FAULT DIAGNOSIS BASED ON ANT COLONY OPTIMAL ALGORITHM

MINGZAN WANG, JINZHONG HE, AND YUAN XUE

Abstract. This paper introduces a new kind of simulated evolutionary algorithm, ant colony optimal algorithm (ACO). By analyzing the resemblance between this algorithm and the cluster problem, we propose a mathematic model for cluster analysis based on ACO, put forward a new improved ACO based on rudimentary ACO, and apply it to diagnose operation state of diesel engine fuel system. The conclusion shows that this method is feasible.

Key Words. ant colony optimal algorithm, cluster analysis, fault diagnosis, pattern recognition.

1. Introduction

Ant Colony Optimal algorithm (ACO) [1] was firstly put forward by an Italian Professor named M. Dorigo in the 1990s. It is one of the branches of Cluster Intelligence. After making a lot of research about self-organizing synergistic behaviors of the ant colony when they looked for food collectively, he introduced a new conception of pheromone form biology. Above all, he had the artificial ants colony simulate the natural ant colony’ attributes, further using the continuous information exchanged among the individuals of ant colony, achieving the purpose of seeking for solution space.

The ACO was called Ant System (AS) when M. Dorigo firstly put forward the algorithm. Later, M. Dorigo and L. M. Gambardella put forward the amendatory ACO; they called it Ant Colony System (ACS). The main difference between ACS and the original ACO lies in that ACS adopted the whole information updating principle and individual moving principle, at the same time added the local updating principle to all kinds of path information. According to different local updating principle, ACS has some different cases [2, 3]. In 1999, M. Dorigo, A. Colorini and L. M. Gambardella provided a uniform descriptive frame, which called ACO Algorithm [4]. M. Dorigo successively used ACO to calculate the typical Travelling Salesman Problem (TSP) [3] and quadratic assignment problems [5], etc. He also studied the problem of arrangement of wire in communications. Though these progeny were elementary, the research had proved that ACO has its superiority in calculating complex optimized problems. Affected by them, other researchers gradually pays attention to the model of Ant System. For the astringency of ACO, researchers didn’t gradually attempt to prove it until 2002. S. Thomas and M. Dorigo proved the astringency of ACO in their studies [6]. In addition, at the base of M. Dorigo’s research, D. Costa and A. Hertz put forward the model of Assignment Type Problem to study the coloring problem [7]. G. Bilchev and IC. Parmee studied

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Ant Colony System about calculating the continuous space optimized problems to solve practical engineering design problems [8].

Nowadays it is proved that this kind of algorithm has turned into a higher efficient and new algorithm after a great deal of research from many experts and scholars. Besides, it has been increasingly applied in many fields such as electric network planning, electrical communication route, channel wiring, route planning, military operation etc and proved to have effectively solved many difficult problems [9,10].

In this paper the author tries to introduce this new algorithm into fault diagnosis fields, accordingly reaching the purpose of processing fault diagnosis. Because the task of equipment fault diagnosis is watching the equipment’s state; verdicting whether it is regular; forecasting and diagnosing the fault of equipment and removing the fault; instructing the equipment’s management and maintenance. In fact, the technology of the equipment’s diagnosis belongs to the problem of mode classification. Namely, the running states of the equipment’s are divided into normal and abnormal types. Furthermore, which fault the abnormal signal sample belongs to is the pattern recognition problem.

2. The principle and improvement of ACO

2.1. The principle of ACO. In the nature, they have a complex active character when they become ant colony, though the action of a single ant is simple. The biologist found that the ant colony always seek the shortest path from ant nest to food resource when they looked for food. The ant colony has a stronger ability to adapt to the environment. For example, when the ant colony met the barrier on the path, they always found a new optimal path. The biologist carefully researched this process and they found that the ants left a special excreted matter—pheromone, which could be found by the other ants and affected their following action during the looking for food on the path. With more ants passing this path, the specific density of pheromone concentration will become the greater, the probability of ants selecting this path will become higher, so they can increase the density of pheromone concentration. It is obvious that the collectivity action of ant colony is a positive feedback; more ants will choose this path with the ants clustering.

