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RESEARCH ARTICLE

An Efficient Method for Optimizing Sensors' Layout for Accurate Measurement of Underground Ventilation Networks

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ABSTRACT Due to the complex spatial hierarchy and large network scale of the mine ventilation system, it is difficult to obtain ventilation information of all branches in real-time, accurately, and comprehensively by arranging sensors. To overcome this difficulty, this paper proposes an optimal layout method of sensors based on the DETMAX algorithm and Tabu search algorithm. Given a known number of sensors, the proposed method can efficiently select an optimal set of branches to arrange these sensors according to the calculated airflow of each branch while considering both the air resistance error and the sensor error. This optimized sensor layout can minimize the airflow error of the undetected branches and obtain the ventilation information of the entire ventilation system accurately with a limited number of sensors. The proposed method has significant economic benefits and can provide technical support for developing intelligent ventilation systems. Finally, the performance and efficiency of this method are verified by comparing it with the Monte Carlo algorithm and the Ant Colony algorithm with data from the Wangjialing coal mine in China.

INDEX TERMS Accurate monitoring, layout optimization, mine ventilation, sensors.

I. INTRODUCTION

The function of a mine ventilation system is mainly to continuously transport sufficient fresh air to the mine while promptly discharging toxic and harmful gases to guarantee the well-being of personnel and the normal operation of equipment [1], [2]. Hence, an efficient and reliable mine ventilation system is crucial for ensuring safe production in the mine [3]. Meanwhile, since most of China's coal resources are buried deep underground, underground mining is the primary extraction method, with open-pit mining accounting for less than 15% of coal production [4], which further demonstrates the importance of the mine ventilation system.

Intelligent ventilation is a new ventilation mode that can adjust the airflow quickly, accurately, and on-demand [5]; also, it is an inevitable trend in the development of mine ventilation technology [6]. Currently, it has become the core of intelligent transformation in mines and is one of the core technologies for guaranteeing the transformation, upgrading, and high-quality development of the coal industry [7], [8]. In an intelligent ventilation system, obtaining the ventilation information in branches accurately, comprehensively, and in real-time is the key to achieving intelligent ventilation [9]. Compared to manual measurement, using a sensor network to collect ventilation data from each branch is a more effective and timely method for obtaining data, and it has become the main means of obtaining ventilation information in the ventilation system [10]. To ensure ventilation effectiveness, timely obtain the on-site situation, and detect

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accidents and hidden dangers, a large number of sensors need to be deployed to obtain the ventilation information in tunnels in real-time [11], [12]. Many studies have indicated that increasing the number of sensor measurement points and optimizing their location can greatly improve the accuracy of ventilation fault diagnosis [13], [14], [15], [16]. Nevertheless, due to the complex spatial hierarchy, the large scale of the mine ventilation system, as well as the high cost of equipment installation and maintenance, it is impossible and unsuitable to deploy sensors in each tunnel [17]. Therefore, achieving real-time and accurate monitoring of the entire ventilation system by deploying a limited number of sensors has been a challenging and urgent issue. This issue involves the layout optimization of sensors; that is, achieving the optimal layout of sensors will be one of the ways to solve this problem.

In the research on mine ventilation, great importance has been placed on optimizing the layout of sensors, especially air velocity and air pressure sensors. This is because air speed and air pressure are key parameters for obtaining the ventilation information of a mine ventilation system. The accurate measurement of these parameters is important for achieving real-time calculation of mine ventilation networks, monitoring and warning of ventilation anomalies, as well as emergency control of disaster airflow. Jiang used the sensitivity matrix of ventilation and the Kruskal algorithm to optimize the layout of air velocity monitoring points [18]. Pan et al. established a fault range library of ventilation branches using ventilation sensitivity to determine the minimum number and location of air velocity sensors required for full monitoring coverage [19], [20]. Xie et al. adopted the mine ventilation network aggregation principle and the Fibonacci method to investigate the layout optimization of monitoring points for a multi-ventilator and multi-fan station ventilation system [21]. Zhao et al. arranged air velocity sensors to monitor corner-linked branches by analyzing the influence of changes in air resistance of associated branches on the corner-linked branches [22]. Si utilized graph theory to optimize and analyze the sensor layout and employed variable fuzzy theory to investigate the layout optimization of air velocity sensors [23]. Li et al. designed a air pressure sensor optimal layout algorithm based on a greedy strategy that can meet the requirements of air volume inversion data [24]. Liu et al. analyzed the relationship between airflow variation and fault location and developed a method to optimize the layout of air velocity sensors based on the neighborhood rough set [25]. Liu et al. used an independent cut-set algorithm to obtain the layout of air velocity sensors and pointed out that setting air velocity sensors in 30% of the branches can accurately determine the airflow in all tunnels [17]. Based on the directed path matrix method, Li et al. presented an air velocity sensor optimization layout that can monitor the airflow changes of all branches with the minimum number of air velocity sensors [26]. Ni et al. developed an optimization layout method for embedded air velocity sensors, and the problem of mismatch between air velocity sensor optimization layout and diagnostic models was solved [27]. Liu et al. pointed out that the reduced branches obtained based on the importance of branch airflow to fault location and fault quantity are the optimal locations for sensor installation [28].

Although the above methods for optimizing the layout of sensors achieved good results, they ignored the influence of air resistance error and sensor error. However, these factors are crucial for accurately obtaining the ventilation information of a ventilation system. Therefore, the results obtained by these methods are not necessarily optimal. To more accurately obtain the ventilation information of a mine ventilation system by using a limited number of sensors, this paper optimizes the layout of sensors in the mine ventilation system by comprehensively considering air resistance error and sensor error based on the calculated airflow of each branch.

The rest of this paper is organized as follows. In Section II, the layout optimization problem to be solved in the paper is formulated by incorporating the air resistance error and sensor error into the quantitative analysis of the ventilation system. Then, for this optimization problem, Section III proposes an optimization method based on the DETMAX algorithm and Tabu technology. In Section IV, the effect of the optimization method is verified through a real example and is compared with those of the Mento Carlo algorithm and Ant Colony algorithm. Finally, Section V gives the conclusions and discussions.

