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Research on Route Optimization of an Express Vehicle based on Particle Swarm Optimization Algorithm

KangjianTang[1]; ZhanWen[2]; Xue Tang[3]

School of Communication Engineering, Chengdu University of Information Technology, Chengdu, China, 610225

E-mail: wenyifan@126.com[2]

Abstract

The rise of online shopping has made the express delivery industry develop rapidly. To satisfy people's convenient shopping experience, the market has also put forward high requirements on the efficiency and convenience of express delivery. Therefore, Vehicle routing problem (VRP) is of great research value. In this paper, a set-based particle swarm optimization (S-PSO) algorithm is optimized and the optimized MyS-PSO algorithm is proposed. Then MyS-PSO algorithm is used to solve the Vehicle routing problem with time windows (VRPTW), and the MyS-PSO-VRPTW model is proposed. The experimental results show that compared with S-PSO-VRPTW, the results obtained by MyS-PSO-VRPTW on Solomon data set are superior. Besides, MyS-PSO-VRPTW was used to solve the express vehicle transport model with a time window, and the experimental results with high accuracy were obtained, which verified the feasibility of the improved algorithm in solving practical problems.

Key words：Express vehicle transport model, Set-based particle swarm optimization (S-PSO), Vehicle routing problem with time window (VRPTW)

1. Introduction

VRPTW, based on VRP, takes into account the time window constraint of the customer being served and has a good application in the fields of express route planning, logistics center location selection, garbage collection, and treatment. VRPTW, as a typical NP-hard problem, often involves large customer groups. The heuristic algorithm has good convergence and can search large space well, so it is often used to solve such problems. The use of a meta-heuristic algorithm to deal with the VRPTW problem has been widely studied and developed rapidly. For example, the interpolation heuristic algorithm proposed by Solomon, the first to propose VRPTW, gives a classic example to solve such problems.Alzaqebah et al. studied an optimized artificial bee colony algorithm that USES a limited number of differential solutions to avoid blind search with high convergence speed[1]. Akpinar et al. proposed a hybrid algorithm for the ant colony and neighborhood search that can improve algorithm diversity [2]. Osaba et al. applied a firefly algorithm to vehicle path problems with a time window and designed a novel asymptotic discrete firefly algorithm [3].

Nalepa et al. proposed an adaptive simulation algorithm to balance the exploration and utilization of the search space[4]. The aggregation degree-based algorithm and theimproved ant colony algorithm proposed by Yu Bin et al solved the multi-center VRPTW[5]. The joint optimization genetic algorithm proposed by Li Zhenping et al. solved the multi-demand mixed-integer programming model [6]. Junfei Li et al. improved the artificial bee colony algorithm and solved the time-varying velocity VRPTW[7]. Xiaofeng He et al. proposed a quantum ant colony algorithm [10]. Kirti's hybrid tabu search algorithm [11].

Particle swarm optimization (PSO) was proposed by Kennedy and Eberhart in 1995. After a long period of research and development, many variants of PSO algorithms have appeared accordingly. Because PSO has an efficient running rate and fast convergence, it can be easily realized when solving practical problems, and the application of PSO in solving VRPTW problems also has high research value. To solve VRPTW better, many PSO algorithms have been optimized. However, the variant algorithm obtained only converts the real value position to the integer value to represent the routing situation, which cannot well represent the discrete characteristics of VRPTW. The method proposed by Amini and Javanshir, T. Zhen, H. Ge et al. for dealing with VRPTW based on PSO can only solve VRPTW for a small number of customers, and their performance in dealing with large VRPTW is unsatisfactory [12][13].

