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Research on Intelligent Control of Regional Air Volume Based on Machine Learning

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Abstract: To address the challenge of intelligently controlling air volume in regions affected by the frequent fluctuations in underground ventilation networks, a remote intelligent air regulation method based on machine learning was presented. This method encompasses three core components: local fan frequency conversion regulation, associated branch air resistance regulation, and a comprehensive integration of both. Leveraging foundational mine ventilation theory, the principles behind branch sensitivity air regulation were dissected. By applying these principles, the key performance indicators crucial for the regulation of air volume within the ventilation system were identified. Subsequently, an intelligent model for regional air volume control was constructed. To validate the approach, an experimental platform for intelligent air volume control was established, guided by geometric, dynamic, and kinematic similarity criteria. Then, the experimental methodologies for simulating various ventilation scenarios were discussed, the data acquisition techniques were introduced, and the obtained results were analyzed. Employing machine learning techniques, we utilized five distinct algorithms to predict the operational parameters of targeted air volume ventilation equipment. It enabled precise and efficient control of air volume within the region. The results indicated that the least squares support vector machine (LS-SVM) stood out by delivering high-precision predictions of target air volume ventilation equipment parameters, all while maintaining a relatively short calculation time. This swift generation of feedback data and corresponding air volume control strategies will contribute to the precise management of air volume in the area. This work served as a valuable theoretical and practical guide for intelligent mining ventilation control.

Keywords: mining ventilation; air volume control; regulation model; machine learning

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1. Introduction

Effective control of air volume within a mine's ventilation network is a critical factor in ensuring the safe, stable, and economically efficient operation of the entire ventilation system. The primary objective is to modify the distribution of air volume within the network while ensuring that the required air volume at each specific location is met. This is achieved through the most economically viable adjustments, ensuring that the air volume at all underground points aligns with safety production requirements, with a focus on the following principles: technological feasibility, reliability, and economic optimization [1–3]. Furthermore, an exemplary air volume control scheme should strive for low total energy consumption in the primary fan devices, high network efficiency, minimal ventilation facility counts, reduced branch resistance adjustments, and logical adjustment positioning [4,5].

Regional air volume adjustment primarily involves the redistribution of air volume within a specific wing or mining area within the underground mine. This redistribution is carefully executed in a manner that ensures minimal or negligible changes in the overall air volume within the entire region. The key objective of regional air volume adjustment is to optimize the use of abundant air volume within the area, effectively meeting the air volume requirements of individual air sites while ensuring that other areas of the mine remain unaffected by these adjustments. This strategic utilization of localized air volume serves to enhance efficiency and save energy [6–11]. Consequently, the study of air volume regulation within a specific area is imperative, as it guarantees that the air volume demands within that area are satisfied while concurrently achieving energy efficiency and economic optimization. This holds significant importance for the effective management and operational efficiency of the mine's ventilation system.

In the study of regional air volume regulation, the main emphasis is placed on modifying the opening and closing angles of air doors within the designated area or adjusting the operating frequency of local fans. This procedure encompasses the utilization of diverse methodologies, such as graph theory, nonlinear model solving techniques, and heuristic algorithms, to formulate the most efficient regulation strategy for the ventilation network. The overarching goal is to bolster the dependability and cost-efficiency of air volume regulation. Graph theory was initially incorporated into the optimization of air volume regulation within ventilation networks. Leveraging the distinctive features of ventilation network structures and airflow parameters, a range of methodologies has been developed to address the optimization challenge related to air volume regulation within ventilation networks. These methodologies encompass the loop method [12], path method [13], double tree method [14], and so on. In the context of the nonlinear model solution method, Johnson, T [15] developed a mathematical model aimed at optimizing the air distribution network with the objective of minimizing ventilation costs. Then, a network planning algorithm to facilitate the solution process was introduced, and the corresponding air distribution scheme was ultimately determined. Huang Yuanping et al. [16] studied the known conditions, unknown conditions, and related constraints of air volume regulation in ventilation network with the energy consumption of fans and regulating facilities in ventilation system as the optimization objective. After establishing the objective optimization function, the constrained variable metric method was introduced to solve the problem, and then the corresponding software program was designed and developed. Cui Chuanbo et al. [17] established a schedulable model for air volume adjustment and used the ventilation network to solve the range and adjustment amount of the adjustable branch. Huang Guangqiu et al. [18] analyzed the flow relationship between the branches of the ventilation system, established an analysis model for the change in air volume between the underground branches by installing the air window, and gave the sensitivity coefficient of air volume response and verified it.

Currently, numerous studies are underway that explore the application of heuristic algorithms in regional air volume regulation [19,20]. The genetic algorithm (GA) [21,22], particle swarm optimization (PSO) [23], simulated annealing algorithm (SAA) [24], grey wolf optimization with differential evolution (DE-GWO) [25], and other intelligent optimization techniques have been introduced into the research of mine air volume optimization regulation. Based on a greedy algorithm (GA) and neighborhood search (NS), Si Junhong et al. [26,27] designed and implemented the corresponding software function to optimize the air volume in a complex ventilation network. Yang Xu et al. [28] developed a linkage control system for on-demand air regulation of multiple coal mining faces in view of the air volume demand of multiple underground air use locations. Wang Kai and Pei Xiaodong et al. [29,30] established a mathematical model of branch air resistance and fan frequency conversion air volume regulation and proposed a method for determining the air volume on-demand regulation. Based on cellular automata (CA), the optimal adjustment branch is calculated, and the branch adjustment air resistance value is solved by the network; the experimental model is then established according to the typical ventilation system for verification. Ren Zihui et al. [31] proposed an intelligent control method of air volume in mine ventilation networks based on the improved beetle antennae search (BAS). The sensitivity and branch dominance theory were introduced to determine the branch set of air volume regulation and the adjustable range of air resistance. The beetle antennae search (BAS) was used to solve the optimal air regulation parameters, and then the corresponding air regulation facilities were controlled to realize air volume regulation. Cheng Xiaozhi et al. [32] used a Bayesian network (BN) algorithm to diagnose the health status of local ventilators and sensor equipment. The rough set (RS) and genetic algorithm (GA) were used to extract the characteristic samples and precursor information of the normal air supply and the fault state of the local ventilation. Based on a support vector machine (SVM), the decision rules of the local ventilation fault were established, and the research and early warning model for a local ventilation anomaly was established. The research and early warning for a local ventilation state and development trend were realized.

