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Research and Application of Intelligent Ventilation Management System for Maping Phosphate Mine

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Abstract

The extensive mining area and multitude of working sites in Maping Phosphate Mine result in a complex ventilation system. This complexity manifests as uneven airflow distribution at working faces, posing considerable challenges for efficient ventilation management. An intelligent ventilation management system based on the Python PyQt5 library was developed for Maping Phosphate Mine to improve ventilation efficiency, lower dust concentration at the working face, and enhance safety by addressing uneven air volume distribution. The implementation of an integrated system, comprising a 3D ventilation network model, remote control capabilities, and smart algorithms, has successfully realized zonal planning and on-demand ventilation in the mine's underground workings. To adapt to the fluctuating air demand at the tunneling face, a remote intelligent control scheme for louvered dampers was implemented. This dynamic demand-based strategy achieves precise distribution of air volume throughout the ventilation network. The research results demonstrate that the system effectively addresses the uneven distribution of air volume, thereby improving the overall ventilation environment and reducing the risk of ventilation-related accidents. The system serves dual purposes: it provides an intelligent ventilation control mechanism and integrates seamlessly with the key subsystems for underground safety production. This synergy is instrumental in advancing the mine's digitalization and intelligent transformation initiatives. Field test results indicate that the system achieved a 30% reduction in energy consumption and a 70% decrease in dust concentration at the working face, respectively.

Keywords: local ventilation; ventilate as needed; intelligent management; software development; zonal ventilation

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1. Introduction

Mine ventilation systems are crucial for safety and efficiency in underground operations. However, traditional control methods, relying on static settings or simplistic logic, struggle to adapt to dynamic mine environments, leading to energy waste and suboptimal air quality. This necessitates the development of more intelligent optimization algorithms.

Early research focused on the fundamental physical phenomena of mine ventilation and descriptive models. For instance, Brovko et al. [1] analyzed airflow stability during fires, while Nguyen et al. [2] evaluated ventilation system performance. El-Nagdy et al. [3] explored alternative solutions and power consumption impacts during ventilation network failures. These studies provided theoretical foundations but were limited by their predominantly static or quasi-static analyses, failing to capture dynamic changes and complex

non-linear characteristics. Pang et al. [4] introduced dynamic processes through Euler–Lagrangian methods for dust-gas two-phase flow simulation but focused on phenomenon simulation rather than real-time control.

With technological advancements, the focus shifted to intelligent algorithms for dynamic optimization. Scholars like Jia [5], Chang [6], and Li [7] introduced novel optimization algorithms. Shang et al. [8] improved genetic algorithms for main fan regulation, and Siddiqui et al. [9] applied fan similarity laws for energy-saving fan speed optimization. These works mark a transition to intelligent optimization. However, most studies still apply single algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), which face challenges such as slow convergence and susceptibility to local optima in large-scale, high-dimensional, and non-linear problems. Kumar [10] developed a non-linear constrained optimization model based on Ventilation on Demand (VOD) theory, An [11] developed an intelligent demand-controlled ventilation system, and Chatterjee [12] explored the energy-saving potential of variable frequency drives. VOD offers significant energy-saving potential, but its effective implementation relies on accurate perception, prediction of mine environmental parameters, and rapidly responsive control strategies. Traditional VOD systems may underperform due to inaccurate sensor data or sluggish control algorithms. Yang [13] proposed a machine learning-based remote intelligent air regulation method, and Heo [14] developed a deep reinforcement learning-based intelligent ventilation control system. Prince [15] combined Adaptive Neuro-Fuzzy Inference System (ANFIS) and GA for predicting energy consumption and airflow. While these hybrid intelligent methods process complex data and achieve adaptive control, deep learning models require extensive training data, and their performance depends heavily on precise hyperparameter tuning, reward function design, and learning process effectiveness. Current research focuses on real-time state perception and actuator optimization in ventilation systems. Feng et al. [16] developed an intelligent control system for real-time monitoring and remote air regulation, Sun [17] proposed an intelligent on-demand air supply solution, Luo [18] established a fault diagnosis and renovation model, and Wan [19] analyzed the application of automation and intelligent equipment. These studies emphasize real-time data acquisition, system diagnosis, and remote control as critical components for closed-loop intelligent ventilation control. However, existing systems still have room for improvement in integration, real-time performance, self-healing capabilities, and adaptability to complex dynamic changes.

The Sparrow Search Algorithm (SSA) and its variants demonstrate significant advantages in optimizing mine ventilation systems. Leveraging their unique bio-inspired mechanisms, they effectively balance global exploration and local exploitation, enabling more precise identification of optimal operating points within complex ventilation networks. Compared to traditional algorithms like PSO and GA, SSA variants exhibit superior performance in convergence speed, solution accuracy, and avoidance of local optima, while also effectively optimizing hyperparameters of deep learning models to enhance prediction and diagnostic accuracy. However, existing research rarely addresses the critical challenge of embedding the physical constraints of mine ventilation systems into the SSA optimization mechanism. Our work bridges this gap by proposing a novel constraint-embedded SSA framework, which directly converts optimal airflow parameters into hydraulic damper angles by solving aerodynamic equations in real time, achieving closed-loop control.

This research selected the Maping Phosphate Mine (Yangliu Mining Area, Yuan'an County, Hubei Province) as a case study. The mine has proven reserves of approximately 315 million tons of phosphate rock at an average grade of 27.38% and a total area of 14.79 km^2. As mining activities progress to deeper levels and the number of operational working faces grows, the ventilation network has become markedly more complex, impos-

ing substantially higher demands on both the efficiency and safety of the ventilation system. The selection of Maping Phosphate Mine is based on its representative challenges in deep mining ventilation, including disordered airflow distribution, frequent dust concentration exceedances, and significant energy waste, which collectively underscore the urgency of intelligent transformation. To address these issues, deploying an intelligent ventilation system has become essential. Such a system would address core needs by allowing for zonal ventilation planning and dynamic on-demand air distribution underground, thereby optimizing airflow control and ensuring operational safety.

