Engine universal characteristic modeling based on improved ant colony optimization

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Abstract: There have been some mathematics methods to model farm vehicle engine universal characteristic mapping (EUCM). Nevertheless, any of different mathematics methods used would possess its own strengths and weaknesses. As a result, these modeling methods about EUCM are not the same among the most vehicle manufacturers. In order to obtain a better robustness EUCM, an improved ant colony optimization was introduced into a traditional cubic surface regression method for modeling EUCM. Based on this method, the test data were regressed into a three-dimensional cubic surface, after that it was cut by some equal specific fuel consumption (ESFC) planes, more than twenty two-dimensional ESFC equations were obtained. Furthermore, the engine speed in every ESFC equation was discretized to obtain a set of ESFC points, and this set of ESFC points was linked into a closed curve by a given sequence via the improved ant colony algorithm. In order to improve the modeling speed, dimensionality reduction and discretization methods were adopted. In addition, a corresponding simulation platform was also developed to obtain an optimal system configuration. There were 48 000 simulation search tests carried out on the platform, and the major parameters of the algorithm were determined. In this way the EUCM was established successfully. In contrast with other methods, as a result of the application of the novel bionic intelligent algorithm, it has better robustness, less distortion and higher calculating speed, and it is available for both gasoline engines and diesel engines.
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1 Introduction

Some intelligent control theories and optimization methods were developed as a result of the researches in bionic engineering technology, which would be certain to let something difficult to deal with previously become workable now, so does the modeling of farm vehicle engine universal characteristic mapping (EUCM). EUCM can show engine's overall performances, consequently it is the key for the matching between engine and transmission system[1]. Furthermore, EUCM can provide the basis not only for the selection of farm vehicle engine, but also for the analysis of vehicle dynamics, economic simulation and optimization of powertrain integration performance[2,3]. It is necessary to use the EUCM in the development phase of the farm vehicle's design process, especially in the early stages. Therefore, the model of EUCM has been studied continuously through a variety of methods. EUCM modeling is one of the major research focus, which the vehicle designers is facing[4]. By modeling, drawing and

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analyzing a farm vehicle's EUCM, its performance, such as power and specific fuel consumption under different conditions, which reflect a degree of perfection in its operating process, can be evaluated. By EUCM, we can not only reduce the wear of engine components and improve vehicle's dynamics and fuel economy, but also reduce the effect from pollutants emissions[2].

At the beginning, the model of the farm vehicle EUCM can only be established by hand, which need about a week to complete the work, a technician had to start to plot each of partial load characteristic curves on the same graph to form a cluster, then project ESFC points of the cluster onto a universal characteristic objective graph and connect these points to form smooth ESFC curves. And different technicians might acquire slightly different model results even with the same set of data. As this method depends on hand-drawn, there are some defects. First, a single experimental point outside of the curve cannot be adopted. When some points measured at a certain speed are not sufficient to fit out a partial load characteristic curve, ordinarily this set of data can only be given up, which would greatly reduce the availability of the experimental data. Next, any contribution of the previous fitting curves to the present curve and the interplay between the curves would not be taken into consideration, which results in an undesirable phase transition between these ESFC curves.

Researchers have made great progress on EUCM recently due to the development of simulation software[5]. Vehicle power and fuel economy analysis can now be calculated and predicted accurately through computer simulations at the product development stage. Consequently, the product design cycle has been relatively shortened. With the rapid development of computer technology, a more accurate, intuitive, visualized and integrated development environment of engines can be now provided to obtain the best match in the drivetrain[6,7]. Simultaneously, some more practical modern methods have been proposed to study the model of EUCM.

A spline interpolation method was proposed by Zeng et al.[8] It is easy and fast to draw engine partial load characteristic curves with the method, subsequently the EUCM can be obtained according to these partial load characteristic curves. Because all the experimental points are employed as the basic points for interpolation in this method, the curves could be smooth and without singularity, which would illustrate the actual operating conditions of an engine more accurately. This method, compared with the earliest one, greatly improves the drawing speed (10 min now/one week past), and this method is relatively scientific. However, this belongs to processing three dimensional one with the two dimensional methods. So it is relatively complicated, and can be of more calculation workload. A surface interpolation technique was also presented to model EUCMs by Li et al.[9] With this method, scattered experimental data points are directly fitted into a surface, and the surface obtained is directly dependent on the raw experimental data points, so as to reduce the randomness and allow the experimental data to be truly reflected. However, some edges (large amplitude oscillation) would occasionally exist in the universal characteristic surface by this method, so a few of the calculated values of some ESFC curves may experience a mutation (distortion, not be true to the original). The mutations occur only at the edges and would not arise at other locations, because these values belong to the interpolating points. Therefore, in most cases, this method is not desirable. Next, the curve regression method was issued by Durković et al.[10,11] This method itself needs to assume a regression model type in advance. The accuracy of a model would become low with this method if there is a big deviation in some samples[12]. Last, the BP neural network method, an intelligent modeling method, was put forward by Yan et al.[13] The main advantage of the BP neural network is that the specific mathematical model of the EUCM needs not to be taken into account. As long as a BP neural network initial condition is set rationally and the sample number is enough for training, the universal characteristic curve of an engine can be fitted out. The artificial neural network method is robust, which could avoid the shortcomings mentioned above. Nevertheless, the neural network needs some data for training samples.

