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Gas Diffusion Simulation in Abandoned Mines and Unmanned Detection Path Generation Based on Fluent Simulation and Improved Path Planning Algorithm

Yehao Su

WA School of Minerals, Energy and Chemical Engineering, Curtin University, Perth, Australia
suzigong63794@gmail.com

Abstract. Smart mining has emerged as a pivotal trend in modern mining development. In high-risk production environments, unmanned systems significantly reduce operational hazards, particularly in scenarios like abandoned mine roadway inspections. This study investigates path planning for unmanned detection equipment, which not only enhances intelligent capabilities but also provides actionable solutions for similar optimal path determination challenges. Building upon single-objective and multi-objective path planning methodologies, our research develops a comprehensive unmanned detection equipment routing algorithm tailored to specific operational conditions. The methodology comprises two key components: First, we characterize the working environment of abandoned mine roadways. Using Fluent software, we simulate gas leakage patterns under varying conditions —including different leakage rates and locations—thereby establishing diffusion patterns of hazardous gases. Second, through Python-based simulations employing our optimized algorithm, we demonstrate real-world application scenarios for unmanned detection equipment in these complex environments.

Keywords: Abandoned mine, unmanned detection equipment, path planning, Fluent simulation

1. Introduction

Smart mining has emerged as a pivotal trend in modern mining development. The adoption of unmanned operations significantly reduces occupational hazards associated with manual labor. Currently, unmanned underground inspection systems predominantly utilize track-guided or pre-programmed navigation modes. Autonomous detection equipment capable of self-planning routes requires no human intervention during operation. After setting predefined start/stop points and constraints, these systems autonomously complete the entire mission from initiation to completion, achieving substantially higher intelligence levels compared to traditional inspection devices. This study investigates path planning for unmanned detection equipment, demonstrating its potential to significantly enhance operational intelligence while providing actionable solutions and conceptual frameworks for similar optimal solution challenges.

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2. Basic assumptions

The research on CFD models aims to provide numerical equations for controlling fluid flow, enabling mathematical interpretation of the overall flow field through spatial-temporal solutions. The Navier-Stokes equations consist of a series of partial differential equations that explain the conservation laws of fluid motion. To simulate the flow process of harmful gases in abandoned mine tunnels after leakage, gas conservation equations are required to solve momentum and mass conservation equations [2]. The mass conservation equation, sometimes referred to as the continuity equation, can be expressed as:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho v) = S_m$$

The equation of conservation of momentum can be expressed in an inertial reference frame without acceleration as:

$$\frac{\partial}{\partial t}(\rho v) + \nabla \cdot (\rho v v) = -\nabla p + \nabla \cdot (\tau) + \rho g + F$$

The energy conservation equation is expressed as:

$$\frac{\partial}{\partial t}(\rho h) + \nabla \cdot (\rho v h) = \nabla \cdot (k + k_t) \nabla \cdot T + S_h$$

Gas state equation, such as the equation

$$pV = nRT$$

The abandoned mine roadway under study can be regarded as a porous medium, in which a momentum source is added to the standard fluid flow equation. This source consists of two parts: the viscous loss term and the inertial loss term [3].

$$S_i = \sum_{j=1}^{3} D_{ij} \mu v_j + \sum_{j=1}^{3} C_{ij} \frac{1}{2} \rho |v| v_j$$

In laminar flow through porous media such as abandoned mine tunnels, the pressure drop is generally proportional to the velocity. Ignoring convective acceleration and diffusion, the Darcy law can be used to simplify the porous medium model, that is:

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$$\nabla p = -\frac{\mu}{\alpha} v$$

The pressure variation in the three coordinate axes (x, y, z) of the pore region is:

$$\Delta p_x = \sum_{j=1}^{3} \frac{\mu}{\alpha_{xj}} v_j \Delta n_x, \Delta p_y = \sum_{j=1}^{3} \frac{\mu}{\alpha_{yj}} v_j \Delta n_y, \Delta p_z = \sum_{j=1}^{3} \frac{\mu}{\alpha_{zj}} v_j \Delta n_z$$

The primary factors controlling gas movement are molecular diffusion driven by concentration and temperature gradients, as well as viscous flow or mass flow caused by pressure gradients. According to Fick's law, the diffusion process is described as follows:

$$J_i = \rho D_{im} \frac{\partial X_i}{\partial x_i} - \frac{D_i^T}{T} \frac{\partial T}{\partial x_i}$$

For non-thin gases, a multi-component diffusion formula can be used instead:

$$J_i = \rho \frac{M_i}{M_{\text{mix}}} \sum_{j, j \neq i} D_{ij} \left(\frac{\partial X_j}{\partial x_i} + \frac{X_j}{M_{\text{mix}}} \frac{\partial M_{\text{mix}}}{\partial x_i} \right) - \frac{D_i^T}{T} \frac{\partial T}{\partial x}$$

