A research into location routing problem based on hybrid genetic simulated annealing algorithm

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Abstract

With the diversified and personalized commodity requirements as well as small batch dispatch and frequent dispatch features under the circumstance of E-commerce, the environment for logistics dispatching system becomes increasingly complicated and the inter-influence between different subsystems in logistics system optimization becomes increasingly significant. As a result, judged from the aspect of logistics system integration, after taking customer's personalized dispatching time into consideration, it's necessary to establish location routing problem with changeable softtime windows model. Based on the feature of the model, this paper adopts hybrid genetic simulated annealing algorithm to gain solution. The experimental result shows that this algorithm is much better than gaining solution solely by adopting hybrid genetic algorithm or simulated annealing algorithm in the aspect of optimal solution, solution quality, calculating efficiency and algorithm stability.

Keywords: hybrid genetic simulated annealing algorithm, logistics system, location routing problem

1 Introduction

The logistics dispatching system mainly includes two parts: the first one is the assignment of dispatching tasks. It's also normally known as the location allocation problem (LAP). The second one is routing between dispatching locations. In other words, it is the vehicle routing problem (VRP). The aforesaid two parts are interdependent and mutual binding. In practice, since both problems need to be taken into comprehensive consideration, the location routing problem is formed.

The location routing problem (LRP) can be described as: after being provided with a serial potential facility points conforming to the actual situation, we need to determine a serial facility locations and a route from different facilities to different customers based on the target of meeting the requirement of the program (shortest road, least expense, least time and least deployed vehicles). Generally speaking, the total cost needs to be minimized.

The location routing problem contains two senses: the location allocation problem is defined as to determine the facility quantity and locations within a geographic range based on geographic distribution and goods allocation relationship. The vehicle routing problem can be defined as the that vehicle designs an optimal goods dispatching route based on one or multiple facility to distributed geographic customer points while meeting a serial of binding conditions within the precondition that the facility location, customer points and route information are known. Based on it, we can design a set of vehicle dispatching rout to meet the target function. Generally speaking, VRP's target function has the least cost.

Under the circumstance of E-commerce, customer has both demand (dispatching) and supply (collecting). As a result, the goods flow is actually bidirectional. In addition, customer has personalized requirement of dispatching time. Based on aforesaid features, the location route problem can be extended to below problems:

Location Routing Problem with Changeable SoftTime Windows (LRPCSTW) can be described as below: to design a serial of facility locations based on the given potential facilities corresponding to actual issues and determine a route from different facilities to different customer points, so that they could try to arrive at all customer points within the given time; otherwise, loss will be contributed by stopping the vehicle for waiting for delay in dispatching. The target is to design the route of minimized cost. LRPCSTW, in addition to fulfilling the classic LRP requirements, also needs to consider visiting time limitation to find out the rational solution.

2 The basic elements of genetic algorithm

The basic operations of GA include encoding, appearance of initial population, fitness calculation, selection, crossover and mutation.

2.1 GENETIC CODE

According to the workflow of GA, when using GA in solving problems, a relationship should be established between the actual presentation of target problems and the bit-string structure of the chromosome in GA, namely the encoding and decoding operations should be determined. The encoding is to express the solutions with a code so as

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to make the problem state space corresponding to the coding space of GA, which relies heavily on the nature of the problems and which will affect the design of genetic manipulation. The optimization of GA is carried out in the code space corresponding to certain encoding mechanism instead of working directly on the parameters of the problems; therefore, the selection of the code is an important element affecting the algorithm performance and efficiency [1]. In function optimization, different code lengths and code systems place a great influence on the accuracy and efficiency of the problems. Binary encoding demonstrates the solutions to the problems with a binary string while decimal encoding presents the solutions with a decimal string. Obviously, the code length will affect the algorithm accuracy and the algorithm will give out larger memory space. Real-number encoding is to show the solutions with a real number and it has been extensively applied in high-dimensional and complex optimization space since it has solved the influence played by encoding on the algorithm accuracy and memory space. For the given optimization problem, the space formed by GA phenotype collection individuals is called problem space while that consisted by GA genotype individuals is called GA coding space. The genetic operators are implemented in the bit-string individuals in GA coding space [2].