Among the modeling methods mentioned above, any different mathematics method used would result in some differences among these models, some specialists have a preference for one model, others for another model. In order to obtain a better robustness EUCM, this paper proposed a new improved mathematics method, which combined with an intelligent method, to model EUCM.

2 Improved ant colony optimization

2.1 Original ant colony optimization and genetic algorithm

Ant colony optimization is a positive feedback mechanism[14,15]. The basic ant colony optimization would take some time to search for a solution, and may be prone to local solution (not a global optimum)[16]. In the process of solving an ant colony algorithm, the probability of state transition, the possibility to go to the next state, needs to be calculated when each ant chooses the next state to visit. Such defects are more obvious when large-scale problems need to be solved[17]. Meanwhile, due to the positive feedback mechanism, it is easy to concentrate on few paths with higher pheromone. Other paths would be ignored, allowing the algorithm to obtain local optimal solutions. In addition, the algorithm's convergence is sensitive to the initial setup of the parameters, i.e., it is affected by the initial value[18].

Genetic algorithms simulate the phenomena of natural selection and reproduction, crossover and mutation which happened in genetics[19]. Genetic algorithms operate based on the probability of individual fitness. There is a greater flexibility in a search process[20,21], and an improved genetic algorithm can be obtained through modifying and matching its operators.

2.2 Improved algorithm

In this research, the ant colony optimization is combined with the genetic algorithm to obtain an improved ant colony optimization used to draw an engine's universal characteristic curve. The drawing flowchart is given in Figure 1.

The aim of this study is to find the shortest round-trip among a series of given points (a set of ESFC points), and every artificial ant (hypothesis ant) must visit each point exactly once. As shown in Figure 2, in order to seek an optimum route, after passing through the point A to point B from point O, the ant would seek the next nearest point from among point C, D, E and F in the light of the normal ant colony algorithm, point C would be chosen because it is the point nearest to present point B by the algorithm. In some cases, if point C is chosen, the locale optimum solution could only be obtained (the closed curve OABFDECO with dotted and solid lines is the real global optimum solution, because the distance of this closed curve is the shortest). In order to obtain the global optimum solution, the mutation technique which come from the genetic algorithm is added to avoid choosing point C (mutating is to delete a point, and point C is to be deleted here). On this account, point F, the second nearest point to the present point B, may be selected, and the global optimum solution has an opportunity to be obtained at last.

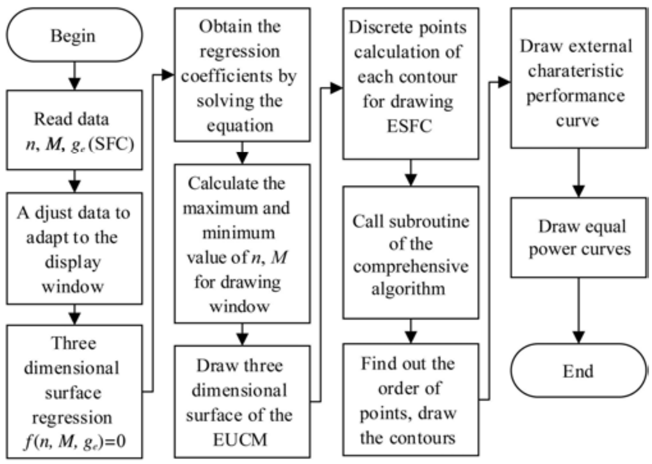


Figure 1 EUCM's drawing flowchart

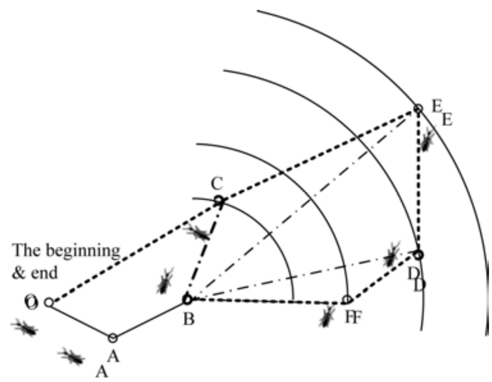


Figure 2 Optimal algorithm searching process

3 EUCM modeling

3.1 Mathematics modeling method

In order to obtain a better EUCM model, a traditional cubic surface regression method combined with an improved ant colony optimization was proposed in this study. The surface fitting function, with the actual experimental data set as (x_i, y_i, z_i) (i =1, 2,… , n), can be expressed as:

