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# STUDY ON MINE VENTILATION RESISTANCE COEFFICIENT INVERSION BASED ON GENETIC ALGORITHM

# BADANIE INWERSJI WSPÓŁCZYNNIKÓW OPORU WENTYLACJI KOPALNIANEJ NA PODSTAWIE ALGORYTMU GENETYCZNEGO

The frictional resistance coefficient of ventilation of a roadway in a coal mine is a very important technical parameter in the design and renovation of mine ventilation. Calculations based on empirical formulae and field tests to calculate the resistance coefficient have limitations. An inversion method to calculate the mine ventilation resistance coefficient by using a few representative data of air flows and node pressures is proposed in this study. The mathematical model of the inversion method is developed based on the principle of least squares. The measured pressure and the calculated pressure deviation along with the measured flow and the calculated flow deviation are considered while defining the objective function, which also includes the node pressure, the air flow, and the ventilation resistance coefficient range constraints. The ventilation resistance coefficient inversion problem was converted to a nonlinear optimisation problem through the development of the model. A genetic algorithm (GA) was adopted to solve the ventilation resistance coefficient inversion problem. The GA was improved to enhance the global and the local search abilities of the algorithm for the ventilation resistance coefficient inversion problem.

**Keywords:** coal mine ventilation, ventilation coefficient, inversion, genetic algorithm

Współczynnik oporu oporu wentylacji jezdni w kopalni węgla jest bardzo ważnym parametrem technicznym w projektowaniu i renowacji wentylacji kopalnianej. Obliczenia oparte na wzorach empirycznych i badaniach terenowych w celu obliczenia współczynnika oporu mają ograniczenia. W niniejszym badaniu proponuje się inwertowaną metodę obliczania współczynnika oporu wentylacji kopalni za pomocą kilku reprezentatywnych danych dotyczących przepływu powietrza i ciśnienia w węzłach. Model matematyczny metody inwersji jest opracowywany na zasadzie najmniejszych kwadratów. Zmierzone ciśnienie i ob-

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liczone odchylenie ciśnienia wraz z zmierzonym przepływem i obliczonym odchyleniem przepływu są uwzględniane przy określaniu obiektywnej funkcji, która obejmuje również ciśnienie w węźle, przepływ powietrza i ograniczenia współczynników oporu wentylacji. Problem odwrotności współczynnika oporu wentylacji został przekształcony w nieliniowy problem optymalizacji poprzez opracowanie modelu. Zastosowano algorytm genetyczny (GA) w celu rozwiązania problemu inwersji współczynnika oporu wentylacji. GA został ulepszony w celu zwiększenia globalnych i lokalnych możliwości wyszukiwania algorytmu problemu odwrotności współczynnika oporu wentylacji.

**Słowa kluczowe:** wentylacja kopalni węgla, współczynnik wentylacji, odwrócenie, algorytm genetyczny

# 1. Introduction

Underground mining is the primary method of coal mining in China. This method is subject to various complex and serious disasters, such as gas explosion and outburst, fire, and coal dust, all of which can be prevented and controlled by mine ventilation (El-Nagdy, 2013). The operating conditions of the main fans depend mainly on total mine ventilation resistance, and the ventilation resistance distribution determines the distribution of air volume in the underground mine (Cheng et al., 2012). The main fans and distribution of air are the main factors responsible for safe production in coal mines.

The shape of the section, the length, and the supporting method of mine roadways have remained unchanged over a considerable period; hence, the ventilation resistance, which is the inherent property of a roadway, is a constant value. Meanwhile, ventilation resistance that can be obtained by empirical formula calculation and ventilation resistance test are important parameters in the simulation of the ventilation system. The friction resistance coefficient obtained by the empirical formula calculation is based on the mine roadway design rules, but this value deviates from the actual value significantly. The ventilation resistance test can measure the pressure and air volume; however, as the mine ventilation system has been installed and is operational, air volume and pressure measurement errors exist.

Based on the above discussion, it can be said that the study of the method to inverse the mine ventilation system resistance coefficient in operation by measuring the pressure and air volume representative node in mine roadway is worthwhile. It also has very practical significance for ventilation system fault identification and sensitivity analysis of the ventilation system. Inoue Masahiro first proposed mine ventilation resistance coefficient inversion by testing the pressure and air volume in parts of mine roadways (Masahiro, 1987). Wang and Liu presented three methods for adjusting the estimated value of mine ventilation resistance (Wang et al., 1989). An algorithm for choosing the optimum circuit for the minimum regulation number of the measured airflow and evaluated resistance model was proposed by Si and Chen; and a method for solving the parameters of the Tikhonov regularisation based on the greedy algorithm was proposed to revise the model (Si et al., 2012). Ju and Wang proposed an orthogonal optimal design method for adjusting the air volume governing equations for known mine ventilation resistance intervals (Ju et al., 1991). Li et al. introduced an analytical calculation method based on the node pressure energy to solve the problem with the ventilation resistance measurement in some roadways (Li et al., 2012). An increasing number of successful applications of intelligent optimisation algorithms can be found in the engineering community. Increasing number of studies have been conducted on genetic algorithms in order to identify the pipe network resistance coefficient (Schaetzen et al., 2000; Kapelan et al., 2003a; Kapelan et al., 2003b).The basic idea of a genetic algorithm is to convert the nonlinear model established by the least squares method into a nonlinear objective function, and then to solve the objective function using optimisation method. Vitkovsky, Simpson, and Lambert have improved the standard genetic algorithm to evaluate the resistance coefficient and to locate leakage in pipe network (Vítkovský et al., 1999). Lingireddy and Ormsbee corrected the model parameters of a pipe network by using genetic algorithm and added linear and nonlinear constraints to the objective function by the use of the penalty function (Lingireddy et al., 1999).