II. OPTIMIZATION PROBLEM

Given a known number of sensors, this paper aims to efficiently find an optimal set of branches in which to arrange these sensors, thereby obtaining the ventilation information of the entire ventilation system most accurately.

If a mine ventilation network consists of m branches and n nodes, the number of independent circuits b in this ventilation network can be calculated by $b = m-n+1$. Assuming that the change in air density is negligible, the laws of node airflow balance and circuit air pressure balance can be expressed as follows [29]:

$$f_i(\boldsymbol{q}) = \begin{cases} \sum_{j=1}^{m} C_{ij} q_j = 0 \quad (1 \leq i \leq n-1) \\ \\ \sum_{j=1}^{m} N_{ij} \left(r_j q_j |q_j| - h_j \right) = 0 \quad (1 \leq i \leq b) \end{cases} \tag{1}$$

where i is the node number in the airflow balance equation and the circuit number in the air pressure balance equation; j is the branch number; q_j, r_j, and h_j represent the airflow, the air resistance, and the fan air pressure in the j-th branch, respectively; C_{ij} is a multiplier representing the relationship between branch j and node i; $C_{ij} = 0$ if the i-th node is not in the j-th branch, $C_{ij} = 1$ if the j-th branch starts at the i-th node, and $C_{ij} = -1$ if the j-th branch ends at the i-th node; N_{ij} is a multiplier representing the relationship between branch j and circuit i; $N_{ij} = 0$ if the j-th branch is not in the i-th circuit, $N_{ij} = 1$ if the direction of the j-th branch is similar to that of the i-th circuit, and $N_{ij} = -1$ otherwise.

Referring to (1), given the construction of the mine ventilation network, the air resistance of branches, as well as the characteristics of fans, the airflow of each branch can be calculated to realize a quantitative analysis of the entire ventilation system.

In the traditional quantitative analysis of the ventilation system, the measured or calculated air resistance of branches is considered accurate. However, since the air resistance of branches is affected by many factors, such as branch roughness, branch section types, and airflow patterns, errors exist in the measurement or calculation results, and these errors will cause the calculated airflow of branches to be inaccurate. Therefore, when calculating the airflow of branches, it is necessary to consider the influence of air resistance error. Thus, this paper corrects (1) by introducing the air resistance error as follows:

$$f_i\left(\boldsymbol{q}+\delta \boldsymbol{q}, \boldsymbol{r}+\delta \boldsymbol{r}\right)=0 \tag{2}$$

where $\delta \boldsymbol{q}$ is the airflow error of branches caused by the air resistance error, and $\delta \boldsymbol{r}$ is the air resistance error of branches.

To obtain the ventilation information of a mine ventilation system in real-time, sensors need to be deployed to obtain the airflow information of branches to ensure the safety of ventilation. However, considering the complex spatial hierarchy and the large network scale of the mine ventilation system, it is unnecessary and impossible to obtain the air volume information of each branch by arranging sensors. Meanwhile, the sensors also have errors, and this factor should be considered when analyzing the airflow information of branches. Assuming that d sensors are deployed to obtain the airflow information of the branches, the airflow of branches detected and not detected by the sensors is defined as $\boldsymbol{q}_s$ and $\boldsymbol{q}_u$, respectively. By incorporating the sensor error into the airflow analysis, (2) is further extended to:

$$f_i\left(\boldsymbol{q}_u+\delta \boldsymbol{u}, \boldsymbol{q}_s+\delta \boldsymbol{s}, \boldsymbol{r}+\delta \boldsymbol{r}\right)=0 \tag{3}$$

where $\delta \boldsymbol{u}$ denotes the airflow error in the undetected branches, and $\delta \boldsymbol{s}$ denotes the airflow error in the detected branches.

This implicit function equation can be solved by using the partial differential method:

$$\frac{\delta f_i}{\delta \boldsymbol{q}_u}\delta \boldsymbol{u}+\frac{\delta f_i}{\delta \boldsymbol{q}_s}\delta \boldsymbol{s}+\frac{\delta f_i}{\delta \boldsymbol{r}}\delta \boldsymbol{r}=0 \tag{4}$$

The airflow error $\delta \boldsymbol{u}$ can be derived as follows:

$$\delta \boldsymbol{u}=-\left(\frac{\delta f_i}{\delta \boldsymbol{q}_u}\right)^{+}\left(\frac{\delta f_i}{\delta \boldsymbol{q}_s}\delta \boldsymbol{s}+\frac{\delta f_i}{\delta \boldsymbol{r}}\delta \boldsymbol{r}\right) \tag{5}$$

where $\left(\frac{\delta f_i}{\delta \boldsymbol{q}_u}\right)^{+}$ denotes the left inverse of $\frac{\delta f_i}{\delta \boldsymbol{q}_u}$.

Equation (5) can be rewritten as:

$$\delta \boldsymbol{u}=-\left(\frac{\delta f_i}{\delta \boldsymbol{q}_u}\right)^{+}\begin{bmatrix}\frac{\delta f_i}{\delta \boldsymbol{q}_s} & \frac{\delta f_i}{\delta \boldsymbol{r}}\end{bmatrix}\begin{bmatrix}\delta \boldsymbol{s}\\ \delta \boldsymbol{r}\end{bmatrix} \tag{6}$$

Let

$$A=-\left(\frac{\delta f_i}{\delta \boldsymbol{q}_u}\right)^{+}\begin{bmatrix}\frac{\delta f_i}{\delta \boldsymbol{q}_s} & \frac{\delta f_i}{\delta \boldsymbol{r}}\end{bmatrix}$$
$$\delta_Y=\begin{bmatrix}\delta \boldsymbol{s}\\ \delta \boldsymbol{r}\end{bmatrix} \tag{7}$$

Then

$$\delta \boldsymbol{u}=A\delta_Y \tag{8}$$

According to the law of covariance propagation, the covariance matrix of the airflow error $\delta \boldsymbol{u}$ can be represented as:

$$\sum\nolimits_u=A\sum\nolimits_Y A^{\mathrm{T}} \tag{9}$$

where A can be derived from the implicit function characteristics; $\sum_Y$ denotes the covariance matrix of the airflow error $\delta \boldsymbol{s}$ and air resistance error $\delta \boldsymbol{r}$.