To better represent combinatorial optimization in discrete space, Chen et al. improved the traditional PSO and proposed a set-based particle swarm optimization(S-PSO) based on set theory [14]. S-PSO takes the entire search space of practical problems as a universal set, and the position of each particle as a candidate solution of the problem, and each candidate solution is a subset of the universal set. As a result, S-PSO can well represent Discrete Combinatorial optimization problems (COPS). Yue-jiao Gong et al used S-PSO to optimize VPRTW(S-PSO-VRPTW)[15]. The main approach is to treat the entire search space of VRPTW as a general set of directional complete graphs whose elements are composed of extended subgraphs representing VRPTW candidate solutions. S-PSO-VRPTW can satisfy the constraints of VRPTW, and the two optimization objectives of VRPTW (the number of paths and the total time spent) are combined into one optimization objective by novel decision methods, and the objective is normalized by arctangent function. This simple and useful approach not only solves S-PSO-VRPTW well but also applies to other methods of VRPTW.

However, the speed update strategy of S-PSO only considers the local optimal effect of particles, the search rate is very slow, and the time and computing resources consumed are very large. Therefore, this algorithm is optimized, and the optimized algorithm MyS-PSO is proposed. The performance of S-PSO and MyS-PSO is compared on the Solomon dataset, and then MyS-PSO is used to solve VRPTW, and the MyS-PSO-VRPTW model is proposed to solve the problem of garbage vehicle transportation route selection in practice. The experimental results show the feasibility and superiority of the

MyS-PSO algorithm, and the final model also obtains higher accuracy, indicating that MyS-PSO is also feasible for solving practical problems.

2. Vehicle routing problem with the time window

The vehicle routing problem with time windows (VRPTW) can be described as an assumption that is receiving point c_i service time window for [e_i , l_i], delivery point c_0 time window for [e_0,l_0].So the vehicle can service$c_i$only for when time e_i to l_i. All the earliest times of the vehicles starting from $c_0$ise_0 and thelatest return time is l_0. The vehicle will not be able to serve the corresponding receiving point while outside the time window, so another vehicle will be considered to serve the receiving point.

Use variables x_{ij}^k indicates whether the vehicle $k$travels from customer $i$to customer j. If so, $x_{ij}^k = 1$. Otherwise $x_{ij}^k = 0$. Use variables y_i^k indicates whether the customer $i$is serviced by vehicle k .If so, $y_i^k = 1$; Otherwise, $y_i^k = 0$ [8][9]. The primary optimization goal of VRPTW is to minimize the number of vehicle paths, while the secondary goal is to minimize the total time under the same number of paths. The objective function formulas (1) and (2) respectively represent the number of paths and the travel time to minimize VRPTW.

$$minz_1 = v. \tag{1}$$
$$minz_2 = \sum_{i=0}^{n} * \sum_{j=0}^{n} * \sum_{k=1}^{v} * t_{ij} \times x_{ij}^k. \tag{2}$$

Formula (3) and (4) represent the vehicle k relationship with the receiving point i and receiving point j. As long as there are two receiving points on ties between the two, the vehicle for its services. Formula (5) indicates that a load of each vehicle cannot exceed the capacity constraint Q. Formula (6) indicates that each receiving point is only serviced by one car. Formula (7) indicates that all vehicles start to serve each receiving point from the delivery point. Formulas (8) - (10) defines the time constraints. t_i said the vehicle time of arrival in receiving point i. ω_i said the vehicle time of reached after point i until the e_i.s_i is the time of servicing for point i. t_{ij} said the transport time from point$i$ to point j.

$$\sum_{i=0}^{n} * x_{ij}^k = y_j^k \quad \forall k = 1, \dots, v, \quad \forall j = 1, \dots, n. \tag{3}$$
$$\sum_{j=0}^{n} * x_{ij}^k = y_i^k \quad \forall k = 1, \dots, v, \quad \forall i = 1, \dots, n. \tag{4}$$
$$\sum_{i=0}^{n} * y_i^k \times q_i \le Q \quad \forall k = 1, \dots, v. \tag{5}$$
$$\sum_{k=1}^{v} * y_i^k = 1 \quad \forall i = 1, \dots, n. \tag{6}$$
$$\sum_{k=1}^{v} * y_0^k = v. \tag{7}$$
$$t_i + \omega_i + s_i + t_{ij} = t_j \quad \forall i,j = 0, \dots, n, \quad i \ne j. \tag{8}$$
$$e_j \le t_j \le l_j \forall j = 0, \dots, n. \tag{9}$$
$$\omega_i = max\{e_i - t_i, 0\} \quad \forall i = 0, \dots, n. \tag{10}$$

