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Research Article

MINE VENTILATION NETWORK OPTIMIZATION TO REDUCE POWER CONSUMPTION WITH AN IMPROVED PSO ALGORITHM

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A B S T R A C T

Underground mines are becoming deeper due to the depletion of shallower mineral resources. An effective mine ventilation network can save tremendous of electricity cost used by fans. This requires the ventilation system to be regulated so that the required airflow to the mine key areas are met with minimum power consumption. But mine ventilation networks are internal coupled strongly. The air-flow of all the other branches may be changed if only one of the branches air-flow is regulated. Such a problem becomes more complicated if multiple main fans are installed. The Hardy Cross method can determine the flow in pipe network systems where the inputs and outputs are known with iterative method. But it is difficult to find the optimum regulating scheme with iterative method such as Hardy Cross, because the inputs of the network systems are the regulating variables. They are not known or constant. This paper established a mine ventilation optimization model, and proposed a λ-PSO optimization algorithm to solve the model. By applying it to a typical mine ventilation network case, it is demonstrated that the proposed algorithm can reach the global optimal solution in shorter computational time. It is recommended to incorporate the algorithm to commercial ventilation network analysis software to assist with cost effective ventilation planning.

INTRODUCTION

The main aim of mine ventilation is to supply fresh air to designated areas, which increases underground oxygen concentration and removes underground contaminants effectively [1, 2]. It helps to create a safe and comfortable working environment for mining. With the increasing of mining depth and the development of mechanization, the cost of safety operation, maintenance and management of a mine ventilation network increases continuously. The research and application of ventilation network optimization that aims at reducing energy consumption of mine ventilation are becoming more and more important.

The main fans are responsible for providing the total air quantity required for the whole mine. However, more often than not, certain working places in the mine requires different amount of air to be delivered [3]. One common way of achieving this is by the use of regulators to adjust the resistances of one or more airways. This will change the main fan's operating points and thus influence their power consumption.

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In a complex ventilation network, there are several main fans and many different combinations of regulator adjustment solution to achieve the same airflow requirement on one specific airway. But these different combinations result in mine total resistance and total fans power consumption differences [4]. Optimization method can be used to find a solution that use minimum total fans power. The optimization aim is to minimize the total power of the ventilation network by satisfying the demand for air flow in each branch, the balance law of air quantity and pressure, and the ability of resistance regulation on the branches. This is a nonlinear programming problem. The number of the unknown variables is more than that of the constraint equations, thus, it is an indefinite solution problem [5]. It will become more complicated if multiple fans are applied in the ventilation network. Thus, an effective solution for such problems is challenging and has attracted more research attention [6]. The nonlinear programming method in many previous studies require the derivative solution for a function, the inversion of matrixes, and the solutions are sensitive to the initial values. These make the method more complex and less effective [7-9]. H Wang *et al* [10] attempted to solve the problem by firstly solve the required flow in each branch, and then find the optimal regulator adjustment method that consumes the least fan power. However, as the problem is simplified to a local optimization problem, it is still a non-convex and nonlinear optimization model, which has the same shortcomings of the previous nonlinear programming method.

With the development of intelligent optimization algorithms, genetic algorithms have been applied to solve such problems [11-14]. However, due to the limited exploration ability in the unknown spaces, it is more likely for the method to fall into the local optimal solution. In addition, its processing capacity for high-dimensional optimization problems is limited, which makes it computationally expensive to deal with ventilation network with large scale and complex structures. A hierarchical encoding method and a way to eliminate the infeasible solutions were proposed by Y Guo [15]. To shorten the computational time, she introduced the cultural particle swarm optimization algorithm (CPSO) to deal with this problem without considering the possible high dimensional combinatorial explosion issue [16]. She found that the PSO algorithm has the disadvantage of local convergence in solving high-dimensional constrained optimization problems [17], especially when there are large number of nonlinear constraint conditions [18].

