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A Modified Tabu Search Algorithm to Solve Vehicle Routing Problem

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Abstract. A modified tabu search algorithm (TS) is designed to enhance the efficiency of TS, the relevant data structures are redesigned; in order to solve the precision of TS, the algorithm flow is adjusted under the premise of retaining the essence of TS, besides, and the modified algorithm uses three neighborhood functions to generate candidate solutions sorted to better the precision and efficiency of VRP. Comparing the efficiency with the classical TS, the computation time of the modified algorithm is obviously shortened. Mean-while, Solomon instance of different scales are tested, the result shows that the optimum solution obtained by the modified algorithm is better than the classical TS, the search time is also greatly shorten and the deviation rate is further reduced. Furthermore, comparing the experiment result with Artificial Bee Colony algorithm (ABC), the modified algorithm that can find the optimum solution is better than ABC, in addition, com-pared with the ACO algorithm, the result is not much better than the ACO algorithm, but the computing time is nearly half of the reduction, which explains TS to solve vehicle routing problem has a certain advantage and proves the effectiveness and efficiency of the modified algorithm.

Keywords: algorithm efficiency, data structure, tabu search, VRP

1 Introduction

Vehicle Routing Problem (VRP) is first modified by Dantzig and Ramser in 1959 [1], VRP refers to a certain number of customers, each with a different number of goods demand, the distribution center provides goods to customers, a certain number of vehicles are responsible for the distribution of goods, the organization of the appropriate route, which aims to satisfy the needs of customer with certain constraints (such as goods demand, delivery volume, delivery time, the vehicle capacity constraints, mileage limit, time limit and so on) [2]. For over 50 years, VRP has been one of the most concerned problems in the field of operational research, combinatorial mathematics and computer application, so how to solve VRP is extremely meaningful [3]. From the definition, it is not difficult to find that VRP is a NP problem [4]. So theoretically, how to solve VRP is valuable.

Due to the inherent complexities and usefulness of VRP, more and more scholars and researchers pay close attention to this problem and a variety of methods were presented to handle it [5, 7]. These methods can be broadly divided into two categories: exact algorithms and heuristic algorithms. The Exact algorithms, including branch-and-bound algorithm [8], k degree central tree algorithm [9], set covering method [10], etc., merely solve the optimal solution of the problem of small scale. However, VRP is a NP hard problem, as the number of customers increases, the number of alternative vehicle routing schemes increases exponentially [11]. Therefore, it is an important research direction to solve the problem with heuristic algorithm. Heuristic algorithms are usually devised to find the optimal or near-optimal solutions for VRP within a reasonable computing time.

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The commonly used heuristic algorithms include simulated annealing algorithm (SA), tabu search algorithm(TS), particle swarm optimization algorithm (PSO), ant colony optimization algorithm (ACO) and so on. TS is one of the most general theory and mature algorithms in artificial intelligence algorithms, which conforms to four criteria for good heuristics: accuracy, rapidity, simplicity, and adaptability [12]. It has become a trend to develop faster, simpler (fewer parameters) and more robust algorithms, TS algorithm in solving VRP shows the individual characteristics, which is fully consistent with these requirements. Accordingly, there are so many scholars who apply and study it in different problems. For recent survey on TS algorithm for VRP, see the following papers. Yuan established a hybrid tabu search algorithm for dynamic vehicle routing problem [13]. Ho and Haugland develop C-W heuristic algorithm to construct initial solution, then solves the VRPTW with the neighbor moving method of customer exchange (insertion) or route switching [14]. Gendreau and Laporte design a kind of TS algorithm for stochastic VRP [15]. Liu and Qi divide planning horizon and partitions dynamic vehicle routing problem into a series of static sub-problems [16]. Liu et al. present a new solution indicating method then builds a new tabu search algorithm for VRP [17]. These methods have obtained satisfactory results. However, most literatures are concerned with how to improve the accuracy of the algorithm, in today's rapidly developing society, efficiency has become a more and more important direction [18-19]. How to improve the efficiency of the algorithm under the condition of ensuring accuracy has become a research hotspot [20-21].

