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Tao Ning
*Dalian University of Technology, Dalian, China*, daliannt@126.com

Xuping Wang
*Dalian University of Technology, Dalian, China*, wxp@dlut.edu.cn

MingQian Sun
*Dalian University of Technology, Dalian, China*, mqsun367@126.com

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# A Hybrid Quantum Algorithm Based on Magtd to Solve The Problem of The Last Mile in Electronic Commerce

Tao Ning, Dalian University of Technology, Dalian, daliannt@126.com
XuPing Wang, Dalian University of Technology, Dalian, wxp@dlut.edu.cn
MingQian Sun, Dalian University of Technology, Dalian, mqsun367@126.com

## ABSTRACT

For the purpose of solving the problem of the last mile in electronic commerce, this paper establishes the mathematical model to minimize the travel cost and stability value, an improved double chains quantum genetic algorithm was proposed. Firstly, it proposes the method of double chains structure coding including vehicle chain and customer chain. Secondly, it proposes non-dominated sorting based on the crowding distance selection strategy. Thirdly, the most satisfying solute is obtained by the MAGTD (multi-attribute grey target decision model). Finally, the novel method is applied to a dynamic simulation, and the result of comparing with other classical algorithms verifies its effectiveness.

*Keywords*: double chains quantum, last mile, distribution model, multi-attribute grey target decision

## INTRODUCTION

E-commerce and logistics distribution has many features, such as the large number of the orders, the small scale of the orders, uncertain individual specifications, the high dispersity of the consumers, etc. Although “the last mile” is a little part of the whole supply chain, it is the most significant part because people can contact the customers directly. American researcher Mohammad (2013) put forward the idea of adjusting the delivery time of the business district and setting up the picking points in the customer's pick-up address, which is to ease traffic pressure when the “the last mile” distribution of e-commerce logistics imposes great pressure on the urban traffic[1]. Antonio (2012) combined with the characteristics of B2C e-commerce logistics distribution. The solution which has the minimal impact on the the urban environment is found by comparing three common delivery solutions to the “the last mile”[2]. Feliu, J. G (2012) analyzed the applicability of the “the last-mile” distribution model in China based on data from Taobao, and found that the convenience of traditional distribution was the major factor to impact of e-commerce customers to select voluntary pickup[3]. Ehmke J (2014) et al. summarized the features of the online retailer's logistics distribution network, analyzed the way of logistics distribution sites [4]. Bushuev□M (2012) proposed a model of community distributed network delivery which has a specialty of all-weather service, small service radius, short distance, redeliver convenient and so on[5]. Based on the development of community service, Liu R(2013) analyzed the difference and applicability of various kinds of new models that end-to-end logistics, on the basis of the supply chain relationship of e-commerce, he proposed the decision path to choose suitable cooperation mode for each node enterprise in the supply chain of e-commerce [6]. Edwards J. B. (2010) raise the option of electronic commerce terminal distribution model should follow the three principles by the analysis of Amazon in the end of the distribution model [7].

Therefore, it is the key problem to be solved that the comprehensive distribution logistic of “the last mile” should be built. In this paper, three different distribution models are analyzed, and the improved double chains quantum genetic algorithm based on MAGTD is proposed to make the decision of distribution efficiency and cost.

## DISTRIBUTION EFFICIENCY MODEL OF DIFFERENT MODELS

### Description of problem

The efficiency of the different distribution models varies greatly in the last mile problem, and the efficiency of different distribution models is very important to calculate the total cost of distribution. The distribution efficiency can be represented by the average distribution time as $t_i$, $i$ is used to distinguish the types of models [8]. The greater the $t_i$ is, the lower the distribution efficiency.

No matter what kind of distribution model, the total distribution time of $t_i^a$ are composed of the following three parts: the travel time of $t_i^r$, the waiting time (stop or start) of $t_i^w$ and the service time of $t_i^s$, as is shown in Eq.1. In the model of “door to door” (model *D*), $t_i^s$ includes the time for the courier to walk to the customer, to wait for customer to check the package and sign, to scan the bar code and update the distribution information. In the model of “self-service box” (model *S*), $t_i^s$ includes the time for the courier to walk to the self-service boxes, to scan the bar code and update the distribution information, and to pack into the appropriate lockers. In the model of “customer self extracting station” (model *C*), $t_i^s$ includes the time to load packages and to scan the bar code on the package.

$$t_i^a = t_i^r + t_i^w + t_i^s \tag{1}$$

The calculation method is same for $t_i^w$ and $t_i^s$ in the three distribution models. The solving process of $t_i^r$ is relatively more complicated than the other two variables.