Yue-jiao Gong[15] also considered defining VRPTW's spatial problem as a complete directed graph $G = (V, A)$. V is a set of nodes, $V = (C_0, C_1, \dots, C_n)$; A is arc set, $A = \{\langle C_i, \ C_j \rangle \text{ I } C_i, \ C_j \in V, C_i \ne C_j\}$. Where C_0 represents delivery point and C_i represents receipt point$i$($i = 1,2, \dots, n$). $\langle C_i, \ C_j \rangle$represents an arc from node C_i to node C_j.C_i is associated with node demand q_i (where q_i =0 of the delivery point). Arc $\langle C_i, \ C_j \rangle$ associated with service time t_{ij} . t_{ij} is represented by the Euclidean distance between node C_i and C_j.

3. S-PSO-VRPTW Algorithm

The particle position of S-PSO-VRPTW is defined as:

$$X_i = [X_i^0, X_i^1, \dots, X_i^n]. \tag{11}$$

$$X_i^d = [\langle nb_1, d \rangle, \langle d, nb_2 \rangle], nb_1, nb_2 \in \{0,1, \dots, d-1, d+1, n\}, nb_1 \ne nb_2. \tag{12}$$

X_i is represented by a set of arcs, and X_i^d on each dimension is represented by two arcs adjacent to node d. n is the number of nodes. nb_1 is the previous node of node d and nb_2 is the last node of node d.

The particle velocity of S-PSO-VRPTW is defined as:

$$V_i = [V_i^1, V_i^2, \dots, V_i^n]. \quad (13)$$

$$V_i^d = \{\langle u,v\rangle \,/\, p(u,v) | \langle u,v\rangle \in A^d\}. \quad (14)$$

In formula (14), A^d represents an arc that is adjacent to node d. $p(u,v) \in [0,1]$ represents the possibility of selecting arc $\langle u,v\rangle$ when updating speed. If $p(u,v) = 0$, the arc is not selected.

3.1 Speed update

S-PSO-VRPTW defines sets and possibilities using novel operators whose operators are redefined as shown in (15)-(18) [15].

$$c \times V_i^d = \{\langle u,v\rangle \,/\, p'(u,v) | \langle u,v\rangle \in A^d\},$$
$$p'(u,v) = \begin{cases} 1, & c \times p(u,v) > 1 \\ c \times p(u,v), & otherwise \end{cases}. \quad (15)$$

$$V_i^d + V_j^d = \{\langle u,v\rangle \,/\, max\left(p_i(u,v), p_j(u,v)\right) | \langle u,v\rangle \in Ad. \quad (16)$$

$$X_i^d - X_j^d = U^d = \{\langle u,v\rangle | \langle u,v\rangle \in X_i^d and \langle u,v\rangle \notin X_j^d\}. \quad (17)$$

$$c \times U^d = \{\langle u,v\rangle \,/\, p'(u,v) | \langle u,v\rangle \in A^d\},$$
$$p'(u,v) = \begin{cases} 1, if \langle u,v\rangle \in U^d and c > 1 \\ c, if \langle u,v\rangle \in U^d and\ 0 < c \le 1. \\ 0, if \langle u,v\rangle \notin U^d \end{cases} \quad (18)$$

Where, the coefficient × velocity operator and the velocity + velocity operator are defined as changing the value of $p(u,v)$, the position−position operator is defined as the subtraction of two sets of arcs, and the coefficient ×(position−position) operator is defined as converting the set into a set with possibility.