2.2 GENETIC OPERATOR

The operators of the standard genetic algorithm often include three basic forms: selection, crossover and mutation, which make up the core that GA has strong search capacity and which are the main carriers of the reproduction, hybridization and mutation produced in the simulation of the natural selection and the genetic process. GA realizes the group evolution by using the genetic operators to reproduce a new generation of groups and the design of the operators is not only a key component of the genetic strategy, but also a basic tool to adjust and control the evolution process [3]. This paper will discuss the effect the genetic operators play on the convergence separately, which helps to learn about the characteristics and importance of genetic operators better.

2.2.1 Selection Operator

Selection is to choose the individuals with high fitness value from the current group to produce the matingpool and it mainly includes fitness-proportionate selection, Boltzmann selection, rank selection, tournament selection and elite-preserving selection. In order to prevent the optimal individuals of the current group from losing in the next generation due to selection errors or the destructive effects of crossover and mutation, DeJong has come up with the elitist selection. In addition, Holland and others have also brought forth steady-state selection. The selections operators are mainly used to prevent gene delection and improve the global convergence and the calculation efficiency and the most commonly-used selection operators are fitness-proportionate selection operator and the elite-preserving selection operator.

Proportional model, also called Roulette wheel, is a method of playback random sampling and its basic idea is that the probability of every operator to be selected is directly proportional to its fitness. Because of random computation, the selection error of this method is so big that some individuals with high fitness fail to be selected; however, this is still one of the commonly-used selection operators.

Assume that the group size is M and the fitness of the individual i is F_i. Then the probability p_i of the individual i to be selected is [4]:

$$p_i = \frac{F_i}{\sum_{i=1}^{M} F_i}, (i = 1, 2, \cdots, M).$$

In running GA, new individuals emerge continuously from such genetic operations as crossover and mutation on the individuals. Although more and more excellent individuals will appear in the group evolution, they may destroy the individuals with optimal fitness due to the randomness of selection, crossover and mutation. We hope that the individuals with optimal fitness can be preserved till the next-generation group as much as possible; therefore, we need to apply Elitist Model, meaning that the individuals with the highest fitness in the current group won't participate in the crossover and mutation but replace the individuals with lowest fitness produced by the current group after crossover and mutation.

2.2.2 Crossover Operator

The so-called crossover operation in GA means that two matching chromosome individuals replace part of their genes in accordance with a certain way and form two new individuals. As a significant characteristic of GA, crossover operation plays a key role in GA and it is also a main method to produce new individuals.

Crossover operation is usually divided into the following several steps:

a) Randomly take out a pair of mating individuals from the matingpool;

b) Randomly take one or more integers k from [1, L-1] as the crossover position of the pair of mating individuals according to the bit string length L;

c) Carry out crossover operation according to the crossover probability $p_c (0 < p_c \le 1)$; the mating individuals replace part of their contents and form a pair of new individuals at the crossover positions [5].

The most commonly-used crossover operator is One-point Crossover, which refers to set a crossover point randomly in the individual encoding string and replace some chromosome in these two mating individuals at this point. One-point Crossover has an important characteristic: if the relationship between the neighbouring loci can provide better individual character and higher individual fitness, then it will be less possible for this One-point Crossover to destroy such individual character and lower the individual fitness.

It will be faster to solve knapsack problem with and/or swap operation, the specific realization methods of which include:

a) Choose two parent strings A and B according to the roulette wheel selection mechanism;

b) Produce a substring A' from A and B according to logic and operation;

c) Produce a substring B' from A and B according to logic or operation.

2.2.3 Mutation Operator

As a local random search, mutation can avoid the eternal loss of some information caused by selection and crossover operators if combined with these operators. If mutation operation is conducted on the individuals with certain probability instead of single hybridization operation, mutation will randomly change the vectors of the individuals with small probability; in this way, it may result in some new and useful structures may appear and increase the probability to converge to the overall optimization. Mutation operation is a measure to prevent the prematurity of algorithm as well as non-mature convergence. Never take a big mutation rate in the mutation operation. If the mutation rate is bigger than 0.5, GA will degrade into random search and some important mathematic characteristics and search capability will no longer exist [6].