TS is a highly efficient search algorithm, therefore, this paper takes TS algorithm as an effective tool for solving VRP [22]. In general, TS algorithm can avoid circuitous searching by using the flexible memory mechanism and respective tabu criteria [23]. Also according to aspiration criteria, TS algorithm can assoil some good solution status which have been tabued, in doing so it can ensure the diversification search and obtain the globe optimum [24]. Based on the existing research, this paper adopts the encoding method of customer direct permutation in consideration of the discrete characteristics of the solution of vehicle routing problem. Then the accuracy of the algorithm is improved by adding other neighborhood search methods, and the data structure and the whole process of the algorithm are improved to solve the vehicle routing problem. After a number of examples of simulation results and comparison with other algorithms, it is proved that the efficiency in a reasonable amount as well as the precision with an acceptable degree are both improved, which means TS algorithm performs well in case of VRP.

The remaining parts of this paper are organized as follows. Section 2 states the problem to solve. Section 3 proposes the classic TS algorithm for solving VRP. In the Section 4, the modified TS is employed to solve VRP. In the Section 5 the experimental results show the feasibility and effectiveness of the improved algorithm. And finally, concluding remarks in Section 6.

2 Problem Formulation

Combinatorial optimization problems widely exit in the field of engineering and science [25]. As a typical class of combinatorial optimization problems, VRP can be simply stated as the problem of determining optimal routes through a set of locations and defined on a directed graph $G=(V, A)$ where $V=(v_0, v_1, \ldots, v_n)$ is a vertex set and $A=((v_i, v_j)| v_i, v_j \in V, i \neq j)$ is an arc set. Vertex v_0 represents a depot where a fleet of N_v vehicles of the same capacity are located. The value of N_v can be either prespecified or free, i.e. bounded above by a constant $N \leq n$-1. All remaining vertices represent customers. A non-negative (distance/time/cost) matrix $C=(c_{ij})$ is defined on A. Here since $c_{ij}=c_{ji}$ for all (v_i, v_j), the problem is said to be symmetric, and arcs are represented by undirected edges. A on-negative weight q_i is associated with each vertex to represent the customer demand, and naturally the weight assigned to any route may not exceed the vehicle capacity Q. Thus, the single-depot VRP aims at determining N_v vehicle routes of minimal total cost, each starting and ending at the depot, so that every customer is visited exactly once, subject to the above-mentioned constraints. A typical mathematical formulation for the single depot VRP is provided below [26]:

Minimize
$$\sum_i \sum_j \sum_v c_{ij} X_{ij}^v . \tag{1}$$

Subject to
$$\sum_i \sum_v x_{ij}^v = 1 \quad \text{for all } j . \tag{2}$$

$$\sum_{j}\sum_{v} X_{ij}^{v} = 1 \quad \text{for all } i . \tag{3}$$

$$\sum_{i} X_{ih}^{v} - \sum_{j} X_{hj}^{v} = 0 \quad \text{for all } h,v . \tag{4}$$

$$\sum_{i} q_i (\sum_{j} X_{ij}^{k}) \le Q \quad \text{for all } v . \tag{5}$$

$$\sum_{j=1}^{n} X_{0j}^{v} \le 1 \quad \text{for all } v . \tag{6}$$

$$\sum_{i=1}^{n} X_{i0}^{v} \le 1 \quad \text{for all } v . \tag{7}$$

Eq. (1) expresses the objective function of distance/cost/time minimization, Eq. (2) and (3) together state that each demand vertex be served by exactly one vehicle. Eq. (4) states that a vehicle leaves the demand vertex it has already entered. Vehicle capacity constraints are expressed by Eq. (5). Eq. (7) and (8) express that vehicle availability not be exceeded.

