Automatic Generation of Mine Ventilation Network Diagrams Based on Ant Colony Algorithm

Xueyuan Zhao[*], Jingyu Wang and Heng Zhang

College of Safety Science and Engineering, Liaoning Technical University, Huludao, China

[*]851540571@qq.com

Abstract. As contemporary mines continue to scale in size and complexity, the generation and optimization of mine ventilation network0 diagrams has emerged as a critical problem for the industry. Based on the current ant colony algorithm and graph theory modeling framework, multi-level topological representation and improved heuristic functions are proposed, and dynamic pheromone update, combination of local and global search, and adaptive constraint processing and other innovative methods are used to realize the automatic generation and optimization of mine ventilation network in multi-objective and multi-constraint scene. The model precisely applies the Boolean line segment and node merge method to modify the expression of the ventilation roadway and wind flow intersection, by the adaptive weight distribution mode, it explores the energy consumption, safety, and operation cost indexes, and realizes the automatic identification and dynamic configuration of the main gas path and the redundant loop in the complex ventilation network with the collaborative effect of hybrid ant colony algorithm at the global and local search stage. Meanwhile, this model also formulates the iterative correction mechanism of the fan and regulating facilities layout to guarantee the generated ventilation network with better adaptibility and reliability. It is shown by experiment results that the generation speed and optimization quality of the model is significantly improved.

Keywords: Mine ventilation network, Ant colony algorithm, Multi-objective optimization, Topology design.

1 Introduction

Industrial ventilation systems (IVS) are a core component of underground mining operations that can directly impact the health and safety of miners. A good lubrication, ventilation system could rapidly discharge harmful gases in the mine (methane (CH_4), carbon monoxide (CO), etc.) [1], control dust concentration, adjust temperature and humidity, to get a good capacity in preventing gas explosion, coal spontaneous combustion and other disasters. The mine will be able to achieve both goals if proper ventilation design is accomplished, through which we can improve the working environment of the mine, energy consumption, and it will lower operating costs [2].

The diagram of the ventilation network of the mine is an important basis for the planning and management of mine ventilation systems, and it is a visual representation of the mine's airstream path, including the layout distribution of ventilation facilities such as the roadway, ventilation shaft, damper, and fan. Ventilation network diagrams are used by engineers to analyze air flow, assess ventilation efficiency, and optimize ventilation control programs. The original method of manual production of the air ventilation network diagram can not meet the practical needs any more, especially with the continuous expansion of mine scale and the increasing complexity of the structure [3].

Ant colony optimization (ACO) is an intelligent optimization algorithm derived from ants' foraging behavior. In the nature, when ants find food sources, they have to go back to the nest, they release pheromones to mark the path, pheromones for the food source!Over time, more pheromones accumulated along shorter paths, so eventually, the ant colony will always find the best path [4].

2   Related Work

Novella-Rodriguez et al. [5] proposed a systematic modeling framework to improve the analysis of mine ventilation networks, in particular in low-scale mine environments. Xu et al. [6] together with IoT technology to research using intelligent sensor technology to monitor key parameters such as mine airflow, gas concentration, etc. in real time, in order to realize the dynamic adjustment of ventilation schemes. In particular Saleem et al. [7] computes the frictional resistance of the network of mine ventilation system to optimize the air flow path for minimal loss of energy.

Rodriguez-Diaz et al. [8] which emphasis on ventilation control strategies for underground works in small scale and introduced an experimental benchmark model to analyze the usefulness of different control mechanisms in ventilation systems. Wang et al. [9] targeting optimization of mine airflow distribution with a view of decreasing energy consumption and operating cost of ventilation systems, based on improved Sooty Tern Optimization Algorithm (STOA) and simulated for solving network optimization.

Hati and Kuma [10] proposed an optimization method based on adaptive neural fuzzy reasoning system to focus on energy consumption prediction and airflow optimization of mine ventilation system. However, combining the self-learning ability of neural network and the reasoning ability of fuzzy logic, it can accurately predict the energy consumption and air flow of ventilation system in complex mine environment.