### Model of distribution

The model *D* can be abstracted as the vehicle routing problem with time windows (VRPTW), the model *S* can be abstracted as the classical vehicle routing problem (VRP) and the model *C* can be abstracted as the VRP on the basis of clustering [9]. According to the three different models, the corresponding efficiency models are established respectively.

The constant symbolic meanings in the model are expressed as follows:

m: the number of customer points;

$\lambda$ : the average service time for one customer;

$\delta$ : the average waiting time;

$Q_v$ : rated load for the vehicle;

$v$ : the average speed;

*T*： rated working time;

$[a_j, b_j]$ : time windows;

The variable symbolic meanings in the model are expressed as follows:

$d_{ij}$ : the distance between point i and point j;

$R$ : the total number of route;

$q$ : the demand for the entire area;

$s_j$ : the start service time on the point j;

$x_{ijr}$ : the edge of (*i,j*) is included in the route of *r* or not;

$y_{jr}$ : the point of j is included in the route of *r* or not;

$q_j$ : the demand on the point *j*;

The model of model *D* is as follows:

Objective function:

$$\min t^r = \sum_{r=1}^{R} \sum_{i=0}^{m+1} \sum_{j=0}^{m+1} x_{ijr}(d_{ij} / v) \tag{2}$$

Constraint condition:

$$\sum_{j=1}^{m} q_j = q; \tag{3}$$

$$\sum_{r=1}^{R} y_{jr} = 1, \ \ j = 1,2,3_{\dots} m \tag{4}$$

$$\sum_{j=0}^{m} x_{ijr} = y_{ir}, \ \ i = 1,2,3_{\dots} m+1; r = 1,2_{\dots} R \tag{5}$$

$$\sum_{i=1}^{m+1} x_{ijr} = y_{jr}, \ \ j = 0,1,2,3_{\dots} m; r = 1,2_{\dots} R \tag{6}$$

$$\sum_{i=1}^{m+1} x_{i0r} = 1, \quad r = 1,2,3_{\dots} R \tag{7}$$

$$\sum_{j=0}^{m} x_{(m+1)jr} = 1, \quad r = 1,2,3_{\dots} R \tag{8}$$

$$\sum_{j=1}^{m} y_{jr} q_j \le Q_v, \quad r = 1,2,3_{\dots} R \tag{9}$$

$$s_j + \lambda q_j + \delta + d_{ij} / v - M(1 - \sum_{r=1}^{R} x_{ijr}) \le s_i \quad j{=}0,1,2,_{\dots} m; i = 1,2,_{\dots} m+1 \tag{10}$$

$$a_j \le s_j \le b_j \le T \quad j{=}0,1,2,_{\dots} m+1 \tag{11}$$

Eq. 3 indicates that the sum of the demand for each distribution point is exactly equal to the total demand in the region; Eq.4 – Eq.6 ensure that each distribution point is served only once; Eq.7- Eq.8 show that each vehicle is starting from the distribution center and finally return to the distribution center; Eq.9 shows that the amount of cargo carried per vehicle must not exceed the vehicle's deadweight; Eq.10 - Eq.11 ensure that the vehicle delivery time can meet the special requirements of a small number of customers.

In this paper, real-coding is used to solve the above problem [10]. Taking the way of sequence encoding, each delivery point is assigned a sequence number, in which 0 represents the distribution center. Each chromosome contains $m$+$R$+1 gene. 100 individuals are generated randomly as the initial solutions, and they are tested to eliminate undesirable ones and generate new ones until all the 100 individuals meet the requirements [11]. The parental is selected to reproduce by the wheel method according to the fitness function Eq.12.

$$\min z = \sum_{r=1}^{R} \sum_{i=0}^{m+1} \sum_{j=0}^{m+1} x_{ijr} (d_{ij} / v) + M \sum_{r=1}^{R} \max(\sum_{j=1}^{m} y_{jr} q_j - Q_v, 0) \tag{12}$$

Eq.12 integrates the vehicle weight constraints into the objective function. $M$ is an infinite number acting as a penalty factor when the vehicle load exceeds the dead weight.

The calculation method for $t_i^r$ in the model $C$ is different from the other two models. The model $C$ has almost no capacity limitations, so first to make one clustering analysis for delivery point based on Euclidean distance. In order to simplify the calculation, it is assumed that the self service station is located at the center of each service area. Therefore, K-means clustering algorithm is used in this paper.

