high-precision detection and data analysis technologies, accurate positioning and automated control of the coal mining machine are achieved. This enables the coal mining machine to adjust its cutting trajectory based on real-time data, thereby achieving more precise and efficient mining [7,8].

In recent years, scholars at home and abroad have conducted extensive research on key technologies related to planned cutting and geological modeling. Hao et al. [9] proposed a construction method and dynamic update mechanism for a digital coal seam model suitable for shearer autonomous navigation cutting. By integrating geostatistical inversion and C-SLAM advanced exploration technology, they improved the resolution and real-time performance of the model, providing accurate navigation coordinates for shearer cutting. Zhu et al. [10] developed an off-site geological survey method for longwall faces based on multi-source monitoring data fusion. By combining hydraulic support attitude data and image segmentation technology, they realized the automatic extraction of coal-rock columns and roof lines, which helped improve the efficiency and accuracy of geological model updates. Cui et al. [11] compared and analyzed various spatial interpolation methods for high-precision 3D geological modeling of coal mining faces, providing technical support for optimizing the accuracy of geological model construction. Ren et al. [12] aimed at the problem of intense mining pressure in deep multi-coal seam mining, proposed a deep-hole blasting roof cutting and pressure relief technology, which indirectly verified the importance of geological condition perception for mining safety and efficiency. Bo et al. [13] developed a dynamic prediction model for mining-induced ground subsidence based on the Hook function, providing a reference for understanding the dynamic evolution law of geological environments during mining.

However, planned cutting technology still faces critical challenges in practical applications. Firstly, the accuracy of the geological model is difficult to meet the requirements of precise control of the coal mining machine. Although existing interpolation methods and multi-source data fusion technologies have improved model accuracy to a certain extent, they still struggle to effectively capture small-scale geological structures such as small-amplitude faults within the working face. Secondly, there is a technical barrier between geological information and production control information, and the effective conversion of geological model parameters into coal mining machine control parameters remains to be further studied. More importantly, small-amplitude geological faults in the working face are difficult to accurately predict through near-working-face detection information. In contrast, coal seam thickness changes can be quickly and accurately updated using new data obtained during mining. The low prediction accuracy of small-amplitude faults not only affects the accuracy of mining planning but also may lead to water inrush hazards from aquifers, which poses a serious threat to the safe production of coal mines in China.

The water inrush accident in the Xinhua Coal Mine in Anhui Province, as studied by Sakhno et al. [14], vividly reflects this engineering risk. During the mining of the 815 longwall in the 81 mining area of the Xinhua Coal Mine, the activation of the 815F16 high-angle fault (with a displacement of 7.5 m) led to sandstone fractures in the overlying rock, forming a water-conducting channel. The maximum water inflow reached 300 m³/h, which not only seriously affected the normal mining order but also posed a great threat to the safety of underground personnel. This case shows that the lack of accurate prediction of small-amplitude faults in the geological model is one of the important causes of water inrush accidents. Therefore, improving the prediction accuracy of small-amplitude faults in the geological model is an urgent engineering problem to be solved in current intelligent coal mining.

In view of the above research status and existing gaps, this paper focuses on the key technical problems of planned cutting technology. It proposes an improved smooth discrete interpolation method for geological model updating to enhance the ability to capture small-scale geological structures. At the same time, it studies the parameter conversion method between geological models and coal mining machine control, aiming to break the technical barrier between geological information and production information. Through field tests, the feasibility and accuracy of the proposed method in achieving precise control of the coal mining machine are verified, providing technical support for improving the safety and efficiency of intelligent coal mining and preventing water inrush hazards.

Our main contributions are as follows:

The main contributions of this paper are summarized as follows. An improved smooth discrete interpolation method is developed for geological model updating, which enables the dynamic update of geological models. By optimizing neighborhood discretization and roughness constraint conditions, this method enhances the identification ability of small-amplitude faults, thereby improving the accuracy of local geological models and laying a foundation for water inrush risk prevention. In addition, a conversion method from geological information to control parameters for coal mining equipment is proposed, which realizes the effective transformation of geological model parameters such as coal seam thickness and fault location into control parameters including the drum height of coal mining machines, thus breaking the technical barrier between geological information and production information. Furthermore, through planned cutting tests of coal mining machines based on transparent geological models, the feasibility of controlling the cutting path via geological models is verified. The proposed method exhibits favorable adaptability especially in dealing with small-amplitude faults, providing a new technical approach for the realization of unmanned and intelligent mining while ensuring mining safety.

2. Problem Statement

During the planned cutting test process, the coal mining machine automatically plans the cutting path according to the geological model of the working face and the preset cutting parameters, achieving precise and efficient mining. Planned cutting refers to the cutting path generated by the geological model for the operation of the coal mining machine drum as the cutting curve [15,16]. The cutting curve can integrate geological information with comprehensive mining equipment parameters, transforming them into control parameters required by the coal mining machine, to achieve automated control of coal mining, as shown in Figure 1.

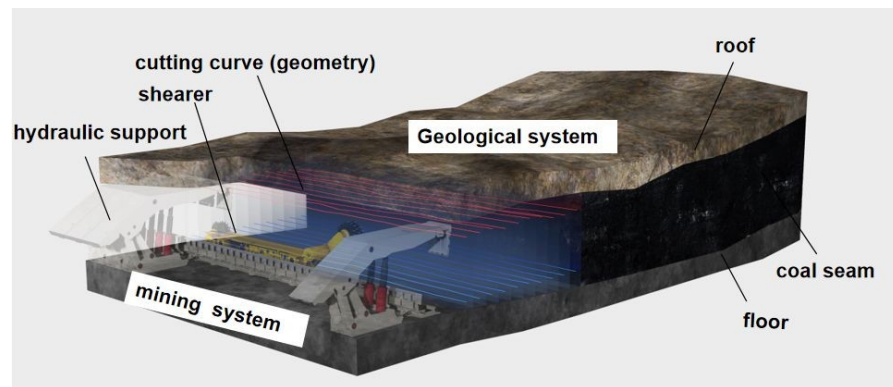


Figure 1. Schematic diagram of the planned cut-off.