ACO is a kind of simulated evolutionary algorithm based on positive feedback principle of information. This algorithm has the following virtues:

1. The stronger robustness. Though it still stays at the phase of theoretical research, the model can transplant other problems, especially all kinds of assembled optimized problems.

2. The stronger ability to find the better result. The algorithm adapted positive feedback principle, so it quickens the evolution processing and can’t get into the local furthest optimized result.

3. Distributing parallelism calculating. ACO is an evolution algorithm based on ant colony and has parallelism of it. The individual of ants can continue to exchange and transfer the information, which can find a better result.

4. It’s easy to combine with other methods. The algorithm can integrate other enlightened methods to improve the performance of the algorithm.

The algorithm has two defects:

1. The computing time is too long. The algorithm needs a long time to search compared with other methods. The complexity of ACO can reflect it. ACO can make up this defect with the development of computer and the improvement of computing.
The algorithm has Stagnation Behavior. It’s difficult to find the better answer when the search does to some extent. For the two questions, many researchers have paid attention to them and put forward some improvements. For example, Thomas and other persons put forward Max-Min Ant System (MMAS) [11].

Its formulation about proposition was combined with the solving of TSP, so we will introduce it from TSP.

Suppose there are n cities. Let \(d_{ij}\) be the distance between city \(i\) and \(j\). The TSP is to find the shortest closed path that contains every city exactly once. TSP problems can be expressed by following objective function:

\[
\min D = \sum_{i=1}^{n-1} d(i, i+1) + d(n, 1).
\]

Suppose \(m\) is the total amounts of ants. During the travelling of all ants, the probability of the ant \(k\) moving from city \(i\) to \(j\) is defined as the following:

\[
P_{ij}^k(t) = \begin{cases} 
\frac{\tau_{ij}^k(t)\eta_{ij}^k}{\sum_{l \in \text{tabu}(k)} \tau_{il}^k(t)\eta_{il}^k}, & j \in \text{tabu}(k), \\
0, & \text{otherwise}.
\end{cases}
\]

where \(\text{tabu}(k)\) is the city set that ant \(k\) hasn’t visited yet at the moment, \(\eta_{ij}\) is the expecting level of ant moving from city \(i\) to \(j\), usually it can be concretely determined by some kind of heuristic algorithm, \(\tau_{ij}(t)\) is the pheromone density between city \(i\) and \(j\) at a certain moment \(t\). The initial value \(\tau_{ij}(0)\) of \(\tau_{ij}(t)\) is a positive constant \(c\) set artificially, \(\alpha, \beta\) are the density factor of pheromone and expecting factor respectively, they reflect the relative significant level of pheromone and expecting.

At \(t\) moment, each ant may choose a next city, and the arriving moment of each ant moving the next city turns into \(t+1\). Thus after \(n\) moving, each ant will complete one tour, that is to say, they finish one path search, now the time will be \(t+n\). Of all the paths that the whole ants travel, the shortest can be saved. At the same time, the pheromone concentration on the paths among cities will be updated as:

\[
\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij}(t, t+n).
\]

Where \(\rho\) is the residue coefficient, \(1-\rho\) is the volatility of information.

Let \(\Delta\tau_{ij}(t, t+n)\) be pheromone per unit length that the ant \(k\) releases on the path \(ij\) from the time \(t\) to \(t+n\). So it can be shows as follows:

\[
\Delta\tau_{ij}(t, t+n) = \sum_{k=1}^{m} \Delta\tau_{ij}^k(t, t+n).
\]

If ant \(k\) travels the path \(ij\), \(\Delta\tau_{ij}^k\) can be expressed by Equation (5), and if not, \(\Delta\tau_{ij}^k\) is 0, so the equation can be shows as

\[
\Delta\tau_{ij}^k = \begin{cases} 
Q/L_k, & \text{ant } k \text{ travels the path } ij, \\
0, & \text{otherwise}.
\end{cases}
\]
Professor M. Dorigo put forward other two models, known as Ant-quantity and Ant-density respectively, their main differences are presented in Equation (5).