3 The mathematical model of location routing problem (LRP) with changeable SoftTime Windows

3.1 THE CONSTRUCTION OF LRP MODEL WITH CHANGEABLE SOFTTIME WINDOWS

The previous research objective of LRP is to consider cost minimization; however, modern logistics not only consider cost minimization, but also service quality and customer satisfaction of the distribution centre (DC) [7]. Therefore, this paper has also deemed the delivery time restrictions as a part of the optimization objective as well as the cost. LRP with time windows can be divided into hard time window and softtime window. The so-called hard time window refers to a fixed time point while the softtime window is a time period, which can be further divided as fixed softtime window and changeable softtime window. The fixed softtime window means that the start-stop service time intervals required by the customers are the same; on the contrary, the changeable softtime window means that the customers require different start-stop service time intervals. In order to get closer to the practical problems, this paper has investigated the Location Routing Problem (LRP) with Changeable SoftTime Windows (LRPCSTW) and the fundamental objectives of LRP model with changeable softtime window are classified as follows:

1) In order to improve the logistics service quality and customer satisfaction, the cargo is required to be delivered within the required time. Under this circumstance, the top priority of the entire logistics system is how to reasonably arrange for the distribution to meet the time requirements made by the customers;

2) Reasonably plan the driving route with the shortest distribution route and the lowest vehicle-dispatching cost;

3) The entire distribution system realizes total cost minimization to satisfy the high-efficient requirements of the logistics company.

The above objectives form a system and they interact on and affect each other; therefore, LRP is a multi-objective optimization problem.

3.2 LRPCSTW MODEL HYPOTHESIS

Every customer has his/her own requirements on cargo delivery time; there are several distribution centres available; the supply and demand are stable at a certain time; there are sufficient vehicles starting from and stopping at the same centre and the aggregate demand of every service line doesn’t exceed the maximum loading of the vehicles and the vehicle models are the same; every customer can only be supplied by one centre; every customer has the same unloading time; select one or several potential distribution centres to complete the specific distribution in every decision and there is only one kind of cargo to be distributed; specially stipulate that the operating range is directly proportional to the transportation cost for the simplified model [8].

3.2.1 The Parameters in the Model

M: There are M customers in this service, who are numbered: 1, 2, , M;

N: There are N potential distribution centres, which are numbered: M+1,M+2,…,M+N,

K: There are k callable vehicles, which are numbered: 1,2,…,K;

K_Q: The maximum load of the kth vehicle;

F_i: The operating cost of the distribution centre i;

C_{ijk}: The unit transportation cost of the vehicle k from the customer i to customer j;

C_k: The unit cargo loading cost of the kth vehicle;

q_i: The cargo quantity demand of customer i;

d_{ij}: The distance from customer i to customer j;

t_{ijk}: The earliest cargo arrival time of vehicle k from customer i to customer j;

LT_i: The earliest cargo arrival time required by customer i;

RT_i: The latest cargo arrival time required by customer i;

T_i: The time when the vehicle arrives at the customer i, $LT_i \le T_i \le RT_i$.

3.2.2 The Decision Variables in the Model

$$S_k = \begin{cases} 1, \text{Vehiclekstarts from the distribution center}, k \in K \\ 0, \text{Otherwise} \end{cases}$$

$$X_{ijk} = \begin{cases} 1, \text{Vehicle } k \text{ drives from customer } i \text{ to customer } j, & i, j \in M, k \in K, i \neq j \\ 0, \text{Otherwise} \end{cases}$$

$$Z_i = \begin{cases} 1, \text{Distribution center } i \text{ opens}, i \in N \\ 0, \text{Otherwise} \end{cases}$$

3.3 THE CONSTRUCTION OF LRPCSTW MATHEMATICAL MODEL

Objective Function:

$$f_1 = \min \sum_{i=1}^{M} \left\{ \max\left[\left(LT_i - T_i \right), 0 \right] + \max\left[\left(T_i - RT_i \right) 0 \right] \right\}, \quad (1)$$

$$f_2 = \min \left[\sum_{i=1}^{N} F_i Z_i + \sum_{k=1}^{K} \sum_{i=1}^{M+N} \sum_{j=1}^{M+N} C_{ijk} q_i d_{ij} + + \sum_{k=1}^{k} C_k \sum_{i=1}^{M+N} \sum_{j=1}^{N} X_{ijk} q_i \right]. \quad (2)$$