The cutting curve is provided by the high-precision geological model of the working face. Therefore, the key to improving the control accuracy of the coal mining machine's trajectory lies in enhancing the precision of the working face model. As shown in Figure 2, as with the fully mechanized mining face progressively advances, new geological data are continuously revealed during the mining process. The area close to the working face reveals more geological information compared to the distant areas. Therefore, dynamic updating of the geological model can be carried out for the area near the working face, improving the accuracy of the local geological model. The model of the working face is essentially a surface model composed of a series of point data, which are a combination of sampled data and interpolated data. The dynamic updating process of the working face model is essentially a process of interpolation calculation [17,18]. However, traditional interpolation methods find it difficult to quickly update the geological model. Therefore, a new interpolation method is needed to meet this requirement.

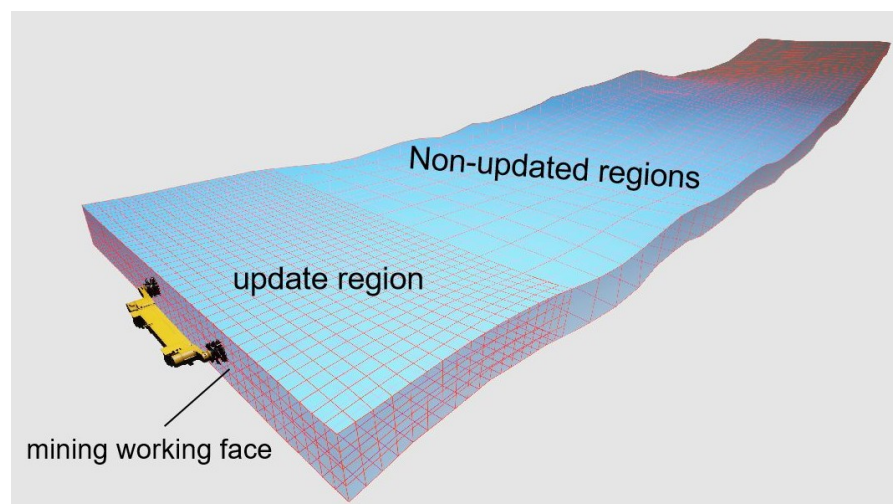


Figure 2. Schematic diagram for updating the geological model of the working face.

3. The Construction Method of Dynamic Geological Models

The interpolation algorithm serves as the basis for the construction and updating of the geological model of the working face. The discrete smooth interpolation algorithm operated by creating a network of mutual contacts for a discretized natural body model, where the values of unknown nodes are obtained by solving a system of linear equations, provided that the values of the points in the network satisfy certain criteria [19,20]. This method relies on the topological relationships between the mesh nodes. It is a dimensionless interpolation method that is not influenced by spatial coordinates. The smooth discrete interpolation method can support local dynamic updating and modeling of complex

geological conditions. Accordingly, the present study presents a novel interpolation method for dynamic updating of the comprehensive mining face that is based on the smooth discrete interpolation algorithm by combining the characteristics of the discrete data of the comprehensive mining face. The method consists of several components, including domain discretization, development of a discrete model of the comprehensive mining face, application of roughness constraints, establishment of interpolation formulas and their solution, and dynamic update of the model.

3.1. Discretization of the Neighborhood

In implicit functions, the values of unknown nodes are computed based on the relationships between scattered points in proximity, although it is greatly challenging to define the neighborhood [21]. In previous studies, scholars defined the neighborhoods using Delaunay triangles or Cartesian coordinate grids [22,23]. Since the working face model requires “slices” of uniformly spaced grids [24,25], it is reasonable to utilize the coordinate grid to model grid neighborhoods. It is assumed that all points lie on the Cartesian grid. The entire set of grid points is sub-categorized into three different sets that can be represented as the following union, as shown in Figure 3:

$$\Omega = \{\Omega_E \cup \Omega_B \cup \Omega_I\} \quad (1)$$

where Ω is the set of all points within the work face, Ω_E is the set of points located at the corners of the grid, Ω_B is the set of points positioned on the grid boundaries, and Ω_I is the set of points lying within the grid. All the distinct sets of grid points are illustrated in Figure 3, which includes three typical grid types: the central-node grid, corner-node grid, and edge-node grid; each point X_j has its own neighborhood $N(x_j)$.

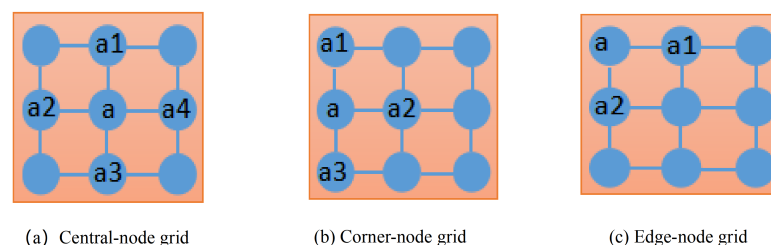


Figure 3. Schematic representation of the neighborhood.

3.2. Discrete Model of Integrated Mining Face

A discrete model of the comprehensive mining work face $M^n(\Omega, N, \phi, C)$ is established. Here, $\phi(a)$ is an n -dimensional vector function defined for the set; C represents the constraints for interpolating the workplace; $N(a)$ represents the neighborhood of point a , as has been described in the previous section.

Set Ω can be divided into two subsets: set $\phi(l)$ of unknown nodes ‘I’ and set $\phi(i)$ of known nodes ‘L’.

$$\begin{cases} L = \text{node } l \in \Omega \text{ set, Where } \phi(l) \text{ known} \\ I = \text{node } i \in \Omega \text{ set, Where } \phi(i) \text{ unknown} = \Omega - L \end{cases} \quad (2)$$

As mentioned earlier, the nodes defined in the discrete model for the comprehensive mining face are located on a Cartesian grid. Therefore, it is presumed that all data on the initial grid is known. Subsequently, a new grid is established. The interpolation constraints for the comprehensive mining face solely take into account roughness as a constraint

and do not consider soft constraints. Based on this, the non-crossing constraint condition is implemented.

$$\left. \begin{array}{l} \text{C No cross-cutting constraints.} \\ R^*(\phi^v) \text{ minima} \end{array} \right\} \Rightarrow R^*(\phi) \text{ minima} \quad (3)$$

This simplifies the complexity of the interpolation function and the computation process.