For Ant-quantity model, to obtain

\[
\Delta \tau_{ij}^k = \begin{cases} 
Q/d_{ij}, & \text{ant } k \text{ travels the path } ij, \\
0, & \text{otherwise.}
\end{cases}
\]

For Ant-density model, to obtain

\[
\Delta \tau_{ij}^k = \begin{cases} 
Q, & \text{ant } k \text{ travels the path } ij, \\
0, & \text{otherwise.}
\end{cases}
\]

Experimental result show that model Equation (5) has more favorable performance than model Ant-quantity and Ant-density, because they first make use of overall information, but later only make use of local information.

### 2.2. The choice of ACO parameter

#### 2.2.1. The choice of the pheromone volatility

The size of the pheromone volatility directly relates to the whole search capacity and the constringency speed of ACO: because the existence of the pheromone volatility, when the disposal scope is big, the pheromone on the paths which are never searched before will reduce to zero and so depress the whole search capacity; but when \(1 - \rho\) is too big, the probability is also big that the paths have been searched before will be selected again. On the contrary, reducing the pheromone volatility can improve the random property and the whole search capacity of ACO, but which will depress the constringency speed of ACO.

Therefore, the choice of the pheromone volatility in ACO should synthetically consider the whole search capacity and the constringency speed. Aiming at the applied condition and practical requirement of concrete problems, we will make the reasonable or compromised choice at the whole search capacity and the constringency speed. Generally, when \(\rho = 0.5 \sim 0.7\), the property of ACO is relatively steady and unanimity, the whole search capacity and the constringency speed are good. So the suitable choice of the pheromone volatility in ACO is \(1 - \rho = 0.3\).

#### 2.2.2. The choice of the ant colony quantity

For the TSP, the path that the single ant passed in one circulation is a solution of the feasible solution mass, the path that the \(m\) ants passed in one circulation is a sub-class of the problem mass. Obviously, the bigger of the sub-class can increase the whole search capacity and the stability; for the whole updating principle, the increase of the ants’ amount will make the information quantity of the solutions that had been searched change relatively averagely, the function of positive feedback is not obvious, the randomness of search gained is reinforced, but the constringency speed becomes slow. On the contrary, when the sub-class is small (the amount of ants is small), especially the big scope of disposal problem, will reduce the information quantity that has never been search before to zero. The randomness of search weakens, though the constringency speed becomes quickly, the whole property fell and the stability is poor, the ACO is easy to stagnate too early.
The choice of ants’ quantity about ACO should synthetically consider the whole search capacity and the constringency speed. Aiming at the applied condition and practical requirement of concrete problems, we make the reasonable or compromised choice at the whole search capacity and the constringency speed. The result showed that the properties of ACO are relatively stable when \( m = 3 \sim 6 \) (relative to the scope of the problem is \( n = 10 \)). So the suitable choice of the ants’ colony in ACO is \( m = \sqrt{n} \sim n/2 \).

2.2.3. The choice of expecting factor and density factor of pheromone.

The size of the expecting factor \( \beta \) reflects the intensity of the apriority and certainty factors function when the ants search path. The bigger the \( \beta \), the bigger the probability that ants choose the local shortest path, the searched constringency speed is quickened, but the randomness reduces when ants search the optimal path and is easy to get into the local optimum. The size of the specific density of pheromone concentration \( \alpha \) reflects the intensity of the random factor function when the ants search path. The bigger the \( \alpha \), the bigger the probability that ants choose the passed path before, the randomness of search reduces, when \( \alpha \) is too big, it also makes ants search get into local optimum. The property of ACO’s whole searched optimum requires the strong randomness of the searched process; the fast constringency requires more certainty. The effect and function of both are cooperated and closely related to each other. The different choices of \( \beta \) and \( \alpha \) have a great impact on the property of ACO:

1. The bad searched results lead to the early stagnancy (\( \beta \) and \( \alpha \) are too bigger). For the bigger \( \alpha \), the importance of the pheromone \( \tau_{ij} \) on the path pays full attention, ants entirely depend on the leading of the pheromone \( \tau_{ij} \) to search. If the expecting information \( \eta_{ij} \) and the expecting factor are also bigger which will make the function of the positive feedback too strong on the local optimal path, ACO will appear the early constringency phenomenon. When the scope of the problem is big, the searched results are usually local optimal solutions.

2. The bad searched results does not lead to the early stagnancy (\( \beta \) and \( \alpha \) are too small). For smaller \( \alpha \), the importance of the pheromone \( \tau_{ij} \) on the path pays not enough attention, ants entirely depend on the leading of the pheromone \( \tau_{ij} \) to search. If the inspired information \( \eta_{ij} \) and the expecting factor are also smaller which will lead the ACO to the purely and ceaselessly randomly search, the searched results are difficult to find the optimal solutions.

3. The good searched results. Properly choose the scope of \( \beta \) and \( \alpha, \beta \) is about 1.5, \( \alpha \) is 0.5 ~ 5, ACO has good searched results, the cyclic index of ACO is few (constringency speed is fast) and the property is closed.

2.2.4. The choice of information quantity.

In Ant-cycle model, the total information quantity \( Q \) is the total pheromone quantity when ants circle hebdomad released on the passed path. Generally, the bigger \( Q \), the quicker the total pheromone quantity accumulated on the passed path, which can strengthen the property of positive feedback during ants colony searching and contribute to accelerate constringency. In fact, the function of every algorithm parameter \( \alpha, \beta \) and \( \rho \) in ACO is tightly coupling, for the property of the algorithm the parameter , and have the most functions. The total pheromone quantity \( Q \) can be analyzed and confirmed by computer simulation test. The experimental results showed that the total pheromone quantity had no evident effect on model ACO. So \( Q \) can randomly choose without extra consideration.
2.3. The improvement for ACO. After many scholars’ researches, there are many improved ACO at the base of essential ACO. The essential factors that decide the algorithm property in basic ACO are the following:

(1) The pheromone is the core factor that decides the algorithm property. The stagnancy in the search of the algorithm is owing to assembling too much pheromone in part of path, accordingly making the ants excessively intend to choose the path with more pheromone, the other path is difficult to be chosen. So the difference of the pheromone altermode will have an important effect on the algorithm.

(2) Choosing strategy is the key factor that decides the algorithm property. The method of wholly and randomly choosing path according to the pheromone size in the basic algorithm is one reason that makes the calculating speed become slow. So adopting the associative choice of certainty choice and random one to improve is a feasible method.

(3) The algorithm parameter is the importance factor that decides the algorithm property. How dynastically and reasonably to choose basic algorithm parameter is also a feasible method to improve the algorithm.

This paper put forward the improved thoughts that are following:

(1) The modified rules will increase the pheromone density whether the searched solution is excellent in ACO. In order to overcome this problem, we have to modify the pheromone density of the path that the ants have passed. This has improved the algorithm property, but the utilization ratio of ant is too low, the change of solution space is very small, and at the same time it’s disadvantageous to the accelerating calculation. In view of this, this paper absorbs the merit of MMAS, at the same time trying to modify the pheromone of the best and the worst solution on the two paths to improve the utilization ratio. For the path of the best solution, we increase the density; but for the worst one, we reduce the density. The modification had a little change to calculating quantity, but the utilization ratio of the pheromone increased twice as much after each iteration. The modified principle is following:

\[
\Delta \tau_{ij} = \begin{cases} 
Q/d_{ij}, & d_{ij} \in \text{path(best)}, \\
-Q/d_{ij}, & d_{ij} \in \text{path(worse)}, \\
0, & \text{otherwise}. 
\end{cases}
\]