2. Mine Ventilation System

Structured around five key subsystems, the intelligent ventilation management system enables data-driven control. The process begins with a monitoring system that gathers real-time data on underground environmental conditions, such as concentrations of dust, carbon monoxide, and oxygen. This information feeds into a calculation system, which dynamically computes the air demand for different zones based on comprehensive inputs, including the number of workers present and the operational state of machinery. The control system regulates the ventilator, air windows and air doors to achieve precise air supply. The data analysis subsystem processes collected underground parameters to perform fault diagnosis and assess ventilation efficiency. These insights are then utilized by the visualization subsystem, which employs a 3D mine ventilation simulation model to dynamically simulate airflow and other parameters, thereby providing real-time monitoring and an intuitive display of the overall ventilation status. This system distinguishes itself by placing the "computing system" and "data analytics subsystem" at the core of its architecture. This design enables the system to not only respond to sensor data but also to perform continuous self-evaluation and optimization. For instance, the computing system can dynamically adjust the air volume for working faces based on personnel positioning information, while the data analytics subsystem can diagnose issues such as decreased fan efficiency or air leakage within the network, thereby proactively triggering maintenance or adjustment commands.

As illustrated in Figure 1, the intelligent ventilation management system for Maping Phosphate Mine adopts a hierarchical framework comprising a perception layer, a network transmission layer, and an application layer. Within this structure, the anemometer serves as the core monitoring device of the perception layer. Its widespread deployment enables the continuous provision of critical data for airflow calculation and ventilation assessment. To ensure stable data transmission, underground equipment is connected to the power supply, anemometers, and switches through mining-use intrinsically safe three-way junction boxes. The network transmission layer then links these sensing devices to the system via an underground ring network and switches, forwarding the data to the system's front-end machine. Serving as the system's command center, the application layer is responsible for monitoring, as well as for the storage and processing of data on the system servers. Operational reliability is maintained by the backup machine through regular backups, while the front-end machine enhances server performance and system security. The resulting processed data is made available for display on the main station, the dispatch room's large screen, and client computers, delivering essential real-time support for ventilation management.

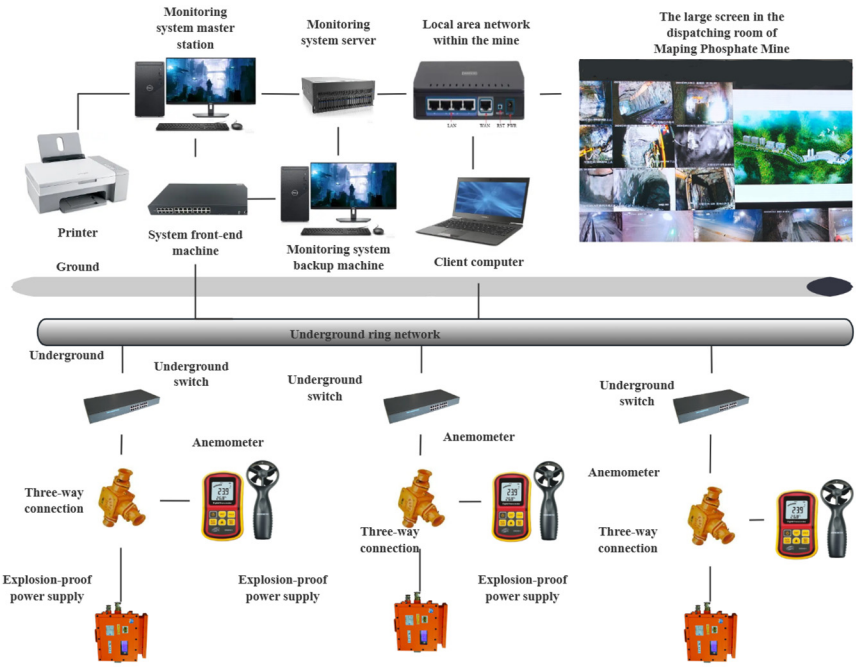


Figure 1. Overall system architecture.

3. Design and Development of Intelligent Ventilation Management System

Traditional mine ventilation management is often characterized by untimely manual monitoring, insufficient data accuracy, and imprecise equipment control, making comprehensive ventilation oversight difficult. The emergence of digital and intelligent technologies now provides new technical avenues to significantly enhance ventilation management capabilities [20]. In response to the ventilation issues outlined above, an intelligent ventilation management system was designed and implemented for the Maping Phosphate Mine. The development was grounded in an assessment of the mine's existing ventilation system and carried out using the PyQt5 library in Python 3.11.13.

3.1. Optimal Air Demand Calculation Based on Sparrow Search Algorithm

Traditional mine ventilation relies on static empirical formulas and standard coefficients for air volume calculation, which often fail to adapt to the dynamic and variable underground environment. To overcome the issues of delayed response and insufficient data accuracy inherent in manual monitoring, this study introduces the Sparrow Search Algorithm (SSA) as a core optimizer to construct an intelligent, dynamic model for calculating air demand [21]. By simulating the foraging and anti-predation behaviors of sparrow populations, the proposed model transcends the limitations of conventional formula-based calculations. This bio-inspired approach enables it to dynamically solve for the global optimum in ventilation control schemes under complex, variable conditions.