Constraint Conditions:

$$\sum_{i=1}^{M} \sum_{k=1}^{K} X_{ijk} q_i \le Q_k, \forall j \in M, \quad (3)$$

$$\sum_{i=N+1}^{M} \sum_{k=1}^{M} X_{ijk} - Z_i \ge 0, \forall k \in K, \quad (4)$$

$$\sum_{i=N+1}^{K} \sum_{J=1}^{M} X_{ijk} \le 1, \forall k \in K, \quad (5)$$

$$\sum_{k=1}^{k} \sum_{i=1}^{M} X_{ijk} = 1, \forall j \in M, \quad (6)$$

$$\sum_{i=1}^{M+N} X_{ihk} - \sum_{i=1}^{M+N} X_{hjk} = 0, \forall k \in K, \quad (7)$$

$$\sum_{i=M+1}^{M+n} \sum_{n=1}^{N} X_{ink} + \sum_{n=1}^{N} \sum_{j=M+1}^{M+N} X_{njk} \le 1, \forall k \in K, \quad (8)$$

$$\sum_{k=1}^{K} X_{ijk} + Z_i + Z_j \le 2, \forall i, j \in N, \quad (9)$$

$$X_{ijk} \left(T_i - T_j \right) \le 0, \forall k \in K; i, j \in M, \quad (10)$$

$$T_j = \sum_{i=1}^{M} \left[S_{ijk} \sum_{i=M+1}^{M+N} \sum_{o=1}^{M} \cdots \sum_{i=1}^{M} \left(S_{ink} t_{ink} + S_{olk} t_{olk} + \ldots + S_{ljk} t_{ljk} \right) \right]. \quad (11)$$

Equation (1) means that the cargo must be delivered within the required time by the customer; Equation (2) shows that the total cost minimization to complete this distribution is made up of three parts: the operating cost of the opened distribution centre; the transportation cost of the vehicles and the unit loading cost of the vehicles in the distribution centres; Equation (3) demonstrates that the aggregate demands of the same vehicle won't exceed the maximum load of this vehicle; Equation (4) makes sure that every opened distribution centre will have callable vehicles; Equation (5) means that the same vehicle can only be called by one distribution centre; Equation (6) means that one customer can only be served by one vehicle; Equation (7) stands for the connectivity of the routes between the customers; Equation (8) means that any two distribution centres won't be at the same route; Equation (9) means that any two distribution centres won't connect each other; Equation (10) refers to the route succession of the vehicles; Equation (11) gives the Equation of T_j in the objective Equation (1) [9, 10].

4 Solve LRPCSTW problems through hybrid genetic stimulated annealing algorithm

To maintain the population diversity is a solution to overcome the premature convergence of the genetic algorithm, which makes the genetic algorithm explore the search region in succession in the evolution. The thought of niche technology comes from the fact that the creatures usually live and copulate with their own species for reproduction. Niche technology is an organizing function to gather the groups with similar biological features and characters together in certain environment and to separate those groups with different features and characters. The organization with the same features and characters is called a species [11]. Niche technology is similar to preserve the excellent individuals in different species and conduct such selection operation, crossover operation and mutation operation as choice mechanism and crowing mechanism in the population or between the populations. The improved genetic algorithm with niche technology can effectively protect the population diversity.