In summary, the aforementioned research has significantly advanced the optimal regulation of air volume. While heuristic algorithms have found widespread application in air volume optimization and regulation, there remain challenges in achieving real-time processing and intelligent control of actual air volume fluctuations. The majority of existing research primarily centers on the study of the overall air network, with comparatively fewer investigations into regional air volume regulation. Therefore, there is an urgent need to address how to manage changing air volume parameters and implement automatic control of branch air demand within regions affected by frequent ventilation network fluctuations. In this paper, a control method for handling air volume fluctuations within a specific area is proposed, and an intelligent control model for regional air volume is established, which is validated through experiments. In this study, the real-time data of the associated branches and the air sites in different control states under normal ventilation conditions were collected. Machine learning techniques were applied to validate and analyze the regional air volume control model, which provided critical theoretical and practical insights for the automation of ventilation system control.

The rest of the paper is organized as follows: Section 1 is the introduction. Section 2 conducted an in-depth analysis of the sensitivity air regulation principle, grounded in the basic theory of mine ventilation. This section further scrutinizes key indicators for air volume regulation, leading to the formulation of the intelligent control model for regional air volume. Section 3 provided an overview of the experimental platform and the methods employed to experimentally verify the proposed model. Moving to Section 4, five distinct algorithms were employed to predict the operating parameters of the target air volume ventilation facilities and equipment. Section 5 is dedicated to the discussion of findings, and Section 6 presents the overall conclusion of the study.

2. Theory and Model

In a mine ventilation system, the stability of airflow stands as the critical determinant of ventilation quality and safety. This challenge is not confined to diagonal air paths alone but is a common concern in various ventilation routes. Due to interdependencies among branches within the air network, changes in the aerodynamic characteristics of one branch, such as alterations in air resistance and air speed, can impact the air volume distribution across other branches. Modifications in the air resistance or resistance of a single branch may result in shifts in the distribution of air volume, potentially influencing the ventilation effectiveness of other branches. This intricate interaction can lead to instability in the ventilation system, subsequently compromising ventilation quality and safety. Consequently, comprehending and effectively managing airflow stability within the ventilation system is of paramount importance to ensure the normal operation and safety of mining activities.

2.1. Mine Ventilation Theory

Numerous factors influence the stability of a ventilation network. Constraints related to the aerodynamic characteristics among network branches often exhibit intricate and nonlinear relationships that resist straightforward mathematical expressions. Therefore, by leveraging principles, like the ventilation system node, air volume balance, and the loop air pressure balance law, we can analyze the constraints related to aerodynamic characteristics within the ventilation network. This analytical approach offers a theoretical solution, helping to eliminate the influence of human or empirical factors and addressing the network's stability more effectively. The law of node air volume balance and loop air pressure balance [33] is shown as follows:

$$\begin{cases} \sum\limits_{j=1}^{N} a_{ij}Q_j = 0 \\ f_k = \sum\limits_{j=1}^{n} b_{kj}[R_j|Q_j|Q_j - P_k - F_k(Q_k)] = 0 \end{cases} \tag{1}$$

where a_{ij} represents the elements of the incidence matrix, meaning that node i is positively associated with branch j when a_{ij} = 1, node i is negatively associated with branch j when a_{ij} = −1, and node i is not associated with branch j when a_{ij} = 0. Q_j represents the air volume of branch j, m^3/s. f_k represents the algebraic sum of the air pressure of loop k, Pa. b_{kj} represents the independent loop matrix elements. R_j represents the air resistance of branch j, kg/m^7. P_k represents the algebraic sum of the natural air pressure of loop k, Pa. $F_k(Q_k)$ represents the algebraic sum of the fan air pressure of loop k, Pa. i = 1, 2, . . ., m, j = 1, 2, . . ., n, k = 1, 2, . . ., l.

2.2. Principle of Regulating Air Principles of Branch-Sensitive

The core problem addressed by the branch regulation sensitivity model is how the air volume of other branches in the ventilation system should respond to changes in the friction air resistance of one branch. Let m represent the change in frictional air resistance and let the change in frictional air resistance be ΔR_m. Due to the change in the frictional air resistance of branch m, its ventilation resistance also changes accordingly. In order to maintain the resistance balance of the ventilation system, the air volume of each branch must be adjusted accordingly, with the change amount set to ΔQ_i for each branch. Obviously, regardless of any changes that occur, the ventilation network must adhere to the law of node air volume balance, which can be expressed as follows:

$$\sum\nolimits_{j=1}^{N} a_{ij}(Q_J + Q_j) = 0, (i = 1, 2, \cdots, J-1) \tag{2}$$

Combining Equations (1) and (2) allows us to obtain the following:

$$\sum\nolimits_{j=1}^{N} a_{ij}\Delta Q_j = 0, (i = 1, 2, \cdots, J-1) \tag{3}$$

According to the law of air pressure balance, an equation for air pressure balance is established. It can be expressed as follows:

$$\begin{gathered} b_{im}(R_m + \Delta R_m)(Q_m + \Delta Q_m)|Q_m + \Delta Q_m| + \\ \sum\nolimits_{j=1, j\neq m}^{N} b_{ij}\left[R_j(Q_j + \Delta Q_j)\left|Q_j + \Delta Q_j\right| - P_j - F_j(Q_j + \Delta Q_j)\right] = 0, (i = 1, 2, \cdots, m) \end{gathered} \tag{4}$$

Since Equation (3) determines $J-1$ independent equations and Equation (4) also determines $M = N - J + 1$ independent equations, the set of N equations formed by combining Equations (3) and (4) can fully determine the variation in air volume for N branches. Equations (5) and (6) are as follows:

$$\begin{gathered} f_i(\Delta Q_1, \cdots \Delta Q_N) = b_{im}(R_m + \Delta R_m)(Q_m + \Delta Q_m)|Q_m + \Delta Q_m| + \\ \sum\nolimits_{j=1, j\neq m}^{N} b_{ij}\left[R_j(Q_j + \Delta Q_j)\left|Q_j + \Delta Q_j\right| - P_j - F_j(Q_j + \Delta Q_j)\right] = 0, (i = 1, 2, \cdots, m) \end{gathered} \tag{5}$$

$$f_{M+1}(\Delta Q_1, \cdots \Delta Q_N) = \sum\nolimits_{j=1}^{N} a_{ij}\Delta Q_{j'}, (i = 1, 2, \cdots, J-1) \tag{6}$$