3.3. Roughness Constraint

The interpolation method applied to the working face is adapted from the smooth discrete interpolation method proposed by Professor Mallet, as expressed in Equations (4) and (5). The global roughness is calculated based on the definition of smooth discrete interpolation as follows:

$$R(\varphi) = \sum_{a \in \Omega_C} \mu(a) \cdot R(\varphi | a) \quad (4)$$

where a represents a certain grid node in the stratum surface; $\mu(a)$ is a non-negative weight function within the global domain, reflecting the contribution of each point within the working surface to the overall roughness; $R(\varphi | a)$ represents the local roughness and it is calculated as follows:

$$R(\varphi | a) = \left\{ \sum_{\beta \in N(a)} v^v(\alpha, \beta) \cdot \varphi^v(\beta) \right\}^2 \quad (5)$$

where a represents a certain grid node in the stratum surface, β denotes another grid node on the stratum surface that is different from a ; $v^v(\alpha, \beta)$ represents the weight at node a ; v represents different dimensions, which can be determined based on the neighborhoods mentioned in the previous section. For instance, in Figure 3a, there are four points in the neighborhood of the node, resulting in v being equal to 4. Similarly, as shown in Figure 3b,c, v is equal to 3 and 2, respectively; $\varphi^v(\beta)$ is a known point vector function in the comprehensive mining face.

From the above, the roughness constraint is primarily determined by the global weight function and the local weight function. To perform interpolation calculation for the comprehensive mining working face, the local weight function is selected as the harmonic weight coefficient. $v^v(\alpha, \beta)$ is calculated using the following formula:

$$\forall v : v^v(\alpha, \beta) = v(\alpha, \beta) = \begin{cases} 1 & \text{if } \beta = \alpha \\ -|N^0(a)| & \text{if } \beta \in N^0(a), \beta \neq \alpha \end{cases} \quad (6)$$

Given that the data types of the known points are the same, their respective weights will also be the same. Therefore, the global weight function $\mu(a)$ is defined as:

$$\mu(a) = 1 \quad \forall a \in \Omega \quad (7)$$

3.4. Establishment of Interpolation Formulae and Solutions

Once the global roughness and local roughness are defined, the implicit function equations within the working surface are established. As previously mentioned, the soft constraints are not taken into account. Therefore, the constraint equations are expressed as follows:

$$R^*(\varphi) = R(\varphi) + \rho(\varphi) = R(\varphi) = \sum_{a \in \Omega} \mu(a) R(\varphi | a) \quad (8)$$

where $\rho(a)$ is a soft constraint, where

$$R(\varphi | a) = \left\{ \sum_{\beta \in N(a)} v^v(\alpha, \beta) \cdot \varphi^v(\beta) \right\}^2 = \varphi^T v(\alpha, \beta) v(\alpha, \beta)^T \varphi \quad (9)$$

Equation (9) is substituted into Equation (8) and $a = 1$ to get the following formula:

$$R(\varphi) = \sum_{a \in \Omega} \mu(a) R(\varphi | a) = \sum_{a \in \Omega} \varphi^T v(\alpha, \beta) v(\alpha, \beta)^T \varphi \quad (10)$$

First-order partial derivation of the constraint equations is performed to get the solution:

$$\frac{\partial R(\varphi)}{\partial \varphi(a)} = 2\varphi(a) \sum_{a \in N(a)} v(\alpha, \beta)^2 + 2 \sum_{a \in N(a)} \left\{ v(\alpha, \beta) \sum_{\substack{\beta \in N(a) \\ \beta \neq \alpha}} v_{\beta}(k) \varphi(\beta) \right\} = 0 \quad (11)$$

The following solution is achieved:

$$\varphi(a) = -\frac{1}{M(a)} \left\{ \sum_{a \in N(a)} \left[v(\alpha, \beta) \sum_{\substack{\beta \in N(a) \\ \beta \neq \alpha}} v_{\beta}(k) \varphi(\beta) \right] \right\} \quad (12)$$

where

$$M(a) = \sum_{a \in N(a)} \varphi(a) v(\alpha, \beta)^2 \quad (13)$$

The solution of the objective function is obtained by iteratively solving Equation (11) using the most rapid descent method to find $\varphi(a)$.

3.5. Local Dynamic Update

The most effective method to improve the model accuracy during model dynamic updating is to increase the amount of interpolated data [26]. During the coal excavation from the mine, new data are continuously exposed. The addition of new data expands the local database, and effectively utilizing these data can improve the accuracy of the local model.

The local dynamic update process of the working face is executed using the smooth discrete interpolation algorithm, which is a relatively simple operation. A subset of the determined iterative calculations can be used to dynamically update the local part of the synthesized working face depending on the extent of the necessity for local updating.

4. Experiments

4.1. Data Acquisition

The proposed method is implemented at a shaft coal mine in Shaanxi, China. The mining operation involves the use of a working face to extract coal from the working face in a single operation. The coal seam being extracted is part of the Yan'an group. The length and width of the working face are 1500 m and 300 m, respectively. The coal seam has a thickness ranging from 1.3~3.0 m, with an average thickness of 2.72 m. The estimated recoverable reserve of the mine is 836,000 tonnes. There are no trapped pillars or igneous rocks present within the working face. The general trend indicates that the coal seam ascends along the stopping line towards the cutting eye. The data used for modeling mainly

include roadway measurement data, cut eye measurement data, ground drilling data, and downhole drilling data, as shown in Figure 4.

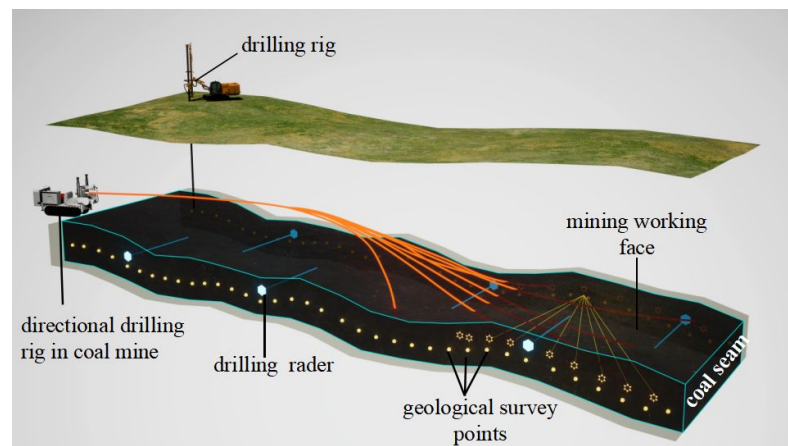


Figure 4. Comprehensive map of exploration data for the integrated mining face.

The working face uses the Xi'an Coal Machine MG1660-WD coal mining machine, suitable for an inclined angle of less than or equal to 45 degrees, with a drum diameter of 1800 mm, a cutting depth of 800 mm, and a maximum cutting depth of 240 mm; it uses the ZY6800/12/25D support, with the internal width of the support being 1.5 m, the number of supports being 157, and suitable for a maximum inclined angle of less than or equal to 20 degrees.