The standard k-ε model is a semi-empirical formulation primarily based on turbulent kinetic energy and diffusion rates. The turbulent kinetic energy equation (k) and diffusion equation (ε) are exact, while the turbulent dissipation equation (ε) is derived from empirical formulas. The standard k-ε model equations, which do not account for self-defined sources, are expressed as follows:

$$\rho \frac{dk}{dt} = \frac{\partial}{\partial x_i} \left[\left(\mu_l + \frac{\mu_t}{\sigma_k} \right) \frac{\partial k}{\partial x_i} \right] + G_k + G_b - \rho \varepsilon$$

The turbulent energy dissipation rate ε equation is

$$\rho \frac{d\varepsilon}{dt} = \frac{\partial}{\partial x_i} \left[\left(\mu_l + \frac{\mu_t}{\sigma_\varepsilon} \right) \frac{\partial \varepsilon}{\partial x_i} \right] + C_{\varepsilon 1} \frac{\varepsilon}{k} \left(G_k + C_{\varepsilon 3} G_b \right) - C_{\varepsilon 2} \rho \frac{\varepsilon^2}{k}$$

$$\mu_t = \rho C_\mu \frac{k^2}{\varepsilon}$$

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This demonstrates that, with constant molar gas constant R and temperature T, gas pressure is directly proportional to molar concentration, which can be directly converted from gas concentration. Since the color cloud map generated by Fluent software represents gas pressure, the pressure distribution and variation trends observed in this study can be interpreted as corresponding to the distribution and variation trends of gas concentration [4].

This study employs the Computational Fluid Dynamics (CFD) software Fluent to simulate the leakage and dispersion of hazardous gases in abandoned mine tunnels. Fluent, a module of ANSYS, solves the Navier-Stokes equations using finite volume fluid dynamics. To analyze gas distribution, the simulation process begins with constructing a 3D tunnel model, followed by meshing it at appropriate computational scales. The meshed model is then imported into the computational module, where boundary conditions and initial values are specified before conducting numerical simulations to generate relevant cloud diagrams. The Fluent version used in this simulation is ANSYS 2021 R1, running on Windows 10 21H1.

The Fluent software simulation process based on ANSYS 2021 R1 mainly includes the following steps: (1) Construct a 3D roadway model; (2) Divide the 3D roadway model into a mesh according to appropriate computational dimensions; (3) Import the meshed model into the computational module and set boundary conditions and initial values for each part; (4) Perform numerical simulation to obtain relevant cloud diagrams.

3. Model developmentand solution

Before the simulation, certain assumptions need to be made on the working conditions: first, in order to facilitate the calculation and simulation, it is assumed that the gas composition is 100% methane (CH4); second, it is assumed that the internal part of the roadway is completely closed, and no gas leakage occurs in other positions except the gas leakage point.

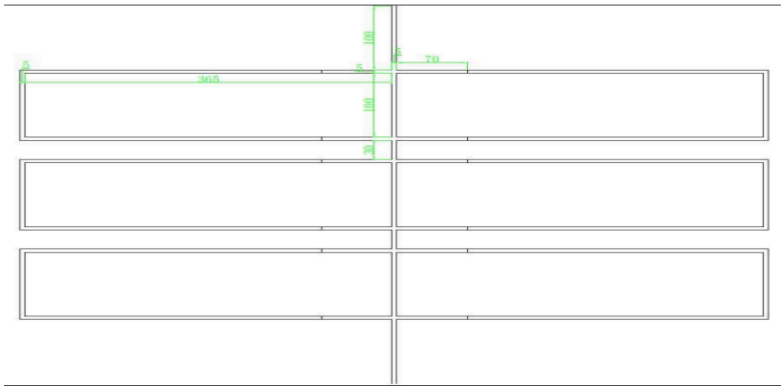

Figure 1. Examples of abandoned mine tunnels

A model of abandoned mine roadway is developed for subsequent software simulation. For clarity, each closed surface starting from the main roadway is labeled with letters A to N, while all intersections within the roadway are numbered 1 to 6.