Yu et al. [11] analyze the impact of coal and gas outbursts on ventilation networks When coal and gas outbursts occur, the gas flow in the mine will be extremely disturbed, resulting in turbulent flows, making it difficult to predict the changes in gas flow direction and concentration. Cao et al. [12] conducted uncertainty analysis on the modeling of mine ventilation systems and explored how to improve the accuracy of ventilation network simulations.

3   Methodologies

3.1   Multi-Level Topology and Multi-Objective Optimization

We first establish a multi-level topology to describe the mine ventilation network more flexibly. The bottom layer is mainly composed of the original roadway and nodes, and any two line segments L_i and L_j are subjected to Boolean operations to generate intersections. If the distance between the generated new node v_{new} and the existing node v_k is less than δ, it is regarded as the same node to reduce redundancy, and finally the merged node set $\hat{V}$ is obtained.

In order to take into account the global layout and local details, we divide the network into several subgraphs according to different granularities, so that the evaluation scale can be dynamically switched in the subsequent optimization. In terms of multi-objective optimization, let's assume that the main objectives we focus on include total energy consumption f_1, safety violation f_2, and operating cost f_3. The three objectives are synthesized into Equation 1 by the adaptive weighting method:

$$F(x,t) = \omega_1(t)f_1(x) + \omega_2(t)f_2(x) + \omega_3(t)f_3(x), \tag{1}$$

where x represents the feasible solution of the ventilation network (i.e., the selected air path configuration, fan layout and model, location and opening of the adjustment facility, etc.), $\omega_1(t)$, $\omega_2(t)$, and $\omega_3(t)$ represent the adaptive weights of each objective function in the t-round iteration. In order to determine the weights, this paper synthesizes the standard deviation of the distribution of each target value in the current solution set and the ranking of the solution: Let $\sigma_i(t)$ be expressed as Equation 2:

$$\sigma_i(t) = \sqrt{\frac{1}{|\Omega_t|} \sum_{x \in \Omega_t} \left(f_i(x) - \overline{f}_i(x) \right)^2}. \tag{2}$$

Calculate the normalization factor $\alpha_i(t)$, as shown in Equation 3:

$$\alpha_i(t) = \frac{\sigma_i(t)}{\sum_{j=1}^{3} \sigma_j(t)}, \tag{3}$$

Combined Ranking Factor $\beta_i(t)$, update the weights with linear weighting, as shown in Equation 4:

$$\omega_i(t+1) = (1-\eta)\omega_i(t) + \eta\left(\lambda_1\alpha_i(t) + \lambda_2\beta_i(t)\right). \tag{4}$$

If the solution does not meet the hard constraints such as minimum air volume or fan power, the adaptive penalty function is used to introduce the degree of violation $\mathscr{E} \cdot P(x)$ to $F(x,t)$ and local patching within the feasible solution range to balance multiple objectives and ensure the practical feasibility of mine ventilation.

3.2 Improved ant Colony Algorithm and Collaborative Search

In the implementation of the algorithm, we use the improved ant colony algorithm to efficiently solve the above multi-objective and multi-constraint problems through dynamic pheromone update and local-global cooperative search. Specifically, the transition probability of each ant from node i to node j when constructing the path is represented by Equations 5 and 6:

$$p_{ij}(t) = \frac{\tau_{ij}(t)^\alpha \eta_{ij}(t)^\beta}{\sum_{k \in N_i} \tau_{ik}(t)^\alpha \eta_{ik}(t)^\beta}, \tag{5}$$

$$\eta_{ij} = \frac{1}{1 + \gamma_1 Resist_{ij} + \gamma_2 Cost_{ij} + \gamma_3 Risk_{ij}}, \tag{6}$$

where $\tau_{ij}(t)$ is the concentration of pheromones on edges (i, j), N_i is the set of feasible edges connected to i, and α and β measure the relative importance of pheromones to heuristic functions, $Resist_{ij}$, $Cost_{ij}$, and $Risk_{ij}$ represent the comprehensive amount of channel resistance, potential operating costs, and safety risks, respectively, in order to prevent the rapid concentration of pheromones into a few paths, the ants also carry out local updates after each step, as shown in Equation 7:

$$\tau_{ij}(t) \leftarrow (1 - \phi)\tau_{ij}(t) + \phi r_0, \tag{7}$$

where ϕ is the local update rate and r_0 is the initial pheromone value, which reduces the risk of local optimal traps by maintaining search diversity in the early stage.