The problem can be solved using the following recursive algorithm:

$$\begin{cases} \Delta Q^{(k+1)} = \Delta Q^{(k)} - B_k f(\Delta Q^{(k)}) \\ B_{k+1} = B_k + (p_k - B_k q_k) \frac{p_k^T B_k}{p_k^T B_k p_k} \end{cases} (k = 0, 1, 2, \cdots) \tag{7}$$

where $\Delta Q^{(k)} = \left[\Delta Q_1^{(k)}, \cdots, \Delta Q_N^{(k)}\right]^T$; $f(\Delta Q^{(k)}) = \left[f_1(\Delta Q_1^{(k)}), \cdots, f_N(\Delta Q_N^{(k)})\right]^T$; $B_k = H_k T_k^{-1}$; $H_k = [p_{k-1}, p_{k-2}, \cdots, p_{k-N}]$; $T_k = [q_{k-1}, q_{k-2}, \cdots, q_{k-N}]$; $p_k = \Delta Q^{(k+1)} - \Delta Q^{(k)}$; $q_k = f(\Delta Q^{(k+1)}) - f(\Delta Q^{(k)})$;

When the air resistance of branch m changes, the air volume of branch j also changes. This relationship can be expressed as follows:

$$\varepsilon_j = \frac{\Delta Q_j / Q_j}{\Delta R_m / R_m} \tag{8}$$

where ε_j represents the sensitivity index of the change in the air volume of branch j to the change in air resistance of branch m. There are three possibilities for this sensitivity index, namely:

a. When $\varepsilon_j > 0$, there is a positive sensitivity index. With the increase in air resistance in branch m, the air volume of the affected branch also increases. The sensitivity index will not cause the airflow to reverse.
b. When $\varepsilon_j < 0$, the inverse sensitivity index is undefined. As the air resistance change in branch m increases, the air volume change in the affected branch also increases inversely. The sensitivity index can cause the airflow to reverse.
c. When $\varepsilon_j = 0$, there is no sensitivity index. With the change in air resistance in branch m, the air volume of the affected branch remains constant.

For a specific ventilation network, the sensitivity index of the air volume change in each branch to the air resistance change in other roadways is a fixed value. Calculating the sensitivity index is of great value for selecting the position for adjusting the ventilation network. By utilizing the sensitivity model for air resistance adjustment, the optimal placement and quantity of air doors are determined. Subsequently, a remote intelligent automatic adjustment wind door is installed in the designated location to facilitate the regulation of air volume within the local ventilation network.

2.3. Construction of Regional Air Volume Control Model

The current condition of the ventilation network serves as the foundational reference point for the subsequent air volume regulation. This state encompasses various airflow parameters in each roadway, including air speed, air volume, temperature, humidity, and more. Additionally, it accounts for the operational status of each ventilation facility and fan, such as the positions of air doors, the angles of air doors, fan speeds, and so on. It also encompasses other factors, like pressure differentials across air doors and local fan pressure differentials.

2.3.1. Airflow Status Indicators

The airflow state in each roadway within the current air network, particularly the air volume in each branch of the current air network, serves as the foundation for regulating the airflow within the air network. The distribution of air volume in all branches of the ventilation network corresponds to the distribution of resistance in the ventilation network. When the resistance distribution is known, the air volume of all branches in the ventilation network can be easily obtained using the method of ventilation network calculation. However, it is unrealistic to monitor the air volume or air resistance of all branches in the air network in practical applications. Therefore, when adjusting the local ventilation air volume, technical personnel primarily focus on the total air volume of the current network and the air volume at the main air use location. They then use their experience to redistribute the air volume by adjusting the ventilation facilities. The total air volume of the air network and the air volume of the main air-using locations are the fundamental indicators of the current air volume adjustment. They also indicate the adjustability of the ventilation network.

2.3.2. Facilities and Equipment Status Indicators

On the one hand, the state of facilities and equipment refers to the operational state of ventilation facilities and equipment, including the opening and closing of air doors, the angle of air doors, the speed of fans, and so on. The redistribution of air volume in the ventilation network is facilitated by these facilities and equipment. The current working state determines the distribution of air volume in each branch of the current ventilation network. In order to redistribute the air volume in the ventilation network and meet the preset requirements, it is necessary to reset all or part of the ventilation facilities and equipment.

In addition, the role of ventilation facilities and equipment in the existing ventilation network, as well as their contribution to the distribution of air volume, can indicate the significance of these facilities and equipment. This information serves as a crucial reference for regulating air volume. In general, the greater the atmospheric pressure difference on both sides of the ventilation facility, the more significant the facility's role in the ventilation system, and the stronger its impact on the distribution of current air volume. Here, the difference in atmospheric pressure on both sides of the ventilation facility is used as another indicator of the operational status of the ventilation facility. For local fans, the air pressure of the fan can indicate the fan's role in distributing air volume within the network and its significance in the current network. Therefore, the air pressure of the local fan is selected as another state indicator of the fan.

In summary, it is not realistic to fully grasp the air volume or air resistance of all branches in the ventilation network when controlling the air volume of the actual ventilation network [34]. According to the practices of engineering and technical personnel in adjusting the air volume of the ventilation network, factors, such as the total air volume of the network, the air volume of the air site, the opening and closing of air doors, the pressure differentials on both sides, the angle of air doors, the operation frequency of fans, and the fan pressure, can be considered as the basis for adjusting the air volume of the ventilation network. Additionally, the use of machine learning methods can be explored for air volume adjustment in the ventilation network. According to the above analysis of the air volume control index, the machine learning method is used to predict the prediction control index. Figure 1 shows the model for the intelligent adjustment of regional air volume.

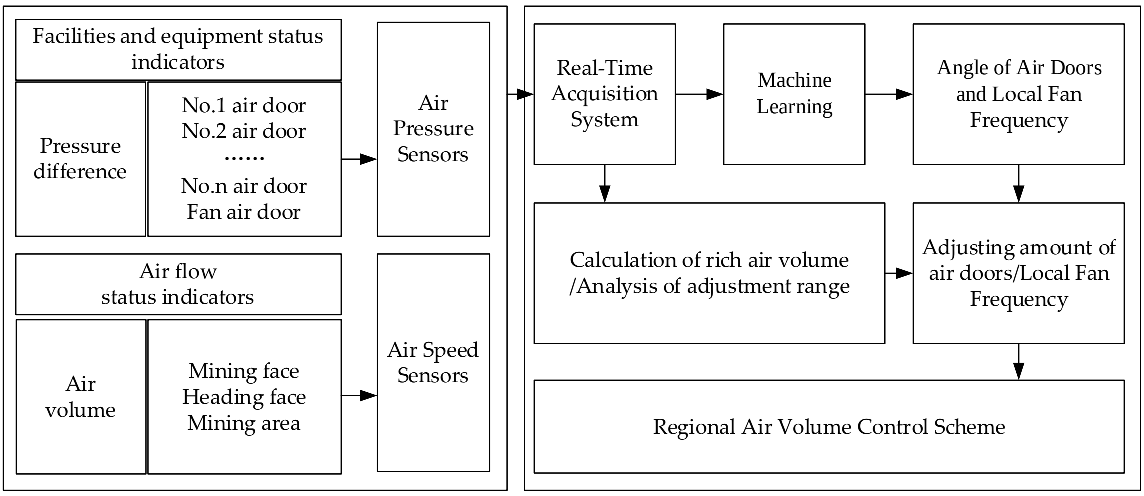

Figure 1. Intelligent control model of regional air volume.

