

# A Novel Hybrid Stochastic Searching Algorithm Based on ACO and PSO: A Case Study of LDR Optimal Design

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**Abstract**—With the rapid development of electronic commerce, the logistics distribution system brings to the widespread attention. And the logistics distribution routing (LDR) optimization is playing the very important role as one of core technologies in the logistics distribution system. This paper proposed a novel hybrid stochastic searching algorithm to solve the LDR optimization design problem, the algorithm unified the ant colony optimization (ACO) and particle swarm optimization (PSO) algorithm effectively, which uses the randomness, the rapidity and the global characteristics of PSO to obtain the initial pheromone distribution firstly, then uses the ACO advantages of the concurrency, the positive feedback and the higher solving precision to find the exact solution. The results of simulation experiment show that the hybrid algorithm has superior global seeking optimization ability and the rapid convergence rate. The method is quick and effective to optimize the LDR problem, and can obtain the optimal solution or approximate optimal solution.

**Index Terms**—hybrid stochastic searching algorithm; ACO; PSO; LDR optimal design; B2C electronic commerce

## I. INTRODUCTION

B2C (Business to Customers) electronic commerce is the business mode to provide the product and service to the individual network consumers directly through Internet, namely on-line retail sales. B2C electronic commerce is composed of three basic contents: the internet markets that provide on-line shopping for the customer, the logistics distribution system that is responsible to commodity distribution, the bank and authentication system that is responsible for the customer authentication and the loans settlement. And, the logistics distribution system decides whether B2C electronic commerce does realize finally, logistics distribution routing (LDR) optimization is one of core technologies in the logistics distribution system.

### A. The Influence of B2C Electronic Commerce Environment to Logistics Distribution Routing

Under the B2C electronic commerce environment, the logistics distribution must face large numbers of customers, and has the characteristics of fast, prompt, accurate, safe, high quality and effective, the logistics distribution organization is extremely complex, and especially the LDR optimization is difficult. To ensure the distribution demands of the customers can be realized and send the goods to the customers, we should dispatch the vehicles fast and accurately, use the least numbers of vehicles and the most short-path the shortest path. This paper discusses the LDR problem under the B2C electronic commerce environment, the LDR is refers to organize the proper driving route, make the vehicles to pass the loading point (or unloading point) in order, achieve to a certain goal, cause the minimum total cost (for example the shortest distance, least expense, less time, as far as possible few vehicles, and so on) under a certain constraints (for example cargo demands, transmission quantity, vehicle capacity limit, travel course limit, time limit, and so on). And the following conditions must be satisfied simultaneously:

- ① All distribution vehicles start from the home-delivery center and return to the center finally;
- ② Every distribution path is not longer than the travel distance of the distribution vehicles in a distribution;
- ③ The sum of demand in every demand points is not more than the maximum load-carrying capacity;
- ④ Each customer's demand must be satisfied, and the goods only can deliver by a distribution vehicle.

### B. The LDR Current Situation and Problem in China

Although the modernization step is speeding up unceasingly in China, the LDR optimization is still in the start or the initial stage. Compared with the developed

countries, it also has the big disparity, its main existence problems are as follows:

① The existing multi-spot logistics distribution plan is not very mature under BtoC environment. At present, the most middle and small scale logistics distribution service providers have not the intellectualized routing system, and lack of understanding about the distribution particularity under the BtoC environment. These made the companies is lesser formerly can provide the perfect, mature, and under economical multi-spot logistics distribution plan under BtoC environment.

② At present, the LDR research is limited to the model with the definite parameters, namely the fixed routing research. In fact, the Customer quantity, the demand, the position as well as vehicles' transportation time, the path information are not necessarily knew beforehand that should treat as them to the extraneous variable.

③ The existing distribution path research is mainly the static model, and the parameter characteristic analyses that change along with the time is seldom. For example, the fuel expense changes along with the time, the different period possibly will have the fluctuation. In a certain time, the company needs to decide the distribution of allocation center and the sales network point again according to the situation change. Therefore, adding the static characteristic to the LDR optimization model, which can realize the real-time or the online logistics distribution management, enhance the close degree with the reality enormously.