Minimizing the trace of the covariance matrix is a standard objective function for optimizing the expected error distribution. To obtain the minimum airflow error $\delta \boldsymbol{u}$, it only needs to guarantee that the sum of the diagonal elements of the covariance matrix is minimized, i.e., to minimize the trace of this covariance matrix. Thus, the optimization problem to be solved in this paper can be defined as:

$$\begin{aligned}&\text{minimize} \quad \tilde{f}_{obj}=tr\left(\sum\nolimits_u(\hat{\boldsymbol{s}})\right)\\&\text{subject to}: T=[T_1, T_2, \ldots, T_m]^{\mathrm{T}}\\&\qquad V=\left[v_1, v_2, \ldots, v_p\right]^{\mathrm{T}}\\&\qquad \hat{\boldsymbol{s}}=[s_1, s_2, \ldots, s_d]^{\mathrm{T}}\\&\qquad \hat{\boldsymbol{s}}\in C_T V\end{aligned} \tag{10}$$

where tr is the symbol for taking the trace of the covariance matrix; T is a set of all branches in the mine ventilation network; V represents a set of branches with fans; $\hat{\boldsymbol{s}}$ represents a set of branches with sensors; m denotes the total number of branches; p denotes the number of branches with fans; $C_T V$ represents a set of branches whose elements belong to set T but not belong to set V.

III. OPTIMIZATION METHOD

In this problem, the observability index is the trace of the covariance matrix of the airflow error $\delta \boldsymbol{u}$. The main idea to solve the optimization problem is to find an optimal set of branches from a large number of candidate branches to minimize the observability index. To this end, the DETMAX algorithm is introduced in this paper. The DETMAX algorithm was proposed by Mitchell [30], and it is the best-known and most widely used optimization algorithm at present. The algorithm is designed based on a simple exchange principle. In each iteration, the algorithm chooses a branch from a large pool of candidate branches and then uses it to replace one in a selected set of branches to decrease $\tilde{f}_{\mathrm{obj}}$.

Let

$$\tilde{T}=\left[\tilde{T}_1, \tilde{T}_2, \ldots, \tilde{T}_l\right]^{\mathrm{T}} \tag{11}$$

be a candidate pool consisting of $\boldsymbol{l}$ branches with unknown airflow information. Hence, the value of $\boldsymbol{l}$ can be calculated by $\boldsymbol{l} = m - p - d$. Here, the airflow information of the branches with fans is considered to be known.

Then,

$$\xi = \left[\hat{s}, V\right]^{\mathrm{T}} \tag{12}$$

is the set including $\boldsymbol{d} \, \mathcal{C} \, \boldsymbol{p}$ branches with known airflow information at a specific DETMAX iteration.

The implementation of this algorithm consists of the following two operations:

1) Add a candidate: Choose a candidate from the candidate pool in turn and add it into ξ, and an extended set with $d + p + 1$ branches is found finally, which has the minimum $\tilde{f}_{\mathrm{obj}}$. This operation can be described as follows:

$$\xi_{\mathrm{ex}} = \left[\hat{\boldsymbol{s}}, s_{d+1}, V\right]^{\mathrm{T}} \tag{13}$$

where

$$s_{d+1} = \tilde{T}_k \tag{14}$$

$$k = \underset{i=1}{\overset{l}{\operatorname{argmin}}} \tilde{f}_{\mathrm{obj}} \left(\xi_{\mathrm{ex}}\right) \tag{15}$$

Note that the solution of k needs to be obtained through $\boldsymbol{l}$ iterations.

2) Remove a selected branch: Remove a branch from the extended set ξ_{ex} in turn so that the remaining $d + p$ branches correspond to the smallest $\tilde{f}_{\mathrm{obj}}$. Note that the branches with fans will not be deleted. This operation can be expressed as:

$$k = \underset{i=1}{\overset{d+1}{\operatorname{argmin}}} \tilde{f}_{\mathrm{obj}} \left([s_1, \ldots, s_{i-1}, s_{i+1}, \ldots, s_{d+1}, V]\right) \tag{16}$$

$$\xi = [s_1, \ldots, s_{k-1}, s_{k+1}, \ldots, s_{d+1}, V]^{\mathrm{T}} \tag{17}$$

The above two operations can be called "AddBranch" and "RemoveBranch", respectively. Using the two operations alternately will continuously decrease the value of $\tilde{f}_{\mathrm{obj}}$ corresponding to ξ, and finally, the set ξ corresponding to the minimum $\tilde{f}_{\mathrm{obj}}$ is obtained.

Since the DETMAX algorithm is greatly affected by the initial data set, it converges to the local optimum easily [31]. Hence, the Tabu search algorithm is adopted in this paper to guide the search for the global optimal solution. The Tabu search was introduced by Glover [32], and it is a global step-wise optimization algorithm. The core of this algorithm is to store the local optimal solutions using the Tabu list to guide the next search direction, which can prevent roundabout searches and avoid falling into the local optimum. The procedure of applying the Tabu search algorithm in this paper can be summarized as follows. First, set the length n_{tabu} of the Tabu list and initialize it by randomly selecting n_{tabu} branches in $\hat{\boldsymbol{s}}$. Then, enter the loop of the algorithm: In each iteration, the optimal candidate found in "AddBranch" will be put into the Tabu list, and it will not be removed in the next "RemoveBranch". The Tabu list will be updated by deleting the oldest element. Let

$$B = \left[s_1^+, \ldots, s_{n_{\mathrm{tabu}}}^+\right]^{\mathrm{T}} \tag{18}$$

be the set of Tabu list.