$$f(x,y)=\sum_{i=0}^{n}\sum_{j=0}^{n}a_{ij}x^{i}y^{j} \qquad (i,j=0,\,1,\,2,\ldots,n)$$

where, a_{ij} (i, j = 0, 1, 2,… , n) is polynomial regression coefficient. The error function of the function is $E(a_{ij})=\sum_{i=0}^{n}[z_i-f(x_i,y_i)]^2$, and S.T. $\frac{\partial E(a_{ij})}{\partial a_{ij}}=0$ (i, j = 0, 1, 2,… , n) to obtain a_{ij} (i, j = 0, 1, 2,… , n) and a fitting surface $z=f(x, y)$. If the engine's specific fuel consumption z is regarded as a function of the engine's speed x and torque y, then the regression matrix model can be expressed as follows:

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}=\begin{bmatrix} 1 & x_1 & y_1 & x_1^2 & x_1y_1 & y_1^2\ldots x_1^s & x_1^{s-1}y_1\ldots y_1^s \\ 1 & x_2 & y_2 & x_2^2 & x_2y_2 & y_2^2\ldots x_2^s & x_2^{s-1}y_2\ldots y_2^s \\ & & & \vdots & & & \\ 1 & x_n & y_n & x_n^2 & x_ny_n & y_n^2\ldots x_n^s & x_n^{s-1}y_n\ldots y_n^s \end{bmatrix}\cdot\begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_{k-1} \end{bmatrix}+\begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \tag{1}$$

Equation (1) can also be expressed as: $\boldsymbol{Z}=\boldsymbol{G}\cdot\boldsymbol{A}+\boldsymbol{E}$. In Equation (1), $k=(s+1)(s+2)/2$ is the item number of the polynomial, s is the high power of the polynomial, $\boldsymbol{A}$ = (a_0, a_1, …, a_{k-1}) is undetermined coefficient of the model, and $\boldsymbol{E}$ = (e_1, e_2, …, e_n) represents the random error, or residual[6]. These undetermined coefficients of the equation are obtained through calculating the partial derivatives of the unknown items' coefficients of the function. In order to establish a model of an engine, we made an experiment of the engine. Table 1 is the experimental data of the engine from FAW (First Auto Works), which includes one external characteristic data and some partial load characteristic data. This experiment was made by FAW in 2008, the engine type was EA113 1.6L2VMPI and manufactured by FAW.

3.2 Formation of a cubic surface model

Take Equation (1) as a third power equation (the third power equation is enough by experience), and these data in Table 1 were substituted in Equation (1), then its cubic surface model shown as Equation (2) was derived.

$$\begin{aligned} z=&-0.000112917x^3-0.00106327x^2y+0.00148387xy^2- \\ &0.0125854y^3+0.0485014x^2-0.0108442xy+ \\ &0.654746y^2-0.984033x-11.209y+96.0326 \end{aligned} \tag{2}$$

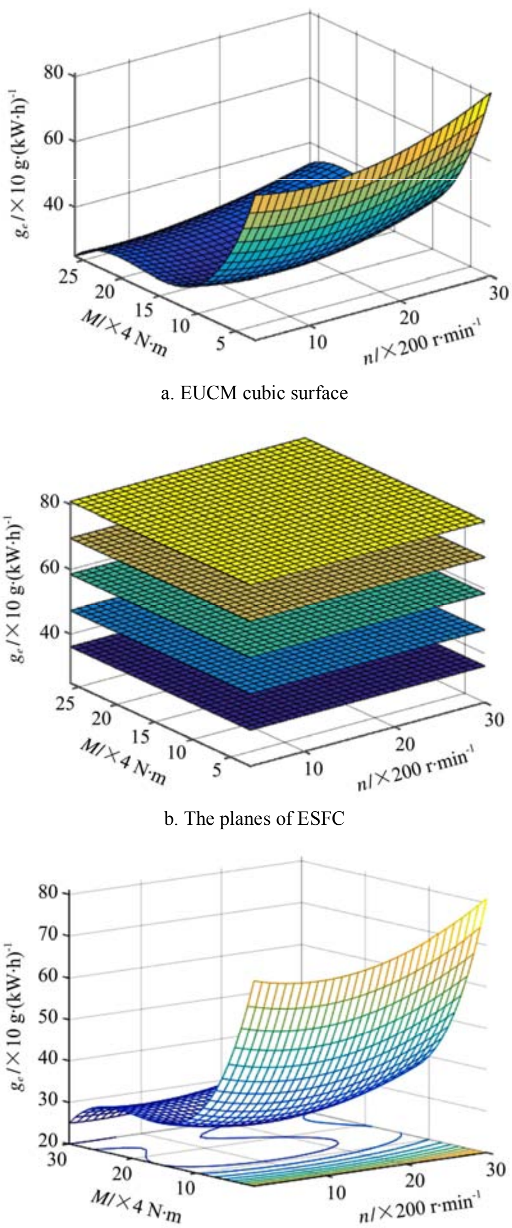
where, z is specific fuel consumption (g_e); x is speed (n); y is torque (M).