An in-depth study on mine ventilation resistance coefficient inversion was undertaken in this study. An algorithm with improved mathematical model of ventilation resistance coefficient inversion based on least squares method was introduced to solve the problem. Furthermore, research methods, results of the water supply network and heating pipe network in identifying resistance coefficients, and the three basic laws of fluid networks were used in this study.

## 2. Ventilation resistance coefficient inversion mathematical model

Utilising the mathematical model built by the least squares method to solve the problem of mine ventilation resistance coefficient inversion, an optimal or satisfactory solution is obtained by observing the data and utilising optimisation algorithm. Thus, the problem of mine ventilation resistance coefficient inversion under few measured points and multiple observations is translated into the problem of nonlinear function optimisation.

### 2.1. Objective function

Measured pressure values in X and air values of the roadway in Y were used to match the inversion model containing Z unknown system parameters. The process of finding a group of parameters to maximise the probability of uniformity between the measured values and the calculated values from the ventilation network solution is called maximum likelihood estimation, which works under the condition that a group of parameters of ventilation resistance coefficient are provided. The reason for the above process is that the pressure values and roadway air values of the node are the actual measured values rather than the fitting parameters (Shi et al., 1997). If a random error, which obeys the normal distribution under the condition that the standard deviation is $\sigma_i$, occurs in the measured pressure value and roadway air value in each node, the total likelihood of the probability of the range of measured pressure value and roadway air value in each node between $p_{di} + \Delta p$ and $q_{dj} + \Delta q$ is:

$$\xi \propto \prod_{i=1}^{X} \left\{ \Delta p \cdot \exp\left[ -\frac{1}{2} \left( \frac{p_{di}^{x} - p_{di}(\alpha)}{\sigma_{p_{di}}} \right)^2 \right] \right\} \times \prod_{j=1}^{Y} \left\{ \Delta q \cdot \exp\left[ -\frac{1}{2} \left( \frac{q_{dj}^{y} - q_{dj}(\alpha)}{\sigma_{q_{dj}}} \right)^2 \right] \right\} \tag{1}$$

The optimal solution of the parameter $\alpha$ was found by seeking the maximum value of probability $\xi$. A mathematical transformation using logarithmic operation was performed on the above equation, resulting in:

$$\ln(\xi) \propto -\frac{1}{2}\sum_{i=1}^{X}\left(\frac{p_{di}^{x}-p_{di}(\alpha)}{\sigma_{p_{di}}}\right)^{2} + X\ln(\Delta p) - \frac{1}{2}\sum_{j=1}^{Y}\left(\frac{q_{dj}^{y}-q_{dj}(\alpha)}{\sigma_{q_{dj}}}\right)^{2} + Y\ln(\Delta q) \tag{2}$$

When $\ln(\xi)$ reaches its maximum value, then $-\ln(\xi)$ reaches its minimum value.

$$-\ln(\xi) \propto \frac{1}{2}\sum_{i=1}^{X}\left(\frac{p_{di}^{x}-p_{di}(\alpha)}{\sigma_{p_{di}}}\right)^{2} - X\ln(\Delta p) + \frac{1}{2}\sum_{j=1}^{Y}\left(\frac{q_{dj}^{y}-q_{dj}(\alpha)}{\sigma_{q_{dj}}}\right)^{2} - Y\ln(\Delta q) \tag{3}$$

After removing the constant term, the following formula was assumed.

$$E(\alpha) \propto \sum_{i=1}^{X}\left(\frac{p_{di}^{x}-p_{di}(\alpha)}{\sigma_{p_{di}}}\right)^{2} + \sum_{j=1}^{Y}\left(\frac{q_{dj}^{y}-q_{dj}(\alpha)}{\sigma_{q_{dj}}}\right)^{2} \tag{3}$$

Eq. (3) can be simplified into the following equation under the assumption that the standard deviation of the measured value is a constant term and the weight can be represented by the reciprocal of the square of standard deviation.

$$E(\alpha) \propto \sum_{i=1}^{X} w_{pi}(p_{di}^{x}-p_{di}(\alpha))^{2} + \sum_{j=1}^{Y} w_{qj}(q_{dj}^{y}-q_{dj}(\alpha))^{2} \tag{4}$$