Assuming a certain state where the entire population consists of n sparrows, each sparrow can be represented by the set (X_i, F_i), where X_i is the position of the i-th sparrow, $F_i = f(X_i)$ is the fitness value of the i-th sparrow, and $f(X_i)$ is the fitness function. The position information of the n sparrows can be expressed as follows:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,d} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,d} \end{bmatrix} \quad (1)$$

Among them, d is the variable dimension of the fitness function to be solved. Therefore, the overall fitness value of the sparrow population can be expressed as follows:

$$F = \begin{bmatrix} f(X_1) \\ f(X_2) \\ \vdots \\ f(X_n) \end{bmatrix} = \begin{bmatrix} f([X_{1,1} & X_{1,2} & \cdots & X_{1,d}]) \\ f([X_{2,1} & X_{2,2} & \cdots & X_{2,d}]) \\ \vdots & \vdots & \vdots & \vdots \\ f([X_{n,1} & X_{n,2} & \cdots & X_{n,d}]) \end{bmatrix} \quad (2)$$

The algorithm begins by randomly initializing a population of sparrow individuals within the solution space. These individuals are then categorized into three distinct roles: explorers, followers, and vigilantes. The search for the optimal solution is driven by simulating the collective foraging behavior of this sparrow population. Among them, the explorer undertakes the task of random search within the feasible air volume range of the solution space, i.e., algorithm search, to find the optimal region. Its position formula is

$$X_{i,j}{}^{t+1} = \begin{cases} X_{i,j}{}^{t} \cdot \exp\left(-\frac{i}{\alpha \cdot iter_{\max}}\right), & R_2 < ST \\ X_{i,j}{}^{t} + Q \cdot L, & R_2 \geq ST \end{cases} \quad (3)$$

In the formula, t represents the current number of iterations, $iter_{\max}$ represents the maximum number of iterations, $X_{i,j}$ are the position coordinates of the i-th sparrow in the j-th dimension, α is a random number with a value range of [0, 1], Q is a random variable that follows a normal distribution, L is a $1 \times j$ matrix where all elements are 1, R_2 is the warning threshold, and ST is the safety valve value. When R_2 is greater than or equal to ST, it indicates that the area is in a dangerous state, meaning there is no optimal solution. Conversely, there exists an optimal solution.

The local search effect of followers is better than that of explorers. Their position updates are affected by explorers, and their position formula is

$$X_{i,j}{}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{\text{worst}}}{\alpha \cdot iter_{\max}}\right), & i \geq \frac{n}{2} \\ X_P^{t+1} + \left|X_{i,j}{}^{t} + X_P^{t+1}\right| \cdot A^{+} \cdot L, & i < \frac{n}{2} \end{cases} \quad (4)$$

In the formula, X_p represents the optimal position of the current explorer, "X_{worst}" represents the position of the worst individual in the current population, A^{+} a $1 \times j$ order matrix with values of 1 or -1. Regarding $i > n/2$, i represents the i-th individual in the population and n represents the population size. When $i > n/2$, it indicates that the fitness of the i-th follower is low and no food has been obtained, suggesting that there is no optimal solution near this position. Conversely, an optimal solution exists.

The role of the vigilante is to conduct a "global" search to discover new optimal solutions. Its position formula is

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^{t} + \beta\left|X_{i,j}^{t} - X_{\text{best}}^{t}\right|, & f_i \neq f_g \\ X_{i,j}^{t} + K\left(\frac{\left|X_{i,j}^{t} - X_{\text{worst}}^{t}\right|}{(f_i - f_g) + \varepsilon}\right), & f_i = f_g \end{cases} \quad (5)$$

In the formula, X_{best} represents the current optimal position; β is a random value that follows a normal distribution with a mean of 0 and a variance of 1. K is a random value that follows a uniform distribution within the interval [0, 1], used to control the direction and step size of sparrows when they move. When $f_i > f_g$, it indicates that the vigilante has discovered the optimal solution. Conversely, it indicates that there exists an optimal solution outside this region.

In the context of mine ventilation, the equations of the Sparrow Search Algorithm (SSA) dynamically optimize air volume allocation by simulating sparrow population behavior: In Equation (1), the position update mechanism of sparrow explorers is mapped to random searches constrained by air volume safety boundaries. When monitored values exceed safety thresholds, disturbances are introduced to escape invalid solutions. In Equation (2), the local optimization behavior of followers corresponds to the fine-tuning of air volume in various zones, with low-fitness individuals moving away from ineffective air volume schemes. Equation (3) employs a dual global verification mechanism to ensure no superior solution exists within the solution space.

The sparrow algorithm optimizes air volume via iterative approximation, gradually converging toward an optimum from an initial range through repeated calculations. The solution's global optimality is safeguarded by a dual-validation process defined in Equation (3), the first step of which preliminarily checks for the existence of an optimal solution within the current interval. The second validation level assesses the potential for a better solution outside the current interval. The iterative process concludes upon satisfying dual conditions: the presence of an internal optimal solution and the absence of a superior external one. Meeting this criterion triggers the output of the current optimal parameters for real-time ventilator control. If a potentially better external solution is detected, the algorithm dynamically adjusts the search boundary and resumes calculation until global optimality is assured.

According to the "Technical Specifications for Ventilation in Metal and Non-metal Underground Mines—Appraisal Indicators for Ventilation Systems" (AQ2013.1-2008) [22], the calculation module of the intelligent ventilation management system integrates the following ventilation calculation formulas into the core algorithm, serving as the mathematical basis for the automatic parameter adjustment of the control system.

The formula for the total designed air volume of the mine is the total designed air volume of the mine (m^3/min):

$$Q_z = K_b \times (Q_r + Q_c) \tag{6}$$

Among them, K_b denotes air volume reserve coefficient (dimensionless), generally taken as 1.20 to 1.45.

$$Q_r = n \times q \tag{7}$$

Among them, n denotes the maximum number of people working simultaneously underground; q denotes the minimum air supply standard per person (m^3/min per person), with the specification requiring 4 m^3/min per person.

$$Q_c = (\sum P_i \times k_i) \times q_d \tag{8}$$

Among them, P_i denotes power of a single device (kW); k_i denotes Working Time Utilization coefficient (dimensionless), reflecting the actual load rate of the equipment; q_d denotes air volume required per unit power (m^3/min·kW), with the specification requiring 4 m^3/min·kW.