④ Lacking the specialized logistics distribution service providers that are engaged in the BtoC service and the nationwide distribution network. At present, the quality of service of the logistics distribution service providers is not high, the service content is limited, the majority distribution enterprise only can provide the single item or the partition delivery service, cannot form the complete logistics distribution supply chain.

⑤ The LDR optimization is mainly using the road traffic resources, because many big cities has carried on the strict traffic control to the freight transportation distribution vehicles, moreover the customers of logistics distribution companies distribute in the city, such as the large-scale supermarket and so on, therefore it is influenced by the traffic control and the traffic jam, then it affects the accuracy of dispatching arrangement and the time reliability of the allocation.

### C. LDR Optimal Design Problem Description under BtoC Environment

Under the B2C electronic commerce environment, the LDR optimization problem may describe: For the client base of the certain position and the cargo demand, the enterprise's logistics distribution allocation center delivers goods with many vehicles to many customers according to the customer. Load-carrying capacity of each vehicle is certain; the total demand of each distribution routing is not to surpass the allocation vehicle capacity. The enterprise should arrange the distribution allocation routing quickly and reasonably, enable the cargo to deliver to the customer precisely, and make the

allocation cost to be lowest. Supposes the allocation center delivers goods to  $k$  customers, the cargo demand of each customer is  $g_i (i = 1, 2, \dots, k)$ , the load-carrying capacity of each allocation vehicle is  $q$ , and  $g_i < q$ . In order to arrange the routing, we should estimate the needed vehicle number firstly. We can determine the least number of available vehicles using the following formula:

$$m = \left\lceil \sum \frac{g_i}{aq} \right\rceil + 1$$

And,  $m$  is needed vehicle number,  $\lceil \cdot \rceil$  indicates to take INT,  $a$  is a parameter,  $0 < a < 1$ . The constraint condition is more, the cargo loading and unloading is more complex, the value of  $a$  is smaller. In the ordinary circumstances, the value of  $a$  is 0.85.

Then we can construct the model about the problem:  $c_{ij}$  expresses the transportation cost from  $i$  to  $j$ , including the time, distance, expenditure, and so on. The serial number of allocation center is 0, the serial number of various customers is  $i (i = 1, 2, \dots, k)$ . we defined the variables as follows: the vehicle  $s$  from  $i$  to  $j$ , then  $x_{ijs} = 1$ , otherwise,  $x_{ijs} = 0$ ; the freight transportation task of  $i$  is completed by the vehicle  $s$ , then  $y_{is} = 1$ , otherwise,  $y_{is} = 0$ ,  $i, j = 0, 1, \dots, k$ ;  $s = 1, 2, \dots, m$ . Then we can obtain the following mathematical model:

$$\min Z = \sum_{i=0}^k \sum_{j=0}^k \sum_{s=1}^m c_{ij} x_{ijs} \tag{1}$$

$$s.t. \sum_{i=0}^k g_i y_{is} \leq q \quad s = 1, 2, \dots, m \tag{2}$$

$$\sum_{s=1}^m y_{is} = 1 \quad i = 1, 2, \dots, k \tag{3}$$

$$\sum_{i=0}^k x_{ijs} = y_{is} \quad j = 1, 2, \dots, k; s = 1, 2, \dots, m \tag{4}$$

$$\sum_{j=1}^k x_{ijs} = y_{is} \quad i = 0, 1, 2, \dots, k; s = 1, 2, \dots, m \tag{5}$$

In above model, formula (2) is the vehicle capacity restraint, formula (3) expresses the transportation task for each customer completed only by a vehicle, and formula (4) and formula (5) expresses the vehicle that arrived and left some customer has the only one.