The objective function of the mathematical model in mine ventilation resistance coefficient inversion can be chosen from Eqs. (3) and (4), which are both derived according to the principle of least squares. Eq. (4) was chosen to be the final objective function form in this study. After considering the characteristics of ventilation network, the final objective function was the minimisation of the deviation between the real and calculated pressure values and the deviation between the real and the inverted air values in the measured node.

$$\min F(\boldsymbol{R}) = \sum_{t=1}^{L}\left[\sum_{i=1}^{X}\omega_{p}(p_{di}-p_{di}^{*})^{2} + \sum_{j=1}^{Y}\omega_{q}(q_{dj}-q_{dj}^{*})^{2}\right] \tag{5}$$

where $R$ — ventilation resistance coefficient in the roadway, N×s$^2$/m8; $p_{di}$ — the solution of the pressure value in I-th measured node, Pa; $p_{di}^{*}$ — the real measured pressure value in $I$-th measured node, Pa; $q_{dj}$ — the inversion air volume in $J$-th measure node, m$_3$/s; $q_{dj}^{*}$ — the real measured air volume in $J$-th measure node, m$^3$/s; $\omega_{pi}$ — the weight factor of the $I$-th measure node; $\omega_{qj}$ — the weight factor of the $J$-th measure node; $X$ — the number of measured nodes for pressure; $Y$ — the number of measured nodes for roadway air value; $L$ — the number of the cases for ventilation resistance coefficient inversion.

In the system that arranges pressure measured node only, Eq. (5) can be converted to the following equation:

$$\min F(\boldsymbol{R}) = \sum_{t=1}^{L}\left[\sum_{i=1}^{X}\omega_{p}(p_{di}-p_{di}^{*})^{2}\right] \tag{6}$$

In the system, which only arranges air value measure node in branches, Eq. (5) can be converted to the following equation:

$$\min F(\boldsymbol{R}) = \sum_{t=1}^{L}\left[\sum_{j=1}^{Y}\omega_q (q_{dj} - q_{dj}^{*})^2\right] \tag{7}$$

## 2.2. Constraint conditions

Under any working condition, the ventilation system must meet the following constraints:

(1) Flow constraint

The air flow at the mine ventilation network nodes follows the flow conservation law. Moreover, the flow out of the node is positive, while the flow into the node is negative. Any node inflow equals the flow out of the node and the algebraic sum of flow at any node equals 0. The law of conservation of mass is thus met.

$$\sum q_{m,ij} = 0 \quad (i = 1, 2, \cdots, m) \tag{8}$$

where $q_{m,ij}$ — the flow of the $J$-th associated roadway of node $I$, m$^3$/s.

(2) Pressure constraint

Each loop of the ventilation network satisfies the Kirchhoff's second law, whereby the algebraic sum of resistance loss of any closed loop equals to 0. The law of conservation of energy is thus met.

$$\sum_{i=1}^{|C_k|} h_i^{(k)} - \delta h_k = 0 \quad (k = 1, 2, \cdots, L) \tag{9}$$

where $h_i^{(k)}$ — the resistance loss of the branch $i$ in the loop $k$, Pa; $\delta h_k$ — the adjustment accuracy of the loop, Pa; $|C_k|$ — the number of branches in the $k$-th loop; $L$ — the number of the basic loops.

Inside, the resistance loss of branches is

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Where $h_{ij}$ — the resistance loss of branch $J$ associated with node $I$, Pa; $r_{ij}$ — the wind resistance of branch $J$ associated with node $I$, N×s$^2$/m$^8$, $q_{ij}$ — the flow of branch $J$ associated with node $I$, m$^3$/s, $h'_{ij}$ — the additional resistance of branch $J$ associated with node $I$, Pa.

(3) Range constraint of the ventilation resistance coefficient

There is a range constraint in roadway wind resistance of operating mine ventilation system to ensure the validity of the result of inversion. The constraint range can be represented by the following equation:

$$\boldsymbol{0} < \boldsymbol{R}_{\mathbf{min}} \le \boldsymbol{R} \le \boldsymbol{R}_{\mathbf{max}} \tag{10}$$

where $\boldsymbol{R}_{\mathbf{min}}$ — the column vector of the lower limits of the ventilation resistance coefficient and $\boldsymbol{R}_{\mathbf{max}}$ — the column vector of the upper limits of the ventilation resistance coefficient.

In summary, the complete mathematical model of mine ventilation resistance coefficient inversion can be represented by the following equations:

$$\min F(\boldsymbol{R}) = \sum_{t=1}^{L}\left[\sum_{i=1}^{X}\omega_p(p_{di}-p_{di}^{*})^2+\sum_{j=1}^{Y}\omega_q(q_{dj}-q_{dj}^{*})^2\right]$$

$$\text{s.t.}\begin{cases}\sum q_{m,ij}=0 \quad (i=1,2,\cdots,m)\\ \sum_{i=1}^{|C_k|}h_i^{(k)}-\delta h_k=0 \quad (k=1,2,\cdots,L)\\ h_{ij}=r_{ij}\left|q_{m,ij}\right|q_{m,ij}-h'_{ij} \quad (i=1,2,\cdots,m)\\ \boldsymbol{0}<\boldsymbol{R}_{\mathbf{min}}\le\boldsymbol{R}\le\boldsymbol{R}_{\mathbf{max}}\end{cases} \tag{11}$$