4.1 THE DETERMINATION OF FITNESS FUNCTION

Fitness function plays a significant role in the entire division, which directly affects the quality of the optimal solution. Used to evaluate the individual adaptive capacity, fitness function increases the probability that the individuals with strong adaptive ability to reproduce a next generation and the weak individuals to reproduce another generation. Based on this idea, this paper adopts penalty function method in constructing fitness function and the purpose to use penalty on the invalid individuals is to reduce its probability to be reproduced to the next generation in calculating the individual fitness. The invalid individuals here refer to those individuals, which fail to meet the constraint conditions. The constraint condition of this paper is the optimal price at time limit and the invalid individuals exceed the maximum constraint. After analysing the thought of penalty function, this paper constructs the penalty item by adopting $Time(\mathrm{S}) < T_{\max}(S)$. In addition to considering the inconsistency in magnitude between the consumption time and price in constructing objective function and the unifying the magnitude, this paper uses normalization factor just as Equation (12) and Equation (13).

$$\sigma_p = PH - PS\,, \tag{12}$$

$$\sigma_t = \max\left(TS - T_{\max}, T_{\max} - TH\right). \tag{13}$$

The objective function in this paper is as the following formula:

$$OBJECT = \alpha \cdot e^{\frac{Time - T_{\max}}{T_i \sigma_t}} \cdot \frac{\left|Time - T_{\max}\right|}{\sigma_t} + \beta \cdot \frac{price}{\sigma_p}. \tag{14}$$

This paper discusses minimization problem; therefore, the optimum of this algorithm means the maximum fitness function corresponds to the minimum value of the objective function. The fitness function in this paper is seen as the following Equation:

$$Fitness = \frac{1}{1 + OBJECT}\,. \tag{15}$$

Time (S) in Equation (14) stands for the aggregate consumption time of the system; Price (S) refers to the aggregate consumption cost of the system and $T_{\max}(\mathrm{x})$ means the time limits of the system. In this formula, $e^{Time - T_{\max}/T_i \partial_t}$ is the penalty item of the invalid individuals. Obviously, only when $Time(\mathrm{S}) - T_{\max} > 0$, $e^{Time - T_{\max}/T_i \partial_t} > 1$; then the objective function in Equation (14) increase while its corresponding fitness function in Equation (15) decreases; therefore, it effectively reduces the fitness value of the invalid individuals. When $Time(\mathrm{S}) - T_{\max} < 0$, $e^{Time - T_{\max}/T_i \partial_t} < 1$, then according to Equation (14), the objective function reduces while the corresponding fitness function increases in the corresponding Equation (15); thus greatly improving the fitness value of the effective individuals. T_i in Equation (14) is similar to the annealing system in SA. Initialize $T_0 = 1$ and $T_{i+1} = 0.98 T_i$. This paper makes $\alpha = 0.6, \beta = 0.4$ when $\alpha > \beta$.

4.2 GENETIC MANIPULATION

The selection of genetic operation attaches significant importance to GA efficiency and solution quality and they are also the core of GA. The genetic selecting operation, crossover operation and mutation operation simulate the multiply, hybridization and mutation in the nature.

Adopt Boltzmann selecting operation on the problem investigated in this paper and the probability to select the individual is as follows [12, 13].

$$P_s\left(S_i\right)\frac{1}{\sum_{i=1}^{n} e^{f(S_i)}/T}, i = 1, 2, ..., n\,, \tag{16}$$

where $T > 0$ and T refers to the temperature parameter in the annealing process.

Crossover operation uses ingle-point crossover and reverse operation is also adopted in this process. In this way, it can make the important genes more compact, which is equal to redefine the gene block in the algorithm. See the example of this operation is as follows:

As for the binary string with a length of 10, mark the important genes with underline:

$\underline{1}\ \ \underline{0}\ \ \wedge\ \ 1\ \ 1\ \ 1\ \ 0\ \ 1\ \ \underline{1}\ \ \wedge\ \ 0\ \ 1$

$\left(\text{And } \wedge \text{ is the inverse transposition}\right)$.

Produce new binary string after reverse operation:

$\underline{1}\ \ \underline{0}\ \ \underline{1}\ \ 1\ \ 0\ \ 1\ \ 1\ \ 1\ \ 0\ \ 1.$

From the new binary string, it can be seen that the important genes are more compact, thus reducing the probability that the important genes will be dispersed in the single-point crossover.

Mutation operation: In the genetic algorithm, mutation operation is usually realized by mutating the binary string according to the mutation probability P_m and SA annealing temperature is used to decide the selection of mutation probability with the mutation probability: P_m=0.01.