To overcome the disadvantage of the PSO algorithm in solving high-dimensional constrained optimization problems [19], a γ-PSO ventilation network optimization algorithm was proposed in this paper. By using a broader range of solutions searching variable, this algorithm has the advantage of finding the global optimal solution and avoiding local convergence. We have used a mine ventilation network example with three main fans and compared the solution acquired by the γ-PSO with three other algorithms. Results showed that the γ-PSO algorithm is the fastest and the solution had the lowest power consumption.

The optimization model

The objective function of the ventilation network optimization is to minimize the ventilation energy consumption with the least branches regulated. Total fans power is the major component of energy consumption, thus, it is set as the objective function [20]:

$$\min f(FH, FQ, FR) = FR + \sum_{j\in L} FH_j FQ_j \tag{1}$$

Where: L is fans quantity, FH_j, FQ_j are air pressure and air quantity, respectively; j denotes the branch number. FR is the total number of resistance-adjusted branches

The ventilation pressure and air quantity are governed by the Kirchhoff's Laws of Flow [21]. It forms the constraint condition in the optimization model:

1. Kirchhoff's 1st Law: in the ventilation network, the inflow rate is equal to the outflow rate at any node at any time [22].

$$\sum_{j=1}^{N_i} a_{ij} Q_j = 0 \qquad i = 1,2\cdots,J$$
$$a_{ij} = \begin{cases} 1 & i \text{ is a node on } j \text{ branch}, Q_j \text{ flows to } i \\ -1 & i \text{ is a node on } j \text{ branch}, Q_j \text{ flows out f}\text{ı} \\ 0 & i \text{ is not a node on branch } j \end{cases} \tag{2}$$

Where: Ni is the total number of branches associated with node i in the network, Q_j is the air quantity of branch j, and J is the number of nodes in the ventilation network.

2. Kirchhoff's 2nd Law: in a ventilation network, the algebraic sum of various energy is zero in any closed circuit [23].

$$\sum_{j=1}^{M_j} b_{ij}(H_j + \Delta H_j - P_j - FH_j) = 0 \qquad i = 1,2,\cdots,O\,.$$
$$b_{ij} = \begin{cases} 1 & \begin{array}{c} branch\ j\ is\ part\ of\ circit\ i\ and\ the\ flow\ direction \\ is\ the\ same\ with\ the\ circit\ defined\ direction. \end{array} \\ -1 & \begin{array}{c} branch\ j\ is\ part\ of\ \ circit\ i\ while\ the\ flow\ dirce- \\ tion\ is\ oposite\ the\ circit\ defined\ direction. \end{array} \\ 0 & branch\ j\ is\ not\ part\ of\ circit\ i. \end{cases} \tag{3}$$

Where: M_j is the number of branches in closed circuit i, O is the number of closed circuit in the ventilation network, H_j, ΔH_j, P_j, FH_j represents air pressure, airway resistance, natural ventilation pressure, and fan pressure, respectively. The air quantity and air pressure should be within the upper and lower limits [24]:

$$\begin{aligned} Q_{j\_min} \le Q_j \le Q_{j\_max} \\ H_{j\_min} \le H_j \le H_{j\_max} \end{aligned} \tag{4}$$

Where: Q_{j_min}, Q_{j_max} represent upper, lower ventilation quantity limits of branch j respectively. H_{j_min}, H_{j_max}, represent upper, lower ventilation pressure limits of branch j respectively.