As shown in the Figure 1, the primary task in the intelligent adjustment of regional air volume is to accurately monitor the indicators of facilities and equipment, as well as the indicators of airflow status. Secondly, an intelligent air conditioning model is established to determine the input and output parameters. The input indicators include the current state parameters of the air network (total air volume of the network, air volume at each air supply location, opening and closing status of each air door and pressure on both sides, angle of each air door and pressure on both sides, operating frequency of each fan, and fan pressure) and predicted target parameters (air supply volume after adjustment of each air supply location). The output indicators are the angle of each air door and the operating frequency of the local fan. Then, the air conditioning model calculates the abundant air volume and adjustment range of each branch. It outputs the air door angle and local fan frequency for the target air volume. Finally, the adjustment amount of the angle of air doors and the local fan frequency are calculated to generate a scheme for controlling the regional air volume.

3. Intelligent Control Experiment of Regional Air Volume

In order to simulate the fault scene of mine ventilation resistance and to collect data, it is necessary to design a corresponding experimental model based on the actual mine ventilation system. The experimental model should be built according to similarity criteria, such as geometric similarity, dynamic similarity, and kinematic similarity.

3.1. Experimental Platform

The experimental platform simulates the regional ventilation in a mining area, which consists of a transport alley, a return air roadway, uphill transport, uphill track, a mining face, and a heading face, as shown in Figure 2. Four adjustable air doors and one explosion-proof air door are installed in the utilization area of the model. These air doors are labeled as AD-1, AD-2, AD-3, AD-4, and AD-5. By adjusting these air doors, the ventilation mode of the working face can be converted to different modes, such as U-type ventilation, U + L-type ventilation, and partial Y-type ventilation. Additionally, the air volume at each location can be adjusted accordingly, as shown in Figure 3.

A high-precision and high-speed air pressure sensor is installed at each air door position of the model, with a pressure accuracy of 2 Pa and a sampling rate of 50 Hz. The main roadways and air vents are equipped with an average speed sensor, which is used to monitor the airflow velocity in the branch of the roadway, in order to determine the airflow volume of the roadway. The adjustable air doors can be controlled remotely through electrical means or manually to achieve a 0~90-degree range of opening and closing. The ventilation direction of the entire model utilizes extraction ventilation. The main fan is controlled by a frequency converter, allowing the operating frequency to be adjusted within the range of 0~50 Hz.

(**a**) (**b**)

Figure 2. Experimental platform: (**a**) main view; (**b**) side view.

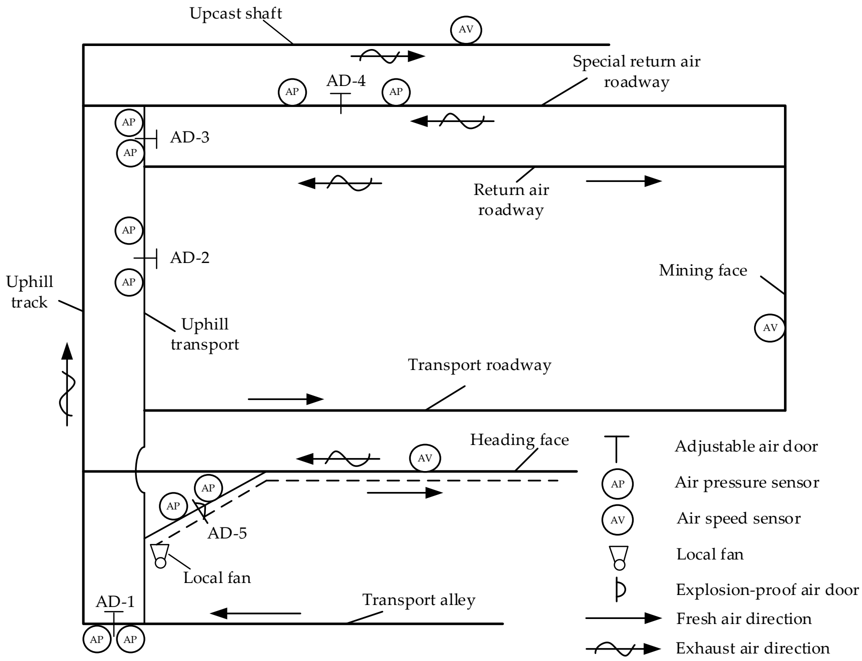

Figure 3. Regional air volume control experimental platform system diagram.

As depicted in Figure 3, pressure difference sensors are positioned at each explosion-proof air door location on the experimental platform, while air speed sensors are placed at the mining face, heading face, and upcast shaft. The data acquisition system of the experimental platform integrates a self-developed atmospheric pressure acquisition device that interfaces with each high-precision sensor. A comprehensive setup comprising three air speed sensors and five pressure difference sensors is implemented for the dynamic monitoring of air volume in each branch and the pressure differential across each air door. The IIC interface is used for data transmission between the acquisition device and the sensor. The LAN communication is used between the acquisition device and the data acquisition terminal computer, and the communication rate is up to 100 Mbps.

3.2. Experimental Method

According to the on-site airflow transmission characteristics, combined with the regional air volume intelligent control model, in order to avoid the destruction of the experimental system caused by the short circuit of the airflow and insufficient air volume during the experiment, the similarity criterion is used to calculate the air speed threshold of the coal mining face and the tunneling face in advance, and to determine the reasonable sensor placement location. The fan frequency conversion air conditioning and the associated branch air conditioning are used, respectively. The combination of the two methods is used to study the variation law of the air volume of each branch in the area under the control state. The predictive capability of the intelligent control model for regional air volume is verified by comparing the target air volume at each air site under different control states.

Preparatory Work: Select a day with favorable weather conditions to conduct the experiment. Ensure the experimental environment is stable to minimize the impact of external factors on the experiment. Connect the calibrated experimental platform and data acquisition instrument to the data acquisition cabinet and display the results on the data acquisition software. The data acquisition software is connected to the database, the experimental equipment is started for preheating, and the experiment begins once the data is stable.

Experimental Method: Based on the characteristics of on-site airflow transmission and air volume distribution, the experimental platform is equipped with air speed sensors and air pressure sensors. The regional air volume control model is combined with the method of local fan frequency conversion regulation, associated branch regulation, and combined regulation of the two. This allows for the collection of dynamic airflow parameter data under different ventilation conditions by remotely adjusting the working parameters of ventilation facilities and equipment. After each state, the airflow is allowed to stabilize. The data is then recorded and uploaded to the database for one minute. This process collects all state ventilation data, integrates and processes the experimental data, and forms air volume intelligent control data samples. Some of the collected data are shown in Table 1.