Objective function:

$$\sum_{j=1}^{m} \min_{i \in \{1,2,_{\dots} k\}} \left\| o_j - P_i \right\|^2 \tag{13}$$

Constraint condition:

$$\overline{O_j} = \frac{1}{|L_j|} \sum_{o \in L_j} o \tag{14}$$

$$E = \sum_{j=1}^{k} \sum_{o \in L_j} \left| o - \overline{o_j} \right|^2 \tag{15}$$

$o_j$ is the position of the customer point; $P_i$ is the average value of $L_j$ (cluster );$E$ is the sum of average errors. Eq.14 is the average value of update cluster; Eq.15 is the calculation criterion of the proposed algorithm. After clustering, the route will be scheduled acting the cluster center as the delivery point to optimize the distribution.

## IMPROVED QUANTUM ALGORITHM

An improved double chains quantum genetic algorithm (IDQGA) was proposed to overcome the shortcomings of complex encoding and decoding with common quantum algorithm.

### Improvement of quantum rotation angle

The improved quantum rotation angle is divided into two parts which are deflection and direction of rotation. The data of each qubit is as follows: $f(x_i)$ says the fitness of quantum individual $x_i$, $w_{ij}$ represents the angle of probability amplitude,$K_1$,$K_2$,…,$K_n$ represent the first n elite individual with the highest fitness in the current state, $w_{0j}^n$ represents the $j^{th}$ qubit angle of the $n^{th}$

elite individual [12]. The paper proposed an improved method for the rotation angle of qubit combining the chaos theory. The specific steps are as follows:

Step 1: Initialize the parameters. Make *j*=1 and generate the initial value by the Logistic equation;

Step 2: Calculate the direction of the rotation angle. *K*1 represents the optimal elite individual and meets $f(x_i) \le f(K_1)$, the direction of the rotation is shown in Eq.16:

$$X_j = sgn(\alpha_{ij}\beta_{ij}(k_{1j} - 0.5) ) \tag{16}$$

sgn( ) is the symbol function, $\alpha_{ij}\beta_{ij}$ represent the probability amplitude of the $j^{th}$ qubit, $K_{1j}$ represents the value of the $j^{th}$ qubit in $K_1$;

Step 3: Calculate the deflection of the rotation angle guided by the elite quantum;

Step 4: Calculate the chaos perturbation of the qubit, i.e.

$$\begin{aligned} &\lambda_i = \mu\lambda_{i-1}(1-\lambda_{i-1}), \\ &\lambda_0 \in [0,1], \mu \ge 4. \end{aligned} \tag{17}$$

Step 5: Calculate the rotation angle of the qubit, and the positive or negative value is decided by the direction of rotation, i.e.

$$\theta_{ij} = x_j \Delta\theta_{ij}(1 + x_j\lambda_j) \tag{18}$$

Step 6: Judge whether the calculation for the qubit is completed, if the calculation is not completed, it will make *j*=*j*+1 and turn to Step 2.

**Double chains quantum algorithm**

A new compensation factor $\gamma$ ($\gamma \ge 1$) on the basis of probability amplitude coding was proposed in this paper. $p_i$ is assumed as a quantum chromosome, and the coding scheme of the $i^{th}$ chromosome is as follow:

$$p_i = \begin{bmatrix} \begin{vmatrix} \alpha_{i1} \\ \beta_{i1} \end{vmatrix} \begin{vmatrix} \alpha_{i2} \\ \beta_{i2} \end{vmatrix} \cdots \begin{vmatrix} \alpha_{im} \\ \beta_{im} \end{vmatrix} \end{bmatrix} = \begin{bmatrix} \begin{vmatrix} \cos(\gamma t_{i1}) \\ \sin(\gamma t_{i1}) \end{vmatrix} \begin{vmatrix} \cos(\gamma t_{i2}) \\ \sin(\gamma t_{i2}) \end{vmatrix} \cdots \begin{vmatrix} \cos(\gamma t_{im}) \\ \sin(\gamma t_{im}) \end{vmatrix} \end{bmatrix} \tag{19}$$