According to the theory of ventilation network solution of circuit air-quantity method, if there is a spanning tree with m nodes and n branches, adding each branch of the $b=n-m+1$ cotree can determine an independent circuit [25]. The airflow rate is equal to that of the cotree branch [26]. Suppose there are k branches with known airflow rate and b-k branches with unknown airflow rate in b cotree branches, the airflow rate of any branch in the ventilation network can be expressed as [27]:

$$Q_j = \sum_{s=1}^{k} C_{sj} Q_s + \sum_{s=k+1}^{b} C_{sj}\, Q_s \qquad j = 1,2,\cdots n \tag{5}$$

Where $\sum_{s=1}^{k} C_{sj} Q_s$ represents total air quantity of known branches, while $\sum_{s=k+1}^{b} C_{sj} Q_s$ is the total air quantity of unknown branches. C_{sj} represents element of independent circuit matrix corresponds to the selected spanning tree. Obviously, Equation (5) satisfies Kirchhoff's 2nd Law.
Constraints for the above equation is given as:

$$\sum_{l\in L} R_{il} FH_l - \sum_{j=1}^{n} R_{ij} r_j \left(\sum_{s=1}^{k} C_{sj} Q_s + \sum_{s=k+1}^{b} C_{sj} Q_s \right)^2 = 0 \tag{6}$$
$$i = 1,2,\cdots,n_p$$

Where n_p represents the number of closed circuit in ventilation network, r_j is the air way resistance of branch j. R_{ij} represents selected independent path matrix element：

$$R_{ij} = \begin{cases} 1 & branch\ j\ belongs\ to\ circuit\ i. \\ 0 & branch\ j\ doesn't\ belong\ to\ circuit\ i. \end{cases}$$

Combining the above equations, the optimization model can be expressed as:

$$\min f(FH,FQ,FR) = \sum_{j\in L} FH_j\left(\sum_{s=1}^{k} C_{sj}Q_s + \sum_{s=k+1}^{b} C_{sj}Q_s\right) + FR$$
$$s.t.$$
$$\sum_{l\in L} R_{il}FH_l - \sum_{j=1}^{n} R_{ij}r_j\left(\sum_{s=1}^{k} C_{sj}Q_s + \sum_{s=k+1}^{b} C_{sj}Q_s\right)^2 = 0 \quad (7)$$
$$\sum_{j=1}^{N_i} a_{ij}\left(\sum_{s=1}^{k} C_{sj}Q_s + \sum_{s=k+1}^{b} C_{sj}Q_s\right) = 0$$
$$Q_{min} \le Q_j \le Q_{max}$$
$$H_{min} \le H_j \le H_{max}$$

This model has one objective function and 4 constraint conditions. In order for the PSO algorithm to be able to solve such a problem, the constraint conditions are converted to exterior penalty functions [28]. The range of upper and lower limits of the adjustable resistance for branches are wide, and a reasonable search value range is set to save computation time. Finally, the ventilation network optimization problem is transformed into an unconstrained optimization problem as shown in Equation (8).

$$\begin{aligned}\min f(FH,FQ,FR) &= \sum_{j\in L}\left|FH_j\left(\sum_{s=1}^{k} C_{sj}Q_s + \sum_{s=k+1}^{b} C_{sj}Q_s\right)\right| + FR \\ &+\emptyset\sum_{i=1}^{n_p}\left|\sum_{l\in L} R_{il}FH_l - \sum_{j=1}^{n} R_{ij}r_j\left(\sum_{s=1}^{k} C_{sj}Q_s + \sum_{s=k+1}^{b} C_{sj}Q_s\right)^2\right| \\ &+\varphi\sum_{i=1}^{n}\left|\min\{0,(Q_{max}-Q_j)\} + \min\{0,(Q_j-Q_{min})\}\right|\end{aligned} \quad (8)$$

Where$\emptyset$ and φrepresent penalty factor of the upper and lower limits for air pressure and quantity. They increase with iteration number.