Table 1. Real-time monitoring data samples.

SN	AP-1/ (Pa)	AP-2/ (Pa)	AP-3/ (Pa)	AP-4/ (Pa)	AV-1/ (m/s)	AV-2/ (m/s)	AV-3/ (m/s)	AP-5/ (Pa)	LFF/ (Hz)	Op1/ (°)	Op2/ (°)	Op3/ (°)	Op4/ (°)
1	62.09	5.23	62.15	60.86	0.55	0.41	1.59	85.97	40.00	10.00	10.00	20.00	20.00
2	83.62	3.73	88.16	89.88	0.38	0.57	1.59	118.2	50.00	10.00	10.00	0.00	30.00
3	58.98	4.22	62.53	63.37	0.27	0.51	1.92	83.34	50.00	20.00	10.00	0.00	30.00
4	51.95	5.63	51.61	49.94	0.64	0.32	1.89	71.36	10.00	10.00	10.00	20.00	30.00
5	75.18	5.28	75.50	76.12	0.53	0.30	2.03	104.7	10.00	10.00	10.00	20.00	10.00
6	48.07	4.69	48.05	47.54	0.42	0.35	1.86	66.57	30.00	20.00	10.00	10.00	40.00
7	38.45	4.78	37.45	36.77	0.52	0.52	1.83	52.36	50.00	20.00	10.00	20.00	30.00
8	44.38	3.80	45.61	44.26	0.42	0.52	1.57	61.15	30.00	20.00	20.00	0.00	40.00
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
93	40.49	6.82	38.00	35.99	0.87	0.40	1.82	54.65	30.00	10.00	20.00	0.00	60.00

It should be noted that the air volume sensitivity of each air usage location and its related branches is high under different conditions. Therefore, it is important to avoid the short circuiting of airflow and insufficient air volume during the experiment. The collected data should be screened to ensure that the air volume of the air site and the associated branches is within the range of the air speed threshold, so as to ensure the accuracy and practicability of the rich air volume control data in the region.

3.3. Experimental Result Analysis

In order to verify the feasibility of the intelligent control method of air volume under different control states in the region, the curve is drawn based on the relationship between the opening and closing angle of the key branch No. 4 air door and the change in air volume and other air door pressure differences in different control states, and the supply and demand characteristics of ventilation air volume under the control state are analyzed. Figure 3 shows the characteristic curve of the opening and closing angle of the No. 4 air door and the air volume and other air door pressure difference in different control states.

It can be seen from Figure 4 that the opening and closing angles of the different control states of AD-4 have a significant effect on the air volume and other door pressure differences at the air location when the other door angles remain unchanged. As the angle of AD-4 increases from 10° to 60°, the pressure difference between the inside and outside of AD-1, AD-3, and AD-5 decreases, while the pressure difference between the inside and outside of the AD-2 does not change significantly. At the same time, the air volume of the coal mining face gradually increases, the air volume of the tunneling face gradually decreases, and the total air volume in the area does not change much. It can be seen that the opening and closing angle of the air door in the area greatly influences the distribution of air volume in that area. It is necessary to collect data on ventilation parameters in different control states through the air volume control experiment. According to the data collected from the experiment, we are attempting to use machine learning techniques to redistribute the air volume.

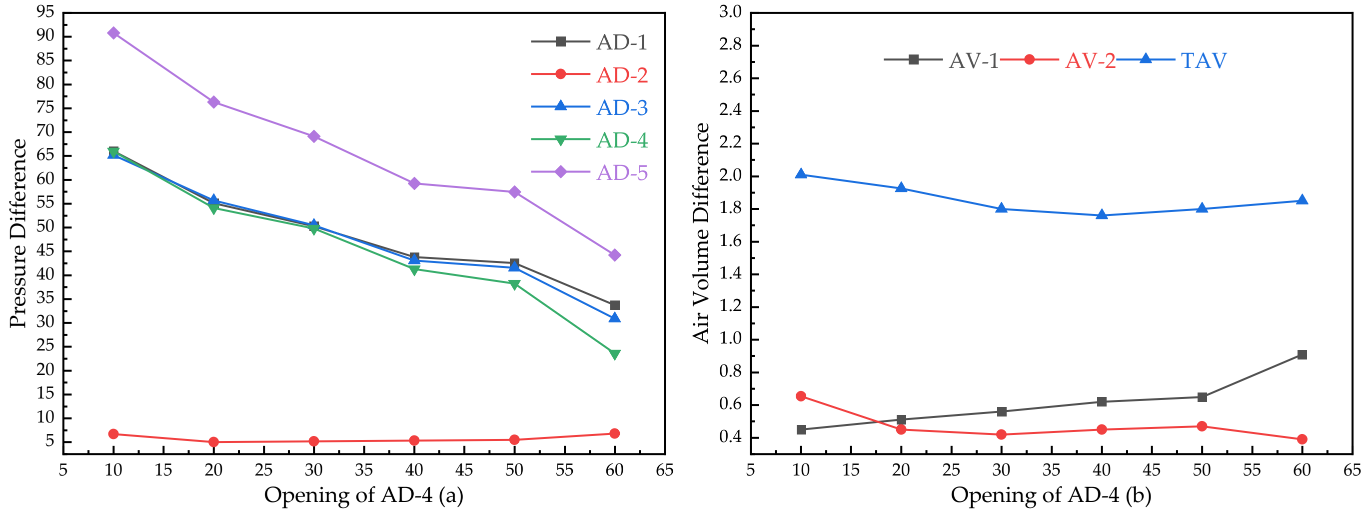

Figure 4. The angle influence of AD-4 (**a**) on the pressure difference in other air doors and (**b**) on the total air volume of the main air site and the area.

4. Verification of Regional Air Volume Intelligent Control Model

By conducting air volume control experiments, a sample database is established, and machine learning techniques are employed to predict air door angles and local fan frequencies. To enhance the promptness and precision of air volume control, this study harnesses various semi-supervised learning methods for regression prediction, including a BP neural network (BP), a particle swarm optimization BP neural network (PSO-BP), a genetic algorithm optimization BP neural network (GA-BP), an extreme learning machine (ELM), and a least squares support vector machine (LS-SVM). The performance and accuracy of the prediction models are comprehensively evaluated using metrics, such as the determination coefficient (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean relative error (MBE).