3.2 Location update

Before position update, first convert V^i to set $Cut(V_i^d)$, as shown in formula (19):

$$Cut(V_i^d) = \{\langle u,v\rangle | \langle u,v\rangle / p(u,v) \in Vidandpu,v \ge rand. \quad (19)$$

Where $rand \in [0,1]$ is a random number. Formula (19) is as long as the arc $\langle u,v\rangle$ corresponding probability $p(u,v)$ is not less than the $rand$, to arc $\langle u,v\rangle$ retained in the set $Cut(V_i^d)$. The $Cut(V_i^d)$ then represents the set of arcs with high probability.

Consider vehicle load limits and time window limits when building a new location $(X_i)'$. First, set $(X_i)'$ as an empty set, each car starts from the delivery point, then starts from $(X_i^0)'$ in $(X_i)'$, selects the arc adjacent to node 0, and iterates to select the next service point. Assuming that the current service point is k, the next service point $k+1$ is from arc set (20)-(22):

$$S_V = \{k+1 | \langle k, k+1\rangle \in V_i, \langle k, k+1 satisfies \Omega. \quad (20)$$

$$S_X = \{k+1 | \langle k, k+1\rangle \in X_i, \langle k, k+1 satisfies \Omega. \quad (21)$$

$$S_A = \{k+1 | \langle k, k+1\rangle \in A, \langle k, k+1 satisfies \Omega. \quad (22)$$

If nodes are meeting the requirements in S_V, select node $k+1$ from S_V. Otherwise, if nodes are satisfying the requirements in S_X, select node $k+1$ from S_X; Otherwise, choose $k+1$ from S_A; Then $\langle k, k+1\rangle$ is added into the collection $(X_i)'$. When none of the three arcs meet the requirements, the vehicle returns to the point of delivery and another vehicle starts from the point of delivery to re-serve node $k+1$. After $(X_i)'$ is constructed, X_i is replaced by $(X_i)'$, and the new position of particle i is updated.

4. MyS-PSO-VRPTW

The velocity update strategy of S-PSO-VRPTW only considers the influence of particle local optimal on velocity update, so it belongs to local PSO. Although local PSO has a strong global searching ability, its convergence speed is slow and it takes a long time to find the global optimal solution. Moreover, because only the local optimum of particles is considered, the learning factor in the formula is set as 2.0, and the learning level of the local optimum cannot be dynamically adjusted in the updating process. To solve the problem of slow convergence speed of local PSO, the global PSO is considered to balance the performance of the algorithm. The global PSO mainly considers the influence of the global optimal of particles on the speed update, its convergence speed will be greatly accelerated, and the time to find the global optimal solution will be greatly shortened. However, because the influence of individual particles in the neighborhood is ignored, the global PSO is easy to fall into the local optimal solution. If the local PSO or global PSO is used alone to update the speed, it is not the optimal solution. Therefore, MyS-PSO-VRPTW considers use the combination of local PSO and global PSO to update the speed, combined with the advantages of the two, it can avoid premature convergence and slow convergence.

Based on the characteristics of the two PSO, the speed update is defined as:

$$V_i^d = \omega \times V_i^d + C_1 \times rand^d \times \left(pBest_{f_i(d)}^d - X_i^d\right) + \left[C_2 \times \left(gBest1_{f_i(d)}^d - X_i^d\right) + C_3 \times \left(gBest2_{f_i(d)}^d - X_i^d\right)\right]. \quad (23)$$

Where, ω is the weight coefficient, which is defined as:

$$\omega_0 = log_{10}^{e_i} + rand \times min\left(log_{10}^{e_i}\right). \quad (24)$$

$$\omega_1 = 1 - \frac{\omega_0}{\sum \omega_0}. \quad (25)$$

$$\omega = \frac{\omega_1}{\sum \omega_1}. \quad (26)$$

ω_0 is a logarithmic perturbation of the start time of each node window; ω_1 is to set a larger weight value for nodes with an early start time of time window in removable nodes; ω is a normalized operation. With this setup, you can select the next window to start the node service earlier, saving more time.