The λ-PSO algorithm

The particle swarm optimization algorithm (PSO) is an evolutionary computation technique derived from the study of predicting birds' behaviours. This optimization tool was first proposed by Dr. Barnhart and Dr. Kennedy in 1995[29]. The underlying principle is initializing a set of random solutions and iteratively searching for the optimal values. In the basic PSO algorithm, the particle swarm is composed of *n* particles, and the position $\vec{X_i}$ of each particle represents the potential solution of the optimization problem in the *D* dimensional search space. The particle travels in the search space at a certain speed, which dynamically adjusts the next flight direction and distance based on the flight experience of its own and companions [30]. All the particles have an adaptation value determined by the objective function, and the best position that they have found so far (local extreme$\vec{P_i}$) and their current position ($\vec{X_i}$) are memorized. Each particle also knows the best position of all particles (global extremum $\vec{P_g}$), which is the best position in all the local best positions. Each particle *i* contains a *D* dimensional position vector $\vec{X_i} = (x_{i1}, x_{i2}, \cdots, x_{iD})$ and velocity vector$\vec{V_i} = (v_{i1}, v_{i2}, \cdots, v_{iD})$. When the particle *i* searches for the solution space, the optimal experience location $\vec{P_i} = (p_{i1}, p_{i2}, \cdots, p_{iD})$ is saved. At the beginning of each iteration, the particle adjusts its position through changing velocity vector, based on its inertia and experience and swarm's optimal experience location $\vec{P_g} = (p_{g1}, p_{g2}, \cdots, p_{gD})$. In the expression (10), c_1 and c_2 represent acceleration factors, both of which are positive constant; *rand(0,1)* generates random numbers distributed on interval [0, 1]; *d* is dimension; *ω* is the inertia weighting factor ($0<\omega<1$) which decreases as the number of iterations increases. Each particle's position and velocity are updated as following:

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad (9)$$
$$\begin{aligned}v_{id}^{t+1} &= \omega v_{id}^{t} + c_1 rand(0,1)(p_{id}^{t} - x_{id}^{t}) \\ &+ c_2 rand(0,1)(p_{gd}^{t} - x_{id}^{t})\end{aligned} \quad (10)$$

Equation (10) consists of three parts. The first item on the right hand of Equation (10) is the original particle velocity. A larger velocity benefits global search, while smaller velocity is good for local search. Therefore, the method has the balanced ability for global and local search. The second item in Equation (10) is the influence of the history best location to the current location. Randomly adjusted by c_1*rand(0, 1)*, it makes use of particles' history experience to obtain a strong global searching capability. The third part in Equation (10) is the influence of all particle's best location to the current location. It reflects the information sharing and social collaboration between particles. This is also randomly adjusted by c_2*rand(0,1)*. Under the combined effect of these three factors, the particle adjusts its speed and position to effectively reach the best position.

The optimization model constructed in Section 2 has high dimensional, complex, and nonlinear constraints. It is difficult for the PSO algorithm to converge in the feasible solution domain[31]. At the beginning of iterations, particle velocities are high, and it is easy for them to fly to the boundary of the searching space that is far away the optimal solution. After a certain number of iterations, most particles would converge to a very small domain around a certain position $\vec{X}$, given as:$|\vec{P_i} - \vec{X_i}| \to 0$ and$|\vec{P_g} - \vec{X_i}| \to 0$. As $\omega<1$, when the iteration reaches to a certain number, the flying speed of particles also tends to 0 with a single flight direction. This may lead to the potential issue of converging too fast and fall into the local extremum. To solve these problems, the *rand ()* of PSO algorithm was extended from (0, 1)to (-1, 1), thus, Equation (10)was transformed to (11). This revised PSO algorithm is called the γ-PSO algorithm.

$$\begin{aligned}v_{id}^{t+1} &= \omega v_{id}^{t} + c_1 rand(-1,1)(p_{id}^{t} - x_{id}^{t}) \\ &+ c_2 rand(-1,1)(p_{gd}^{t} - x_{id}^{t})\end{aligned} \quad (11)$$

Optimization case study

A ventilation network from the literature was chosen as a case for validating the proposed optimization method. As shown in Figure 1, it is an exhausting ventilation network system with 3 fans, 17 branches, 11 nodes and 7 independent circuit [13]. The fans are locates on branches e1, e2 and e3.