Therefore, Equations (16) and (17) should be revised to:

$$k = \underset{i=1}{\overset{d+1-n_{\mathrm{tabu}}}{\operatorname{argmin}}} \tilde{f}_{\mathrm{obj}} \left(\begin{bmatrix} s_1, \ldots, s_{i-1}, s_{i+1}, \\ \ldots, s_{d+1-n_{\mathrm{tabu}}}, B, V \end{bmatrix} \right) \tag{19}$$

$$\xi = \left[s_1, \ldots, s_{k-1}, s_{k+1}, \ldots, s_{d+1-n_{\mathrm{tabu}}}, B, V\right]^{\mathrm{T}} \tag{20}$$

The implementation of the optimization method is shown in Figure 1. A brief description of the iteration process is provided below:

1) The initial values of the airflow and air resistance for each branch and the characteristics of the fans are known. Set up the circuit matrix $\boldsymbol{N}_{ij}$ and the node matrix $\boldsymbol{C}_{ij}$ of the mine ventilation network, and initialize the parameters required by the algorithm, including the length of the Tabu list $\boldsymbol{n}_{\mathrm{tabu}}$, the maximum number of iterations $\boldsymbol{n}_{\mathrm{iter}}$, and the set of branches with sensors $\hat{\boldsymbol{s}}$, etc.
2) Select a candidate from the candidate pool that makes the extended set ξ_{ex} correspond to the minimum observability index.
3) Remove a candidate from the extended set ξ_{ex} that makes the remaining branches correspond to the smallest observability index. The branches in the Tabu list and the branches with fans cannot be removed from the extended set.
4) When all elements of the set $\hat{\boldsymbol{s}}$ no longer change, or the number of iterations exceeds the allowable upper limit, the iteration will be stopped, and the algorithm is considered to reach convergence at this time; otherwise, return to Step 2.
5) Output result.

IV. AN EXAMPLE

The Wangjialing Coal Mine is located in Shanxi Province, China. The current mine area is about 119.7 km^2, the proven coal reserve is 1.086 billion tons, the workable reserve is 688 million tons, and the designed production capacity is 6 million tons per year. Now, there are two mining working faces and four tunneling working faces in the coal mine. The mine's ventilation method adopts centralized appose exhausting-type ventilation. In the ventilation system, main and auxiliary branches and air-intake slopes are used to intake air, and air-return slopes are used to return air. The total air-intake of the ventilation system is 18170 m^3/min, and total air-return is 18358 m^3/min. With the continuous increase in the mining scale and the number of branches, the ventilation system has become more and more complex. To ensure safe production, it is necessary to obtain the airflow information of the ventilation system.

Note that the comparison of the proposed algorithm and other algorithms is conducted under the same hardware and software environment. The hardware device is a computer equipped with an 8-core processor with 32 GB main memory and a 3 TB hard disk. All algorithm codes are performed on Matlab 2020b.