C_1, C_2, and C_3 are learning factors respectively, among which C_1 measures the influence of local optimal $pBest$ on speed updating, C_2, and C_3 measure the influence of global optimal $gBest1$ and neighborhood optimal $gBest2$ on speed updating respectively. Set $C_1 = 2$, $C_2 + C_3 = 2$. Among them:

$$C_2 = 2 \times \frac{t}{T}. \quad (27)$$

$$C_3 = 2 \times \left(1 - \frac{t}{T}\right). \quad (28)$$

Where, t represents the current number of iterations, and T represents the total number of iterations. At the beginning of the iteration, neighborhood optimization plays a larger role, but as the iteration goes on, global optimization plays a larger role. Therefore, with the increase in the number of iterations, the global optimal will have more and more influence on the speed. The neighborhood optimum has less and less influence on the speed. It is helpful for the particle to search more carefully locally and finally find the global optimal solution. Considering the local, global, and neighborhood optima at the same time, the particle updating speed can be accelerated and the premature convergence can be avoided.

5. Analysis of experimental results

This section introduces the setting of experimental parameters and the specific experimental process and then analyzes the experimental results. The experiment was tested by Solomon data set, which contains 6 different types of data, namely $\boldsymbol{C}$ data set representing clustering customers, $\boldsymbol{R}$ data set representing randomly generated customers, and $\boldsymbol{RC}$ mixed data set with both $\boldsymbol{C}$ and $\boldsymbol{R}$ data sets. The time window of the class $\boldsymbol{C}$ data set is generated by the customer's known vehicle route, and the random customers generated by class $\boldsymbol{R}$ data set are evenly distributed on a square. Among them, $\boldsymbol{C1}$, $\boldsymbol{R1}$, and $\boldsymbol{RC1}$ have a small time window and delivery volume, and the service objects of vehicles are few. While $\boldsymbol{C2}$, $\boldsymbol{R2}$, and $\boldsymbol{RC2}$ have larger time window and delivery volume, and more service objects are served by vehicles. 5 categories were selected from the data set of the above categories for experiments, and tests were conducted on 25 customers, 50 customers, and 100 customers. In the experiment, the inertia weight $\omega$was initialized to 1, the learning factor C_1 was set to 2.0, and the C_2 and C_3 were dynamically adjusted according to the formula (27)-(28). The experimental results of MyS-PSO-VRPTW and S-PSO-VRPTW on data sets are analyzed and compared. Then, an express vehicle transport model is established, which is solved by MyS-PSO-VRPTW, and the results are analyzed. The experiment was run on a computer with an Intel 5 CPU and 2.79 GHz / 512 MB RAM.

5.1 The experimental results of the data set were compared and analyzed

Table 1 shows the results with 25, 50, and 100 customers, respectively. Where "NV" represents the number of routes and "TD" represents the total distance traveled by the vehicle. In the table, the result of MyS-PSO-VRPTW is the average value of the results of 20 experiments. The result of S-PSOVRPTW is the optimal result obtained.

Table 1 Comparison of experimental results

Data Set	S-PSO-VRPTW	MyS-PSO-VRPTW	S-PSO-VRPTW	MyS-PSO-VRPTW	S-PSO-VRPTW	MyS-PSO-VRPTW
	Customer number 25		Customer number 50		Customer number 100	