4.1. Training Parameter

Firstly, the establishment of a training sample set is the premise of model training. Combined with the contents described in Section 2.3. Input indicators should include the air volume of the mining face (AV-1), the air volume of the heading face (AV-2), the total air volume of the ventilation network (AV-3), angle of AD-1 (Op1), internal and external air pressure of AD-1 (AP-1), angle of AD-2 (Op2), internal and external air pressure of AD-2 (AP-2), angle of AD-3 (Op1), internal and external air pressure of AD-3 (AP-3), angle of AD-4 (Op1), internal and external air pressure of AD-4 (AP-4), local fan frequency (LFF), local fan air pressure (AP-5), target air volume of the mining face (AT-1), and the target air volume of the heading face (AT-2). The output indicators are the prediction frequency of local fan LFFT (Ot-1), the prediction angle of AD-1 (Ot-2), the prediction angle of AD-2 (Ot-3), the prediction angle of AD-3 (Ot-4), and the prediction angle of AD-4 (Ot-5).

In the prediction of regional air volume regulation using regression, it is necessary to determine the optimal parameters for each prediction algorithm. After continuous optimization and parameter adjustment, the optimal parameters of machine learning methods, such as the BP neural network (BP), particle swarm optimization BP neural network (PSO-BP), genetic algorithm optimized BP neural network (GA-BP), extreme learning regression machine (ELM), and least squares support vector regression machine (LS-SVM), are shown in Table 2.

Table 2. Optimal parameter settings of each algorithm.

Algorithms	Parameters	Optimal Parameters
BP	Hidden number	13
	Epochs	10,000
	Learning rate	0.0001
	Training precision	0.00001
PSO-BP	Particle swarm size	10
	Update number	1000
	Learning factor	[4.494]
	Speed boundary	[−1.0~1.0]
	Range boundary	[−1.0~1.0]
	The remaining parameters are the same as BP	
GA-BP	Genetic iterations	50
	Population size	10
	Crossover probability	2
	Mutation probability	2 gen 3
	The remaining parameters are the same as BP	
ELM	Number of hidden neurons	50
	Activation function	Sigmoidal
LS-SVM	Gamma	50
	Penalty factor	2
	Kernel function	RBF_kernel

4.2. Performance Evaluation

Through the parameter configuration of five distinct semi-supervised learning algorithms, the regression prediction for each output of the proposed regional air volume control model is conducted in this paper. In this paper, the coefficient of determination R^2 is used to evaluate the performance of each algorithm. The coefficient of determination R^2 is shown in Table 3. The coefficient of determination R^2 is calculated as follows:

$$R^2 = 1 - \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 / \sum_{i=1}^{n} \left(y_i - \bar{y}_i\right)^2 \tag{9}$$

where y_i represents the true value, $\hat{y}_i$ represents the predicted value, and $\bar{y}_i$ represents the average value, $i \in [1, n]$.

In the field of machine learning, error comparison analysis is a crucial step in assessing the performance of different models or algorithms. In this paper, three commonly used error indicators, namely root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE), are used to compare and analyze the errors of the five regression prediction algorithms.

From Figure 5, it becomes evident that the determination coefficient R^2 for various algorithms spans within specific ranges for each output aspect, ranging from −0.1629 to 1 for Ot-1, −0.2016 to 1 for Ot-2, −0.2094 to 0.992 for Ot-3, −0.5892 to 0.982 for Ot-4, and −0.3437 to 0.988 for Ot-5. Comparing the R^2 determination coefficients across different algorithms, it is apparent that the LS-SVM yields the highest R^2 values, with an average of 0.9924, followed by ELM with an average of 0.5859. In contrast, the performance of the BP algorithm is the least satisfactory. Even with the optimization efforts applied to the PSO-BP and GA-BP algorithms, there is only a marginal improvement in model performance, which remains subpar.

When comparing the root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE) results for each output, it is evident that the LS-SVM model demonstrates the most accurate predictive performance. The RMSE, MAE, and MBE values for LS-SVM are significantly lower than those of the other four algorithms. Within each algorithm, the largest error discrepancy is observed in Ot-4, followed by Ot-3. This suggests that Ot-3 and Ot-4 are the most responsive to regional air volume regulation. In other words, regulating Ot-3 and Ot-4 is of paramount importance in meeting the air volume requirements at the air usage locations.

Table 3. Model evaluation and error analysis of each semi-supervised learning algorithm.

Algorithms	Evaluation	Performance Evaluation of Algorithms					Time
		Ot-1	Ot-2	Ot-3	Ot-4	Ot-5	
BP	R^2	−0.1629	−0.0436	−0.2094	−0.58923	−0.3437	25 s
	RMSE	5.3366	5.0846	11.1149	18.1934	0.3131	
	MAE	4.44	4.4497	8.8026	14.8726	0.2399	
	MBE	−1.2493	−0.9857	3.0692	2.8352	−0.0868	
PSO-BP	R^2	−0.0678	−0.2016	0.0392	−0.1575	−0.0128	281 s
	RMSE	4.8136	5.6333	12.8574	14.9195	0.3789	
	MAE	4.1205	4.4003	8.4777	12.3023	0.2358	
	MBE	−0.2128	0.2124	1.493	1.366	−0.0091	
GA-BP	R^2	0.0049	−0.0999	−0.0161	−0.1149	−0.1363	18 s
	RMSE	4.9364	5.2066	10.2332	15.4052	0.3039	
	MAE	4.461	4.3043	8.6077	12.5021	0.2508	
	MBE	0.0125	−1.9356	−0.3678	0.9872	0.06063	
ELM	R^2	0.6212	0.5791	0.6467	0.5223	0.6252	5 s
	RMSE	3.072	3.2356	6.1457	9.9177	0.1942	
	MAE	2.5109	2.5464	4.8736	7.855	0.1571	
	MBE	0.5568	0.3968	1.8956	0.3245	0.1336	
LS-SVM	R^2	1	1	0.992	0.982	0.988	2 s
	RMSE	0	0	0.8911	1.4433	0.024	
	MAE	0	0	0.635	1.296	0.021	
	MBE	0	0	1.90×10^{-17}	-3.25×10^{-11}	2.84×10^{-13}	