4.2. Coal Mining Machine Trajectory Control Parameter Conversion

Achieving control of the coal mining machine based on a geological model requires the registration of the geological model with the equipment coordinates, as well as the transformation of key parameters and control of the coal mining machine drum height.

4.2.1. Coordinate Registration

The key to controlling the operating trajectory of the coal mining machine based on a geological model lies in the precise registration of the 3D geological model with the location of the comprehensive mining equipment [27,28]. The transformation of geological model parameters into three-dimensional equipment control parameters is based on the position of the coal mining machine for parameter calculation. Therefore, achieving the positional registration between the geological model and the comprehensive mining equipment will provide fundamental support for the transformation of geological model parameters and the control of the three-machine equipment.

Currently, the data for obtaining the three-dimensional spatial position of the coal mining machine is acquired through the following methods: by measuring the data of the targets in the two entries and the advance distance to determine the advance distance of the intake and return airways; by using the encoder of the coal mining machine and the laser data of the supports to determine the position of the coal mining machine within the working face; and by obtaining the elevation data of the coal mining machine through inertial navigation data.

The construction of a three-dimensional geological model needs to be unified with the coordinates of the coal mining machine; therefore, it is necessary to perform coordinate transformation on the geological model to construct a new coordinate system. In the actual process, the intersection point of the stope line and the belt entry is usually taken as the origin, with the direction towards the cutter entry along the belt entry as the X-axis, the direction towards the return airway along the belt entry as the Y-axis, and the vertical

upward direction as the Z-axis. For the roadway measurement coordinates, a coordinate transformation is required with the geological model coordinates, as shown in Equation (14). The coordinate system for the construction of the three-dimensional geological model needs to be registered with the position of the coal mining machine. By registering the newly created coordinate system of the three-dimensional geological model with the coal mining machine data, the X-coordinate represents the distance from the stope line; the Y-coordinate represents the position on the working face, with the machine head located at the belt entry, and the Z-coordinate represents the elevation. This completes the registration of the geological model with the positions of the three machines.

$$\begin{cases} x = (X_0 - n) \cos \theta + (Y_0 - p) \sin \theta \\ y = (Y_0 - p) \cos \theta - (X_0 - n) \sin \theta \\ z = Z_0 - q \end{cases} \quad (14)$$

In the equation, (X_0, Y_0, Z_0) represents the coordinate system under the total station; (n, p, q) represents the origin of the new coordinate system; and θ represents the angle between the two coordinate systems.

The results obtained by converting the coordinates of drilling data and working face roadway survey data through the aforementioned methods are shown in Table 1, and these data are used as the basic data for geological modeling.

Table 1. Basic data table for 3D geological model construction.

Serial Number	X	Y	Floor Elevation	Roof Elevation	Serial Number	X	Y	Floor Elevation	Roof Elevation
1	52,681.60	89,108.77	839.00	842.13	61	52,409.22	89,235.47	852.53	852.53
2	52,680.83	89,132.86	839.62	842.72	62	52,409.16	89,255.90	853.36	856.49
3	52,679.97	89,151.44	840.01	843.08	63	52,407.17	89,274.18	854.03	854.03
4	52,679.12	89,171.74	840.71	843.72	64	52,406.60	89,293.33	854.69	854.69
5	52,678.27	89,190.48	841.30	844.31	65	52,406.69	89,313.06	856.34	859.34
6	52,677.24	89,211.58	841.21	844.41	66	52,404.41	89,354.18	858.61	858.61
7	52,676.18	89,233.81	841.76	844.80	67	52,403.83	89,375.14	859.90	862.94
8	52,675.52	89,255.89	842.77	845.72	68	52,402.46	89,396.41	861.04	861.04
9	52,674.56	89,276.63	843.33	846.44	69	52,401.65	89,415.66	862.32	862.32
10	52,673.40	89,300.65	843.82	846.94	70	52,401.38	89,434.05	863.67	866.89
11	52,672.70	89,320.94	844.64	847.63	71	52,400.65	89,454.64	864.77	864.77
12	52,671.71	89,343.33	845.32	848.59	72	52,399.15	89,472.15	865.66	865.66
13	52,670.92	89,357.48	846.10	849.29	73	52,398.68	89,492.95	866.99	870.13
14	52,670.30	89,376.40	846.86	849.97	74	52,397.42	89,512.00	867.86	867.86
15	52,669.45	89,395.23	847.25	850.60	75	52,396.78	89,530.26	868.80	868.80
16	52,668.45	89,417.68	848.26	851.21	76	52,395.88	89,556.20	870.13	873.27
17	52,667.59	89,436.97	849.11	852.12	77	52,394.86	89,578.97	870.96	870.96
18	52,666.80	89,455.51	849.77	852.88	78	52,394.10	89,601.37	871.35	871.35
19	52,665.99	89,472.46	850.56	853.55	79	52,393.27	89,618.91	871.59	874.75
20	52,664.94	89,496.40	851.27	854.57	80	52,392.33	89,637.02	871.64	871.64
21	52,664.03	89,516.55	852.40	855.60	81	52,391.21	89,656.29	871.62	871.62
22	52,663.16	89,535.94	853.39	856.50	82	52,390.85	89,677.87	871.63	874.55
23	52,662.41	89,555.27	853.86	857.24	83	52,389.65	89,699.10	871.68	871.68
24	52,661.53	89,574.03	854.78	858.01	84	52,388.91	89,718.54	871.57	871.57
25	52,660.95	89,590.13	855.23	858.22	85	52,387.78	89,745.02	871.76	871.76
26	52,659.99	89,608.45	855.73	858.85	86	52,386.37	89,774.47	871.82	871.82
27	52,659.11	89,627.41	856.05	859.17	87	52,386.18	89,791.11	871.24	874.07
28	52,658.24	89,647.31	856.35	859.44	88	52,384.80	89,810.32	871.10	871.10

Table 1. Cont.