3 The Classic TS Algorithm to Solve VRP

The idea of TS algorithm was put forward by Glover in 1986, and a complete set of algorithms has been gradually formed. TS algorithm is a kind of intelligent and general heuristic algorithm for global optimization. The tabu is to forbid repeating the work ahead, the local neighborhood search is based on greedy thought to search continuously in the current neighborhood. Although the algorithm is easy to implement and understand, the search performance of the algorithm completely dependents on the neighborhood structure and the initial solution, which is easy to fall into local optimum. Therefore, the information in the tabu list is no longer or selectively used to search these points, so as to get rid of the local optimized point, finally to realize the global optimization.

3.1 The Solution Coding Method

When the heuristic methods are used to solve VRP, the solution coding method is the key factor which has an impact on the performance of the algorithm. Common encoding methods include 0-1 coding and sequential encoding. 0-1 coding method is difficult to describe the nature of the problem to be solved (optimization) directly, therefore, sequential encoding is usually selected. For VRP with *m* clients, the arrangement of a number of *m*, each number in the permutation represents each customer. The order reflects the sequence in which the vehicle visits the customer. This encoding satisfies the constraint that each customer point can only be accessed by the vehicle once.

3.2 Neighborhood Search Method and Tabu Object

TS algorithm is an algorithm based on neighborhood search method, so the neighborhood search method is an important step of TS algorithm. The neighborhood search method of the classical TS algorithm uses exchange operator that the two elements in the solution are randomly chosen and exchanged. Tabu objects are those local optimal solutions which are taboo in tabu list. In general, tabu objects can choose the variation of solution, vector and fitness value. On the one hand, the range of the variation of solution is smaller than that of the variation of vector or target, which may result in increasing computing time, but also greatly expanding the search range; on the other hand, and the variation of the solution and the target both have large range which reduces the calculation time and may lead to the local optimum.

3.3 TS Algorithm for Solving VRP

The steps of the classic TS algorithm to solve the VRP are as follows, the whole algorithm flow is shown in Fig. 1:

Step 1. Randomly generate an initial solution *x*, $x \in X$, set *x**=*x*, tabu list $T = \phi$, iterations *k*=0.

Step 2. If $S(x) - T = \phi$ then stop; else set *k*=*k*+1. If *k*>*NG* then stop.

Step 3. If $C(s_k(x)) = Opt\{C(s(x)) \mid s(k) \in S(x) - T\}$, set $x = s_k(x)$, update C(*x*)(C(*x*) is the optimal value of the nearest neighbor.)

Step 4. If $C(s_L(x)) < A(s,x)$, $s_L(x) \in T$ and $C(S_L(x)) < C(x)$, set $x = s_L(x)$, update C(*x*);

Step 5. If *C*(*x*)<*C*(*x**), set *x**=*x*, *C*(*x**)=*C*(*x*), *A*(*s*,*x*)=*C*(*x**).

Step 6. Update T, go to the step2.

Remarks. $S(x) - T = \phi$ represents abnormal termination, the reasons are as follows: the neighborhood is small and the tabu list T is long. Normal setting (table length T < neighborhood size)