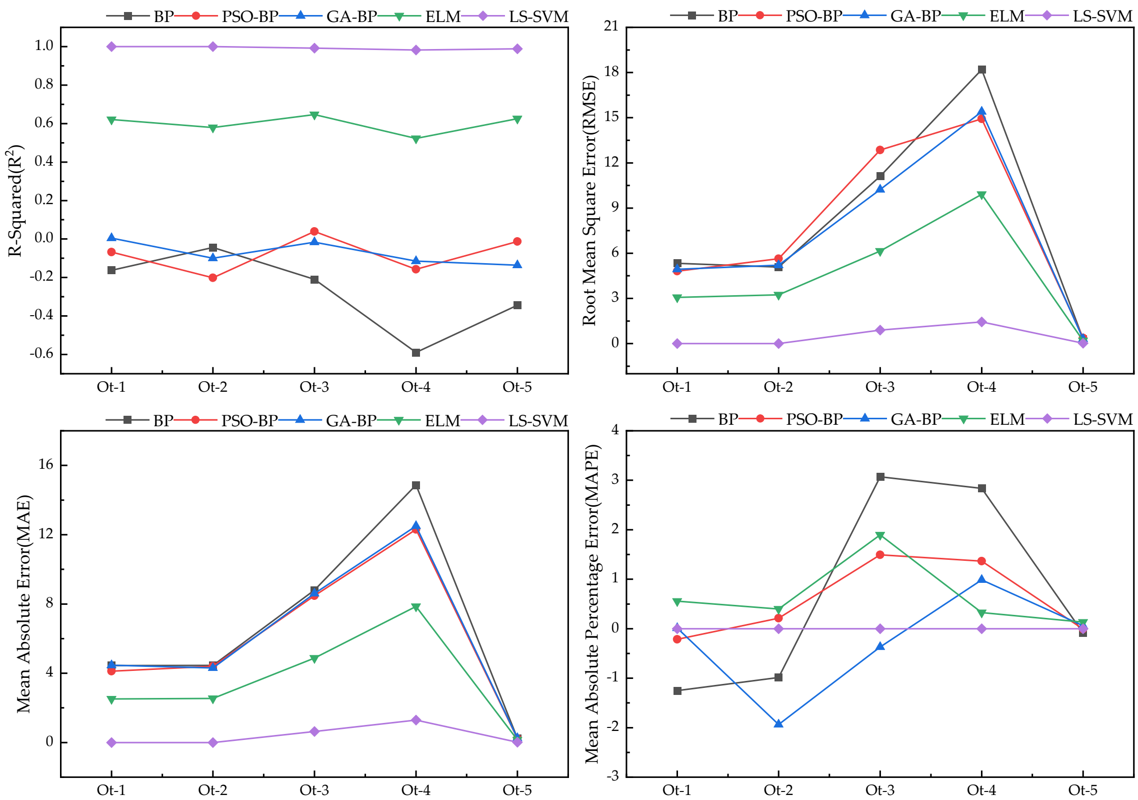

Figure 5. Comparison of the angle errors of each output.

In conclusion, the semi-supervised learning model for air volume regulation based on LS-SVM demonstrates exceptional accuracy in predicting the angles of dampers and the frequencies of local fans during air volume regulation. Furthermore, LS-SVM boasts the shortest training time when compared to other algorithms, allowing for swift information feedback. This not only enhances the promptness and precision of air volume control within the region but also elevates the efficiency of regional air volume management. Importantly, it contributes to the overall stability and reliability of the ventilation system, ensuring safe and effective operation.

4.3. Error Analysis

The LS-SVM air volume control model, as established earlier, is utilized to predict the test set for each damper angle and local fan frequency. The R^2 data for the test set are presented in Table 4.

Table 4. Error comparison analysis of LS-SVM test sample.

Algorithms	Evaluation	Performance Evaluation of LS-SVM				
		Ot-1	Ot-2	Ot-3	Ot-4	Ot-5
LS-SVM	R^2	0.9756	0.9718	0.9178	0.8952	0.9385
	RMSE	0.0458	0.0523	1.4569	1.9456	0.2658
	MAE	0.0364	0.0489	0.8456	1.7496	0.2145
	MBE	1.45×10^{-11}	2.32×10^{-12}	2.56×10^{-7}	-2.96×10^{-5}	6.45×10^{-8}

Table 4 displays the prediction results of the regional air volume control model using the LS-SVM regression prediction algorithm. For regression prediction, a higher R^2 coefficient, closer to 1, indicates a better predictive effect. Additionally, the closer the RMSE (root mean square error), MAE (mean absolute error), MBE (mean bias error), and other error indicators are to 0, the more accurate the predictions. The determination coefficient R^2 for each output ranges between 0.8952 and 0.9756, with Ot-4 having the minimum value (0.8952) and Ot-1 the maximum (0.9756). Simultaneously, the RMSE, MAE, MBE, and other errors for each output are relatively small, signifying a generally strong predictive effect. Based on the experimental model and analysis results, it is evident that AD-3 and AD-4 are highly sensitive to air volume regulation. Figure 6 illustrates the error comparison for the predicted angles of these two air doors.

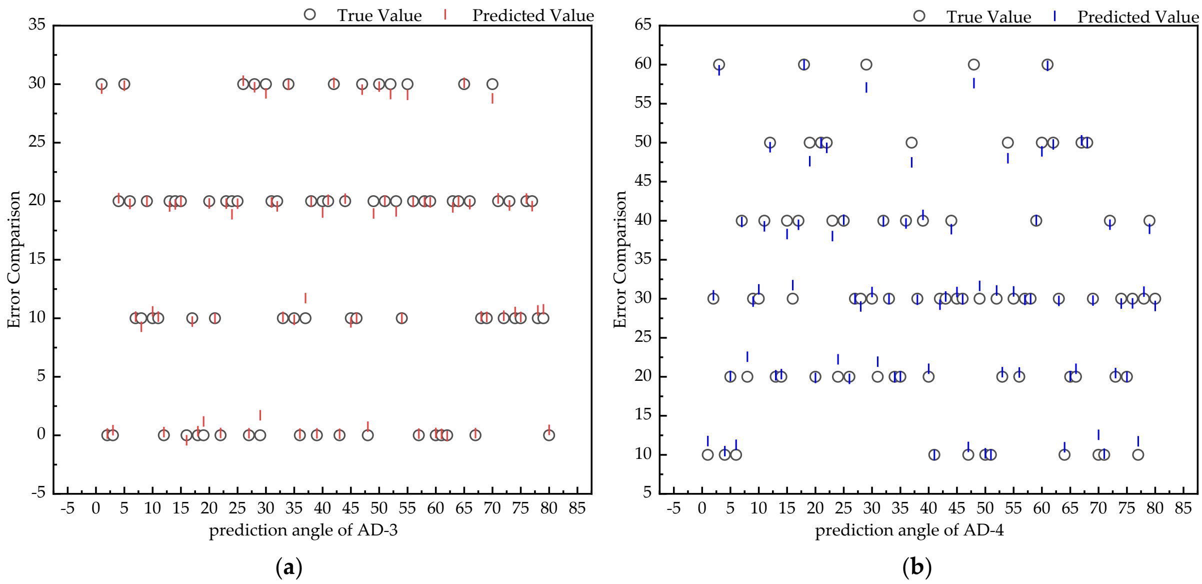

Figure 6. Error comparison of air door angle: (**a**) AD-3 and (**b**) AD-4.