Serial Number	X	Y	Floor Elevation	Roof Elevation	Serial Number	X	Y	Floor Elevation	Roof Elevation
29	52,657.33	89,667.10	856.67	859.74	89	52,383.02	89,834.56	870.67	870.67
30	52,656.60	89,683.99	856.66	859.69	90	52,382.47	89,852.92	870.16	870.16
31	52,655.52	89,706.84	856.73	859.97	91	52,381.60	89,873.63	870.09	870.09
32	52,654.69	89,726.27	855.74	858.78	92	52,380.54	89,911.36	869.87	872.43
33	52,653.94	89,743.02	855.80	858.95	93	52,379.20	89,932.52	869.73	869.73
34	52,653.15	89,768.01	856.41	859.42	94	52,377.83	89,958.41	869.21	869.21
35	52,652.23	89,787.41	856.73	860.06	95	52,376.50	89,987.22	869.62	872.82
36	52,651.25	89,807.53	855.89	858.98	96	52,383.61	89,987.60	869.22	869.22
37	52,649.90	89,831.99	855.48	858.56	97	52,393.57	89,988.30	869.13	869.13
38	52,649.59	89,846.67	855.56	858.51	98	52,403.46	89,989.00	869.20	869.20
39	52,648.57	89,867.11	855.97	859.20	99	52,413.62	89,989.41	869.25	869.25
40	52,647.51	89,887.94	856.21	859.25	100	52,423.80	89,990.23	868.81	868.81
41	52,644.45	89,907.88	856.84	859.83	101	52,433.45	89,990.26	868.34	868.34
42	52,643.64	89,928.16	857.69	860.73	102	52,443.78	89,987.73	867.98	867.98
43	52,641.22	89,950.38	858.79	861.89	103	52,454.13	89,988.17	867.14	867.14
44	52,425.43	88,895.18	839.71	842.89	104	52,463.62	89,988.71	866.61	866.61
45	52,422.96	88,917.79	840.30	840.30	105	52,474.11	89,988.54	865.86	865.86
46	52,421.83	88,936.63	840.67	840.67	106	52,484.25	89,989.40	865.65	865.65
47	52,422.04	88,953.55	841.09	844.13	107	52,494.32	89,989.70	865.39	865.39
48	52,421.03	88,974.77	841.79	841.79	108	52,504.13	89,990.19	865.02	865.02
49	52,419.84	88,995.41	842.12	842.12	109	52,516.07	89,990.90	864.48	867.13
50	52,418.73	89,018.13	842.79	845.90	110	52,524.24	89,991.40	864.14	864.14
51	52,417.82	89,038.85	843.72	843.72	111	52,534.18	89,991.80	863.85	863.85
52	52,416.95	89,057.38	844.55	844.55	112	52,544.54	89,992.29	863.68	863.68
53	52,416.74	89,076.19	845.55	848.66	113	52,554.21	89,992.80	863.48	863.48
54	52,415.48	89,095.90	846.10	846.10	114	52,564.24	89,993.23	863.25	863.25
55	52,414.54	89,113.32	846.35	846.35	115	52,574.86	89,993.68	862.92	862.92
56	52,413.50	89,135.84	847.40	850.79	116	52,574.77	89,993.68	862.93	862.93
57	52,412.65	89,154.15	848.33	848.33	117	52,585.10	89,994.12	862.63	862.63
58	52,411.60	89,174.45	849.39	849.39	118	52,595.11	89,994.49	862.39	862.39
59	52,411.49	89,197.54	850.50	853.42	119	52,605.36	89,994.88	862.04	862.04
60	52,409.71	89,216.82	851.74	851.74	120	52,615.49	89,995.36	861.78	861.78

4.2.2. Parameter Transformation

The process of converting three-dimensional geological model data into geological parameters required for comprehensive mining equipment mainly includes the following steps:

Step1: Set the grid interval in the strike and dip directions of the mining face. Divide the digital model of the coal seam into a grid along both directions and project the grid onto a 2D horizontal plane. Project the planned cutting path of the coal mining machine onto the grid plane projection diagram, and approximate the planned cutting path into a finite number of straight-line segments. Project the surfaces of the coal seam roof and floor onto the 2D horizontal plane. For each straight-line segment, calculate the straight-line equation $y = ax + b$ between the starting and ending points of the cutting sequence, and compute the planar coordinates of the intersection points of the straight-line segments with the grid lines and the corresponding roof/floor elevations. Connect the obtained roof/floor control points in the order of the straight-line segment direction to obtain the roof/floor interface curves.

Step2: The planned cutting route is projected onto the grid plane and the projected curve is discretized into n line segments; the grid interval in the length and width directions of the working face is set, and the coal seam is gridded on a two-dimensional plane to obtain two-dimensional plane grids, roof grids, and floor grids; the planned cutting route is projected onto the grid plane and discretized into a finite number of line segments, and

the planar coordinates of the intersection points of each line segment with the grid lines are determined to obtain the projected point sequence of the planned cutting route on the two-dimensional plane. Assuming that the projected curve is discretized into n line segments, for the i th line segment, the coordinates of the two endpoints are (x_i, y_i) and (x_{i+1}, y_{i+1}) , respectively.

For each projected point, search for the grid point closest to the projected point in the two-dimensional plane within both the roof and floor grids, and take the elevation of the roof and floor at that point as the elevation value of the roof and floor at the projected point, obtaining the roof point and floor point. Connect the roof point sequence and floor point sequence in order along the cutting direction to obtain the roof/floor interface curve, which is the cross-section of the coal seam to be cut.

Step3: For the j th projected point (x_j, y_j) , a neighborhood parameter r is set, and all grid points with plane coordinates falling within the neighborhood area $\{x_i + r < x < x_j + r, y_i + r < y < y_j + r\}$ in both the roof and floor grids are searched; the roof and floor elevations (x_j, y_j) corresponding to the j th projected point can be determined by two methods: the nearest distance method and the distance-weighted method. The nearest distance method involves taking the elevation value of the coal seam roof and floor corresponding to the grid point closest to the projected point in the two-dimensional plane within the neighborhood as the control points for the roof and floor (x_j, y_j, z_{li}) and (x_j, y_j, z_{2i}) corresponding to the projected point. The distance-weighted method involves calculating the planar distance from each grid point within the neighborhood to the projected point (x_j, y_j) , allocating the roof and floor elevation weights based on the inverse of the planar distance, and calculating the weighted average of the roof and floor elevations z_{li} and z_{2i} corresponding to the projected point (x_j, y_j) .