After the SSA completes its iterations, the output optimal sparrow position vector is physically defined as the target air volume required for each independent ventilation branch. This vector is received in real-time by the upper-level monitoring and control system developed based on the PyQt5 framework, through memory sharing or inter-process communication (IPC).

3.2. System Control and Visualization Implementation

Acting on the calculated air volume data, the control system optimizes ventilation by executing two core tasks. It adjusts the operational status and power of local fans to match real-time demand. Concurrently, it performs remote, precise regulation of air dampers and ventilation openings to guide airflow and reconfigure the network, ensuring it adapts effectively to different ventilation scenarios.

By calculating the airflow resistance between any monitoring points in the ventilation network, the system provides critical support for airflow calculation and on-demand ventilation design at the working face. The resulting analysis data is simultaneously transmitted in real time to the remote ground-based monitoring platform. During operation, the system's anomaly diagnosis unit continuously monitors the dynamic trends of key parameters, including pipeline resistance, pressure drop per unit length, and the air leakage coefficient. By analyzing variations in resistance parameters between adjacent measurement sections, the unit enables the real-time detection of anomalies. Once the pressure drop in a monitoring section deviates from the preset safety range, the system triggers an alarm. This enables operations and maintenance personnel to promptly identify and pinpoint the faulty section, assess the potential causes, and initiate targeted intervention measures.

The visualization system provides a real-time, holistic overview of the mine's underground ventilation by utilizing the constructed 3D simulation model. A dedicated data panel on the left side of the interface displays key monitoring metrics, including air volume and dust concentration levels across different underground areas. To deliver reliable data for mine safety oversight, the system utilizes dual visual displays. A radar chart positioned at the lower right enables quick, detailed visualization of key parameters—including O_2, CO, CO_2, temperature, humidity, and PM10—at any point. Simultaneously, a panel of indicator lights on the right provides real-time status monitoring for oxygen, dust, wind speed, and carbon monoxide. A two-color scheme is used for the indicator lights: red serves as a warning for potential abnormalities requiring immediate response, whereas green indicates normal operation with all parameters within safe limits. This scheme enables the real-time visualization of system status for operational personnel.

4. Engineering Application for Intelligent Ventilation Management System

The system forms the basis for practical engineering applications in the ventilation management of the Maping Phosphate Mine, facilitating its application in real-world mining conditions. By collecting parameters through the perception layer, relaying them via the network layer to the server for dynamic calculation, and actuating local ventilators and dampers, the system achieves precise air volume control. This capability thereby provides the essential technical foundation for implementing zonal ventilation planning and on-demand ventilation strategies.

4.1. Zoning Ventilation Planning for Maping Phosphate Mine

Disordered airflow within the ventilation system of Maping Phosphate Mine is characterized by the serial connection of air volumes, the recirculation of polluted air at working faces, and a low effective air volume rate. This inefficient airflow pattern directly results in excessive energy consumption. To address this issue, the mine is divided into independent ventilation subsystems based on the current mining situation of Maping Phosphate Mine. Each subsystem achieves directional regulation of air flow through air network isolation, which can effectively ensure that the air volume in each area is independently distributed and does not interfere with each other [23].

At present, Maping Phosphate Mine has formed middle sections of +60 m, +220 m, +340 m, +380 m and +420 m. The internal ramps of 1#, 2#, 3#, 4#, 5#, 6#, 7#, 9# and 10#

have all been formed. Among them, the 550 auxiliary ramp is connected to the +220 m middle section and the bottom 2# belt tunnel. The 580 Belt Inclined Shaft links the bottom No. 1 Transfer Station with the No. 1 and No. 2 Belt Roadways. The 560 Air Intake Pipe/Cable Shaft is connected to the +60 m Middle Section and extends to the +220 m Middle Section through the Drainage Connection Roadway. The +420 m, +380 m and +340 m middle sections are the production middle sections. During the operational period, four test production areas have been arranged: the 340B, 420D, 380B, and 380C areas. The 340B area primarily exploits ore bodies above the +340 m middle section, located north of the No. 7 internal slope. The 420D, 380B, and 380C areas target ore bodies above the +380 m middle section, situated between the No. 6 and No. 7 internal slopes. Currently, all development work for these areas has been completed, as shown in Figure 2.

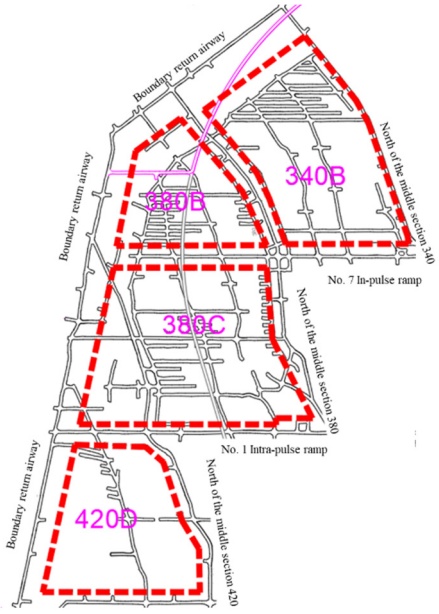


Figure 2. Planning model of the northern mining area of Maping Phosphate Mine.