4.4. Verification of Regional Air Volume Intelligent Control

In this study, the control target is defined as the required air volume for the air site, specifically the mining face and heading face within the defined region. This regulation is achieved by adjusting the angles of one or more air doors and the operating frequency of local fans to meet the target air volume requirements for the region. The trained least squares support vector machine (LS-SVM) model is used to predict the intelligent control of air volume. The angle of each air door and the frequency of the local fan are predicted according to the different demands for air volume of the air site. To assess the accuracy of the model, an analysis of the test dataset is conducted, and the prediction results are presented in Table 5.

Table 5. Regional air volume control data.

Class	State	AV-1 (m/s)	AV-2 (m/s)	Ot-1 (Hz)	Ot-2 (°)	Ot-3 (°)	Ot-4 (°)	Ot-5 (°)
1	Initial	0.55	0.41	40	10	10	20	20
	Goal	**0.77**	**0.30**	**19.31** (20)	**10** (10)	**10** (10)	**29.62** (30)	**11.76** (10)
2	Initial	0.38	0.57	50	10	10	0	30
	Goal	**0.61**	**0.51**	**50.03** (50)	**20** (20)	**10** (10)	**9.72** (10)	**39.48** (40)
3	Initial	0.27	0.51	50	20.00	10	0	30
	Goal	**0.76**	**0.44**	**40.02** (40)	**10** (10)	**20** (20)	**0.19** (0)	**49.35** (50)
4	Initial	0.64	0.32	10	10	10	20	30
	Goal	**0.31**	**0.34**	**11.25** (10)	**20** (20)	**10** (10)	**19.89** (20)	**21.93** (30)
5	Initial	0.53	0.30	10	10	10	20.00	10
	Goal	**0.48**	**0.37**	**30.91** (10)	**10** (10)	**20** (20)	**18.88** (20)	**22.24** (20)

The **bold font** in the table represents the predicted value.

Table 5 shows the data of the initial air volume and the target air volume at the air site under different working conditions. The analysis of the first set of data shows that when the coal mining face needs to increase the air volume, the air speed increases from 0.55 m/s to 0.77 m/s; when the air volume needs to be reduced in the heading face, the air speed is reduced from 0.41 m/s to 0.30 m/s. When the frequency of the local fan is adjusted from 40 Hz to 20 Hz, Ot-2 (AD-1) and Ot-3 (AD-2) remain unchanged. The angle of Ot-4 (AD-3) is increased from 20° to 30°, and the angle of Ot-5 (AD-4) is reduced from 20° to 10°. Moreover, the procedures and data sets for the other groups are consistent with the initial group's approach to air volume control. Within air volume control, it is possible to predict the status of the target air volume ventilation facility based on real-time dynamic airflow parameters and the condition of the ventilation equipment. This predictive approach allows for precise and accurate air volume control.

In summary, the machine learning model based on LS-SVM demonstrates exceptional predictive capabilities for intelligent regional air volume control. It accurately forecasts the operational parameters necessary for achieving the target air volume at specific air usage locations. This method operates swiftly, facilitating rapid information feedback and the generation of air volume control strategies. By utilizing the operational parameters of the targeted air volume ventilation facilities and equipment, it enables remote, rapid control of air volume within the region. This approach has proven to be highly applicable and efficient in the realm of intelligent regional air volume control.

5. Discussion

In response to the pressing need for intelligent air volume control within specific regions, this paper delved into the principles of branch-sensitive air regulation, leveraging fundamental mine ventilation theory. Through an analysis of key performance indicators for regional air volume control, an intelligent control model for managing air volume in the region was established. To validate the model's effectiveness, an experimental platform for intelligent regional air volume control was built, guided by similarity criteria for data acquisition and experimental verification.

With a focus on addressing the requirements for real-time processing and intelligent control of mine ventilation systems in response to air volume fluctuations within specific regions, a comprehensive air conditioning approach was introduced.

The research's focal point resides in the application of machine learning for predicting operational parameters pertaining to target air volume ventilation facilities and equipment within the defined area. This approach, characterized by swift information feedback, adeptly accommodates rapid adjustments to the dynamic working conditions of facilities and equipment. This facilitates the efficient modulation of air volume in subterranean air supply locations, responding promptly to fluctuations and, therefore, meeting the air volume requisites of these specific locations. This innovative methodology culminates in the realization of intelligent control within the mine ventilation system, thereby elevating overall system efficiency and responsiveness.

6. Conclusions

Employing machine learning techniques, five distinct algorithms were employed to predict the operating parameters of target air volume ventilation equipment, ultimately realizing intelligent air volume control within the designated area. The following conclusions are drawn:

(1) Based on the principle of branch sensitivity adjustment, this study identified key performance indicators critical to effective air volume control within the ventilation system. These insights served as the foundation for the development of an intelligent control model designed to manage regional air volume with precision.
(2) Taking into consideration the actual conditions of the mine ventilation system, a model for an experimental platform was meticulously designed. The experimental setup for regional air volume control adheres to similarity criteria, such as geometric similarity, dynamic similarity, and kinematic similarity. This platform was equipped with an innovative method for data acquisition. Furthermore, it delved into the various experimental methodologies employed to simulate diverse ventilation scenarios. The subsequent analysis of the experimental results yielded valuable insights.
(3) Five machine learning algorithms were employed to validate the intelligent control model for regional air volume. The study includes parameter optimization and error analysis of these five semi-supervised learning methods. The results demonstrated that the least squares support vector machine (LS-SVM) is the optimal choice for predicting the operational parameters of the target air volume ventilation facilities and equipment. It also effectively generated the corresponding air volume control scheme, ultimately achieving precise control of air volume within the designated area.

It is imperative to underscore that the confines of this research are delimited to the regulation of air volume within a specific mine region. The imperative task of coordinating air volume control throughout the entire mine necessitates further dedicated inquiry and exploration. The intricacies of data acquisition and linkage control in the broader context of intelligent ventilation across the entire mine pose multifaceted challenges, encompassing real-time monitoring of mine ventilation facilities' operational parameters, fault diagnosis, and energy consumption analysis. Within this context, continued investigation is warranted to facilitate the judicious alignment of mine air demand with the operational parameters of ventilation facilities and equipment. Subsequent development initiatives should orient towards refining the intelligent control model to accommodate a broader spectrum of application scenarios, emphasizing the holistic matching of air volume supply and demand and the concerted linkage control of facilities and equipment throughout the entire mine.

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