Step4: The coal mining machine's cutting curve has roof and floor data points of the coal seam at certain grid intervals, and the coordinates of the coal seam roof and floor corresponding to the position of the coal mining machine's drum can be calculated based on the coal mining machine's position. According to the position of the coal mining machine and the cutting curve, a series of mining heights, bottoming values, inclination angles in the working face direction, and inclination angles in the advance direction can be calculated. When the coal mining machine reaches a specified position, the corresponding parameters are sent to the coal mining machine, and the coal mining machine automatically adjusts the height of the drum to achieve planned cutting. The parameters sent to the coal mining machine are (x_i, H_c, H_w) , where H_c is the mining height of the left drum of the coal mining machine, H_w is the bottoming of the right drum of the coal mining machine, and x_i is the position where the coal mining machine's encoder is located. The calculation formulas for these key parameters are as follows:

$$\begin{cases} H_c = h_{ding}^0(x_i \pm l_1) - h_{di}^0(x_i \pm l_1) \\ H_w = h_{di}^0(x_i \pm l_2) - h_{di}^1(x_i \pm l_1) \end{cases} \quad (15)$$

In the formula, x_i represents the position of the coal mining machine, l_1 is the distance from the encoder position of the coal mining machine to the right drum in millimeters (mm); l_2 is the distance from the encoder position of the coal mining machine to the left drum in millimeters (mm); $h_b^a(c)$ is the elevation data of a certain point on the cutting curve, where a represents the cutting curve, when $a = 0$, it represents the current cutting curve where the coal mining machine is located, and when $a = 1$, it represents the cutting curve corresponding to the next cut of the coal mining machine. b indicates whether it is the roof curve or the floor curve, and c represents the position of the curve.

4.3. Coal Mining Machine Drum Control

The main principle of the coal mining machine drum height adjustment is the telescopic motion of the cylinder driving the lever rotation mechanism [29,30], which determines the longitudinal position of the drum, achieving the purpose of height adjustment. By issuing the geological cutting curve of the coal mining machine, it can be converted into the adjustment angle of the coal mining machine cylinder. The height adjustment of the coal mining machine drum can be regarded as the rotation of the cylinder body around the top point, and the mathematical model of the height adjustment mechanism is as follows:

$$\Delta Y = F(\Delta L2) = F(\Delta \theta) \quad (16)$$

where ΔY is the change in roller height, mm; $\Delta L2$ cylinder stroke change, mm; $\Delta \theta$ is the change in roller angle. When the working face involves both downward and upward mining, the expression for the height adjustment of the coal mining machine drum is:

$$H = H1 + R + L * \sin(\theta) - L2 * \tan(\beta) - B1 * \tan(\gamma) \quad (17)$$

where L is the distance from the drum center to the rotation center, in millimeters mm. H is the mining height of the coal mining machine at this drum position, in millimeters (mm); $H1$ is the height of the machine body, in millimeters (mm); R is the radius of the drum, in millimeters (mm). Among them, H , $H1$, and L are fixed values, while β and γ values are obtained through the cutting curve. By adjusting the θ value, the automatic height adjustment of the coal mining machine drum is achieved.

4.4. Quality Assurance

4.4.1. Quality Control of Data Acquisition

Preprocessing was performed on roadway survey data, open-off cut survey data, and surface as well as underground drilling data. Outliers were removed, including those with coal seam thickness deviating by more than $\pm 30\%$ from the reasonable range and discrete points with total station measurement errors exceeding 5 cm. The final valid data retention rate reached 98.7%. Data cross-validation: A bidirectional verification approach combining surface drilling data and underground radar detection data was adopted to check the consistency of key parameters such as coal seam roof and floor elevations and thickness. The verification deviation was controlled within ± 0.1 m. Equipment accuracy calibration: Before the experiment, standard calibration was conducted for instruments, including the total station, inertial navigation system and shearer encoder. The total station has an angle measurement accuracy of $\pm 2''$ and a distance measurement accuracy of $\pm (2 \text{ mm} + 2 \text{ ppm} \times D)$. The inertial navigation system has a positioning accuracy of ± 5 cm, and the shearer encoder has a resolution of 0.01 mm. During the experiment, accuracy rechecks were performed every 24 h to ensure the stability of data acquisition equipment.

4.4.2. Quality Control of Experiment Implementation

Operational parameter thresholds were defined for the shearer and hydraulic supports. The shearer model is MG1660-WD, and the hydraulic support model is ZY6800/12/25D. For example, the shearer cutting depth was fixed at 0.8 m, which is consistent with the rated parameter, and the support advancing step was set at 1.5 m to avoid experimental deviations caused by parameter fluctuations. During the experiment, areas with abnormal geological structures such as faults and fractured zones were avoided. Real-time monitoring was conducted for the working face inclination, which was controlled within 20 degrees, and coal seam thickness variation rate, which was controlled within 0.2 m per meter.

When environmental parameters exceeded the thresholds, the experiment was paused and adjusted to ensure stable experimental conditions. A dual-recording mode of automatic equipment recording and manual inspection review was adopted. Key data such as shearer drum height, cutting current, and support pressure were recorded every cutting cycle, with each cycle corresponding to a cutting depth of 0.8 m. This resulted in a 100% complete data record without missing or abnormally interrupted data.

4.4.3. Quality Control of Result Verification

Calculation methods for static and dynamic update errors of the model were clearly defined, including Root Mean Square Error and Mean Absolute Error. Uniform rules for selecting measurement points were established, with a profile interval of 30 m and 9 equidistant points set per profile, to ensure the objectivity of error analysis. For the rationality of comparative experiments, manual cutting and model-planned cutting experiments were conducted under the same working face and geological conditions, with irrelevant variables such as shearer traveling speed and cutting intensity kept consistent. The comparison indicators were unified as drum height deviation and cutting curve smoothness to ensure the validity of the comparison results. The experiment covered 7 complete working days, with the working face advancing 56 m and a total of 70 cutting cycles. Model accuracy verification was performed at different advance distances, including 1 m, 5 m, 10 m and 50 m, to ensure the stability of the proposed method in long-term engineering applications.

5. Result and Discussion

Through the aforementioned experiments, the parameters of the geological model were converted into the drum height of the coal mining machine, achieving control over the operating trajectory of the coal mining machine. During the seven-day trial period, the working face advanced by 56 m and extracted 51,000 tons of coal. In the middle of each cutting cycle, there was no human intervention, and the coal mining machine drum adjusted its height automatically, with only some local areas requiring human intervention. Some of the coal cutting cycle curves are shown in Figure 5.