At the end of an iteration, the feasible solution path completed by each ant triggers a global pheromone update, as shown in Equations 8 and 9:

$$\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta r_{ij}^k(t), \tag{8}$$

$$\Delta r_{ij}^k(t) = \begin{cases} \dfrac{Q}{F(x^k, t)}, & (i, j) \in \Pi^k \\ 0, & otherwise \end{cases}, \tag{9}$$

where ρ is the volatility coefficient, Π^k is the path constructed by ant k, x^k is the feasible solution corresponding to the path, $F(x^k, t)$ is the value of the multi-objective function, and Q is the constant. At the same time, in order to identify and adjust the key channels and redundant loops, the model uses importance coefficient, as Equation 10:

$$\kappa_{ij} = \left| \frac{\partial \Theta(x)}{\partial Q_{ij}} \right|, \tag{10}$$

where $\Theta(x)$ can be a measure of air flow safety or a function of the main ventilation demand, and if κ_{ij} is significantly larger than other channels, (i, j) is regarded as the key air path and preferentially retained or strengthened in the subsequent local search.

4   Experiments

4.1   Experimental Setup

In the experiment, Mine Ventilation Network Dataset (VRCs dataset) was used which is available at https://github.com/changtian0509/VRCs. It preserves rich information of structure of ventilation network, nodes (i.e., location of roadway intersects, fan) and edges (i.e., ventilation path wires), with covering scale and complexity of ventilation network models, supported by leading visual ease of understanding and realism. In the experiment, we input the dataset, draw and optimize the ventilation network diagram automatically by using the ant colony algorithm, and compare it with the actual network diagram on the dataset.

4.2   Experimental Analysis

To verify the availability of my ventilation network diagram automatic drawing method based on ant colony algorithm, we selected four associated comparison methods including the pressure energy distribution (PED), B/S shared mode (B/S), adjacency matrix transformation (AMT), and predictive system (PS). The overall structure of the mine ventilation network presented in Figure 1 is based on the node-to-node relationships presented in a spiral layout with contrasting edges referring to the edges highlighting the main ring referring to the core ventilation circuits identified in the network and edges in light colors demonstrating the arterial connectedness of the actual mine.
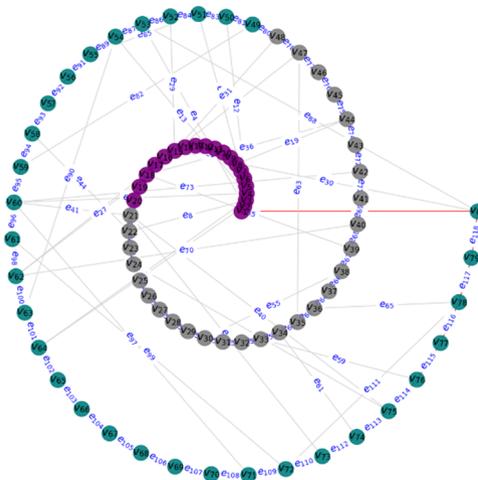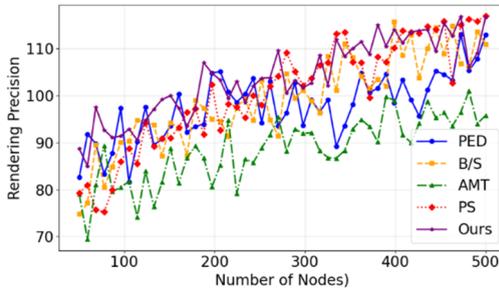

Fig. 1. Mine Ventilation Network

After comparison with the traditional annular layout or random layout, this spiral arrangement can still control the overlap degree well in the case of large number of nodes, and highlight the hierarchical distribution and correlation relationship within

the network. But in very dense local area or extremely deep interlaced network struc-ture appears still some visual interference. Compared with the genetic algorithm and particle swarm optimization algorithm, the ant colony algorithm has the best optimiza-tion effect, especially when dealing with multi-objective and multi-constraint problems, the performance of the ant colony algorithm is more stable than other algorithms.