Table 1 Test data about the EUCM

SFC/g·(kW·h)$^{-1}$	Speed/r·min^{-1}	Torque/N·m	SFC/g·(kW·h)$^{-1}$	Speed/r·min^{-1}	Torque/N·m	SFC/g·(kW·h)$^{-1}$	Speed/r·min^{-1}	Torque/N·m
718.71	800	12.7	831.21	5200	9.9	368.46	6000	60.1
487.54	800	20	514.58	5200	20.1	360.12	6000	70
346.57	800	30.7	407.36	5200	30.4	354.07	6000	79.9
356.44	800	41.6	388.51	5200	40	348.07	6000	90
339.19	800	50.1	354.72	5200	50.1	357.62	6000	95.8
306.49	800	60.4	340.7	5200	59.9	298.89	1200	89.4
324.38	800	70	330.68	5200	70.1	301.78	1600	93
331.97	800	78.6	325.4	5200	80	294.7	2000	95.4
610.59	1000	14.6	321.25	5200	90	286.7	2400	97.3
411.73	1000	20.3	322.05	5200	99.9	286.17	2800	103.9
338.73	1000	31.3	323.41	5200	103.7	289.54	3200	103.3
301.26	1000	40.3	822.51	5600	10.3	293.96	3600	102
308.74	1000	50.4	517.42	5600	20.2	291.39	4000	99.9
315.54	1000	60.5	416.24	5600	29.9	303.89	4400	104.1
286.19	1000	70.3	389.72	5600	40.4	320.86	4800	104.4
278.58	1000	80	362.57	5600	50	331.91	5200	103.7
307.48	1000	82.7	345.07	5600	60.2	347.32	5600	99.3
755.03	1200	10.3	344.65	5600	70.2	363.89	6000	95.5

3.3 Dimensionality reduction and discretization

Cubic surface model is a core for the EUCM and can be illustrated with MATLIB software as Figure 3a. In order to obtain an appropriate universal characteristic cubic surface for display, the experimental data of the engine's speed and specific fuel consumption should be proportionally adjusted with its torque data. Subsequently, this surface was cut by some planes of the ESFC, as shown in Figure 3b, and the points of every contour were projeted onto the plane of the speed and torque. Meanwhile, in order to improve modeling speed, the dimensionality reduction and discretization methods were used as follows.



a. EUCM cubic surface

b. The planes of ESFC

c. The projection of ESFC

Figure 3 Creating process of EUCM

Deduced from Equation (2), the experimental data of the engine's speed (n), torque (M) and specific fuel consumption (g_e) can be regressed into a known three dimensional equation below:

$$g_e = F(M, n) \tag{3}$$

S.T. g_e equal to some constants, i.e., g_e=g_{e1}, g_{e2}, …, $g_{eN,}$ then N (around 20) two dimensional ESFC equations (Equation (4)), which curves are the kernel of the EUCM, can be derived from Equation (3).

$$M = G_i(n) \qquad i=1, 2, \ldots, N \tag{4}$$

In order to draw these curves on speed and torque plane of the EUCM, the engine speed was further discretized and divided into the values between 800 r/min to 6000 r/min, and the interval was set to1, i.e., n=800, 801, 802, …, 6000. After the speed was substituted into Equation (4) (i=1), the corresponding torque value could be determined. Similarly, it is easily and quickly to get the other sets of ESFC points of the speed and torque plane (i=2, 3,…, N).

3.4 Establishing ESFC with the improved ant colony optimization

Furthermore, in order to joint these discrete random points of every set of the ESFC up to complete the curve, the route models of the n sets of the ESFC points could be established by the improved ant colony optimization. Theoretically, every set of the ESFC points would constitute its one or more closed curves if the plane space is big enough. For this purpose, the same set of the ESFC points may be divided into several areas by their positions, and every area has its own closed route model. Meanwhile, every closed route model was established using the improved ant colony algorithm. On the basis of the model, this area of closed curve can be plotted out. So do the other areas and other sets of the ESFC points, finally a cluster of the ESFC curves was formed, as shown in Figures 3a and 4. Next, a boundary line was plotted out through cubic spline algorithm according to the engine's external characteristic data. Last, the equal power curves were plotted out via the formula Power=2π·Torque·Speed/60 to achieve a complete universal characteristic curve, as shown in Figures 4 and 5.