The engineering significance of this mathematical model can be explained as follows. Under the restraint conditions the model needs to satisfy the three basic laws of fluid network and the available range of ventilation resistance coefficient. The aim of mine ventilation resistance coefficient inversion is to minimise the deviation between the real and calculated pressure values and the deviation between the real and inverted air values in the measured node under single or multiple loading conditions. Theoretically, there is an optimal solution to make the deviations equal to zero. However, the deviations cannot be zero as there are some errors in measurement and some changes in observed underground environment. It is unnecessary or impossible to achieve zero-error in practical engineering application. Instead, the commonly used method is to control the deviation beneath a limit error level $\varepsilon$ and to make the minimum F(R) less than $\varepsilon$ so that the problem of ventilation resistance coefficient inversion can be converted to the problem of nonlinear optimisation.

## 3. Inversion method of ventilation resistance coefficient based on genetic algorithms

### 3.1. Improvement of standard genetic algorithms

The problems associated with the ventilation resistance coefficient inversion include large dimensions, large search space, large computation times, and high computational accuracy requirements. The standard genetic algorithms (SGA) cannot meet the demand of ventilation resistance coefficient inversion because SGA suffers from slow and early convergence when used for this purpose. Hence, some appropriate improvements must be made on SGA. The specific improvement measures on SGA in this study include:

(1) Real number encoding instead of binary coding

Floating-point numbers are used to represent roadway ventilation resistance in practical applications. Several factors, such as the support condition of the roadway, the length of the roadway, the sectional area of the roadway, the perimeter of the roadway and the degree of roughness of the wall influence the size of the ventilation resistance. There is a big range for the roadway ventilation resistance from $10^{-4}$ to $10^{4}$ and this is chosen to be the unified interval of the ventilation resistance. The minimum resistance can be found in the short roadway, such as link-roadway and pedestrian ventilation roadway, while the maximum resistance can be found in roadways such as the completely closed air door and the roadway with a seriously deformed roof and floor.

Regarding the problem of the ventilation resistance coefficient inversion, real number coding was chosen to represent the solution vector of resistance coefficient, $R$, which meant that all roadways in the system would be arranged in a certain order to form a real number string. The range of ventilation resistance had to narrowed as the use of a big range resulted in randomisation in the searching process and even stagnation, which worked against the factor operation of genetic algorithms.

$$f(x) = \log_{10}(x) \tag{12}$$

Eq. (12) indicates a reduced range of the wind resistance range in the log scale of 10; therefore, the new range of ventilation resistance $r'$ is from –4 to 4.

(2) Use of the 'elite retention strategy' (Technology of Elitism)

The introduction of the elite retention strategy, also known as the technology of elitism, avoided the loss of the optimum individual that could directly duplicate into the next generation. The rate of convergence of genetic algorithms can be accelerated using an appropriate elite retention strategy.

(3) Use of the tournament selection to replace the roulette selection

The roulette selection is an option based on proportional selection that can easily lead to early convergence or stagnation. In order to avoid this disadvantage, a ranking selection known as the tournament selection was chosen.

(4) Strategy for improving crossover operator

An improvement was made in non-uniform crossover operator after assuming that two new sub-individuals $p_1'$ and $p_2'$ were produced after uniform crossover operation from the two parent individuals $p_1$ and $p_2$. The crossover probability of the two parent individuals was $P_c$.

$$\begin{aligned} p_1' &= p_1 + \beta(p_1 - p_2) \\ p_2' &= p_1 - \beta(p_1 - p_2) \end{aligned} \tag{13}$$

Obviously, the fitness value of $p_1$ is larger than $p_2$ in Eq. (13). The value of the new individual $p_1'$ was outside the interval $[p_1, p_2]$; however, the value of the new individual $p_2'$ was still inside the interval $[p_1, p_2]$. A random number, $\beta$ was chosen within the interval [0, 1] to execute crossover operation continuously until the demand that $p_1'$ was inside the searching space was met.

(5) Strategy for improving mutation operator

A simple and fast uniform variation operator was chosen. Each gene component of the parent individual $p_i$, which was chosen to execute the mutation operation, was operated with the same probability. The mutation operation involved choosing a random value within the range of the variable corresponding to the gene component. In the most extreme case, either all genes mutated or none did.

(6) Adaptive selection of the probability of crossover and mutation

An adaptive method, which chooses a smaller probability of crossover and mutation in order to retain the excellent individual during the evolution, was chosen for those with a big adaptive value. A bigger probability of crossover and mutation was chosen for those with small adaptive value in order to weed them out during the evolution.