(2) For the phenomena of easily falling into local optimal and stagnant phenomena, using the following method to adjust the pheromone when we find the calculating result restrain a regular solution:

\[
\tau_{ij} \leftarrow \tau_{ij} + \delta(\tau_{\text{max}} - \tau_{ij}) \quad 0 < \delta < 1.
\]

This mechanism adjusts the pheromone distribute in the mass, the parameter \(\delta\) decides to keep the amount of the previous pheromone. If \(\delta = 0\), the pheromone is entirely reservation. If \(\delta = 1\), the pheromone entirely get rid of the the previous pheromone distribute, and restart to calculate. The mechanism has a good function in the long time calculation. In this paper, if we can’t find a better solution after the continuous 25 iterations, we believe it falls into the stagnancy. Using the above principle to modify the pheromone, \(\delta = 0.6\).

(3) The original density of the pheromone is \(\tau_{\text{max}}\) in the MMAS, but \(\tau_{\text{max}}\) isn’t a right original parameter to the algorithm, the experiment indicates that the property of the algorithm is not good. So though we adopt some improved methods of MMAS, the choice of the original density doesn’t use MMAS, we use a certain value between \([\tau_{\text{min}}, \tau_{\text{max}}]\) as original value. The experiment indicates that the
selected result is better. The original density is 0.5 in this paper. Furthermore for the other parameters, the paper directly gives right parameter range and windows default. The experiment indicates that for most TSP these values can get a better solution, accordingly leave out a great deal of calculation.

3. Applications of ACO to fault diagnosis

3.1. Mathematic model of clustering analysis method based on ACO. If data are looked as ants with various attributes, cluster centers are looked as cities or foods that ants will seek, and biased errors after clustering are looked as path length of ants travelling, then the process of data clustering can be looked as the process of ants seeking foods. So the process of ant clustering is in fact the pattern classification process of searching minimal biased error.

Let \( X = \{X_i | X_i = (x_{i1}, x_{i2}, ..., x_{im})\} \) be the set within \( I \) data to be clustered, \( Y = \{Y_j | Y_j = (y_{j1}, y_{j2}, ..., y_{jm})\} \) be the set within \( J \) reference points of clustering. Let

\[
d_{ij} = \|P(X_i - Y_j)\| = \sqrt{\sum_{k=1}^{m} p_k (x_{ik} - y_{jk})^2}.\]

Where \( d_{ij} \) is the weighted Euclidean distance form \( X_i \) to the clustering center \( j \), \( P \) is the weighted factor, and can be initialized according to the varying contribution in clustering, \( \varepsilon \) is the statistic error, \( \tau_{ij}(t) \) is the amount of pheromone on the path from \( X_i \) to the clustering center \( j \) at \( t \) moment.

If the amount of pheromone on all paths are equal at \( t=0 \) and with an initial value not equal to 0, then the selection strategy that \( X_i \) chooses kind \( j \) can be determined by Equation (11):

\[
P_{ij}(t) = \frac{\tau_{ij}^\alpha(t)p_{ij}^\beta}{\sum_{l \in tabu(k)} \tau_{il}^\alpha(t)p_{il}^\beta}.
\]

Here \( tabu(k) \) table may vary with different problem. The selection strategy can be realized by roulette wheel selection.

After clustering once, if the kind \( j \) of set within \( s \) data is \( C_j = \{X_1, X_2, ..., X_s\} \), then the new perfect clustering center can be expressed by Equation (12).

\[
C_j = \frac{1}{s} \sum_{k=1}^{s} X_k.
\]

Where \( X_k \in C_j \).

After calculating the new clustering center, the biased error of the clustering \( j \) is computed by Equation (13), and the overall error is defined as \( \varepsilon = \sum D_j \).

\[
D_j = \sum_{k=1}^{s} \sqrt{\sum_{i=1}^{m} (x_{ki} - c_{ji})^2}
\]

where \( x_{ki} \) is the component \( i \) of data \( k \) in kind \( j \).