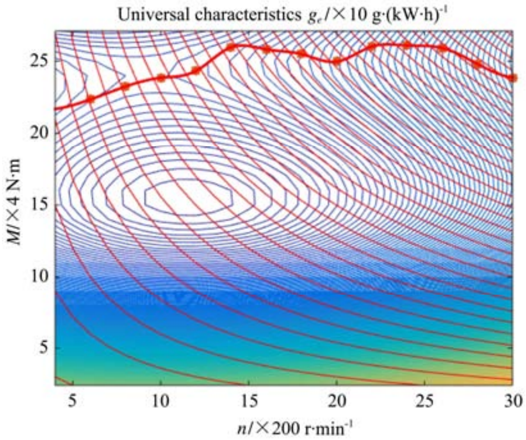


Figure 4 EUCM with 300 contours

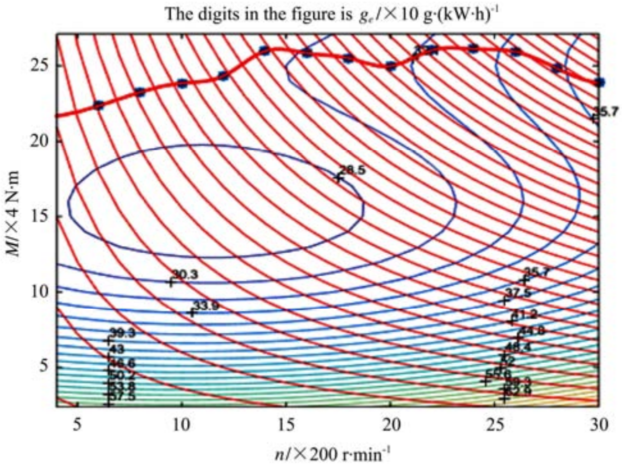


Figure 5 EUCM with 30 contours

As mentioned above, three dimensional Equation (3) can be converted into two dimensional Equation (4), and Equation (4) can be discretized further, then some sets of ESFC points can be directly obtained. This method, due to the dimensional reduction and discretization, has been proved to be an effective method to improve the calculation speed.

The main effect of the EUCM is to find the efficient economic zone of the engine. Being processed above, the experimental data, as listed in Table 1, can be used to draw its EUCM by the improved ant colony algorithm. Figures 4 and 5 illustrate clearly that the efficient economic zone of the engine is located at the engine speed of between 2200 r/min and 2500 r/min, torque of between 70 N·m and 90 N·m, specific fuel consumption of between 260 g/kW·h and 280 g/kW·h, which (Figures 4 and 5) is in good quantitative agreement with the manufacturer's experimental data (Table 1).

4 Simulation experiment setup and its platform development

4.1 Experimental platform

To model EUCM and verify the algorithm mentioned above, a simulation platform corresponding to the algorithm was set up with VB. Ant colony and genetic algorithms are both intellegent algorithms, consequently, some initial conditions and algorithm parameters must be set in advance, and these parameters should be adjusted to make the system optimal. Figure 6 is the simulation platform of the synthesis algorithm. The main buttons and functions are introduced as follows:

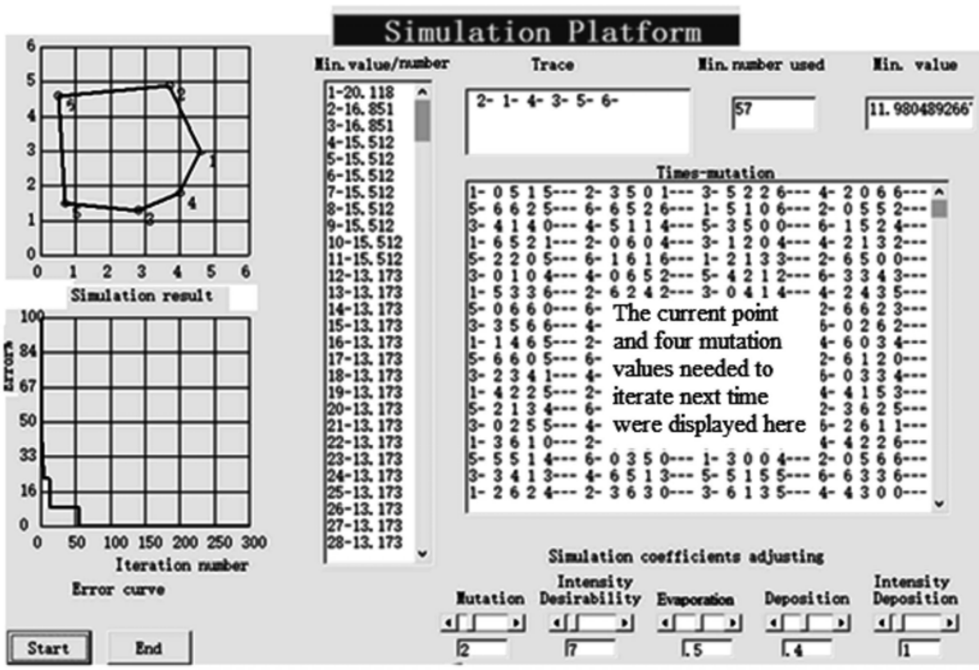


Figure 6 Simulation platform of the synthesis algorithm

1) Simulation results: displaying the points generated randomly for simulation, and linking them into a closed curve by the sequence obtained through this simulation.

2) Error curve: displaying the curve about the relationship between the iteration number and the iteration error.

3) Minimum Value/number: displaying overall intermediate iteration results.

4) Trace: displaying the sequence of points at the optimum solution.

5) Minimum Number: displaying the minimum iteration number needed to get the optimum solution.

6) Minimum value: displaying the path length at the optimum solution.

7) Number-mutation: displaying the current point and four mutation values needed to iterate next time.

8) Simulation coefficients adjusting: adjusting some simulation coefficients, such as mutation, deposition, intensity of deposition, evaporation, desirability and intensity of desirability through their scroll bars on the platform.

4.2 Experimental design and test

To determine and verify some important parameters of the algorithm, the simulation experiment of 48 000 searches was carried out. As shown in Figure 7, a total of 8 groups of searches were designed, and the genetic mutation frequency of the synthesis algorithm was set as 0, 1, 2, …, 7, respectively. There were 20 loops in every group, and the optimal solution was searched for a total of 300 times in every loop. Then the first loop of the first group started with generating six points randomly, and these six points were converted proportionally to the corresponding coordinates for the purpose of being linked into a closed curve for simulation. Meanwhile, all the parameters of the improved ant colony optimization should be set up, and the maximum search number of every optimal solution was set to 300 times. Finished this loop of searching, the optimal value and minimum number of the searching could be obtained and displayed. The next loop of searching was then carried out until 20 loops were all completed. Afterwards, the iteration number per loop, the average iteration number of the 20 loops, and the search failure number of the 20 loops were recorded. The next group was then carried out, until 8 groups were completed. The experimental result was sorted out and given in Table 2.