The LDR optimization is a NP difficult problem that has been proved, with the enlargement of the problem scale, the computing time of the precise algorithm will increase by the index speed. It is very difficult to obtain the global optimal solution in the acceptable time. Therefore, looking from the angle of practical application, it is the mainstream to design the heuristic algorithm in order to obtain the satisfactory solution in the acceptable computing time. And the traditional heuristic algorithm mainly has the saving algorithm, the circle algorithm, two-phase method and so on; the modern heuristic algorithm mainly has the tab search algorithm, the genetic algorithm, the simulation annealing algorithm, ant colony optimization (ACO) algorithm and so on. The ACO algorithm has the shortcoming of the slow speed, easy to fall into the local optimum, so it is relatively little to use the ACO to optimize the LDR. The particle swarm

optimization (PSO) algorithm has the quite quick speed to approach the optimal solution and can carry on the optimization effectively to the system parameters. Therefore, this paper proposed a hybrid stochastic searching algorithm to solve the LDR optimization problem based on ACO and PSO.[1]-[8]

## II. THE ACO-PSO HYBRID ALGORITHM DESIGN

### A. The Improvement of ACO Algorithm

#### 1) The basic principle

In the 1950s, the bionics was established, the people received the inspiration from organic evolution's mechanism, proposed many new method used to solve the complex optimized problem, such as the evolutionary programming, the genetic algorithm and the evolution strategy, etc. In the 1990s, M.Dorigo, V.Maniezzo, A.Coloni and so on, Italian scholar, proposed one kind of new simulation evolution algorithm through simulating the search path behavior among the nature ants which was called ACO algorithm. And the method has obtained the good test result to solve the TSP problem, the assignment problem and the job-shop scheduling. Although the research time is not long, but the present research demonstrated that the ACO algorithm has certain superiority to solve the complex optimization problem.

The bionics found the ants carry on the information transmission through one kind of material called pheromone. In the motor process, the ant can leave behind this material in its passing path, and moreover, the ant can apperceived this material in the motor process, and instruct its motion direction. Therefore, the collective behavior of the ant colony which is composed of massive ants displays one kind of information positive regeneration phenomenon: more ants pass through in some way, then the higher probability to choose this way of the late ants. The ant individual searches food through this kind of information exchange.

#### 2) The improved ACO model construction

We show the ant colony system model through solving the TSP problem of  $n$  city (use  $0,1,\dots, n-1$  to express the city number). The TSP is a famous NP-hard problem, namely assigns the  $n$  city set  $\{1,2,\dots, n\}$  and the touring expenses  $C_{ij}(1 \leq i \leq n, 1 \leq j \leq n, i \neq j)$  between the cities, and finds the smallest touring expenses routing that pass each city and return to the beginning city at last.

Introducing the following symbol:  $m$  is the ant quantity in the ant colony,  $d_{ij}(i, j=0,1,2,\dots, n-1)$  is the distance between the city  $i$  and  $j$ ,  $\tau_{ij}(t)$  is the residual information content at  $t$  time between  $i$  and  $j$ . In the initial time, information content in each way is equal, supposes  $\tau_{ij}(0) = \text{constant}$ , the ant  $k$  ( $k = 1,2,\dots, m$ ) decides the shift direction according to the pheromone quantity when it selects the routing,  $P_{ij}^k$  is probability that the ant  $k$  shifts from city  $i$  to the city  $j$  at  $t$  time.

$$P_{ij}^k = \begin{cases} \frac{\tau_{ij}^\alpha(t) \eta_{ij}^\alpha(t)}{\sum_{n \in allowed_k} \tau_{in}^\alpha(t) \eta_{in}^\beta(t)}, & j \in allowed_k \\ 0, & otherwise \end{cases} \quad (6)$$

In the formula,  $allowed_k = [0,1,\dots, n-1] - tabu_k$  expresses the optional city of ant  $k$  next step,  $\alpha$  expresses the relative important degree of residual information,  $\beta$  expresses the relative important degree of expected value,  $\eta_{ij}$  expresses the expectation from city  $i$  to city  $j$ , which may determine by some heuristic algorithm. The artificial ant colony system has the memory function, the ants complete a circulation after  $n$  time, and the pheromone quantity needs to adjust according to the following equation in each path:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta \tau_{ij} \quad (7)$$

In the formula,  $\rho$  expresses the path's durability;  $1-\rho$  expresses the path's damping degree.