	NV	*TD*	*NV*	*TD*	*NV*	*TD*	*NV*	*TD*	*NV*	*TD*	*NV*	*TD*
R101	8	618.33	7.2	612.33	11.8	1060.11	11.3	1032.45	19	1657.890	19	1658.406
R102	4	475.21	4	469.58	10	927.13	9	853.21	17.8	1506.626	17.8	1506.608
R103	5	556.30	5	556.93	8	808.99	7	810.76	14	1268.591	14	1268.398
R104	4	467.25	4	449.55	6	638.83	5	637.05	10.5	1097.768	11	1103.976
R105	4	438.66	4	438.60	9.0	933.67	8	855.33	14.3	1405.275	15	1454.337
C101	3	191.81	3	194.34	5	363.25	5	339.09	10	828.937	10	828.874
C102	3	192.29	3	194.67	5	373.64	5	373.89	10	850.837	10	850.709
C103	3	194.12	3	194.12	5	368.85	4	368.29	10	886.337	11	934.557
C104	3	192.45	3	192.78	5	362.88	5	360.54	10	958.491	11	983.104
C105	3	191.81	4	193.40	5	363.25	5	372.17	10	830.435	11	882.508
RC10	4	462.39	3	439.21	8	946.66	7	849.02	15	1668.875	15	1668.729
RC10	3	353.12	3	350.80	7	827.89	7	825.45	13.8	1506.805	14	1529.504
RC10	3	334.40	3	333.54	6	714.67	6	711.23	11.7	1305.921	11.7	1305.997
RC10	3	307.31	3	305.69	5	547.95	5	541.28	10.8	1219.324	11	1230.006
RC10	4	413.73	3	371.21	8	860.50	7	860.04	14.9	1581.797	14.9	1581.909
R201	2	532.23	2	512.33	2.6	911.86	2	869.07	4	1298.276	4	1301.101
R202	2	466.97	2	462.91	2	833.90	2	833.23	3.5	1259.839	3	1241.556
R203	2	421.86	2	420.34	2	688.84	2	688.89	3	1100.799	3	1102.380
R204	1	398.32	1	362.42	2	525.78	2	525.43	3	928.040	3	928.970
R205	1	507.775	1	507.80	2	773.24	2	749.82	3	1135.703	3	1135.705
C201	2	216.98	2	215.32	2	444.96	2	529.08	3	621.777	3	621.506
C202	1	230.40	2	249.68	2	407.25	2	407.51	3	616.378	3	616.934

$C203$	1	229.89	1	226.90	2	406.71	2	406.82	3	605.836	3	605.991
$C204$	1	230.17	1	233.35	2	364.02	2	365.93	3.2	678.084	3.5	680.707
$C205$	1	297.55	1	301.60	2	445.45	2	446.79	3	600.308	3	600.597
$RC20$	2	438.70	2	425.34	3	855.61	2	855.61	4	1472.711	4	1477.556
$RC20$	2	382.94	2	382.41	2	889.50	2	887.04	4	1286.522	4	1286.113
$RC20$	1	435.29	1	437.80	2	680.46	2	680.31	3	1222.810	3	1222.330
$RC20$	1	331.40	1	332.17	2	485.54	2	485.35	3	964.591	3	965.307
$RC20$	2	407.60	1	367.83	2	775.59	2	775.61	4	1382.294	4	1388.156

In the comparison of experimental results with 25 customers, MyS-PSO-VRPTW produced one resultin $\boldsymbol{R1}$ data set that was superior to S-PSO-VRPTW (from $\boldsymbol{R101}$). One result is superior to S-PSO-VRPTW in $\boldsymbol{R2}$ dataset (from $\boldsymbol{R201}$); One result produced in $\boldsymbol{C2}$ data set is slightly worse than S-PSO-VRPTW. One result is better than S-PSO-VRPTW in $\boldsymbol{RC}$ data set (from $\boldsymbol{RC101}$); The other results are approximate to S-PSO-VRPTW. It shows that MyS-PSO-VRPTW has a certain optimization effect on instances with small data volume and narrow time window, and it can reduce the number of NV. Of the 30 results given, 29 performed well in all aspects. In the comparison of experimental results with 50 customers, among the 30 results given, MyS-PSO-VRPTW produces 10 new optimal results, and the other 20 results are close to S-PSO-VRPTW. Among them, the optimal results are from data sets $\boldsymbol{R101}-\boldsymbol{R105}$, $\boldsymbol{R201}$, $\boldsymbol{C103}$, $\boldsymbol{RC101}$, $\boldsymbol{RC105}$, and $\boldsymbol{RC201}$ respectively. MyS-PSO-VRPTW is not only applicable to the case of small capacity and narrow time window but also has a certain optimization effect for the case of a wide time window and large capacity. MyS-PSO-VRPTW produces 30 results that perform well for 50 customers. Among the experimental results of 100 customers, 1 result from $\boldsymbol{R202}$ is better than