4.3 THE IMPLEMENTATION PROCESS OF THE ALGORITHM

Step1: Initialize the population and finish the coding of the solution space, $P(0) = \{S_1, S_2 \cdots, S_z\}$.

Step2: Calculate the fitness value of every individual in the initial population and according to the fitness calculation formula, namely Formula (15), determine the initial temperature of the simulated annealing algorithm, namely $T(0) = \left(f_{\min} - f_{\max}\right)/\mathrm{In}p_r$. In the initial temperature formula, f_{max} is the largest fitness value in the initial population; f_{min} is the smallest fitness value in the initial population; P_r is the worst initial acceptance probability and in this paper, P_r=0.7.

Step3: Conduct genetic operation to the population $P(t)$: select single-point crossover operation and mutation operation by adopting Boltzmann in this paper and produce the new population $P(t+1)$. The possibilities to make single-point crossover and mutation operation are P_c=0.8 and P_m=0.01 respectively.

Step4: Produce a new-generation population $P(t+2)$: According to Metropolis criterion, randomly disturb the neighbourhood region of the individual S_i in the population of $P(t+1)$. And $\Delta f = fit(S_i) - fit(S_j)$, Compare Δf with 0. When $\Delta f \le 0$, directly copy S_j to $P(t+2)$; if not, produce a random number r among [0, 1], directly copy S_j to $P(t+2)$ when $r < e^{(-\Delta f / T(N))}$; in other cases other than the above two circumstances, copy S_i to $P(t+2)$.

Step5: Conduct elimination: calculate the Euclidean Distance between individual S_i and individual S_j in $P(t+2)$, namely $\|S_i - S_j\| = \sqrt{\sum_{k-1}^{M} (S_{ik} - S_{jk})^2}$; among them, $i = 1, 2, ..., n-1, j = i+1, ...$, n and M means the quantity of the decision variables in the problems to be settled. In the formula $\|S_i - S_j\| \le L$, when L stands for distance parameter, calculate the fitness value of individual S_i and individual S_j and abandon the individuals with smaller fitness value and do not operate when $\|S_i - S_j\| > L$.

Step6: When Q arrives at the maximum value, the program stops running and quits; otherwise, use the corresponding cooling means to lower the annealing temperature. This paper adopts rapid annealing method with the Equation $T(N) = T_0 / 1 + \alpha N$, where $\alpha = 0.9$. Make $N=N+1$, $t=t+2$ and repeat **Step 3**. The flow chart of genetic simulated annealing algorithm is as follows [14]:

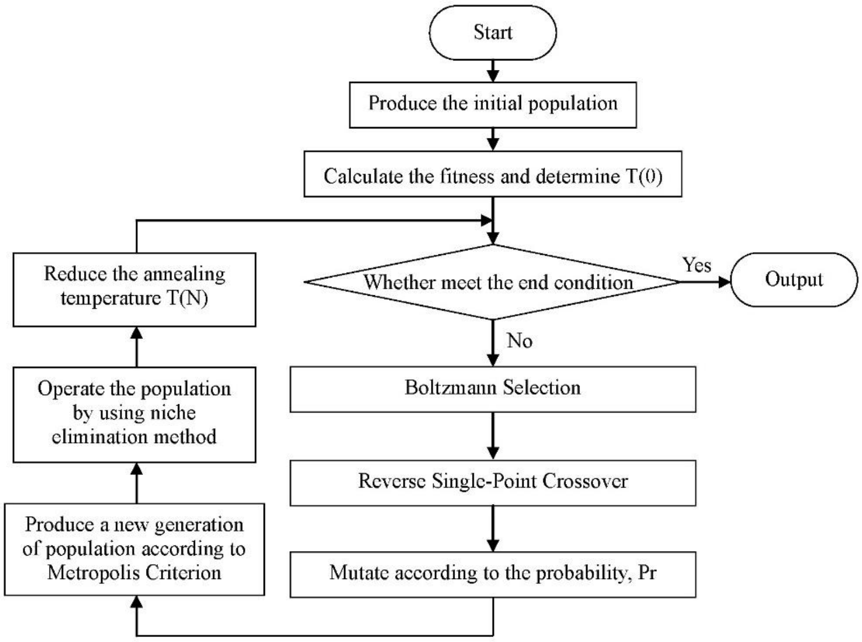

FIGURE 1 Flow Chart of Genetic Simulated Annealing Algorithm

5 Gaining solution with hybrid genetic simulated annealing algorithm

5.1 AN EXPERIMENTAL ANALYSIS ON THE LRP WITH CHANGEABLE SOFTTIME WINDOWS

There are 2 third-party logistics enterprises locating at (38*km*, 70*km*) and (55*km*, 80*km*) respectively. Both enterprises are able to provide 54*t* dispatching capacity independently and fulfil 30 customers' requirements solely. There are 5 potential dispatching canters and 30 customers with time requirements.

The five potential dispatching canters can offer some vehicles with 2 kinds of dispatching capacities, namely vehicle A of 10*t* dispatching capacity and vehicle B of 8*t* dispatching capacity. The fixed vehicle cost g=10 RMB. The unit traveling cost of 8*t* vehicle is C_{ij}=1.5 RMB/*km*, while the unit traveling cost of 10*t* vehicle is C_{ij}=1.6 RMB/*km*. The maximum traveling capacity of both kinds of vehicles is 100*km*. The unit delay expense CCS_k^l of 8*t* vehicle is 50 RMB/*h*, while the unit delay expense CCS_k^l of 10*t* vehicle is 60 RMB/*h*. the waiting cost CS_k^l of 8*t* vehicle is 40 RMB/*h*, while the waiting cost CS_k^l of 10*t* vehicle is 50 RMB/*h*. The five potential dispatching centre has the same capacity, T_r=35*t*, while the cost of establishing and running a potential dispatching centre is F_r=300. The unit dispatching cost between enterprises and dispatching centre is c_r=0.15RMB/*t.km*. The average speed of vehicle is 20*km/h*.

How to make rational arrangement of enterprise quantity and location, dispatching centre quantity and location and vehicle route to minimize the total logistics chain while fulfilling customer's time requirements.

5.2 GAINING SOLUTION WITH HYBRID GENETIC SIMULATED ANNEALING ALGORITHM

Adopt below parameters: group scale N=80, maximum iteration time max_{gen}=300, cross operator p_c=0.90, mutation operator p_{m1}=0.2 and p_{m2}=0.01, initial temperature T_0=250 and temperature dropping coefficient δ=0.90. Adopt C programming Language to fulfil the above mentioned algorithm on a computer with CPU 1.8GHz and 512M memory and solve the problem randomly for 10 times.

Judged from the result, the solutions gained from the hybrid genetic simulated annealing algorithm for 10 times are all of high quality solutions. The average total traveling distance is 480 km and average total cost is 1926.6 RMB. The calculation results are stable while the total distance of worst solution is only 6.6% longer than that of best solution, and the total cost of the worst solution is only 2.5% more than the best solution. In the aspect of calculation efficiency, the average iteration times of 10 calculations is 247.1. As a result, the efficiency is significantly high.

Among the solutions, the 5th calculation gains the solution among the 10 calculations: Enterprise 1 locating at (38*km*, 70*km*), by deploying dispatching centre 2, 4 and 5 to arrange dispatching route with time window for 30 customers, only needs to traveling 470*km* with a total cost of 1905.5 RMB.

Its searching process is indicated as Figure 2. Judged from the figure, this algorithm not only has fast convergence speed but also has outstanding global searching ability. The global most optimal gene protection strategy, use of self-adaptation mutation operation, Boltzmann mechanism from simulated annealing algorithm, control of cross and mutation operation in genetic algorithm are helpful in breaking the local limit for the sake of finding more optimal solutions.