$$\Delta \tau_{ij} = \sum_{k=1}^m \Delta \tau_{ij}^k \quad (8)$$

$\Delta \tau_{ij}^k$  expresses the residual information content of the  $k^{\text{th}}$  ant in the path  $ij$ ,  $\Delta \tau_{ij}$  expresses the information content's increase in this circulation,  $\Delta \tau_{ij}$  values using the method in the ant-cycle system model that proposed by M.Dorigo, namely

$$\Delta \tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, & \text{If the } k^{\text{th}} \text{ ant passes through city } i \\ & j \text{ between the time } t \text{ and } t+1 \\ 0, & otherwise \end{cases} \quad (9)$$

And the  $Q$  is a constant,  $L_k$  expresses the path length of  $k^{\text{th}}$  ant in this circulation, in initial time,  $\Delta \tau_{ij} = 0$  ( $i, j = 0,1,\dots, n-1$ ).

The parameter  $\alpha, \beta, Q$  may influence the algorithm performance seriously,  $\alpha$  value indicates the important degree of the information content that keeps in each node,  $\alpha$  value is bigger, the possibility that the ant chooses the past path previously is bigger, oversized  $\alpha$  enable the search premature to sink into the partial smallest dot prematurely;  $\beta$  value indicates the important degree of heuristic information; The  $Q$  value will affect the convergence rate of the ACO algorithm, oversized  $Q$  will cause the algorithm to restrain in the local minimum, undersized  $Q$  will affect the algorithm convergence rate, the  $Q$  changes with the increasing of problem scale; Ant's number is more, and the global searching ability of the algorithm is stronger, the more number causes the algorithm the convergence rate to reduce, when the ant number is identical, with the enlargement of problem scale, the global searching ability of the algorithm reduces.

#### 3) The algorithm flow

When initializing,  $m$  ant is laid aside in the different city, give the pheromone concentration on each side for  $\tau_{ij}(0) = C$  ( $C$  is constant), namely, the gross information content in various side is equal. The first element evaluation of each ant's tabulist is its city. After the ants

have completed a complete seeking-routing process, we compute  $\tau_{ij}^k$ , and renew the pheromone concentration on each side, then starting the new circulation. When the circulating time achieved the defined  $NC_{max}$  or all ants choose the identical path, the entire program is terminated.

The model program of ant-cycle system is as follows

Step 1:

Initialization:

Set  $t=0$ ,  $NC=0$ , on each side  $\tau_{ij}(0)=0$ , and  $\Delta \tau_{ij}=0$ , lay  $m$  ant in  $n$  city

Step 2:

Make  $s=1$ , ( $s$  is the subscript of tabulist)

For  $k=1$  to  $m$  do

Lay the initial city number of  $k^{th}$  ant in  $tabu_k(s)$

Step 3:

Repeat until tabulist is full

Set  $s=s+1$

For  $k=1$  to  $m$  do

Select the next arrived city according to the probability  $P_{ij}^k$ , transfer the  $Q^{th}$  ant to the city  $j$ , and insert  $j$  to the  $tabu_k(s)$

Step 4:

For  $k=1$  to  $m$  do

Calculate the total path length  $L_k$  of  $k^{th}$  ant, renew the shortest path

For  $k=1$  to  $m$  do

Renew the pheromone concentration on the side

Step 5:

Calculate the  $\tau_{ij}(t+n)$  of every side

Set  $t=t+n$

Set  $NC=NC+1$

Set  $\Delta \tau_{ij}=0$

Step 6:

If  $NC < NC_{max}$  (not all ants choose identical routing)

Then clear all tabulist

Go to Step 2

Print the shortest path

Terminate the entire program

If the program terminates after  $NC$  time circulation, this algorithm's complexity is  $O(NC \cdot n^2 \cdot m)$ . In fact, the complexity of the first step is  $O(n^2 + m)$ , the complexity of the second step is  $O(m)$ , the complexity of the third and fourth step is  $O(n^2 \cdot m)$ , the complexity of the fifth step is  $O(n^2)$ , the complexity of the sixth step is  $O(n \cdot m)$ . The experiment proved that the dereferencing of  $m$  is the same order of magnitude as  $n$ . Therefore the entire algorithm's complexity is  $O(NC \cdot n^3)$ . [9]-[16]