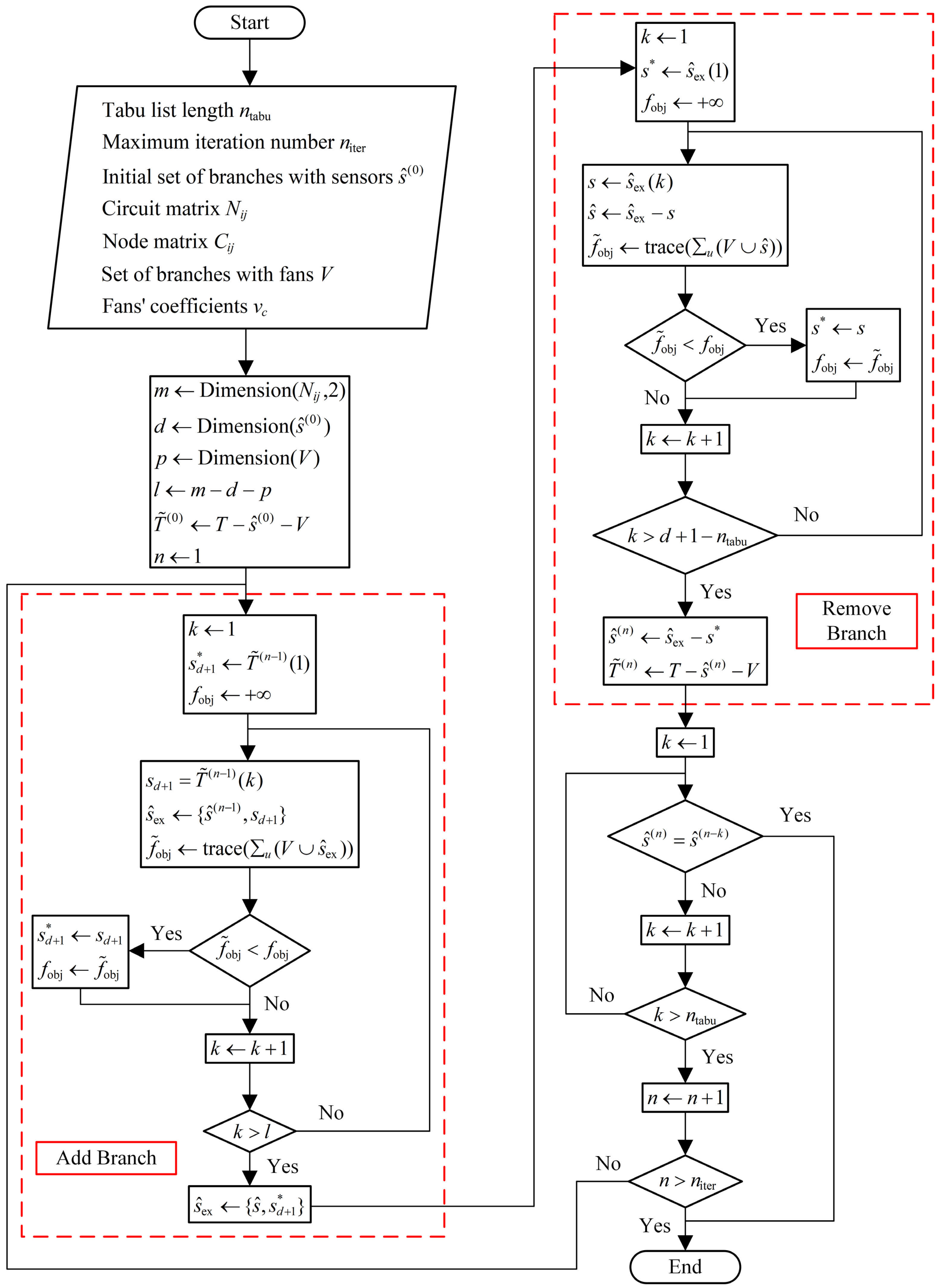

FIGURE 1. **The implementation flowchart of the optimization method.**

The diagram of the ventilation network of the Wangjialing Coal Mine is shown in Figure 2. There are 332 branches, 231 nodes, and 9 fans in this mine ventilation network, i.e., $\boldsymbol{m} = 332$, $\boldsymbol{n} = 231$, and $\boldsymbol{p} = 9$. According to the formula $b = m - n + 1$, the number of independent circuits in the ventilation network is 102. The branches are numbered from 1 to 332, and the nodes are numbered from 1 to 231; then, the circuit matrix N_{ij} and node matrix C_{ij} are set up based on the circuit information. According to the compiled branch numbers, the names of branches with fans are determined to be $V = [22, 97, 141, 159, 164, 170, 175, 182, 332]$. The air pressure $\boldsymbol{h}$ of the branches with fans is calculated based on the air pressure characteristic curve of the fan. Since the air resistance r_j of a branch is considered to be known, which can be obtained by measurement, the airflow q_j of each branch and the air pressure of each circuit can be solved based

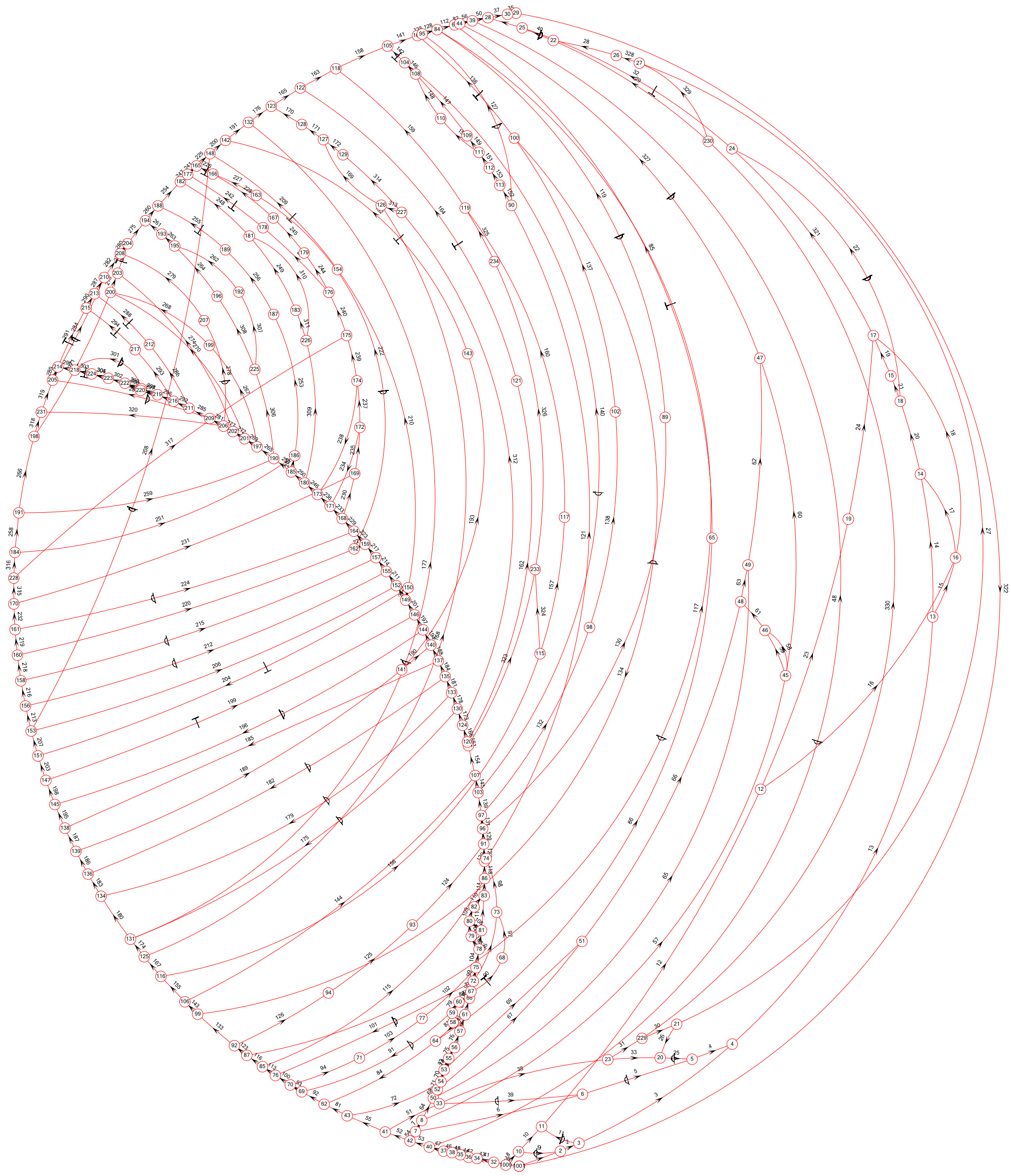

FIGURE 2. The actual ventilation network of the Wangjialing Coal Mine. A circle indicates a node, a line connecting two circles indicates a branch, the direction of the arrows denotes the direction of ventilation, the sign T represents the air regulator, and the sign D represents the air door.

on (1). According to the real situation, the error coefficients of the sensor and air resistance are set to calculate the covariance matrix $\sum_Y$ of the errors. Referring to (9), the covariance matrix $\sum_u$ of the airflow error can be calculated based on the above information.