The model can dynamically adjust the ventilation network based on real-time envi-ronmental, changes in mine ventilation paths, fluctuations in gas concentrations, etc.

Fig. 2. Comparison of Rendering Precision for Multiple Methods

In Figure 2, it can be observed that the plotting accuracy of the five methods gener-ally increases with the increase of parameters, but the Ours method maintains a high performance in most of the parameter intervals. Overall, ours can improve the drawing accuracy more stably in larger or more complex scenes, showing higher effectiveness.

In large-scale mining networks, the computation time of the algorithm increases lin-early with the increase in the number of nodes. By comparing the computation time before and after optimization, the optimized algorithm reduces the computation time by about 20% and the memory footprint by 15% when processing of 10,000 nodes.

5   Conclusion

In conclusion, our model aims to improve the intelligent management level of mine ventilation system, so a way of automatic drawing method of mine ventilation network diagram based on ant colony algorithm was proposed. Experimental results confirm that the proposed method has good performance of drawing accuracy, computation ef-ficiency and adaptability of complex network structure, and explain the superiority of ant colony algorithm in optimizing the layout of ventilation network through evaluation with multiple comparison methods. But there are still many aspects that can be pro-moted, including the computational complexity of the algorithm in the large-scale mine network, and the adaptive optimization ability in the dynamic environment.

References

1. Bhukya, Prasad, and Krishna Naick Bhukya. "Enhancing ventilation fan performance in underground coal mines: a hybrid approach." Electrical Engineering 106.4 (2024): 4969-4992.
2. Yi, Huiuk, et al. "Applications of computational fluid dynamics for mine ventilation in mineral development." Energies 15.22 (2022): 8405.
3. Yu, Bao-cai, and Liang-shan Shao. "A mine ventilation system energy saving technique based on an improved equilibrium optimizer." Frontiers in Energy Research 10 (2022): 913817.
4. Jia, Peng, et al. "Theory of RPOD adjustment of air volume for mine intelligent ventilation." International Journal of Ventilation 21.4 (2022): 316-329.
5. Novella-Rodriguez, David-Fernando, Emmanuel Witrant, and Christian Commault. "Physical modeling and structural properties of small-scale mine ventilation networks." Mathematics 10.8 (2022): 1253.
6. Xu, X. Z., et al. "A comprehensive evaluation of intelligent coal mine ventilation systems in the internet of things." Human-Centric Comput. Inform. Sci. 13 (2023): 46.
7. Saleem, Hussein A. "Energy Consumption Reduction in Underground Mine Ventilation System: An Integrated Approach Using Mathematical and Machine Learning Models Toward Sustainable Mining." Sustainability 17.3 (2025): 1038.
8. Rodriguez-Diaz, Oscar-Oswaldo, et al. "Control strategies for ventilation networks in small-scale mines using an experimental benchmark." Asian Journal of Control 23.1 (2021): 72-81.
9. Wang, Jinmiao, et al. "Optimization of airflow distribution in mine ventilation networks using the modified sooty tern optimization algorithm." Mining, Metallurgy & Exploration 41.1 (2024): 239-257.
10. Hati, Ananda Shankar, and Prashant Kumar. "An adaptive neural fuzzy interface structure optimisation for prediction of energy consumption and airflow of a ventilation system." Applied Energy 337 (2023): 120879.
11. Yu, Jingxiao, et al. "Regularity of mine gas flow disaster induced by gas natural ventilation pressure after coal and gas outbursts." ACS omega 6.30 (2021): 19867-19875.
12. Cao, Peng, et al. "Uncertainty analysis of digital twin model of mine ventilation system." Scientific Reports 14.1 (2024): 26558.