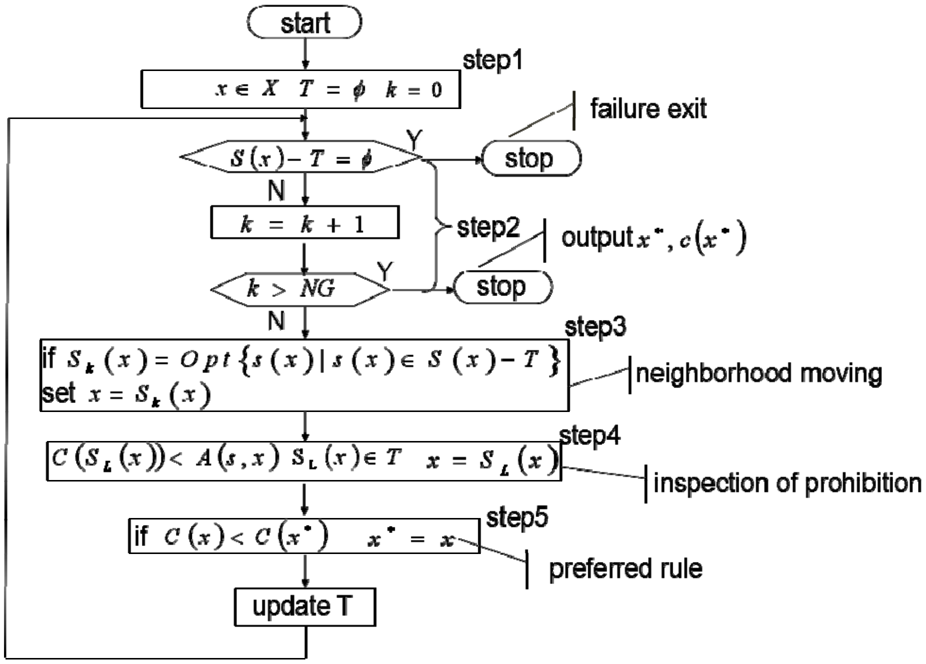


Fig. 1. Algorithm flow

4 Modified TS Algorithm

TS can avoid circuit searching by using the flexible memory mechanism and respective tabu criteria. Also according to aspiration criteria, TS can release some of the forbidden states which have been taboo, in doing so it can ensure the diversification search and obtain the globe optimum. The classical TS has some redundancy in the design process, such as the structure of the tabu list and some complex judgments, which both consume the computation time and occupy the CPU, all of these can be improved. Mainly from two aspects to illustrate the improvement of the algorithm: efficiency and accuracy.

4.1 Improvement of Algorithm Efficiency

Design of tabu list. Data structure is the basis of efficient implementation of the algorithm. Tabu list is the core of the algorithm in TS, and the structure and length of tabu list directly affect the speed and quality of the algorithm. The tabu list of the traditional TS algorithm uses an array of data structures, the operation of the tabu object is shown in Fig. 2.

(5,4)	1
(7,4)	2
(3,6)	3
(2,3)	4
(4,1)	5

(7,4)	1
(3,6)	2
(2,3)	3
(4,1)	4
(2,4)	5

(5,4)	1
(7,4)	2
(3,6)	3
(2,3)	4
(4,1)	5

(5,4)	1
(3,6)	2
(2,3)	3
(4,1)	4

Fig. 2. The comparison of tabu list change process

Suppose path coding is 2-5-7-3-4-6-1, the tabu list is a two-dimensional array $a[4][1]$, $a[i][0]$ is a neighborhood operation, a[i][1] is tabu length. If the next neighborhood operation is to exchange 2 and 4, and the value of the path 4-5-7-3-2-6-1 is better than the current solution value, then add the operation (2,4) to the tabu list and modify the corresponding tabu length. Another situation is amnesty, if exchanging 7 and 4 requires an amnesty, then need to remove (7,4) from the taboo table, the other operations in the taboo form need to move forward, the corresponding tabu length should also be reduced.

From the above transformation process know, tabu lists use an array to store taboo objects that increase the memory storage and the computing time of the algorithm. Based on the above analysis, the structure of the tabu list in this paper uses a singly linked list, as shown in Fig. 3. Then the insertion and deletion of the neighborhood operations do not have to reduce the tabu length each time.

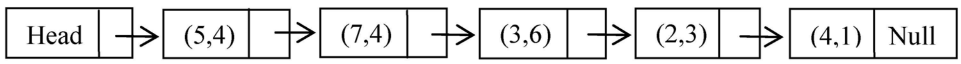


Fig. 3. A singly linked list

Suppose the next insert is (1,6), direct insertion of the tail and deleting the head node. It can be seen that it is very convenient and quick to operate.