To ensure on-demand fresh air distribution and efficient polluted air extraction, the northern working area of the underground mine has been subdivided into four independent ventilation zones, in accordance with the overall mining and excavation plan of the Maping Phosphate Mine. The design of ventilation routes for all mining areas is governed by the "intake air—operation air—return air" principle to ensure unidirectional airflow. Based on this principle, as shown in Figure 3:

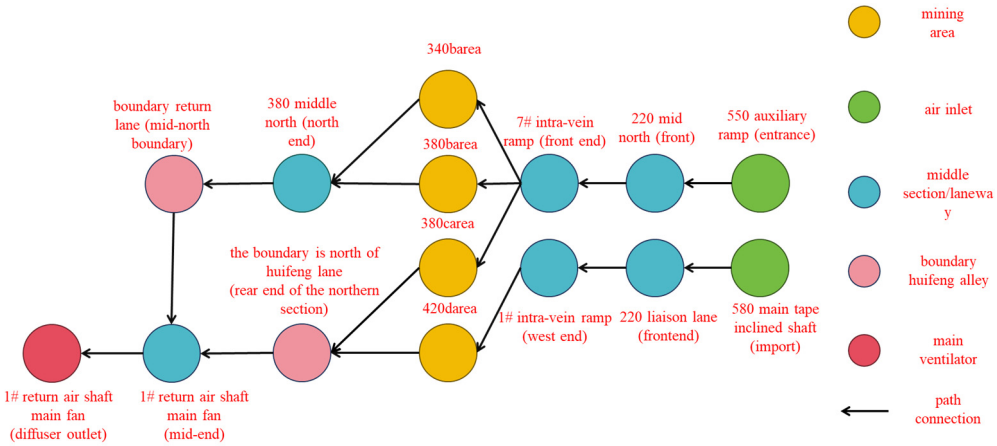


Figure 3. Topological Map of Path Planning for Each Mining Area.

Wind speed measurements were conducted in the primary shafts and roadways corresponding to the ventilation paths, with results summarized in Table 1. Measurement results showed that the highest wind speed in the dedicated ventilation shafts and main intake/return ducts was 12.00 m/s. It is noted that the mine layout does not include dedicated material hoists, air bridges, or shafts currently under repair. The maximum recorded wind speeds were as follows: 7.81 m/s in the main intake and return ducts of the middle section; 5.92 m/s in the intake and return ducts of the transportation roadway and mining area; and 3.14 m/s at the four individual mining sites. All recorded values at the shaft and tunnel sections are below the stipulated maximum wind speed standards.

Table 1. Average Maximum Wind Speed at Shaft and Tunnel Sections.

Name of the Shaft and Tunnel	Actual Wind Speed (m/s)	Maximum Wind Speed (m/s)
Dedicated air shafts, dedicated main air intake and return ducts	12.00	15
Specialized material lifting well	/	12
Wind bridge	/	10
The shaft for lifting materials and personnel, the main intake and return air ducts in the middle section, and the main ramp of the shaft under repair	7.81	8
Transportation roadways, intake and return air ducts in the mining area	5.92	6
"Quarry"	3.14	4

"/" denotes 'Not Applicable' for facility types do not present in the mine.

4.2. Design and Application of On-Demand Ventilation Underground

To ensure a scientifically grounded ventilation system design, the mine's air demand is calculated using a multidimensional approach based on the core formula of the calculation system [24]. The air demand calculation must simultaneously meet the three core requirements of personnel breathing needs, diesel equipment heat dissipation, and dust dilution.

The required air volume for personnel (Q) was calculated as 720 m^3/min, based on a maximum simultaneous occupancy of 180 workers underground. The northern operation area contains four key ventilation points—Areas 340B, 420D, 380B, and 380C—all configured as roadway-type stopes. Measured inlet wind speeds at these locations are 2.57 m/s, 3.14 m/s, 2.87 m/s, and 2.86 m/s, respectively. Each measured speed falls within the mandated range of 0.25 to 4 m/s, confirming compliance with ventilation standards for this stope type. The required air volume for diesel equipment (18,488.4 m^3/min) was calculated based on the following fleet composition and specifications: eight 15-ton vehicles at 162 kW (utilization 0.8); nine 30-ton vehicles at 294 kW (0.8); fifteen 162 kW loaders (0.5); five 92 kW material transport vehicles (0.3); and five 77 kW passenger transport vehicles (0.3). The total mine air volume is calculated by comprehensively considering key sources of demand. Firstly, the air volume required for underground operational personnel is 720 m^3/min. Secondly, the air volume required for diesel equipment is 18,488.4 m^3/min. As all non-essential personnel are evacuated before blasting, the total air demand is the sum of these two components, amounting to 19,208.4 m^3/min, as summarized in Figure 4.

Taking the K_b value as 1.27 for calculation, before optimization, although the measured total intake air volume of the mine reached 26,145.6 m^3/min, the actual air volume in key areas could not meet the demand due to unreasonable airflow distribution. After optimization with SSA, the theoretically optimal total required air volume calculated by the system was 24,394.67 m^3/min (air volume reserve coefficient). The measured total intake air volume of 26,145.6 m^3/min was higher than this value, indicating sufficient total air volume reserve, which provided a basis for on-demand distribution. The inlet air velocities in all areas were confirmed to comply with safety regulations. As previously stated, the

340B, 420D, 380B, and 380C areas are all roadway-type stopes, with measured inlet wind speeds of 2.57 m/s, 3.14 m/s, 2.87 m/s, and 2.86 m/s, respectively. The safety standard specifies a minimum wind speed of 0.25 m/s for individual mining faces. Therefore, the measured values from all four areas satisfy this requirement.