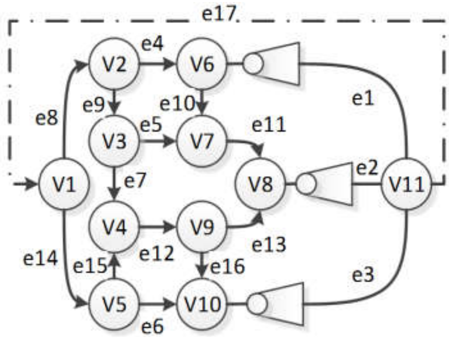


Figure 1 Ventilation network schematic diagram.

Branchese4, e5,e6,e10 and e12 has a fixed ventilation demand of 26, 31, 31, 1, 32 m^3/s, respectively. The basic ventilation parameters can be found in Table1. The original airflow rates are the result of natural split. Choose the spanning tree of T=[{V1,V2,… V11},{e1,e2,e3,e11,e13,e17,e8,e9,e14,e15}], the corresponding cotrees are {e4,e5,e6,e7,e10,e12,e16}. Therefore, 7 independent circuit are obtained by adding the spanning tree with each of the cotree branch. Assume the airflow in the 7 independent circuits are q1 to q7, and the flow directions are the same with that in the cotrees. The independent circuits are listed below:

q1：e4-e1-e17-e8；
q2：e5-e11-e2-e17-e8-e9；
q3：e6-e3-e17-e14；
q4：e7-(-e15)-(-e14)-e8-e9；
q5：e10-e11-e2-(-e1)；
q6：e12-e13-e2-e17-e14-e15；
q7：e16-e3-(-e2)-(-e13)；

The air quantity of each independent circuit equals to the air quantity of the added cotree. The results are:

$q1=Q_{e4}=26m^3/s$;
$q2= Q_{e5}=31m^3/s$;
$q3= Q_{e6}=31m^3/s$;
$q4= Q_{e7}$;
$q5= Q_{e10}=1m^3/s$;
$q6= Q_{e12}=32m^3/s$;
$q7= Q_{e16}$;

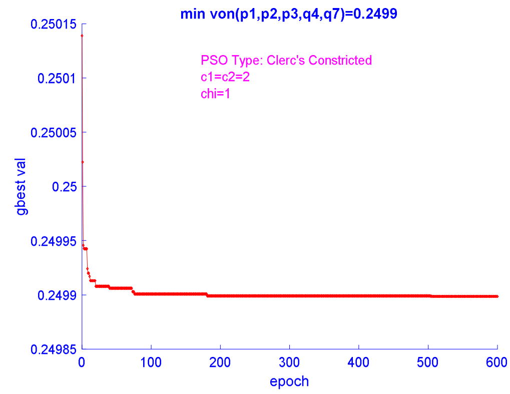
Table 1 Basic ventilation parameters and comparison before and after optimization.

Branch No.	Start point	End point	Resistance / $Ns^2\cdot m$-8	Original air flow rate /$m^3\cdot s^{-1}$	Optimized air flow rate /$m^3\cdot s^{-1}$	Adjustable or not?	Airpressure regulation /Pa
1	6	11	0.80	25.00	25.0	Yes	0.00
2	8	11	0.12	60.00	57.4	Yes	0.00
3	10	11	0.34	35.00	37.6	Yes	0.00
4	2	6	1.20	29.78	26.0	Yes	0.00
5	3	7	1.00	28.97	31.0	Yes	0.00
6	5	10	1.20	30.28	31.0	Yes	30.00
7	3	4	0.65	5.10	5.0	Yes	35.66
8	1	2	0.08	63.85	62.0	Yes	0.00
9	2	3	0.20	34.07	36.0	Yes	0.00
10	6	7	0.30	4.78	1.0	Yes	408.20
11	7	8	0.32	33.75	32.0	Yes	0.00
12	4	9	1.00	30.97	32.0	Yes	0.00
13	9	8	0.33	26.25	25.4	Yes	0.00
14	1	5	0.14	56.15	58.0	Yes	0.00
15	5	4	0.20	25.87	27.0	Yes	0.00
16	9	10	0.30	4.72	6.6	Yes	0.00
17	11	1	0.00	120.00	120.0	No	0.00