Some issues also exist in the method discussed above. One problem is that the probability of crossover and mutation is close to zero when the individual adaptive value is close to the maximum of the adaptive value of the population. A further improvement can be made to make the probability of crossover and mutation of the individual non-zero, with maximum adaptive value, as follows:

$$p_c = \begin{cases} p_{c1} - \dfrac{(p_{c1} - p_{c2})(f_c - f_{avg})}{f_{\max} - f_{avg}} & f \geq f_{avg} \\ p_{c1} & f < f_{avg} \end{cases} \tag{14}$$

$$p_m = \begin{cases} p_{m1} - \dfrac{(p_{m1} - p_{m2})(f_{\max} - f_m)}{f_{\max} - f_{avg}} & f \geq f_{avg} \\ p_{m1} & f < f_{avg} \end{cases} \tag{15}$$

where $p_c$ — the probability of crossover, $p_m$ — the probability of mutation.

(7) Fitness scale

The exponential transformation was chosen to be the fitness scale in this study, as shown below:

$$f' = e^{-\alpha f} \tag{16}$$

## 3.2. Treatment of genetic algorithms toward constraints

The method of using constraints in this paper involved the use of the penalty function method in order to convert the problem of constrained optimisation to that of unconstrained minimal optimisation. The penalty function method was easy and simple, but it was difficult to choose an appropriate penalty factor to ensure that the objective function had a better approximation to original constrained optimisation problem.

$$\boldsymbol{R}_{\mathbf{min}} = (r_{1,\min}, r_{2,\min}, \cdots, r_{n,\min})^{\mathrm{T}}, \ \boldsymbol{R}_{\mathbf{max}} = (r_{1,\max}, r_{2,\max}, \cdots, r_{n,\max})^{\mathrm{T}}$$

The inverted ventilation resistance $r_i$ of branch i in any solution vector $\boldsymbol{R}$ can be defined by the following relation.

$$\varphi_i(r_i) = [r_i - (r_{\min} + r_{\max})/2]^2 \tag{17}$$

A penalty function, $\varphi(\boldsymbol{R})$, was formed to convert the problem of constrained optimisation to the problem of unconstrained minimal optimisation.

$$\varphi(\boldsymbol{R}) = \sum_{i=1}^{n} \omega_i \varphi_i(r_i) \tag{18}$$

Each roadway wind resistance has its reasonable range of range, falls within this range of wind resistance that is a reasonable set of solutions. The penalty function, $\varphi(\boldsymbol{R})$, used the minimum of the square sum of the differences between the reversal wind resistance and the centre of the ventilation resistance constraint range as the standard. The closer the centre value is, the more the inversion ventilation resistance becomes. The greater the distance is, the more ventilation resistance difference is. The value of $\omega_i$ is 1 as usual.

After substituting the penalty function formula (18) into the equation (11), the problem is converted to that of unconstrained minimization optimisation.

$$\begin{cases} f_1 = F(\boldsymbol{R}) \\ f_2 = \varphi(\boldsymbol{R}) \\ \min J_\alpha(\boldsymbol{R}) = f_1 + \alpha f_2 = F(\boldsymbol{R}) + \alpha\varphi(\boldsymbol{R}) \end{cases} \tag{19}$$

Usually, the value of $f_1$ is larger than the value of $f_2$. If the objective function is chosen to be the fitness function directly, the fitness function cannot guide the evolution of the optimisation algorithm effectively. Therefore, an appropriate scale was used, which was different with the fitness scale in genetic algorithms, to create a balance between $f_1$ and $f_2$. In this paper, we used the logarithmic transformation of 10.

$$\begin{cases} f_1 = \log_{10}[1 + F(\boldsymbol{R})], \quad f_2 = \log_{10}[1 + \varphi(\boldsymbol{R})] \\ f = 1 + f_1 + \alpha f_2, \quad (\alpha > 0) \end{cases} \tag{20}$$

In the equation above, both $f_1$ and $f_2$ are zero when $F(\boldsymbol{R})$ and $\varphi(\boldsymbol{R})$ are equal to zero.

## 4. Example analysis

There are twelve nodes, seventeen branches and seven independent circuits in the ventilation network of Figure 1. The branch $e_{17}$ was a branch with a fan. The equation for the characteristic curve of the fan was $h_f = 12\,955.83 + 407.387\,75q - 3.877\,5q^2$. The independent loop of the ventilation network can be seen in Table 1. The original ventilation resistance and inversion air volume can also be seen in Table 2. The air volumes of all branches were obtained by solving the ventilation work using the cross iteration method. Then, the ventilation resistance coefficient, which was inverted from the calculated air volume data, was compared to the origin ventilation

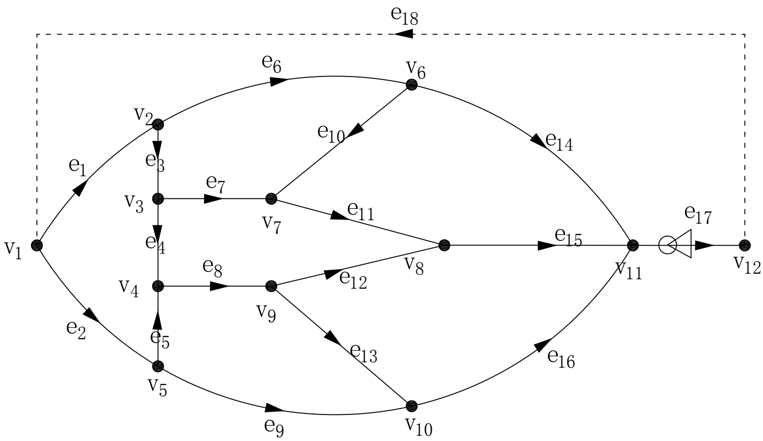


Fig. 1. Simple ventilation network

resistance to analyse the inversion errors and effects. The original ventilation resistance and inversion air volume of this example can be seen in Table 2.