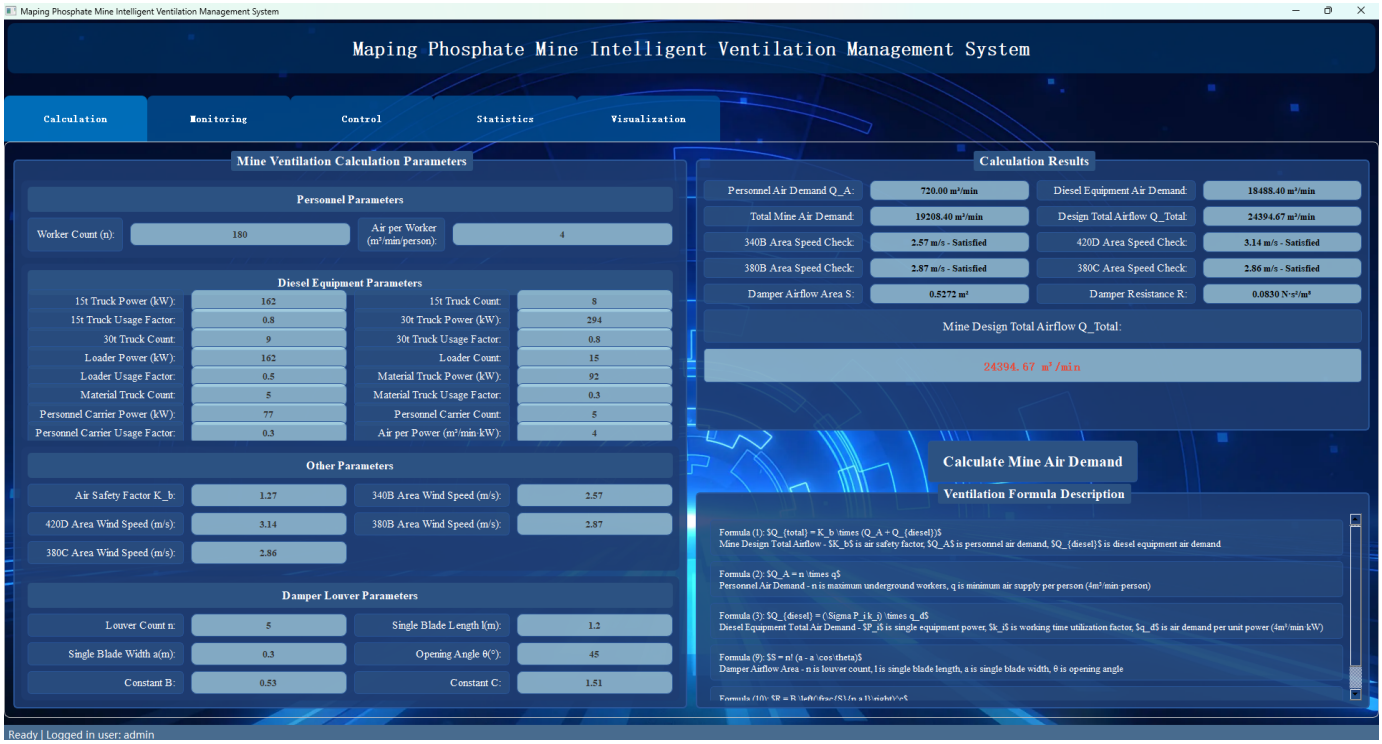


Figure 4. Computing system operation interface.

To ensure safe and efficient ventilation, the air volume distribution and damper layout within a mining area should be determined by a comprehensive assessment of its operational intensity, equipment density, and personnel distribution. Concurrently, air velocity at all stope entrances must be controlled within the prescribed limit of 0.25–4 m/s. The intelligent ventilation management system ensures safety and efficiency by dynamically adjusting air volume based on real-time data to prevent harmful gas accumulation. Corresponding air distribution plans for each mining area are precisely calculated by the system, integrating real-time monitoring with operational demands.

The air volume distribution calculation followed a three-step procedure. First, the required air volume for each stope was determined based on its operational intensity, equipment power, and personnel distribution. Second, the calculated distribution was verified to ensure the inlet wind speed at each stope entrance met the safety standard of 0.25–4 m/s. Finally, a rational air volume distribution scheme satisfying all conditions was formulated, as presented in Table 2.

Table 2. Air Demand Meter for Mining Area.

Region	Air Intake Tunnel Wind Speed (m/s)	Air Demand (m^3/s)
420D Mining area	2.57	67.77
340B Mining area	2.64	69.31
380B Mining area	2.87	74.96
380C Mining area	2.86	74.96

This control technology centers on a louvered air door for ventilation regulation. It integrates an ultrasonic wind speed sensor for data acquisition, a surface-based upper computer for calculation and remote command issuance, and a hydraulic actuator for adjusting the louver angles to achieve automated air volume control. The design also incorporates a motor-driven slider for automated adjustment, complemented by a manual switching function.

The process of determining the opening degree of the damper mainly includes the following steps:

The relationship between the adjustment Angle θ of the damper louver and the air passage area S of the damper follows the following formula:

$$S = nl(a - a\cos\theta) \tag{9}$$

In the formula, n represents the number of slats of the blinds; l is the length of the single-page blinds, m; a represents the width of the single-leaf blinds, in meters; θ represents the opening Angle of the air window, (°).

The relationship between the air passage area of the damper and the air resistance of the damper follows the following formula:

$$R = B\left(\frac{S}{nal}\right)^{-C} \tag{10}$$

In the formula, R represents the wind resistance of the damper; B and C are constant coefficients, with B = 0.53 N·s^2/m^2 and C = 1.51. From this, it can be concluded that the purpose of air distribution as needed can be achieved through the method of increasing resistance and adjustment.

The calculated target opening angle is encapsulated into standard control commands. The host computer sends these commands to the PLC (Programmable Logic Controller) or dedicated hydraulic controller in the corresponding tunnel via industrial Ethernet or RS485 bus. The controller drives the hydraulic cylinder to precisely adjust the louver blades to the specified angle.