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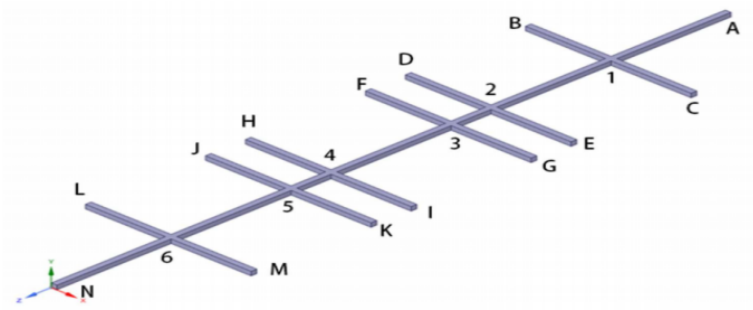

Figure 2. Schematic diagram of the establishment of the abandoned mine roadway model

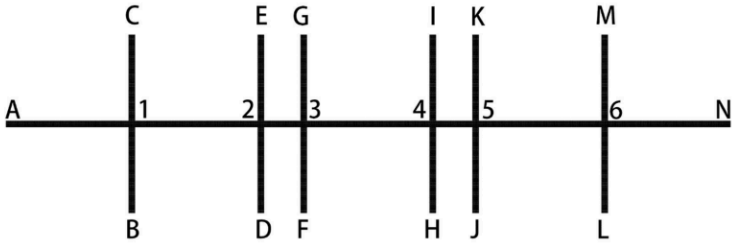

Figure 3. Part of the actual roadway after gridding

To utilize the algorithmic model described earlier for tunnel detection, we first assume a gas leak exists at point B starting from point A. In this scenario, there is only one target point, and the process from A to B can be directly addressed using the A* algorithm. Given the large volume of the tunnel and its dense grid structure, the full path cannot be represented graphically. Therefore, the path maps involving points A and B, along with those generated by the Python algorithm, are partially enlarged. However, this navigation mode remains the simplest approach, as it only requires planning the path between known starting and intermediate points. In this design, the unmanned detection device must autonomously determine detection points and complete navigation tasks, which involves both independently identifying detection locations and planning routes between different detection points.

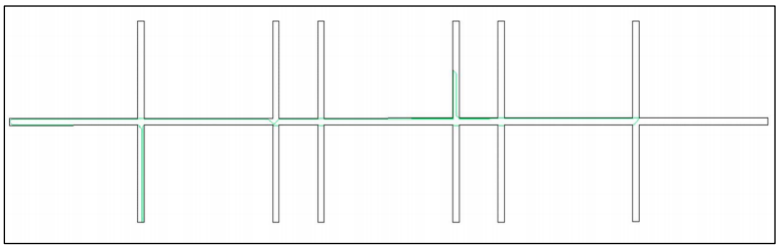

Figure 4. An example of unmanned detection equipment algorithm in roadway navigation

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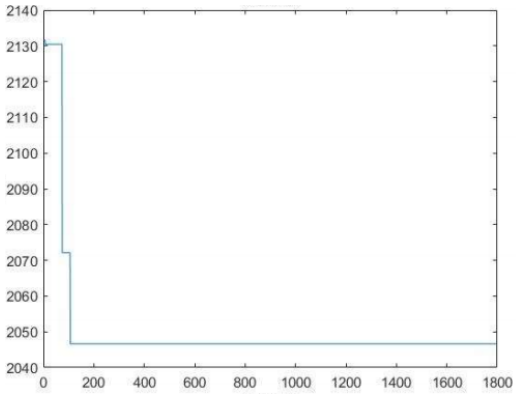

Figure 5. The iterative process of unmanned detection equipment algorithm applied in roadway

The simulation annealing algorithm parameters adjusted in this study demonstrate that approximately 100 iterations are required to achieve the shortest distance. The left route diagram shows the path from left to right at the intersection, while the right route illustrates the return path from right to left. The significant downward deviation in the return route occurs because the upper branch alleyway contains no gas leakage points. Although leakage points exist in the lower section and were detected during initial detection, the surrounding gas concentration field still exerts gravitational pull on the unmanned detection equipment during its return journey. Currently, there is no effective algorithmic solution to this issue. However, integrating inertial navigation systems with detection devices could enable them to maintain memory of their physical movement positions.

4. Conclusion

In the path planning process for unmanned detection equipment in abandoned tunnels containing harmful gases, the devices must rely on their onboard sensors to monitor real-time methane concentration distribution within the tunnel and identify suspected leakage points – the locations requiring equipment deployment. When using autonomous navigation systems to replace manual detection of harmful gases in abandoned mines, external observers cannot perceive the actual methane concentration distribution within the tunnel. However, methane distribution is physically present in the monitored tunnel. Essentially, the abandoned tunnel where the unmanned equipment travels contains a methane diffusion field that directly influences its navigation path. This chapter focuses on establishing a gas flow model for tunnels to analyze methane distribution patterns, while integrating two previously proposed algorithms into the tunnel model. The study demonstrates that the algorithms fundamentally meet the requirements outlined in this paper, and through targeted optimizations, existing limitations in the current algorithms can be addressed.

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