TABLE 1

Circuits of the ventilation network

| Loop number | Base branch | Loop branch |
|---|---|---|
| $C_1$ | $e_4$ | $e_3, e_1, e_2, e_5$ |
| $C_2$ | $e_6$ | $e_{14}, e_{15}, e_{11}, e_7, e_3$ |
| $C_3$ | $e_8$ | $e_{12}, e_{11}, e_7, e_3, e_1, e_2, e_5$ |
| $C_4$ | $e_9$ | $e_{13}, e_{12}, e_{11}, e_7, e_3, e_1, e_2$ |
| $C_5$ | $e_{10}$ | $e_{11}, e_{15}, e_{14}$ |
| $C_6$ | $e_{16}$ | $e_{15}, e_{12}, e_{13}$ |
| $C_7$ | $e_{18}$ | $e_1, e_3, e_7, e_{11}, e_{15}, e_{17}$ |

TABLE 2

Branch resistance and air flow of the ventilation network

| Branch | Origin ventilation resistance (N×s$^2$/m$^8$) | Air volume (m$^3$/s) |
|---|---|---|
| $e_1$ | 0.08 | 64.431 |
| $e_2$ | 0.14 | 55.580 |
| $e_3$ | 0.20 | 32.959 |
| $e_4$ | 0.65 | 4.754 |
| $e_5$ | 0.20 | 25.648 |
| $e_6$ | 1.02 | 31.472 |
| $e_7$ | 1.00 | 28.205 |
| $e_8$ | 1.00 | 30.402 |
| $e_9$ | 1.20 | 29.932 |
| $e_{10}$ | 0.30 | 2.869 |
| $e_{11}$ | 0.32 | 31.074 |
| $e_{12}$ | 0.33 | 22.396 |
| $e_{13}$ | 0.30 | 8.006 |
| $e_{14}$ | 0.80 | 28.603 |
| $e_{15}$ | 0.12 | 53.469 |
| $e_{16}$ | 0.34 | 37.938 |
| $e_{17}$ | 0.13 | 120.011 |

The constraints on the range of ventilation resistance in this example were approximate; however, the actual situation should be combined with the constraints of the ventilation resistance range. For important roadways, a close approximation to the real roadway resistance was made to get an approximate solution of the original ventilation resistance through optimisation.

The symbol, $P$, in the next figures and tables represent the population size.

The objective function and fitness scale function were established according to Eq. 19. The converted ventilation resistance in the fitness scale function was obtained through the penalty function method. The penalty factor, a, was used to estimate the proportional relationship between $f_1$ and $f_2$ based on the result of the test run and its value was 10. The range of the constrained ventilation resistance can be obtained by the multiple of the original ventilation resistance to describe the ventilation resistance coefficient inversion through the GA. The value of $r_{\min}$ was one tenth of that of $r_i$ and the value for $r_{\max}$ was ten times that of $r_i$. Furthermore, the reduced ventilation resistance range, $[\log_{10} r_{\min}, \log_{10} r_{\max}]$, was found through the log operation based on 10 to avoid problems in floating point calculation

Parameters control through a genetic algorithm. As the scale of this ventilation network was small, the controlled parameters were chosen artificially. The controlled parameters in ventilation resistance inversion by the genetic algorithm are shown in Table 6.

The inversion results based on the genetic algorithm were estimated where the population sizes were estimated as 50, 100 and 200 successively. Figures 2-4 show the GA's evolutionary curves, while Table 5 shows the inversion results. With the growth of the evolution population and iterative searching in the genetic algorithm, the four subgraphs in Figures 2-4 were the best fitness, worst fitness, average fitness and fitness of standard deviation respectively.

The four adaptation curves showed a decreasing trend, thereby indicating the tendency of the evolutionary process to converge. However, the variance curve of the fitness of standard deviation was always in a downward trend, which meant that more similar the individuals in the population were becoming, the lower the diversity of the population was getting. In other words, it showed that the genetic algorithm was falling into a local optimum and had not yet converged to the optimal solution. There was a big error in ventilation resistance between the original value and the value from the solution.