### B. The Improvement of PSO Algorithm

American scholar Eberhart E C and Kennedy J proposed the PSO algorithm in 1995 which is based on the simulation to the bird swarm and fish swarm, these researches may be called swarm intelligence. Usually the single natural biology is not the intelligence, but the entire biological community displays the ability to process the complex problem, the swarm intelligence is the application of these swarm behavior in the artificial intelligence. PSO processes the continuous optimization problem at first, at present its application has expanded to the combination optimization. Compared with other

evolution computational method, the PSO feature is as follows:

① Each individual (a particle) was given a stochastic speed and flowed in the whole problem space;

② The individual has the memory function;

③ The individual evolution is mainly realized through the cooperation and competition among the individuals.

As a effective parallel optimized method, PSO may use to solving the massive nonlinearity, not differentiable and the multi-peak value complex optimized problem, in addition the program realization of PSO algorithm is succinct, the adjustable parameters are few, thus it obtains quick development.

#### 1) The basic principle

PSO is the optimized algorithm that obtained the inspiration from the bird swarm. It regards the each optimized problem's solution as a bird in the search space, the bird flies in the searching space at a certain speed, this speed adjusts according to its flight experience and its companion's flight experiences. The bird is abstracted as particle that has not the quality and volume, the position of  $i^{th}$  particle in  $N$  dimensions space expressed by vector  $X_i = (x_1, x_2, \dots, x_n)$ , the flying speed expressed by vector  $V_i = (v_1, v_2, \dots, v_n)$ . Each particle has a fitness value decided by the optimized function, and knows the discovered best position (pbest) so far and present position  $X_i$ . In addition, each particle also knows the best position gbest so far in the entire swarm (gbest is best value in the pbest). Each particle changes its current position using the following information:

① Current position;

② Current speed;

③ Distance between current position and best position;

④ Distance between current position and best position in the swarm.

PSO is also one kind of optimized tool based on the iteration. For the  $k^{th}$  iteration, each particle changes according to formula (10) and (11).

$$v_{id}^{k+1} = wv_{id}^k + c_1 \times rand() \times (p_{id} - x_{id}^k) + c_2 \times rand() \times (p_{gd} - x_{id}^k) \quad (10)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (11)$$

$$w(t) = (w_{ini} - w_{end}) \times (T_{max} - t) / T_{max} + w_{end} \quad (12)$$

Rand is the random number between  $[0,1]$ ,  $c_1$  and  $c_2$  is been called as the study factor,  $t$  is the current evolution generation,  $T_{max}$  is the most evolution generation,  $w_{ini}$  is the initial inertia weight,  $w_{end}$  is the inertia weight when evolving to the biggest evolution generation,  $w$  is the weighting coefficient of inertia weight, it controls the influence of the preceding change quantity to the current change quantity, if  $w$  is comparatively large, then the effect is big, it could search the region before has not been able to achieve, and strengthen the global searching ability of the entire algorithm; If  $w$  is small, then the influence of preceding part is small, it mainly searches in neighbor of current solution, the partial searching ability is strong

To describe the particle swarm condition quantitatively, we will give the definition of the swarm sufficiency variance and the particle swarm convergence.

Defines 1: Supposes the particle number of the particle swarm is  $n$ ,  $f_i$  is the sufficiency of  $i^{\text{th}}$  particle,  $f_{\text{avg}}$  is the present average sufficiency of the particle swarm,  $\delta^2$  is the swarm sufficiency variance, and then  $\delta^2$  is defined as:

$$\delta^2 = \sum_{i=1}^n \left( \frac{f_i - f_{\text{avg}}}{f} \right)^2 \quad (13)$$

In the above formula,  $f$  is the normalized calibration factor; its function is to limit the  $\delta^2$ .  $f$  may take the random value, only need pay attention to two conditions:

- ① After the normalization, maximum value of entire particle swarm  $|f_i - f_{\text{avg}}|$  is not bigger than 1;
- ②  $f$  changes along with the algorithm evolution.