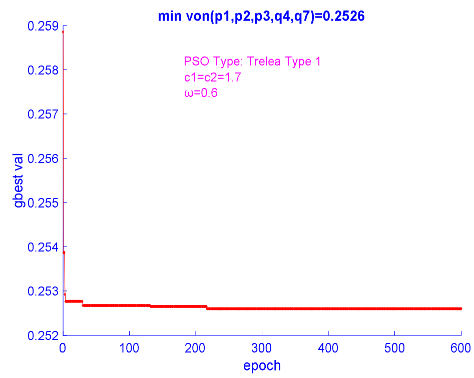
According to the circuitair-quantity method, the airflow rate of each branch is the sum of the airflows of the independent circuit that flows through the branch. It is positive when they have the same direction, otherwise negative. Hereby, the airflow rates of each branches are:

e1: Q1=q1-q5=25;
e2: Q2=q2+q5+q6-q7=64-q7;
e3: Q3=q3+q7=31+q7;
e4: Q4=26;
e5: Q5=31;
e6: Q6=31;
e7: Q7=q4;
e8: Q8=q1+q2+q4=26+31+q4=57+q4;
e9: Q9=31+q4;
e10: Q10=1;
e11: Q11=q2+q5=32;
e12: Q12=32;
e13: Q13=q6-q7=32-q7;
e14: Q14=q3+ q6-q4=63-q4;
e15: Q15=q6-q4=32-q4;
e16: Q16=q7;
e17: Q17=q1+q2+q3+q6=120;

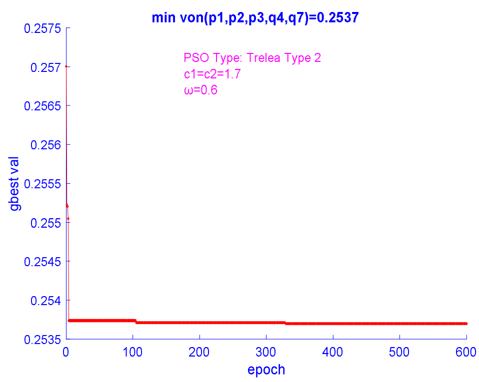
In this case study, fan pressure is restricted to less than 5000 Pa, and airflow rate is constraint within [-100, +100]. The number of particles was set as 30 and the penalty coefficients φ and ψ were set as 100. For performance comparison purposes, the λ-PSO algorithm was compared with the Trelea's types1 PSO, Trelea's type 2PSO, and the Clerc's Constricted PSO algorithm. Figure 2 and Table2 show the convergence performance and the parameter values for each algorithm. The basic principles for these algorithms are the same, but they have different treatment in the key parameters



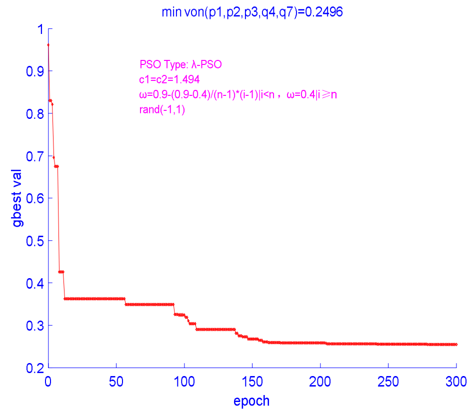
(a)



(b)



(c)



(d)

Figure 2 Comparison of four PSO optimization procedures (**a**) Clerc's Constricted PSO optimization procedure; (**b**) Trelea Type1 PSO optimization procedure; (**c**) Trelea Type1 PSO optimization procedure; (**d**) λ-PSO optimization procedure.