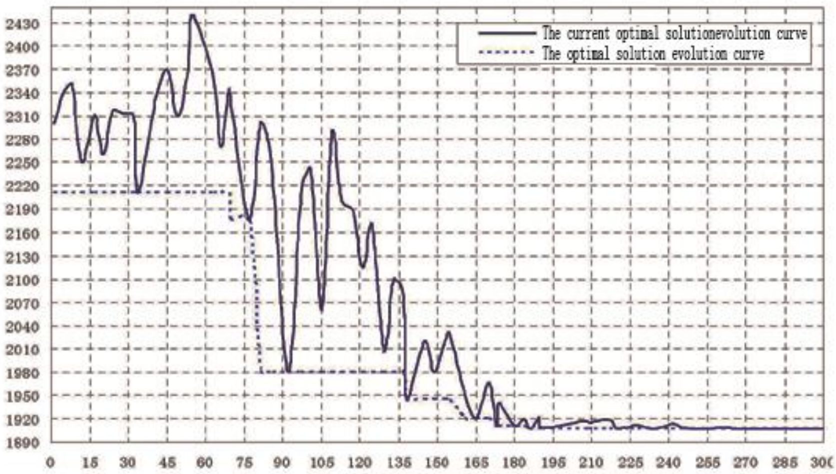

FIGURE 2 Evolutionary curve of LRPCSTW by hybrid genetic simulated annealing algorithm

TABLE 1 Final optimization of LRPCSTW by hybrid genetic simulated annealing algorithm

Dispatching centre	Location route arrangement schedule(*h*)	Dispatching amount(*t*)	Vehicle Model/(*t*)	Traveling Capacity(*km*)	Total distance(*km*)
2	0-11-10-9-8-7-6-5-0 0-0.55-0.8-1.85-2.1-3.0-3.35-3.65-4.8	9.0	*A* /10.0	96	195
	0-13-12-30-0 0-0.75-1.05-1.5-2.75	7.0	*B* /8.0	55	
	0-17-14-15-16-0 0-0.5-0.75-1.25-1.4-2.2	8.0	*B* /8.0	44	
5	0-29-24-23-0 0-0.25-0.65-1.1-1.85	6. 0	*B* /8.0	37	137
	0-22-21-20-19-18-0 0-1.6-2.1-2.4-2.8-3.05-5.0	8.0	*B* /8.0	100	
4	0-1-3-4-2-0 0-0.25-1.5-2.2-3.65-3.8	8.0	*B* /8.0	76	138
	0-27-25-26-28-0 0-1.25-1.6-2.05-2.3-3.1	8.0	*B* /8.0	62	
Total distance (*km*)		470			

TABLE 2 Final total cost of LRPCSTW by hybrid genetic simulated annealing algorithm

Dispatch centre	Fixed cost of vehicle	Fixed cost of dispatching centre	Delivery Cost between dispatching centre and customer	Delivery Cost between enterprise and dispatching centre	Total cost
2	30	300	302.1	144.4	776.5
5	20	300	205.5	55.9	581.4
4	20	300	207	20.6	547.6
total cost			1905.5 (RMB)		

5.3 THE COMPARISON OF THREE ALGORITHMS

The hybrid genetic simulated annealing algorithm is better than sole use of hybrid genetic algorithm or simulated annealing algorithm in the aspect of optimal solution, solution quality, calculation efficiency and algorithm stability.

TABLE 3 Comparison among hybrid genetic simulated annealing algorithm, GA and SA

Algorithm	Hybrid genetic simulated annealing algorithm	Genetic algorithm	Simulated annealing algorithm
Total distance(*km*)	480	517.5	498.5
Standard deviation of solution	16.12	18.45	20.03
Average total cost (RMB)	1926.6	1981.3	1997.2
Standard deviation of solution	21.75	81.46	105.57
Average vehicle quantity	7.2	7.6	7.8
The first time of gaining the most optimal solution	186	237	329
The most optimal total distance (*km*)	470	498	479
The most optimal total cost (RMB)	1905.5	1953.8	1963.2

6 Conclusions

This paper, from the aspect of logistic system integration, establishes a model for location route problem with changeable softtime windows. These models are effective in indicating the diversified feature of dispatching service under the circumstance of E-commerce as well as fulfilling customer’s personalized and diversified requirement. For the location route problem with changeable softtime windows, this paper designs the hybrid genetic simulated annealing algorithm in gaining solution. The simulated calculation result shows that the hybrid genetic simulated annealing algorithm designed by this paper is better than sole use of hybrid genetic algorithm or simulated annealing algorithm in the aspect of optimal solution, solution quality, calculation efficiency and algorithm stability.

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