In the algorithm, the  $f$  value uses the following formula:

$$f = \begin{cases} \max\{|f_i - f_{\text{avg}}|\}, \max\{|f_i - f_{\text{avg}}|\} > 1 \\ 1, \text{others} \end{cases} \quad (14)$$

Defines 1 indicated that the particle sufficiency variance  $\delta^2$  is the convergence degree of all particles in the particle swarm.  $\delta_2$  is smaller, then the particle swarm tends convergence; Otherwise, the particle swarm is at the random searching stage.

Defines 2: Supposes the position of some particle  $t$  in the  $t$  time is  $x(t)$ ,  $p$  is in the optional position in search space, then the convergence definition of the particle is as follows:

$$\lim_{t \rightarrow +\infty} x(t) = p \quad (15)$$

This definition indicated that particle convergence is refers to the particle to pause at some stationary position  $p$  in the searching space. If the PSO algorithm falls into the precocious convergence or achieves to the global convergence, the particles will gather at one or several specific positions in the search space, the swarm sufficiency variance  $\delta^2$  is equal to zero.

## 2) Algorithm flow and solution process

① To initialize the position and speed of the particle swarm at random, the pbest coordinate of each particle is its current position, and calculates its corresponding individual extreme value, but the global value is the best value in the individual extreme value, records the serial number of the best value, and establishes gbest as the current position of the best particle.

② Calculate adaptive value of each particle.

③ Compare the adaptive value with the individual extreme value for each particle, if superior, and then renew the current individual extreme value.

④ Compare the adaptive value with the global extreme value for each particle, if superior, and then renew the current global extreme value.

⑤ According to formula (10) and (11), renew the position and flying speed each particle.

⑥ If not achieves the stop criterion), then returns to step 2, if achieves, then stop calculation. [17]-[20] The

PSO algorithm can be expressed by pseudocode as follows:

```

Initialize the particle swarm
DO
  For each particle
    Calculates its sufficiency
    If the sufficiency is superior to the best history value
      Renew the best history individual  $P_i$  with  $X_i$ 
    End
  Select the best particle in the particle swarm
  If the best particle is superior to the best swarm
  history particle
    Renew  $P_g$  with the best particle of current swarm
  particle
  For each particle
    Renew the particle speed according to formula (10)
    Renew the particle position according to formula (11)
  End
While the biggest iteration number or the least error
has not achieved

```

The PSO algorithm frame is shown as Figure 1.

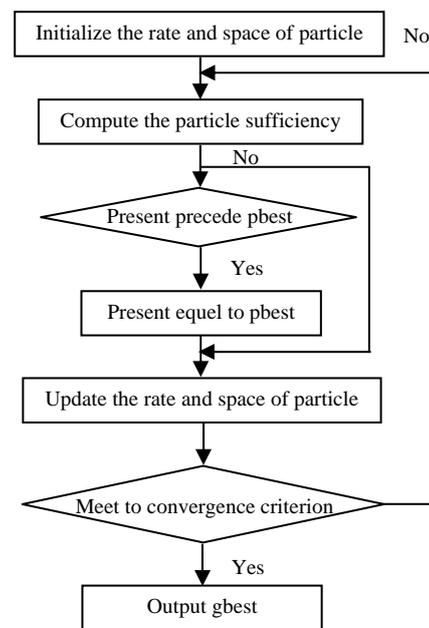


Figure 1. PSO frame diagram

## C. The Integration of ACO and PSO Algorithm

### 1) Fusion algorithm principle

Although the PSO algorithm is fit for solving the continuous optimization problem, but it is inferior to solve the combination optimization problem. For the random distribution of the initial particle, the PSO still has strong global searching ability and the quick solution speed when it is been used to solve the combination optimization; ACO algorithm is superior to the PSO when to solve the combination optimization, because the initial distribution of the pheromone is well-proportioned, it enables the ACO algorithm to have blindness in the early time, and the convergence speed is slow.