In which, the normalization condition should be met for $\alpha$ and $\beta$, that is to say, $|\alpha|^2 + |\beta|^2 = 1$, and $t_{ij} = 2\pi \times rad$, *rad* is the random number in (0,1); *i*=1,2,…,*n*; *j*=1,2,…,*m*; *n* is the size of the population, *m* is the number of the qubit. $\gamma$ changes the periodic from $2\pi$ into multi-periodic to improve the convergence efficiency of the algorithm [13]. Each chromosome consists of two parallel gene chains, and one is the vehicle selecting chain of $p_{i\cos}$, the other is procedure customer points chain of $p_{i\sin}$. Each gene chain represents an optimized solution, which is shown as follow:

$$p_{i\cos} = (\cos(t_{i1}), \cos(t_{i2}), \ldots, \cos(t_{in}))$$

$$p_{i\sin} = (\sin(t_{i1}), \sin(t_{i2}), \ldots, \sin(t_{in}))$$

$p_{i\cos}$ is called cosine solution and $p_{i\sin}$ is called sine solution respectively.

**The scheduling decision based on MAGTD**

This paper uses the model of multi-attribute grey target decision (MAGTD) to get the most satisfactory scheme, which is multi criteria decision making method based on grey system theory [14]. The algorithm is as follows:

(1) Construct effect of sample matrix with *m* evaluation index and *k* scheduling scheme according to the Pareto optimal solution obtained by IDQGA, the weight vector of each index can be expressed as: $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$;

(2) Transform the effect of sample matrix of *G* by using the linear transformation operator in [-1,1] and obtain the decision matrix of $D = (d_{ij})_{m\times k}$;

(3) Get the optimal vector in which is the bull's eye;

(4) Calculate the distance of the bull's eye $\xi_i (i = 1, 2, \ldots, k)$, according to the Eq. 20:

$$\xi_i = |d_i - d| = \sqrt{\omega_1(d_{i1} - d_1^0)^2 + \omega_2(d_{i2} - d_2^0)^2 + \ldots + \omega_m(d_{im} - d_m^0)^2} \tag{20}$$

(5) The optimal scheme is got from $\xi_i$ in ascending order.

## ANALYSIS AND VERIFICATION

It is almost impossible to collect the distribution time of different distribution model at the same time. On one hand, it is difficult to apply three models in same environment as the practice, on the other hand, it involves some business secrets of the logistics service providers [15] [16]. The crossover probability and mutation probability in the genetic algorithm (GA) are set to be 0.8 and 0.2 respectively, and the termination algorithm is updated to the 200 generation.

According to the basic population density, it is reasonable to set 30 delivery points randomly representing the corresponding 30 districts in the square area of 25 square kilometers [17]. The orders of each district are less than 40 to ensure it is enough to set one public self-service box. In the model *C*, it is first to cluster the 30 delivery points and the range of the case is set to be 25 square kilometers, in which 5 self extracting stations are set. It can be seen from Fig.3 that the delivery points with the same shape are in the same cluster [18] [19]. The green point of the center represents the distribution center and the fork at the center of each cluster represents the self extracting station.

In order to verify the efficiency of distribution under standard conditions of different distribution model, in this paper, the correlation value of distribution efficiency is calculated basing on the improved quantum genetic algorithm. The parameter values for the distribution activities of the three models in the standard case are shown in TAB.1.

Table 1: Time spent of different models with normal orders

| | **Model *D*** | **Model *S*** | **Model *C*** |
|---|---|---|---|
| Driving distance (km) | 40.62 | 23.4 | 10.9 |
| Number of order | 756 | 756 | 756 |
| Stop or start time(min) | 40 | 40 | 8 |
| Number of vehicle | 7 | 3 | 1 |
| $t^r$ (min) | 82.6 | 23.7 | 10.4 |
| $t^w$ (min) | 60 | 60 | 20 |
| $t^s$ (min) | 3635 | 728 | 146.7 |
| Total time (min) | 3817.6 | 851.7 | 185.1 |
| Average time/order (min) | 5.05 | 1.13 | 0.24 |

It can be seen from Table 1 that the model *C* is the most efficient, and the model *S* follows, the model *D* is the least efficient. The absolute value of $t^s$ is the smallest in the model *C* but the maximum in the model *D*.

In order to further study the impact of the number of order on the efficiency of different models, the number of order in the example will be doubled to calculate the different distribution efficiency. The result is shown in Tab.2.