Based on the air demand analysis, regulating air doors were deployed in the roadways of each mining area. The system operates by first calculating the optimal damper louver angle via the specified formula and issuing an adjustment command. This command drives a hydraulic system to modulate the damper's open area, thereby controlling the airflow. The actual air volume is continuously monitored by sensors, forming a closed-loop control system as illustrated in Figure 5.

To compensate for the inadequate intake airflow in the trial mining areas, local ventilators and regulating dampers have been strategically installed in critical tunnels. This adjustment ensures sufficient air volume throughout the ventilation network for production, with the specific layout detailed in Figure 6.

Integrating the ventilation zoning design, working-face air volume analysis, and the mine's current ventilation conditions, the air passage area and wind resistance for each regulating damper were determined. This was achieved using the louver control system within the ventilation management system and applying Formulas (7) and (8). The detailed results are provided in Table 3 and illustrated in Figure 7.

The integration of intelligent control schemes, ventilation network simulation, and zonal ventilation planning has yielded significant improvements in ventilation performance at the working faces of the Maping Phosphate Mine. Following system deployment, field tests conducted over a one-month operational period demonstrated a reduction in average energy consumption from 2.012 × 10^6 kWh to 1.4084 × 10^6 kWh (a 30% decrease), as well

as a decrease in dust concentration exceedance incidents from 37 to 11 per month (a 70% decrease), compared to baseline levels. This solution delivers a dual benefit: it significantly improves both the safety and comfort of the working environment, while also reducing equipment maintenance costs and production disruption risks by mitigating dust pollution.

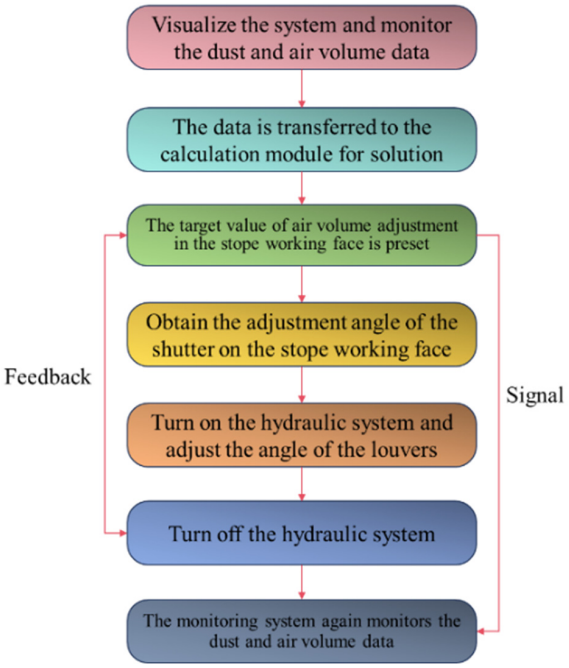


Figure 5. Flowchart of on-demand ventilation technology.

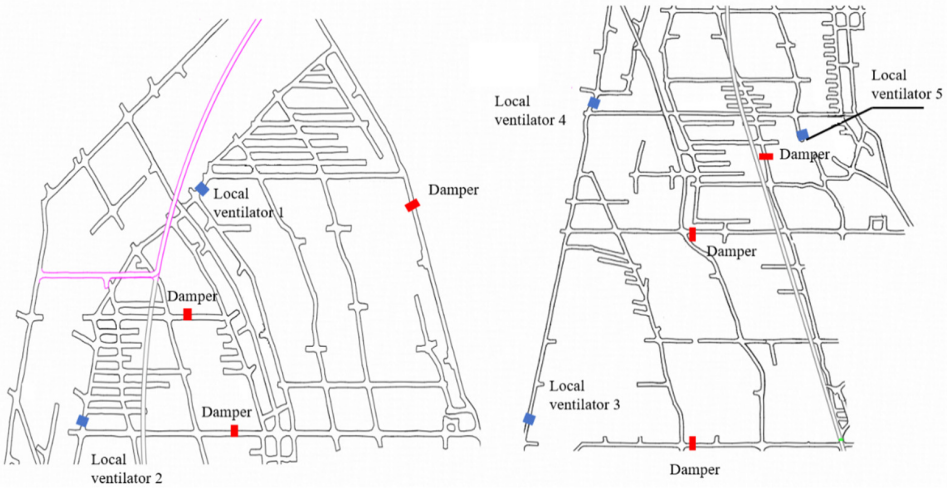


Figure 6. Layout diagram of fans and dampers in the test production area.

Table 3. Cross-sectional area and Wind Resistance of the damper.

Trial Production Area	Damper Position	Cross-Sectional Area for Air Passage (m^2)	Wind Resistance ($N \cdot s^2/m^8$)
340B Trial production area	North of the middle section 340	0.2	42.1
380B Trial production area	No. 7 In-pulse ramp	0.6	27.0
380B Trial production area	Ramp of Disk Area 1	0.5	28.6
380C Trial production area	No. 6 Intra-pulse ramp	0.2	42.1
380C Trial production area	400 section north	0.3	39.5
420D Trial production area	No. 1 Intra-pulse ramp	0.4	32.8