The paper proposed the fusion algorithm to include the superiority of the ACO and PSO. In the first stage of the

fusion algorithm, we use the improved PSO algorithm (use its randomness, the rapidity, the global characteristics fully) to obtain the suboptimal solution; adjust the initial distribution of the pheromone in the ACO using the suboptimal solution. In the second stage, we complete the solution of entire problem using the pheromone distribution which obtains in the first stage, and use the ACO advantages of the concurrency, the positive feedback and the higher solving precision fully.

2) *Fusion algorithm engagement*

Consider the continuous function optimization problem; we reset ants position and the initial pheromone distribution.

Position  $X(i)$  of the ant  $i$  is corresponding with the most superior history position  $P(i)$  of each particle in the PSO algorithm, namely:

$$X(i) = P(i) \tag{16}$$

The evaluation function value of the initial ant pheromone distribution, the formula is:

$$T(i) = k \cdot a^{-f(X_i)} \tag{17}$$

And  $k$  is a constant greater than 0,  $0 < a < 1$ ,  $f(x_i)$  is the goal function value,  $X_i$  is the position of the ant  $i$ . Defines the  $a, k$  value according to the actual problem, the goal function value is bigger, then the pheromone in the position  $X_i$  is more.

3) *Fusion algorithm flow*

Step 1: Produce the initial solution using the ACO algorithm. Set the initial condition of ant colony algorithm  $nc=0$  ( $nc$  is iterative step or searching times), the particle counts  $np$ , the iterative times  $nmax$ . Produce  $np$  initial solution stochastically  $C_0$ , choose the superior solution, cause these paths to leave behind the pheromone.

Step 2: Calculate the adaptive value  $T_0$  according to the current position, set the current adaptive value is the individual extreme value, the current position is the individual extreme value position  $pcBest$ , according to individual extreme value  $pBest$  of each particle, discover the global extreme value  $gBest$  and global extreme value position  $gcBest$ .

Step 3: Put the initial starting point of the various ants in the current solution, for each ant ( $k=1,2,3,\dots, m$ ), move from apex  $i$  to next apex  $j$  according to probability  $p_{ij}(k)$ , put the apex  $j$  in the current solution collection.

Step 4: Carry on the following operation to each ant, we obtain  $C'_1(j)$  through intersecting the  $j^{th}$  ant path  $C_0(j)$  with  $gcBest$ , and obtain  $C''_1(j)$  through intersecting the  $C'_1(j)$  with  $pcBest$ ,  $C''_1(j)$  changes into  $C_1(j)$  by certain probability, calculate the adaptive value  $T_1$  according to current position.

Step 5: Calculate the variable quantity  $\Delta E$  of the adaptive value between two positions, if  $\Delta E < e$ , to accept the new value, otherwise reject. The processing sequence  $C_1(j)$  of  $j^{th}$  particle is still  $C_0(j)$ .

Step 6: Discover the individual extreme value  $pBest$  and extreme value position  $pcBest$  of each ant, discover the global extreme value  $gBest$  and global extreme value position  $gcBest$ .

Step 7: Record path length of various ants and the best current solution.

Step 8: Make  $nc=nc+1$ , and judge whether to satisfy with the termination condition of ACO algorithm, if not, transfer to Step 2.

Step 9: Output the present optimal solution. [21]-[25]

III. SIMULATION EXPERIMENT

This paper takes the following problem as the benchmark test data, experiment is including 1 allocation center and 7 demand points, and the distance between various paths is as shown in Table 1. Average velocity of the vehicles among the spots is 50 km/h, the vehicle capacity is 1.0 t, not permit to overload. Demand operating time information of each spot is as shown in Table 2. The Other parameters are:  $c=100$ ,  $C_{ij}=2.5$ ,  $c_0=c_1=c_2=10.0$ , the optimum solution is  $0 \rightarrow 1 \rightarrow 0 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 0 \rightarrow 7 \rightarrow 6 \rightarrow 0$ ,  $G^*=824.5$ .