A. CASE 1: $d = 20$ AND $n_{tabu} = 0$

20 branches are chosen from the set of branches without fans to minimize the observability index $\tilde{f}_{\text{obj}}$. First, 20 branches are randomly selected from the set of branches without fans. This can be achieved by using the randperm and sort commands in Matlab. The set of branches selected at the first time in this case is $\hat{\mathbf{s}}^{(0)} = [32, 41, 44, 50, 89, 130, 151, 173, 202, 242, 248, 264, 281, 292, 293, 298, 302, 303, 314, 322]$. Secondly, the iteration of the DETDAX algorithm is started. The total number of branches, the number of detected branches, and the number of branches with fans are $m = 332$, $d = 20$, and $p = 9$, respectively. Hence, the number of branches with unknown airflow information is $\boldsymbol{l} = 303$. The length of the Tabu list is set to $n_{\text{tabu}} = 0$, and the maximum number of iterations

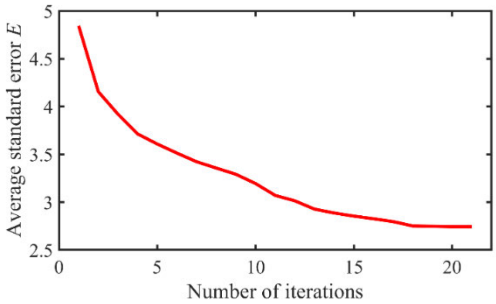

FIGURE 3. The changing trend of the *E* value for case 1.

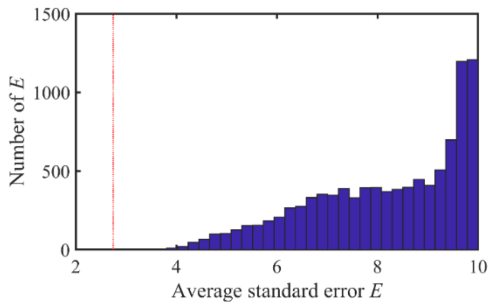

FIGURE 4. The changing trend of the *E* value using Monte Carlo.

allowed is set to $n_{\text{iter}} = 100$. Finally, the algorithm converged after 21 iterations, and the entire calculation process took 121 seconds.

The optimal set of branches $\hat{s}_{\text{opt}}$ obtained for arranging the sensors is $\hat{s}_{\text{opt}} = [12, 86, 89, 90, 91, 92, 93, 101, 115, 138, 161, 168, 177, 224, 247, 248, 251, 316, 322, 325]$, and the observability index $\tilde{f}_{\text{obj}}$ at this time is $\tilde{f}_{\min} = 2.28 \times 10^3$. Then, the average standard deviation E is used to characterize the error of undetected branches, and its value is calculated by $E = \sqrt{\tilde{f}_{\text{obj}}/l}$. Therefore, the average standard deviation E at convergence is $E_{\min} = 2.74$. In the whole iteration, the changing trend of the E value is illustrated in Figure 3. It can be seen that the iteration process is relatively stable, and the change curve is similar to an exponential curve, indicating that the algorithm has good stability and convergence.

To demonstrate the advantages of our algorithm, it is compared with the Monte Carlo algorithm and the Ant Colony algorithm [33]. Given that these two algorithms are widely used to solve the problems of optimal sensor layout [34], [35], [36], [37], [38], [39], [40], it is reasonable to take them for comparison with the proposed method.

The maximum number of iterations of the Monte Carlo algorithm is set to 100000. Each time, 20 branches are randomly selected from the set of branches without fans, and the E value of this sample is calculated. After 100000 samplings, the distribution of the E value is obtained and shown in the blue histogram in Figure 4.

The entire sampling process took 1719 seconds. The optimal set of branches $\hat{s}_{\text{opt}}$ obtained by the Monte Carlo

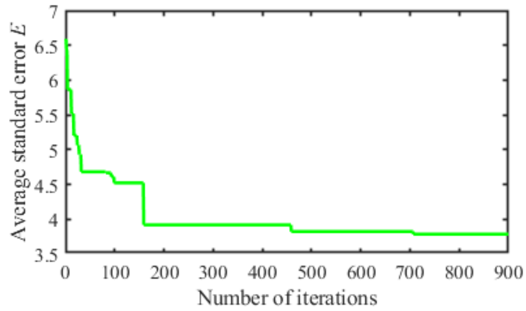

FIGURE 5. The changing trend of the *E* value using the Ant Colony algorithm.

TABLE 1. The comparison of the three algorithms for case 1.

Algorithms	The optimal E	Calculation time (s)	The optimal set of branches obtained
Proposed Method	2.74	121	12,86,89,90,91,92,93,101,115, 138,161,168,177,224,247,248, 251,316,322,325
Monte Carlo	3.59	1719	37,47,56,59,87,90,92,101,106, 127,136,154,163,168,244,248, 251,255,272,319
Ant Colony	3.78	3082	90,64,325,129,59,327,96,100, 160, 322, 42,75, 329,243,111, 313,316,110,76,60

algorithm is $\hat{s}_{\text{opt}} = [37, 47, 56, 59, 87, 90, 92, 101, 106, 127, 136, 154, 163, 168, 244, 248, 251, 255, 272, 319]$. The optimal E value at this time is $E_{\min} = 3.59$. The red dotted line in Figure 4 represents the optimal E value obtained by the proposed algorithm. Figure 5 presents the result of the Ant Colony algorithm. The maximum number of iterations of the Ant Colony algorithm is set to 900. Each time, 35 ants visit the branches according to the previous pheromone and pick 20 branches from the set of branches without fans, and the E value of this branch is calculated. The entire process took 3082 seconds. The optimal E value and the optimal set of branches obtained by the Ant Colony algorithm are $E_{\min} = 3.78$ and $\hat{s}_{\text{opt}} = [90, 64, 325, 129, 59, 327, 96, 100, 160, 322, 42, 75, 329, 243, 111, 313, 316, 110, 76, 60]$, respectively.

The comparison of the three algorithms (see Table 1) indicates that using the proposed method can highly reduce the calculation cost, improve the calculation efficiency, and obtain more optimized solutions.