Table 2: Time spent of different models with double orders

| | **Model *D*** | **Model *S*** | **Model *C*** |
|---|---|---|---|
| Driving distance (km) | 62.4 | 30.8 | 12.9 |
| Number of order | 1512 | 1512 | 1512 |
| Stop or start time(min) | 40 | 40 | 8 |
| Number of vehicle | 13 | 3 | 1 |
| $t^r$ (min) | 126.2 | 30.6 | 11.2 |
| $t^w$ (min) | 60 | 60 | 20 |
| $t^s$ (min) | 7368 | 1465 | 241.4 |
| Total time (min) | 7594.2 | 1595.6 | 280.6 |
| Average time/order (min) | 5.02 | 1.06 | 0.19 |

It can be seen from Tab.2 that the average delivery time in the three model changes synchronized with the number of order. $t^s$ will be distributed to more orders with the increase in orders, but if only the number of order changes, $t^r$ and $t^w$ will change little. If the number of orders were 756 (normal) and 1512(double), the time ratio of unit order are 1: 0.22: 0.048 and 1: 0.21: 0.038 respectively in the three models, as is shown in Fig.1 and Fig.2.

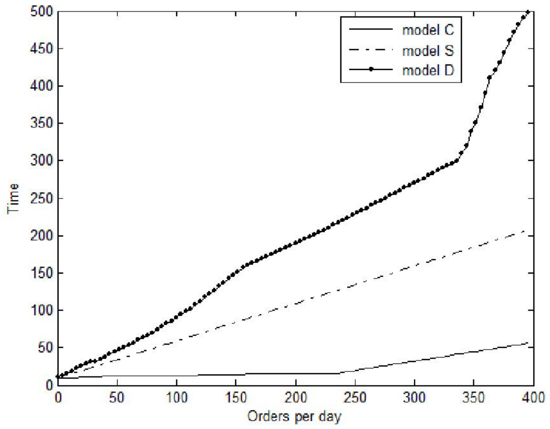

Figure 1: Service time in different models with 756 orders (min)

It can be seen from Fig.1 that the efficiency of the model *C* is enhanced with the increase of the number of order, and the main reason lies in the speed of the model *C* which can effectively reduce $t^s$ and there is no limit to the amount of orders in this model.

In the actual distribution process, it is not enough to only consider the efficiency factor. The proposed research has not considered the influence of the subjective preference of decision makers on the final scheduling results, which may make the following research have more practical value. Therefore, it is necessary to minimize the cost of the vehicle, the cost of the cabinet and the cost of commission cost for the third cooperative shops on the basis of the optimization efficiency. The optimal solution will be obtained by multi-attribute grey target decision

The strategy of MAGTD is used to obtain the most satisfactory solution from the Pareto set. Three groups of the Pareto solutions are shown TAB.3 which are based on efficiency, cost and satisfactory at the same time.

Table 3: Three Pareto solutions got by IDQGA

| **Serial number** | **Efficiency** | **Cost** | **Satisfactory** |
|---|---|---|---|
| 1 | 48 | 2130 | 38 |
| 2 | 49 | 2116 | 40 |
| 3 | 52 | 2149 | 37 |

The following sample matrix of the optimal scheduling scheme is established from the results of TAB.3:

$$G = \begin{bmatrix} 48 & 2130 & 38 \\ 49 & 2116 & 40 \\ 52 & 2149 & 37 \end{bmatrix}$$

The weight vector of each target can be expressed using Delphi method [13] as $\omega = (0.4538, 0.3561, 0.1901)$, and the decision making matrix *D* is shown as follow:

$$D = \begin{bmatrix} 1 & -1 & 0.4999 \\ 0 & 0.5000 & -1 \\ -1 & 0.5000 & 0.4999 \end{bmatrix}$$

Then the optimal effect of vector (bull's eye) is shown as: $d = (1, 0.5000, 0.4999)$.

The distance of bull's eye in each scheduling scheme can be solved according to equation (20) as $\xi_1 = 0.7188$; $\xi_2 = 1.3473$; $\xi_3 = 0.9564$

The order of the optimal schedule according to the above ascending sort is as follow: scheme 1 f scheme 3 f scheme 2

The scheme 1 is the optimal one and its corresponding solution is of (48, 2130, 38).

## CONCLUSION

(1) The efficiency of model *C* is more sensitive to number of order. In general, the distribution efficiency of the model *C* is the highest, the model *S* follows, and the model *D* is the lowest.

(2) Because of the low cost of vehicle, the model *D* has significant advantage when the order is less.

(3) The cost of the model *C* involves the commissioning of third-party cooperative shops and that of the model *S* involves the cost of the self-collection cabinet, therefore, when the number of order is more, the decision to select the model *C* or model *S* depends on the specific commission cost and the cost of the cabinet.

(4) The introduction of MAGTD guarantees the selection of the most satisfactory distribution model of the last mile in actual process.

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