Iterate this process, until the overall error meets required accuracy or reaches the maximum iteration times.
3.2. Applications of clustering method based on ACO to fault diagnosis for diesel engine. There are \( m \) models for running-state parameter, if we want to class correctly the total data and confirm the affiliated state, the clustering method can solve this problem. Selecting \( m \) different data from these data, clustering the data acceding to the minimal biased errors principle and dynastically adjust the cluster centers. At last we can seek the pattern classification of the minimal biased error, the final cluster centers are accordingly considered the perfect cluster centers.

The basic thought of the fault diagnosis based on clustering analysis is the following. Firstly, according to the typical characters of the fault, set up the normal fault model set and cluster the fault models, the clustering results are that each fault model is clustered to different genus according to some principle. Secondly, conclude the character of each genus and form the fault principle of diagnosis. Finally, deal with the measured data gathered from the locale and gaining the factual fault model samples; these samples and typical model samples are input to computer and clustered, compare the clustering results and explain the real meanings. We can estimate these factual fault model samples belong to which kind of fault and reach the object of the fault diagnosis using clustering analysis. In this section, the clustering method based on ACO is applied to pattern recognition of operation state in one kind of diesel engine fuel system, which provides the basis for operation management and maintenance decision of the diesel engine.

Let the main technical operational parameters and combustion process effect parameters make up the five-dimensions eigenvector of diesel engine fuel system fault. Five parameters are injection pressure, injection advance angle, circulating oil feed quantity, exhaust smoke intensity and exhaust temperature, respectively. Using 14 samples in Ref.[12] (Table 1), No.1~No.7 are samples that system has operated 1000h (normal system), No.8~No.14 are samples that system has operated 2500h (fault system). Here discretionarily let No.7 and No.14 be initial clustering reference of normal system and fault system, other samples will be analyzed by clustering method based on ACO.

For the more dimension data samples, the discrepancy is bigger because they belong to the different dimension parameters. The data samples aren’t directly calculated, samples need to be treated as dimensionless parameter, because different dimension parameters can lead to different specific weights in Euclidean distance. By transforming the input data to between 0 ~ −1, which is called returning one treatment, can avoid affecting cluster result because of the difference of the quantity.

\[
T = T_{\text{min}} + \frac{T_{\text{max}} - T_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}(X - X_{\text{min}}),
\]

where \( X \) is value of originality data; \( X_{\text{max}}, X_{\text{min}} \) are the maximal value and the minimal value of originality data respectively; \( T \) is the transformed data, also called objective data; \( T_{\text{max}}, T_{\text{min}} \) are the maximal value and minimal value of objective data respectively, usually they are 0.8~0.9 and 0.1~0.2, here let \( T_{\text{max}} = 0.86, T_{\text{min}} = 0.12 \).

Based on Equation (14), recover the calculating result data according to the following formula.
### Table 1 Experiment Samples of diesel engine fuel system