Meanwhile, it can be seen from the best fitness curves in Figures 2-4 that the fitness scale, $f$,

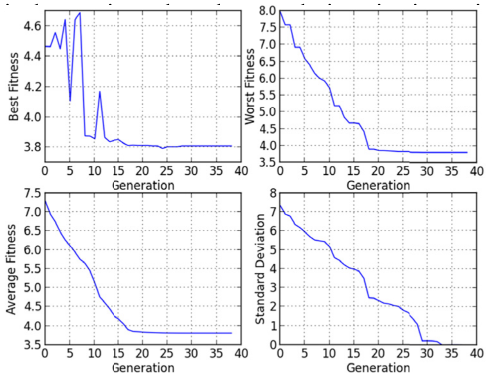


Fig. 2. GA's evolution when $P = 50$

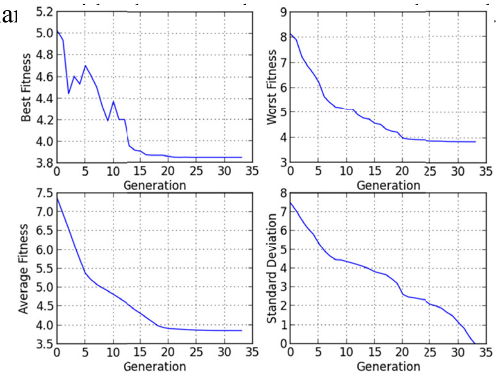


Fig. 3. GA's evolution when $P = 100$

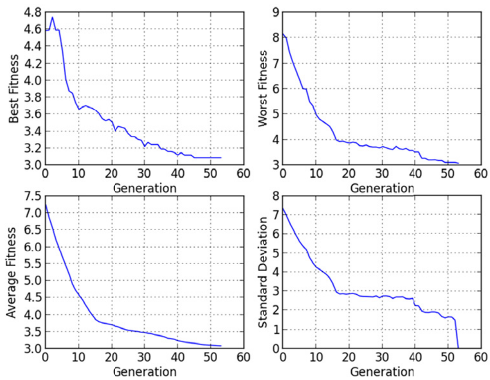


Fig. 4. GA's evolution when $P = 200$

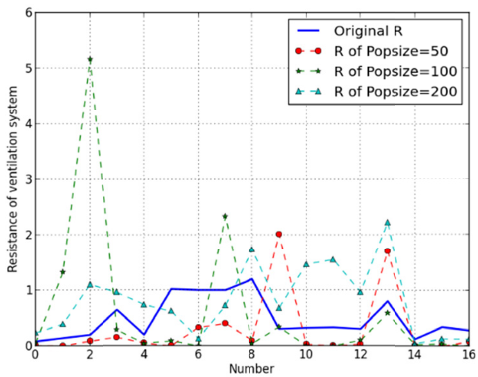


Fig. 5. Ventilation resistances obtained from various population sizes

TABLE 3

GA Parameters for ventilation resistance inversion

| Parameter | Data value |
|---|---|
| Coding scheme | Real number encoding |
| Variable interval | 0.1 to 10 times of the origin ventilation resistance |
| Population size | 50/100/200 |
| End condition | The average fitness of the population is close to the fitness of the population (the value of the error is less than 0.001) |
| The probability of crossover | Adaptive selection |
| The probability of mutation | Adaptive selection |
| Selection operator | Rank Selection |
| Crossover operator | Single-Point Crossover |
| Mutation operator | Single-Point Mutate |

TABLE 4

Objective values of the optimal solutions under various population sizes

| Number | Population size | Fitness value ($f = 1 + f_1 + \alpha f_2$, where $\alpha = 10$) | |
|---|---|---|---|
| | | $f_1$ | $f_2$ |
| 1 | 50 | 3.761 | 0.046 |
| 2 | 100 | 3.817 | 0.035 |
| 3 | 200 | 3.128 | 0.030 |

TABLE 5

Optimal solutions with various population sizes

| Branch | Origin ventilation resistance coefficient $r_i$ (N×s$^2$/m$^8$) | Lower bound of the ventilation resistance range $r_i \times 0.1$ (N×s$^2$/m$^8$) | Upper bound of the ventilation resistance range $r_i \times 10$ (N×s$^2$/m$^8$) | Optimal solution (N×s$^2$/m$^8$) | | |
|---|---|---|---|---|---|---|
| | | | | $P = 50$ | $P = 100$ | $P = 200$ |
| $e_1$ | 0.08 | 0.008 | 0.8 | 0.007 | 0.050 | 0.235 |
| $e_2$ | 0.14 | 0.014 | 1.4 | 0.006 | 1.325 | 0.391 |
| $e_3$ | 0.20 | 0.02 | 2.0 | 0.085 | 5.161 | 1.105 |
| $e_4$ | 0.65 | 0.065 | 6.5 | 0.152 | 0.286 | 0.958 |
| $e_5$ | 0.20 | 0.02 | 2.0 | 0.049 | 0.041 | 0.743 |
| $e_6$ | 1.02 | 0.102 | 10.2 | 0.000 | 0.086 | 0.621 |
| $e_7$ | 1.00 | 0.10 | 10.0 | 0.325 | 0.000 | 0.131 |
| $e_8$ | 1.00 | 0.10 | 10.0 | 0.402 | 2.338 | 0.724 |
| $e_9$ | 1.20 | 0.12 | 12.0 | 0.093 | 0.034 | 1.739 |
| $e_{10}$ | 0.30 | 0.03 | 3.0 | 2.014 | 0.339 | 0.679 |
| $e_{11}$ | 0.32 | 0.032 | 3.2 | 0.027 | 0.000 | 1.468 |
| $e_{12}$ | 0.33 | 0.033 | 3.3 | 0.003 | 0.001 | 1.551 |
| $e_{13}$ | 0.30 | 0.03 | 3.0 | 0.031 | 0.095 | 0.964 |
| $e_{14}$ | 0.80 | 0.08 | 8.0 | 1.706 | 0.583 | 2.228 |
| $e_{15}$ | 0.12 | 0.012 | 1.2 | 0.000 | 0.028 | 0.040 |
| $e_{16}$ | 0.34 | 0.034 | 3.4 | 0.000 | 0.039 | 0.127 |
| $e_{17}$ | 0.28 | 0.028 | 2.8 | 0.075 | 0.004 | 0.120 |