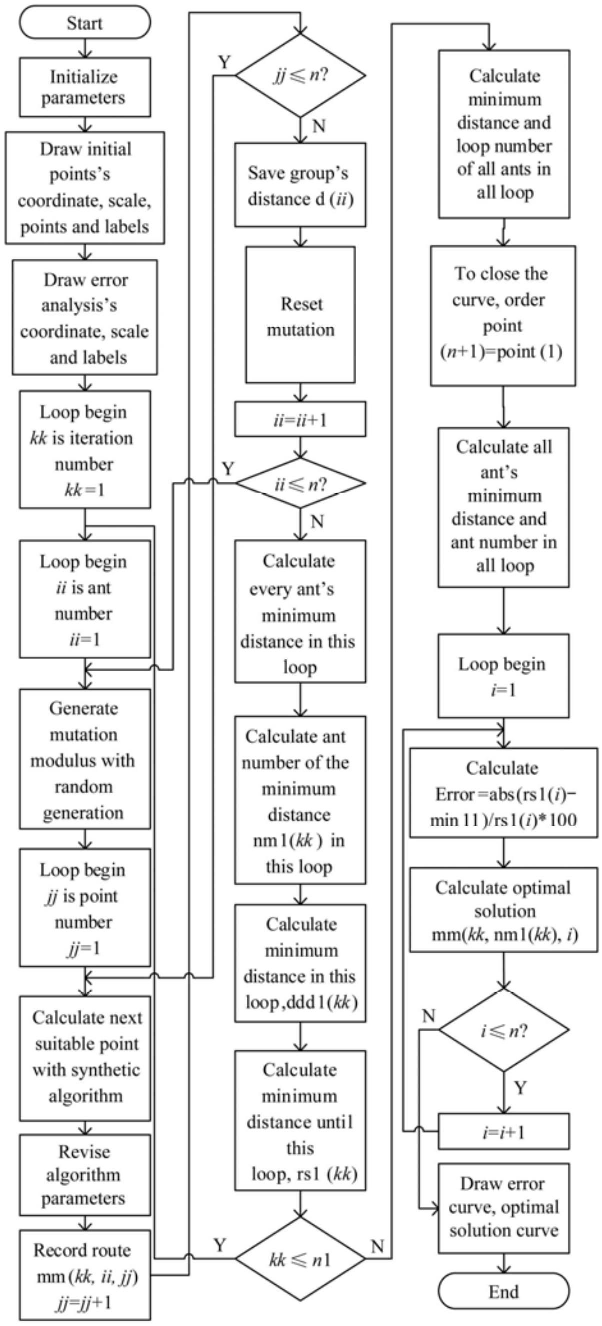
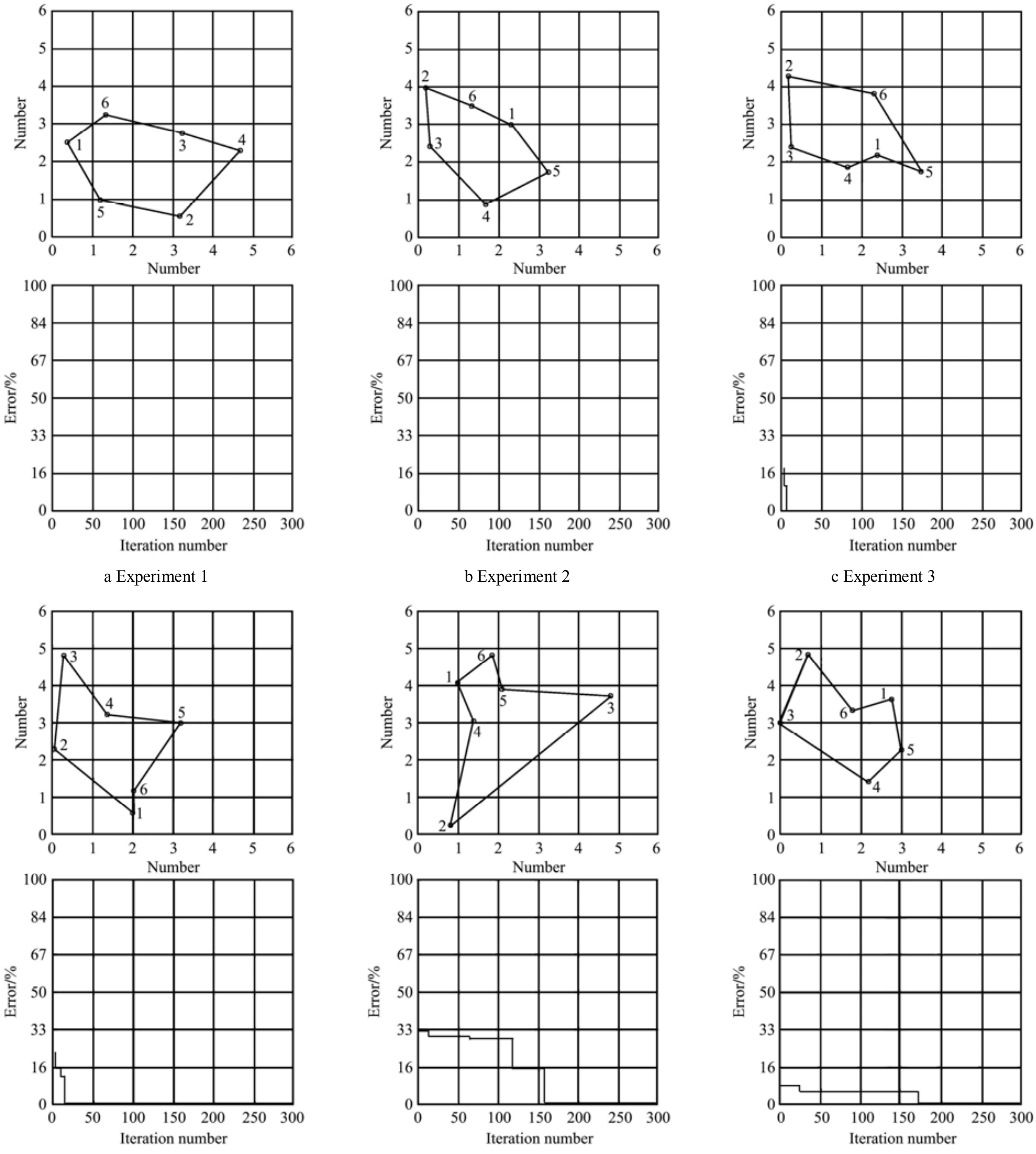


Figure 7 Operation flowchart of the platform

Table 2 Experimental results

Mutation frequency	Mean iteration number	Failed searching number
0	4.55	18
1	8.2	12
2	32.45	5
3	57.55	4
4	56	3
5	64	0
6	81.45	0
7	118.5	0