From the optimization process, it is obvious that Clerc's Constricted PSO has global search capability with relatively slow convergence speed, which converges to the global optimum after more than 500 iterations. Trelea's types1 and type2 PSO, which converged to a local optimum after about 300 iterations. It converges quickly while its global search ability is limited. The λ-PSO algorithm converged to the global optimal solution after only about 200 iterations. Meanwhile, different from the other three algorithms, when the λ-PSO algorithm converges to the global optimal solution, all the particles disperse over the searching space instead of clustered around one solution (demonstrated in Figure.3 which only shows flow quantity in branch q4 and q7). This ensures active and global search capability of particles to prevent limiting the solution local optimal values. Therefore, λ-PSO algorithm over performs the other algorithms in both calculation speed and global searching capability. According to the optimization result, the optimal air quantity and resistance of branches were calculated and shown in Table1. Based on the result of the λ-PSO optimization, the operational point for each fan and their power consumptions are listed in Table 3. It is obvious that the ventilation power consumption was reduced from 261.9 kW to 249.62 kW.

Table 2 PSO algorithms result comparison

PSO type	Clerc's Constricted PSO	Trelea's type 1 PSO	Trelea's type 2 PSO	λ-PSO
power consumption /kW	249.976	252.563	253.729	249.62
Average Number of iterations	539.25	239.5	312.25	216.75

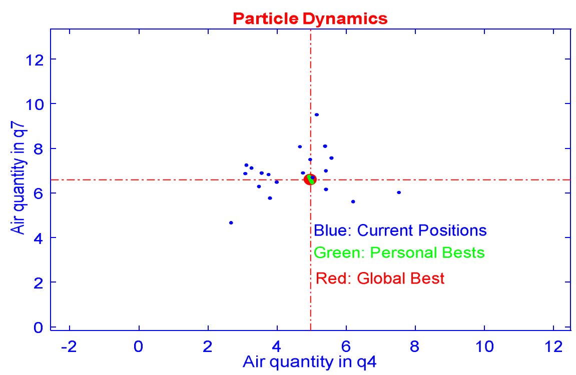


Figure 3 Particle distribution when λ-PSO converges to the global optimum

Table 3 Ventilation energy consumption before and after optimization

Fan No.	Original data			Optimized data		
	air quantity /$m^3 \cdot s^{-1}$	air pressure /Pa	Power /kW	air quantity /$m^3 \cdot s^{-1}$	air pressure /Pa	Power /kW
1	25.0	2055.0	51.4	25.0	1613	40.33
2	60.0	2315.0	138.9	57.4	2173	124.73
3	35.0	2046.0	71.6	37.6	2249	84.56
Total power /kW	261.9			249.62		

CONCLUSION

As shallow mineral resources are depleting, current underground mines become deeper. This requires a more powerful and reliable ventilation system. As air flow paths are longer for deeper mines, the power cost associated with ventilation is tremendous. Thus, an optimized ventilation system is essential for the cost efficiency of a mine. Ventilation needs to be regulated so more air can reach to the area where contamination levels are high or work activities are intensive. This can be achieved by regulating the resistance of one or several airways, and many combinations of ways can result in the required air flow in one area. However, the method with the lowest power consumption should be selected to save ventilation power cost with the least branches regulated.

This paper developed a mine ventilation optimization model and used an improved particle swarm optimization algorithm to solve the model. Through comparison with other algorithms, results show that this method has the ability to find the global optimization value with the lowest power consumption within the shortest time. To the authors knowledge, the current commercially available mine ventilation network analysis software does not have this function yet. The proposed algorithm can be incorporated to these software for fast and cost efficient ventilation planning.

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