S-PSO-VRPTW, 21 results are very similar to S-PSO-VRPTW, and the remaining 8 results are slightly worse than S-PSO-VRPTW in data set performance. Although the number of optimal results produced is small, MyS-PSO-VRPTW performs well on instances of 100 customers, especially when dealing with instances with large time Windows.

5.2 Model building solution

The express vehicle model consists of a warehouse (express sorting center) for delivering packages to 24 randomly distributed delivery points. In the model, the number of vehicles is set as 2, the load of vehicles is 20 tons, the number of examples is 30, and the number of iterations is 50.The target conditions are also set to minimize the values of NV and TD.

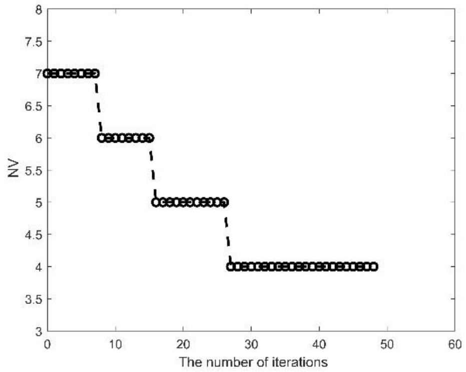

Figure 1 NV **search process diagram**

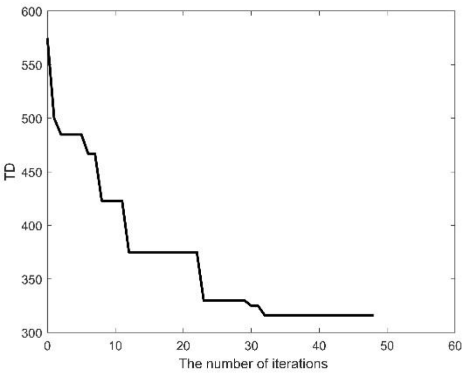

Figure 2 TD **search process diagram**

The convergence behavior of express vehicle transport model is shown in Figure 1 and 2. In Figure 1, NV decreases with the increase of iteration time, and the final result is 4. In Figure 2, TD oscillates somewhat, but the whole decreases with the increase of iteration times, and the final result is 312. Therefore, the convergence behavior of MyS-PSO-VRPTW in garbage vehicle transport model shows the practicability and feasibility of the proposed improved method in solving practical problems.

6. Conclusion

In this paper, the MyS-PSO algorithm is proposed. Different from S-PSO, which only considers the influence of the current particle optimization on the speed update, MyS-PSO adds the influence of global optimal and neighborhood optimal in the speed update strategy, and the influence coefficient of the two changes dynamically as the number of iterations increases, which is more in line with the law in the process of particle update. At the same time, the weight coefficient is modified, so that the particles with earlier service time are given priority in updating, and the service order of nodes is reasonably arranged. MyS-PSO algorithm is used to solve the vehicle path problem with the time window, and the MyS-PSO-VRPTW model is established. The performance of the MyS-PSO-VRPTW algorithm is better than that of the S-PSO-VRPTW algorithm in the experiments on the Solomon data set.Good results are obtained by using MyS-PSO-VRPTW to solve the express vehicle transport model.

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