TABLE 6

Relative error between the original and the optimal solutions with various population sizes

| Origin ventilation resistance (N×s$^2$/m$^8$) | Inversed ventilation resistance (N×s$^2$/m$^8$) | | | Relative error (%) | | |
|---|---|---|---|---|---|---|
| | ***P* = 50** | ***P* = 100** | ***P* = 200** | ***P* = 50** | ***P* = 100** | ***P* = 200** |
| 0.08 | 0.007 | 0.050 | 0.235 | 91.43 | 37.91 | 193.56 |
| 0.14 | 0.006 | 1.325 | 0.391 | 95.62 | 846.52 | 179.44 |
| 0.20 | 0.085 | 5.161 | 1.105 | 57.30 | 480.66 | 452.75 |
| 0.65 | 0.152 | 0.286 | 0.958 | 76.56 | 56.01 | 47.33 |
| 0.20 | 0.049 | 0.041 | 0.743 | 75.35 | 79.57 | 271.27 |
| 1.02 | 0.000 | 0.086 | 0.621 | 99.99 | 91.55 | 39.12 |
| 1.00 | 0.325 | 0.000 | 0.131 | 67.46 | 99.97 | 86.91 |
| 1.00 | 0.402 | 2.338 | 0.724 | 59.80 | 133.81 | 27.58 |
| 1.20 | 0.093 | 0.034 | 1.739 | 92.28 | 97.17 | 44.92 |
| 0.30 | 2.014 | 0.339 | 0.679 | 571.25 | 12.85 | 126.28 |
| 0.32 | 0.027 | 0.000 | 1.468 | 91.56 | 99.96 | 358.67 |
| 0.33 | 0.003 | 0.001 | 1.551 | 99.12 | 99.78 | 370.10 |
| 0.30 | 0.031 | 0.095 | 0.964 | 89.77 | 68.29 | 221.24 |
| 0.80 | 1.706 | 0.583 | 2.228 | 113.19 | 27.19 | 178.54 |
| 0.12 | 0.000 | 0.028 | 0.040 | 99.79 | 76.63 | 66.82 |
| 0.34 | 0.000 | 0.039 | 0.127 | 99.95 | 88.49 | 62.73 |
| 0.28 | 0.075 | 0.004 | 0.120 | 73.24 | 98.44 | 57.04 |
| Average relative error | | | | 114.92 | 264.40 | 163.78 |

This indicates that the increase in the population size can improve the convergence of the algorithm. From the inversion results of Tables 2 and 5, it can be concluded that the genetic algorithm can invert ventilation resistance coefficient.

This can be used to solve the optimisation problem of the ventilation resistance coefficient inversion, but the average relative error between the inversion result and the original ventilation resistance is very large. It is known from previous studies that the problem of ventilation resistance coefficient inversion is an ill-posed problem, where there are infinitely many solutions. In the absence of other constraints, the wind resistance range constraint affects the final inversion results directly.

## 5. Conclusion

(1) The mathematical model of ventilation resistance coefficient inversion is established based on the principle of the least squares. The measured pressure and the calculated pressure along with the flow measured and the calculated flow deviation are considered as the objective function, which also includes the node pressure, air flow and ventilation resistance coefficient range constraints. The ventilation resistance coefficient inversion problem was converted to a nonlinear optimisation problem through the establishment of the model. Genetic algorithm and particle swarm algorithm were adopted to solve the ventilation resistance coefficient inversion problem. GA was improved to enhance the global and the local search abilities of the algorithm for solving the ventilation resistance coefficient inversion problem.

(2) In order to apply the standard GA for the problem of ventilation resistance coefficient inversion, several improvements have been done on factors such as coding, selection,

crossover, variation, fitness scale changes, adaptive crossover rate and mutation rate. However, because the problem of ventilation resistance coefficient inversion is an ill-posed problem, it is obvious to see this algorithm can find local best in the conditions of no constraints.

(3) The final inversion results were directly affected by the constraints of the wind resistance range. These constraints should be matched to the actual situation as much as possible to approximate the true resistance value and to narrow the range of the wind resistance, especially for important roadways. The inversion method can be used on the roadways even if they are irregular or localised. The ventilation resistance in regular roadways can be obtained by using the look-up table and the determination method. This new overall method opens opportunities for getting the ventilation resistance by a small amount of measurement data.

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