As mentioned above, this simulation experiment was consisted by 8 groups of tests, and Figure 8 shows some of the experimental results. The trace (shape) of a set of discrete points is on the top, and the corresponding search number is on the bottom. As can be seen from Figure 8, the trace of a set of discrete points looks like the closer to a circle, the less the optimization search number becomes. Conversely, the more irregular the trace of a set of discrete points looks like, the more the optimization search number becomes.



a Experiment 1 b Experiment 2 c Experiment 3

d Experiment 4 e Experiment 5 f Experiment 6

Figure 8 Simulation curves of iteration number and iteration error at different kinds of routes

5 Results and analysis

Meanwhile, as can be seen from the experimental data, one of the attributes of the improved ant colony algorithm, the mutation frequency, is the major contributor to calculating speed and failed searching number. Here, a failed searching means that only the local optimal solution has been found after searching, and the global optimal solution has not been found. In order to obtain one optimal mutation frequency by simulation, the failed searching number in each loop and the minimum searching number of the global optimal solution were recorded. Finally, the relationship data between the mutation frequency and the mean iteration number, as well as that between the mutation and failed searching number were calculated and were given in Table 2. Furthermore, these relationships were plotted out in Figures 9 and 10, respectively. As can be seen in Figure 9, the higher the mutation frequency, the more the mean iteration number needed to get an optimal solution. After the mutation frequency reached 5, the mean iteration number increased exponentially with it. To improve calculating speed, the mutation frequency must be not over 5. In contrast, as can be seen in Figure 10, the higher the mutation frequency, the less the failed searching number becomes.

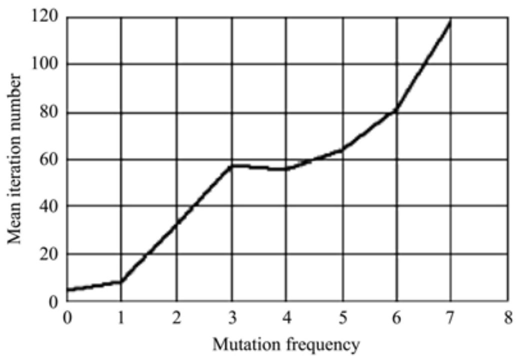


Figure 9 Mean iteration number curve

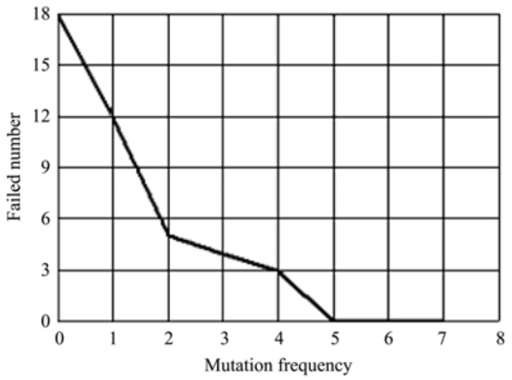


Figure 10 Failed searching number curve

After the mutation frequency reaches 5, the failed searching number decreased to zero. Both Figure 9 and Figure 10 were taken into account, the optimum mutation frequency, to meet both the calculating speed and failed searching number, should be 5. The contribution of the other parameters to the calculating speed and failed searching number is very small.

Furthermore, as can be seen from Figures 8a-8f, the model can be established and fit the actual route perfectly no matter how irregular it may be. In addition, most of searching numbers were not more than 10, seldom longer than 120, so the modeling speed was fast. As a result of dimensionality reduction and discretization, as well as the novel bionic swarm intelligent algorithm, this algorithm possesses good robustness, less distortion and higher calculating speed. Furthermore, this method does not need large amounts of data for training samples, and the model of a set of ESFC points can be obtained directly, hence the efficiency to draw EUCMs is improved.

6 Conclusions

This study aimed at establishing farm vehicle EUCM models using improved ant colony optimization as well as the matching between engine and transmission system. By introducing genetic algorithm, one of the original weaknesses of the ant colony algorithm, prone to reaching a local optimum, is overcome. In addition, dimensionality reduction and discretization methods were used to improve the modeling speed. Furthermore, a corresponding simulation platform was developed. On the platform, through changing the parameters, especially the mutation frequency of the improved ant colony algorithm, the algorithm could find the optimal route faster, which enhanced the efficiency of the whole system. The experimental results also present that the optimal route on the ESFC points can be determined quickly and reasonably to draw farm vehicle EUCMs, by comparing the calculated data on the EUCM model with the manufacturer's experimental data, good quantitative agreement is obtained (mentioned in the part 3.4).

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