TABLE I. THE FUNDAMENTAL TEST DATA UNIT: KM

Distance	0	1	2	3	4
0	0.00	7.21	42.72	—	65.49
1	7.21	0.00	—	50.22	—
2	42.72	—	0.00	13.15	33.97
3	—	50.22	13.15	0.00	27.73
4	65.49	—	33.97	27.73	0.00
5	74.73	72.74	45.67	28.58	11.31
6	13.42	—	—	52.23	59.13
7	6.00	20.39	49.41	61.40	—

CONTINUED TABLE

Distance	5	6	7
0	74.73	13.42	6.00
1	72.74	—	20.39
2	45.67	—	49.41
3	38.58	52.23	61.40
4	11.31	59.13	—
5	0.00	68.88	43.10
6	68.80	0.00	6.32
7	43.10	6.32	0.00

TABLE II. THE DEMAND POINTS INFORMATION

Demand points	1	2	3	4
Operation time	0.80	3.20	2.00	1.25
Demand	0.21	0.41	0.57	0.31
Time window	[3,4.5]	[3,4]	[1,3]	[2,4]

CONTINUED TABLE

Demand points	5	6	7

Operation time	0.60	1.20	3.00
Demand	0.12	0.30	0.91
Time window	[1,2]	[1,3]	[1,2]

According to the above fusion algorithm, we develop a test program with C# under Windows XP, and use this program to carry on many times calculation. The calculation results in the condition of different parameter are as shown in Table 3, the ant number is 50, and the biggest iterative step is 2000.

TABLE III.  
THE INFLUENCE TO THE TESTING RESULT OF ALGORITHM PARAMETER'S CHANGE

$\alpha$	$\beta$	$\gamma$	$\rho$
0.5	1.0	1.0	0.5
0.1	1.0	1.0	0.5
1.0	1.0	1.0	0.5
1.0	0.5	1.0	0.5
1.0	1.0	0.6	0.5
1.0	1.0	0.9	0.5
1.0	1.0	1.0	0.9
1.0	1.0	1.0	0.5
1.0	1.0	1.0	1.0
1.0	1.0	1.0	0.5
1.0	1.0	1.0	0.5
1.0	1.0	1.0	0.5
1.0	1.0	1.0	0.5
1.0	1.0	1.0	0.5
1.0	0.1	1.0	0.5
1.0	1.0	0.3	0.5

CONTINUED TABLE

Q	$G^*$	$\overline{nc}$	Average time-consuming/ms
1.0	839.2	171	278
1.0	831.8	266	408
1.0	830.1	251	383
1.0	837.9	269	411
1.0	835.0	260	367
1.0	831.4	234	391
1.0	827.7	1766	3741
1.0	830.5	243	384
1.0	840.4	126	201
100.0	842.6	237	408
10.0	835.7	212	338
1.0	830.5	216	345
1.0	830.0	270	412

1.0	833.3	240	365
1.0	851.3	1044	2014

The operation result indicated that the ACO algorithm has the quick astringency and validity when solving the LDR problem. In the actual operation process, the algorithm parameter's enactment has the biggish influence to the operation results. We can make a conclusion from Table 3: if the  $\rho$  value increases, its global searching ability weakens, but convergence rate enhances distinctly; if the Q value decreases, the operation result tends to the global optimum, but it is not explicit to influence of algorithm convergence rate; The path importance  $\alpha$  and the visibility the  $\beta$  value changes in the [0.1,1.0], the influence of the change to the algorithm is not obvious.

IV. CONCLUSION

The ACO algorithm is effective to solve the LDR problem, this paper proposed a hybrid stochastic searching algorithm to integrate ACO and PSO according the characteristic of LDR. It has the better global optimization ability and the quicker convergence rate. When solving the LDR optimization design with the soft time windows, it is able to demonstrate its superiority. The simulation result indicated that it may approach the exact solution well, has the good solution performance and the application prospect. Because this algorithm has carried on the particle swarm searching and the ant colony operation simultaneously, therefore, its running time is long. Moreover, in the basic ant colony algorithm, some parameters are needs to establish artificially, this paper has not carried on the verification, and the searching and proofing for the other parameters wait for the further studies.

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