<table>
<thead>
<tr>
<th>Sample serial</th>
<th>Injection pressure (MPa)</th>
<th>Injection angular advance (°CA)</th>
<th>Circulating oil feed quantity (mm³/cyc)</th>
<th>Exhaust smoke intensity (Rb)</th>
<th>Exhaust temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.8</td>
<td>15.3</td>
<td>19.3</td>
<td>0.1</td>
<td>350</td>
</tr>
<tr>
<td>2</td>
<td>12.8</td>
<td>15.8</td>
<td>19.5</td>
<td>0.1</td>
<td>350</td>
</tr>
<tr>
<td>3</td>
<td>12.9</td>
<td>15.3</td>
<td>19.0</td>
<td>0.1</td>
<td>355</td>
</tr>
<tr>
<td>4</td>
<td>12.9</td>
<td>15.3</td>
<td>13.6</td>
<td>0.2</td>
<td>366</td>
</tr>
<tr>
<td>5</td>
<td>13.0</td>
<td>15.3</td>
<td>20.9</td>
<td>0.2</td>
<td>370</td>
</tr>
<tr>
<td>6</td>
<td>13.0</td>
<td>15.7</td>
<td>19.1</td>
<td>0.15</td>
<td>352</td>
</tr>
<tr>
<td>7</td>
<td>12.9</td>
<td>15.9</td>
<td>19.3</td>
<td>0.2</td>
<td>365</td>
</tr>
<tr>
<td>8</td>
<td>12.5</td>
<td>15.2</td>
<td>11.1</td>
<td>0.7</td>
<td>380</td>
</tr>
<tr>
<td>9</td>
<td>12.4</td>
<td>14.5</td>
<td>9.8</td>
<td>0.8</td>
<td>390</td>
</tr>
<tr>
<td>10</td>
<td>12.6</td>
<td>14.5</td>
<td>9.3</td>
<td>0.7</td>
<td>390</td>
</tr>
<tr>
<td>11</td>
<td>12.6</td>
<td>15.0</td>
<td>8.9</td>
<td>0.7</td>
<td>395</td>
</tr>
<tr>
<td>12</td>
<td>12.7</td>
<td>14.8</td>
<td>13.9</td>
<td>0.8</td>
<td>410</td>
</tr>
<tr>
<td>13</td>
<td>12.4</td>
<td>14.5</td>
<td>10.1</td>
<td>0.9</td>
<td>385</td>
</tr>
<tr>
<td>14</td>
<td>12.5</td>
<td>14.3</td>
<td>9.9</td>
<td>0.92</td>
<td>394</td>
</tr>
</tbody>
</table>

Then clustering method based on ACO is applied to classify these samples, the result shows No.1∼No.7 belong to one kind, and No.8∼No.14 belong to another kind. Now, the perfect clustering centers that can be looked as eigenvector of diesel engine fuel system fault are shown in Table 2. The biased error (dimensionless value) is 3.509586. It is obvious that the result by ACO is entirely in agreement with the fact that operation state type is attributed by experiment sample for diesel engine fuel system, and exact ratio of classification reaches 100%, the result is right. Fast recognition of the system state is realized.

### Table 2 Perfect Clustering Center

<table>
<thead>
<tr>
<th>Sample serial</th>
<th>Injection pressure (MPa)</th>
<th>Injection angular advance (°CA)</th>
<th>Circulating oil feed quantity (mm³/cyc)</th>
<th>Exhaust smoke intensity (Rb)</th>
<th>Exhaust temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.9</td>
<td>15.45</td>
<td>18.56667</td>
<td>0.141667</td>
<td>357.1667</td>
</tr>
<tr>
<td>2</td>
<td>12.53333</td>
<td>14.75</td>
<td>10.51667</td>
<td>0.766666</td>
<td>391.6665</td>
</tr>
</tbody>
</table>

### 4. Conclusion

(1) New group intelligent theory. From simulating the behavior of natural ants’ looking for food, ACO uses the artificial ants to search the solution space. Using the conception of pheromone and the principle of positive feedback during the process of search accelerate the search speed, which is a good new simulation optimal algorithm. The algorithm has a good development prospect.

(2) The improvement for ACO has three key points; the pheromone is the key factor that decides the property of ACO; choosing strategy is the key factor that decides the algorithm property; the algorithm parameter is an important factor that decides algorithm property. From the three points, choosing the different pheromone updating principle, selecting the new chosen strategy and right related parameters can construct many improved methods and increase the calculating
speed and astringency property of the basic ACO. The existing improved algorithms basically came from the three points, which showed clearly object and method for the following improvement.

(3) The clustering analyzed method based on ACO can triumphantly apply fault recognition and diagnosis. From the commonness of ACO and clustering analysis to proper transformation can make a good combination between ACO and clustering analysis. Using clustering analysis based on ants colony, we analyzed the running states of the diesel engine, which showed that this method could preferably realize the classification and recognition of the equipments’ running state. So the excellent simulated optimal algorithm can use the fault diagnosis and recognition fields.

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