B. CASE 2: $d = 20$ AND $n_{tabu} = 5$

This case is to verify the influence of the Tabu list on the optimal solution. Except for the length of the Tabu list, all the settings and the initial $\hat{s}$ in this case are the same as those in Case 1. The length of the Tabu list n_{tabu} is set to $n_{\text{tabu}} = 5$ in this case. After 34 iterations, the algorithm achieved convergence, and the entire calculation process took 192 seconds. At this time, the optimal E value and the optimal

TABLE 2. The comparison of the results in case 1 and case 2.

Cases	The optimal E	Calculation time (s)	The optimal set of branches obtained
1	2.74	121	12,86,89,90,91,92,93,101,115, 138,161,168,177,224,247,248, 251,316,322,325
2	2.66	192	12,86,89,90,91,93,94,101,104, 106,115,138,161,168,177,224, 248,251,318,325

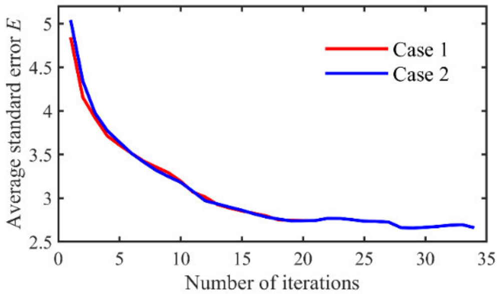

FIGURE 6. Comparison of the changing trends of the E value in two cases.

set of branches $\hat{s}$ obtained are $E_{\min} = 2.66$ and $\hat{s}_{\text{opt}} = [12, 86, 89, 90, 91, 93, 94, 101, 104, 106, 115, 138, 161, 168, 177, 224, 248, 251, 318, 325]$, respectively.

Comparing the results of the two cases (see Table 2), it can be seen that the optimal E value obtained in Case 2 is better than that obtained in Case 1, but Case 2 needs more calculation time, indicating that the introduction of the Tabu list can obtain better optimization results but requires more calculation time. The optimal set of the branches for placing sensors obtained with and without the Tabu list has 75 percent similarity. Figure 6 compares the changing trends of the E value in the two cases. It can be seen from the figure that the changing trends of the E value in the two cases differ slightly in the early stage, but they almost coincide in the later stage. After convergence is achieved in Case 1, the E value in Case 2 continues to iterate, and iteration fluctuations occur during this period. This shows that the introduction of the Tabu list will increase the number of iterations and cause iteration fluctuations.

C. CASE 3: $d = 40$ AND $n_{tabu} = 0$

This case is to illustrate the impact of increasing the number of sensors without using the Tabu list on the optimal solution. Except for the number of sensors and the initial $\hat{s}$, all the settings in this case are the same as those in Case 1. The set of branches selected at the first time in this case is $\hat{s}^{(0)} = [10, 11, 14, 29, 32, 41, 44, 50, 51, 81, 89, 91, 117, 130, 151, 173, 194, 199, 200, 202, 203, 207, 221, 226, 238, 242, 248, 256, 264, 271, 281, 292, 293, 298, 302, 303, 304, 306, 314, 322]$. The algorithm achieved convergence after 41 iterations, and the entire calculation process took 245 seconds.

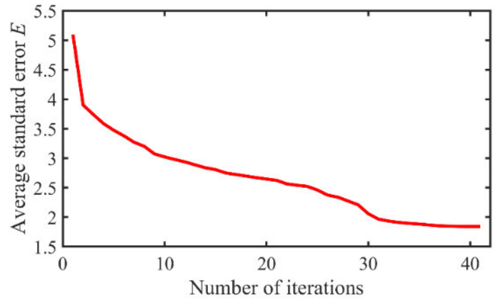

FIGURE 7. The changing trend of the E value for case 3.

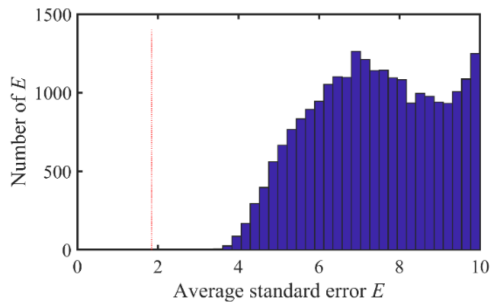

FIGURE 8. The distribution of the E value obtained using the Monte Carlo algorithm.

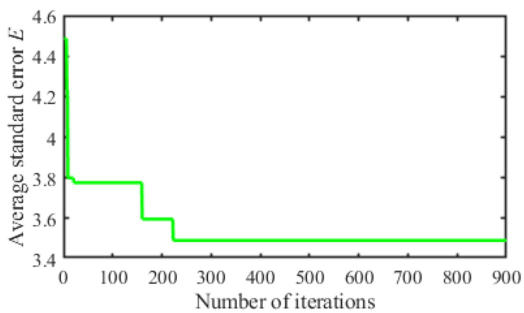

FIGURE 9. The changing trend of the E value obtained using the Ant Colony algorithm.

At convergence, the optimal E value and the optimal set of branches $\hat{s}$ obtained for placing sensors are $E_{\min} = 1.84$ and $\hat{s}_{\text{opt}} = [12, 80, 81, 82, 83, 84, 85, 86, 87, 88, 90, 91, 94, 95, 96, 104, 105, 106, 115, 117, 118, 138, 160, 161, 168, 173, 174, 180, 216, 224, 246, 251, 314, 317, 319, 321, 322, 324, 325, 326]$, respectively. The changing trend of the E value in the whole iteration process is shown in Figure 7. It can be seen that the overall change of the E value is relatively stable, with no evident fluctuations, but a sharp drop can be observed at 28 iterations, and then the E value gradually converges to the optimal value. It shows that the algorithm has a good ability to find the optimal solution.

The Monte Carlo algorithm is introduced to analyze this problem. Except for the number of samples, the other settings of the algorithm are the same as those in

TABLE 3. The comparison of three algorithms for case 3.