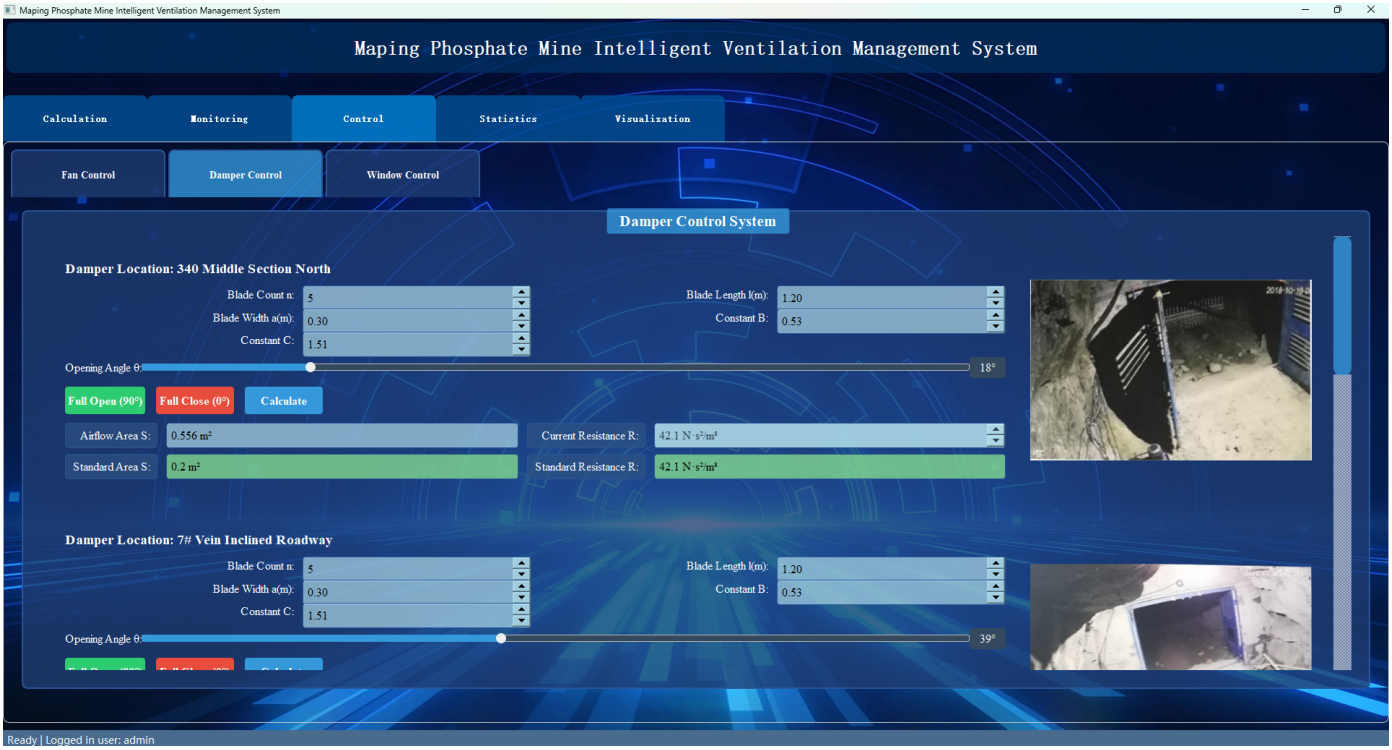


Figure 7. Damper louver control system.

5. Discussion

In this study, SSA is optimized to achieve on-demand air supply in the mine ventilation system. The objective is to ensure that core requirements—such as air supply for personnel respiration, heat dissipation from diesel equipment, and dust dilution—are met, while maintaining the air velocity at the intake of mining faces within the safe range of 0.25–4 m/s. The SSA optimizes air volume distribution through an iterative approximation process, gradually converging from the initial solution space toward the optimal solution. By simulating the foraging behavior of sparrow populations—where individuals are categorized as explorers, followers, and scouts—the algorithm drives the search process for the global optimum.

The application of the SSA in dynamic underground environments demonstrates remarkable robustness and adaptability. This model successfully overcomes the limitations of traditional static empirical formulas, which cannot adapt to dynamic conditions, thereby providing core algorithmic support for "ventilation on demand".

However, the optimization and control of the system highly depend on real-time data provided by air velocity and pressure sensors. Sensor failures or data transmission interruptions represent potential major fault modes. These issues could lead to deviations in the optimization model or force the system to switch to a conservative fixed operational mode, thereby affecting control accuracy.

To further enhance the system's robustness and adaptability, future work will focus on the following:

Developing sensor fault diagnosis and fault-tolerant control strategies based on multi-source information fusion.

Investigating rapid model self-adaptation methods using transfer learning to improve the system's generalization capability across different mines.

6. Conclusions

This study, using the Maping Phosphorite Mine as the engineering context, developed an intelligent ventilation management system integrating monitoring, optimization, and control. By deeply integrating the Sparrow Search Algorithm with the physical and safety constraints of mine ventilation and designing a remote closed-loop control strategy, the study primarily yielded the following conclusions and outcomes:

(1) A dynamic air volume optimization method suitable for mine ventilation was proposed. By mapping the "exploration-following-vigilance" mechanism of the classic Sparrow Search Algorithm to the safety verification process in ventilation networks, a dynamic air volume calculation model was constructed. This model successfully addresses the shortcomings of traditional static empirical formulas that cannot adapt to the dynamic underground environment, providing core algorithmic support for "on-demand ventilation."

(2) Achieved closed-loop integration of algorithm-hardware-software and delivered significant engineering benefits. The system converts the optimal air volume output by the SSA into control commands for hydraulic air doors in real-time via the PyQt5 upper computer, forming an intelligent closed loop of "perception-optimization-execution-feedback." Field applications demonstrate that while addressing airflow disorder issues, the system achieved quantifiable engineering benefits: mine ventilation energy consumption was reduced by approximately 30%, and dust concentration in key working faces decreased by about 70%, validating the effectiveness of the proposed architecture and methodology.

(3) However, the optimization and control of the system heavily rely on real-time data from wind speed and pressure sensors. Sensor malfunctions or data transmission interruptions are the primary potential failure modes, which may lead to inaccuracies in the optimization model or force the system to switch to a conservative fixed operation mode, thereby affecting control precision.

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