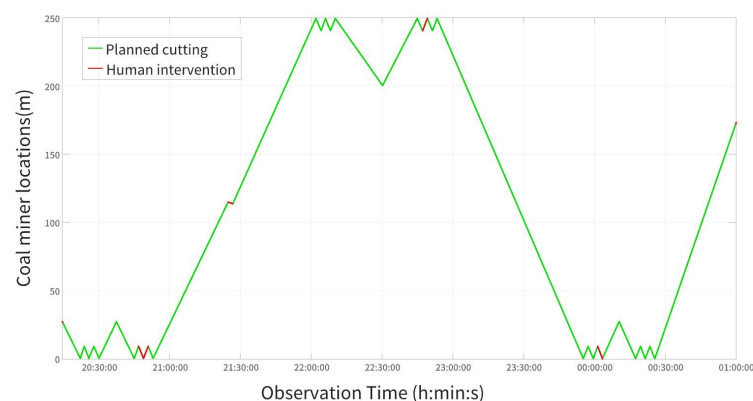


Figure 5. Coal cutting cycle curve.

To compare and analyze the errors between manual cutting and geological model-planned cutting, this study first converted the geological model to obtain the left and right drum heights of the shearer corresponding to each hydraulic support, and compared them with the drum heights during manual mining. Meanwhile, we statistically analyzed the data from four complete cutting cycles in the coal mining process, and conducted a multi-dimensional comparison of the historical manual cutting curves, the planned cutting curves generated by the geological model, and the actual coal–rock interface, yielding the results shown in Figure 6.

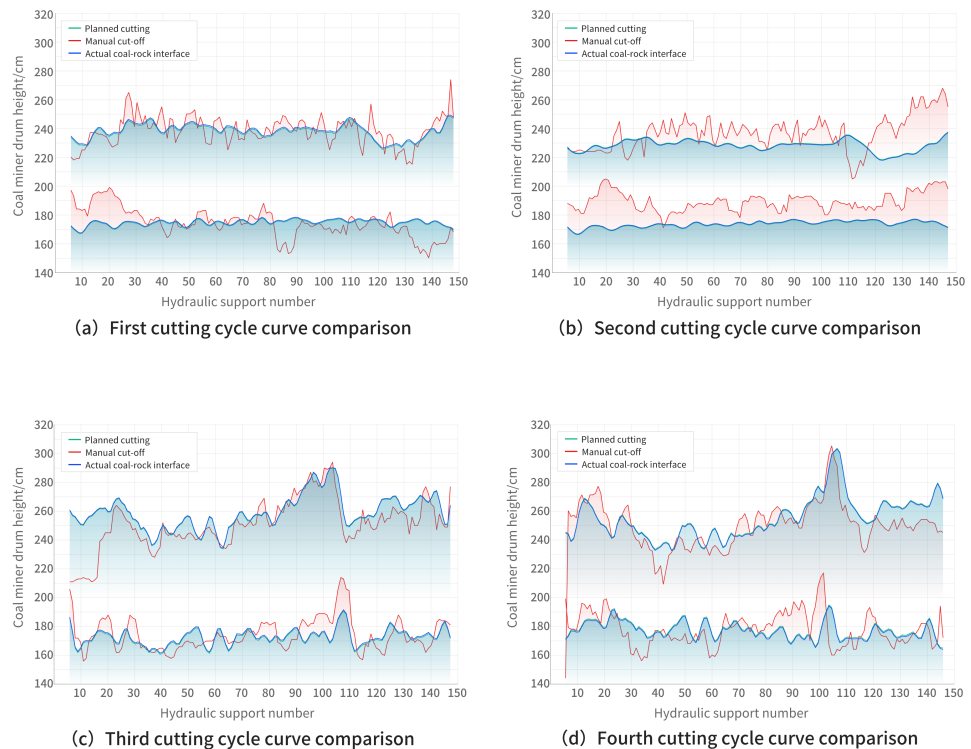


Figure 6. Geological model control roller height vs. manual mining error.

As can be seen from Figure 6a–d, the planned cutting curves generated by the geological model are generally consistent with the trend of the actual coal–rock interface, with low errors; in contrast, the manual cutting curves exhibit significant sawtooth fluctuations, reflecting more frequent manual adjustments of the drum height, whereas the curves generated by the geological model demonstrate better smoothness. During the planned cutting phase in the middle of the working face, the error between the geological model and manual mining is basically controlled within 10 cm; however, from Figure 6a,c, it can be observed that the trends of the geological model cutting curves and manual cutting curves differ significantly at supports 1–10 and 140–150, which is caused by the special cutting conditions in the triangular coal area. Therefore, the cutting curves of the geological model achieve more favorable control effects in the middle of the working face, and it is recommended to set the drum height to a fixed value in the triangular coal area to optimize control stability. In addition, when manual mining encounters areas with large working face slopes, large adjustments of the drum height lead to severe fluctuations in the curve, while the drum height curves generated by the geological model are smoother, which can effectively reduce frequent control of the drum and thus better protect the shearer equipment. The successful application of this method fully verifies the feasibility of accurately controlling the drum height of the shearer through the geological model, providing strong technical support for realizing fewer personnel and higher efficiency in the working face.

Model Precision Analysis

The accuracy of the geological model is a crucial element that impacts the implementation of the intelligent mining of the working face. To achieve intelligent mining based on transparent geology, it is necessary to limit the error of the geological model within 0.2 m. Therefore, conducting a comparative analysis of the error of the constructed geological model is of great significance for the practical application of the geological model.

The geological model of the working face is created and dynamically updated using the proposed method. To verify and analyze the accuracy of the model, both the static error

of the model and the error after the dynamic update of the model are analyzed. The error analysis method for the static geological model involves dissecting the model obtained from the above algorithm model to obtain the curve of the static model. The data of the points are then measured using a total station, and the difference between the model data and the measured data is compared to the static model error. By cutting five profiles across the geological model of the working face, nine points are extracted from each profile at intervals of 30 m. The static model error is then calculated for each point. The obtained results are shown in Table 2.

Table 2. Static model error statistics.