Algorithms	The optimal E	Calculation time (s)	The optimal set of branches obtained
Proposed Method	1.84	245	12,80,81,82,83,84,85,86,87,88, 90,91,94,95,96,104,105,106, 115,117,118,138,160,161,168, 173,174,180,216,224,246,251, 314,317,319,321,322,324,325, 326
Monte Carlo	3.15	1863	15,26,64,65,72,79,80,81,88,92, 93,100,102,103,104,105,106, 124,127,132,153,160,173,184, 195,199,210,215,224,228,236, 238,246,276,277,292,297,307, 313,320
Ant Colony	3.49	3004	84,31,108,33,5,35,315,85,292, 331,210,216,325,3,122,113,95, 71,76,316,7,64,139,11,78,330, 242,99,181,8,100,321,309,121, 93,238,9,45,329,320

Case 1. After 100000 samplings, the optimal E value and the optimal set of branches $\hat{s}$ obtained by the Monte Carlo algorithm are $E_{\min} = 3.15$ and $\hat{s}_{\text{opt}} = [15, 26, 64, 65, 72, 79, 80, 81, 88, 92, 93, 100, 102, 103, 104, 105, 106, 124, 127, 132, 153, 160, 173, 184, 195, 199, 210, 215, 224, 228, 236, 238, 246, 276, 277, 292, 297, 307, 313, 320]$, respectively. The entire sampling process took 1863 seconds. The distribution of the E value is shown in the blue histogram in Figure 8, and the red dotted line represents the optimal E value obtained by the proposed method. As illustrated in Figure 9, after 900 iterations, the optimal E value and the optimal set of branches $\hat{s}$ obtained by the Ant Colony algorithm are $E_{\min} = 3.49$ and $\hat{s}_{\text{opt}} = [84, 31, 108, 33, 5, 35, 315, 85, 292, 331, 210, 216, 325, 3, 122, 113, 95, 71, 76, 316, 7, 64, 139, 11, 78, 330, 242, 99, 181, 8, 100, 321, 309, 121, 93, 238, 9, 45, 329, 320]$, respectively. The entire process took 3004 seconds. The comparison of the three algorithms (see Table 3) indicates that the method proposed in this paper consumes less calculation time and obtains better optimization results than the Monte Carlo algorithm and the Ant Colony algorithm.

Table 4 and Figure 10 show the comparison of the optimal results and iteration process of Case 1 and Case 3. According to Table 4, increasing the number of sensors will reduce the optimal E value obtained, indicating that as the number of sensors increases, a better optimal solution is acquired. This is consistent with the actual situation that the more branches detected, the smaller the average standard error of the undetected branches. However, detecting more branches will increase the calculation cost. According to Table 4, doubling the number of branches selected will double the calculation time, and most of the branches selected in Case 1 were also selected in Case 3. Figure 10 demonstrates that the changing trend of the E value in Case 1 is similar to the early changing trend of it in Case 3, except that the

TABLE 4. The comparison of the results in case 1 and case 3.

Cases	The optimal E	Calculation time (s)	The optimal set of branches obtained
1	2.74	121	12,86,89,90,91,92,93,101,115, 138,161,168,177,224,247,248, 251,316,322,325
3	1.84	245	12,80,81,82,83,84,85,86,87,88, 90,91,94,95,96,104,105,106, 115,117,118,138,160,161,168, 173,174,180,216,224,246,251, 314,317,319,321,322,324,325, 326

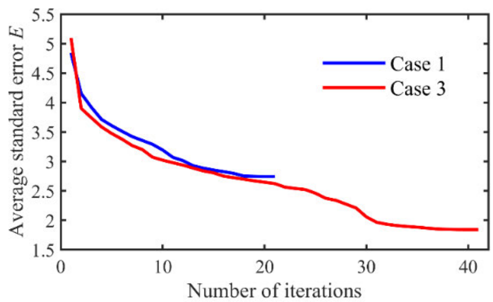

FIGURE 10. Comparison of the changing trends of the E value in two cases.

E value of each iteration is higher than that in Case 3. After convergence is achieved in Case 1, the E value in Case 3 continues to iterate. It indicates that increasing the number of branches selected for placing sensors will affect the result of each iteration and increase the number of iterations.

V. CONCLUSION

Based on the DETMAX algorithm and the Tabu search algorithm, this paper proposes an optimal method of sensor layout, which overcomes the difficulty in obtaining the ventilation information accurately, comprehensively, and in real-time in all branches due to the complex spatial hierarchy and the large network scale in the mine ventilation system. In the proposed method, the observability index is the sum of the diagonal elements of the covariance matrix of the undetected airflow error. The DETMAX algorithm selects an optimal set of branches for placing sensors to minimize the observability index. Then, the Tabu search algorithm is adopted to guide the DETMAX algorithm to find a globally optimal solution. The proposed method fully investigates the path of the error propagation and fully utilizes the problem structure, allowing it to show good performance in finding the optimal solution. Meanwhile, the proposed method is performed in an incremental way, which has the characteristics of low computational cost and high efficiency. By applying the proposed method, the ventilation information of all branches can be obtained in real-time, accurately, and comprehensively with a limited number of sensors, which greatly saves the cost of equipment installation and maintenance. Therefore, this method has huge economic benefits. Moreover, this method can provide technical support for developing intelligent ventilation systems.

The Wangjialing Coal Mine in China is taken as an example to verify the effectiveness of the proposed method. In this example, three cases are analyzed and discussed: Case 1 with $d = 20$ and $n_{\text{tabu}} = 0$; Case 2 with $d = 20$ and $n_{\text{tabu}} = 5$; Case 3 with $d = 40$ and $n_{\text{tabu}} = 0$. From the comparison of the three cases, it can be seen that a better optimal solution can be obtained by introducing the Tabu search technology and increasing the number of sensors, but at the same time, the calculation time is increased. In either case, the proposed method in this paper performs much better than the Monte Carlo algorithm and the Ant Colony algorithm, not only in obtaining the optimal solution but also in the calculation time, fully demonstrating the performance and efficiency of the proposed method.

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