Sampling Point Number	Error (m)	Percentage of Error (%)	Sampling Point Number	Error (m)	Percentage of Error (%)	Sampling Point Number	Error (m)	Percentage of Error (%)
1	0.054	0.26	16	0.91	4.43	31	0.501	2.44
2	0.091	0.44	17	0.617	3	32	0.563	2.74
3	0.337	1.64	18	0.115	0.56	33	0.498	2.42
4	0.468	2.28	19	0.178	0.87	34	0.432	2.1
5	0.885	4.3	20	0.421	2.05	35	0.251	1.22
6	1.01	4.9	21	0.685	3.33	36	0.109	0.53
7	1.03	4.99	22	0.742	3.61	38	0.155	0.75
8	1.051	5	23	0.879	4.28	39	0.004	0.02
9	0.417	2.03	24	1.036	5	40	0.004	0.02
10	0.051	0.25	25	0.98	4.76	41	0.153	0.74
11	0.272	1.32	26	0.89	4.33	42	0.286	1.39
12	0.507	2.47	27	0.357	1.74	42	0.286	1.39
13	0.473	2.3	28	0.141	0.69	43	0.363	1.77
14	0.619	3.01	29	0.02	0.1	44	0.552	2.69
15	0.92	4.48	30	0.287	1.4	45	0.23	1.12

The results indicate that the static geological model has an average absolute error of 0.458 m, with a maximum error of 1.05 m and a minimum error of 0.004 m. The overall error is large and does not satisfy the requirement of intelligent mining.

The geological model is locally updated by incorporating geological write-up data. This involves using the write-up data to update the model (for instance, in the case of inertial guide and radar tuning, the model should be updated with data from the inertial guide). This implies that the data obtained from the write-up is added to the modeling data for re-modeling, and the geological model before updating and the data model after updating can be obtained. In order to verify the suitability of the updated geological model for practical mining operations, the error of the updated geological model can be obtained by comparing the updated geological model with the final model (the real model developed after multiple write-ups).

The model accuracy corresponding to the dynamic updating of the geological model is analyzed in the current mining position. The model accuracy is examined for different time periods: 1 cutting cycle (1 m), 1 mining shift (5 m), 2 days (10 m), and 5 days (50 m) in the following period. Nine equidistant points are chosen to represent the mining position in the write-up profiles. The obtained data is compared to the real model, followed by analysis and comparison of the maximal value of the error at the nine points of each write-up profile. The maximum, minimum, and average values of the errors obtained at the nine points of each write-up profile are analyzed and compared with those of the real model. The results of the analysis are shown in Figure 7.

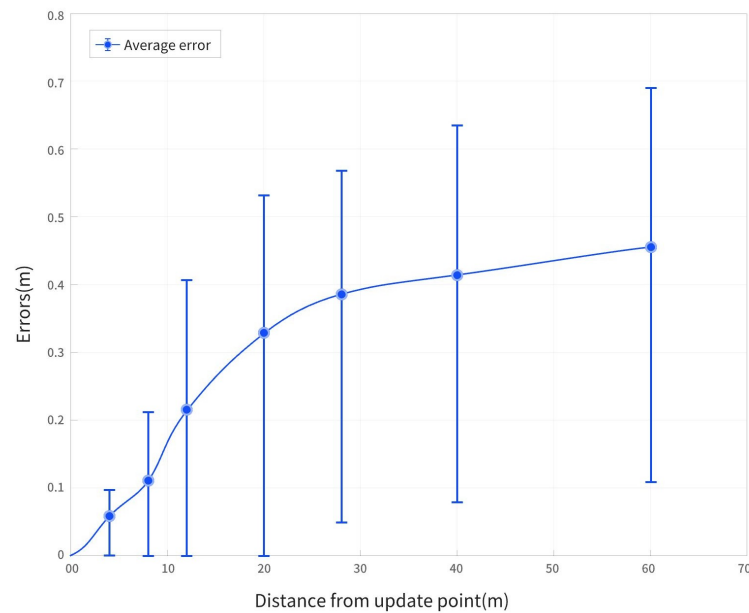


Figure 7. Comparison of error analysis of dynamic geologic models.

It is evident from the figure that at a distance of 1 m from the update point, the model error is 0. This indicates that the update can guarantee an accuracy value of 1 m distance. The average absolute error at the point located 5 m from the update point is 0.029 m, with a maximum error of 0.063 m. Similarly, at a distance of 10 m from the update point, the average absolute error is 0.101 m, and the maximum error is 0.203 m. By dynamically updating the geological model, it is possible to ensure automated cutting for one day.

6. Conclusions

This study proposes a coal mining machine cutting path control method based on dynamic geological models, addressing key challenges in planned cutting technology, such as insufficient geological model accuracy and the disconnect between geological information and equipment control parameters. An improved smooth discrete interpolation method is developed to realize efficient dynamic updating of the working face geological model, optimizing neighborhood discretization, roughness constraints, and interpolation formulas to enhance local model accuracy. Additionally, a method for converting geological information into coal mining equipment control parameters is proposed, achieving precise coordinate registration between the 3D geological model and mining equipment, and scientifically transforming coal seam roof and floor elevations into drum height control parameters. Field tests conducted in a shaft coal mine in Shaanxi verify the method's feasibility: during a 7-day trial, the working face advanced 56 m and mined 51,000 tons of coal with minimal human intervention, and comparative analysis shows the drum height control error of planned cutting is within 10 cm, with smoother curves than manual cutting, reducing equipment wear.

Dynamic model updating significantly improves accuracy compared to static models—while the static geological model has an average absolute error of 0.458 m, failing to meet intelligent mining needs, the dynamic update mechanism integrates real-time mining-exposed data, achieving average absolute errors of 0.029 m at 5 m and 0.101 m at 10 m from the update point, which meets automated cutting requirements. This research enriches the intelligent coal mining technical system, providing a new technical path for transparent geology-based precise control of coal mining machines. The results can be promoted to similar fully mechanized mining faces, contributing to the coal mining indus-

try's transformation toward unmanned, intelligent, safe, and efficient development. Future research may focus on optimizing the interpolation algorithm to accelerate model updating and expanding the method's adaptation to complex geological conditions like faults.

Author Contributions: Methodology, L.A.; software, L.A.; validation L.A.; formal analysis, L.A.; investigation, Y.D.; data curation, Y.D.; writing original draft, Y.D.; writing review and editing, L.A.; visualization, Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (Program No. 42374176). Natural Science Basic Research Program of Shaanxi (Program No: 2024JC-YBQN-0272). Special Project of Technological Innovation and Entrepreneurship Fund of Tiandi Science and Technology Co., Ltd. (2024-TD-ZD004-03).

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Acknowledgments: We would like to thank the technical staff of the shaft coal mine in Shaanxi for their support in field tests and data collection. We also appreciate the editorial team of Applied Sciences and anonymous reviewers for their valuable comments on this manuscript.

Conflicts of Interest: Author Lin An was employed by the company CCTEG Xi'an Research Institute (Group) Co. Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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