Suppose it is necessary to amnesty (2,3), just give the first address of the (3,6) to the pointer field of (4,1). The contrast is known that the new tabu list structure is obvious for the computation time of the shortened algorithm, the process of insert is shown in Fig. 4.

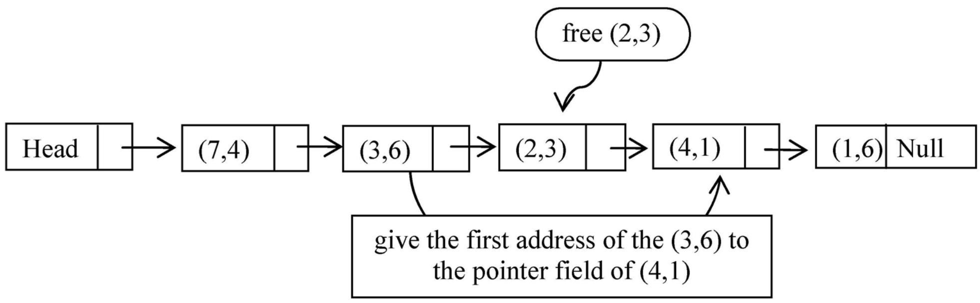


Fig. 4. The insertion of tabu objects

Bring forth the new through the old. The traditional TS algorithm is based on the current solution to confirm the candidate set according to the neighborhood function, then judge whether the aspiration criterion is satisfied. If it is satisfied, set the solution satisfied the aspiration criterion as the current solution, the corresponding object is replaced by the object that first enters the tabu table and updates the optimal state; otherwise, the tabu attribute of the candidate solution is judged. The process of judgment is as shown in Fig 1.

According to Figure 1 and the above description, it appears that the traditional TS algorithm takes a lot of time to determine whether the mobile is taboo or not, and whether the candidate solution satisfies the amnesty criterion, It is precisely because of this, the TS algorithm does not play the advantage of fast convergence. In view of this defect, the following improvement measures are put forward, which is shown in Fig 5.

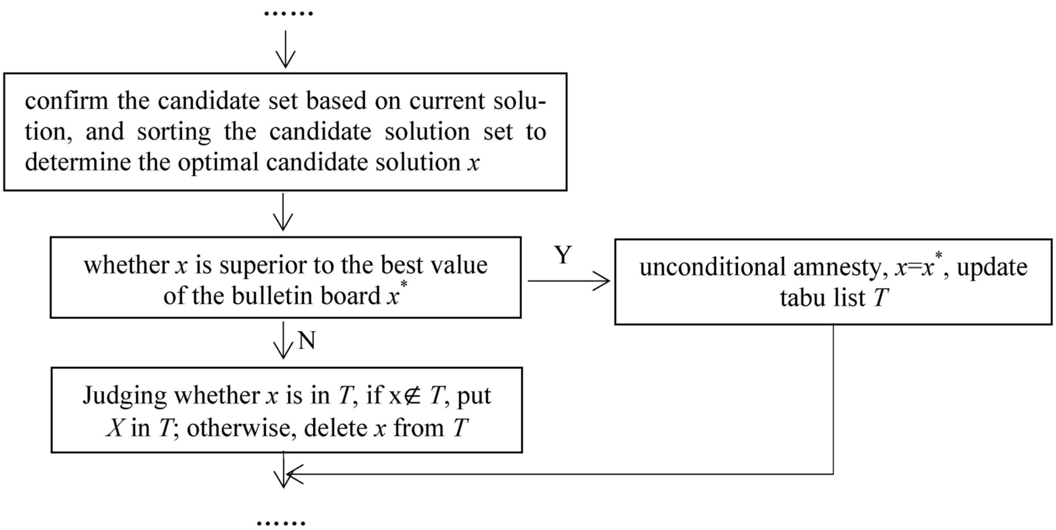


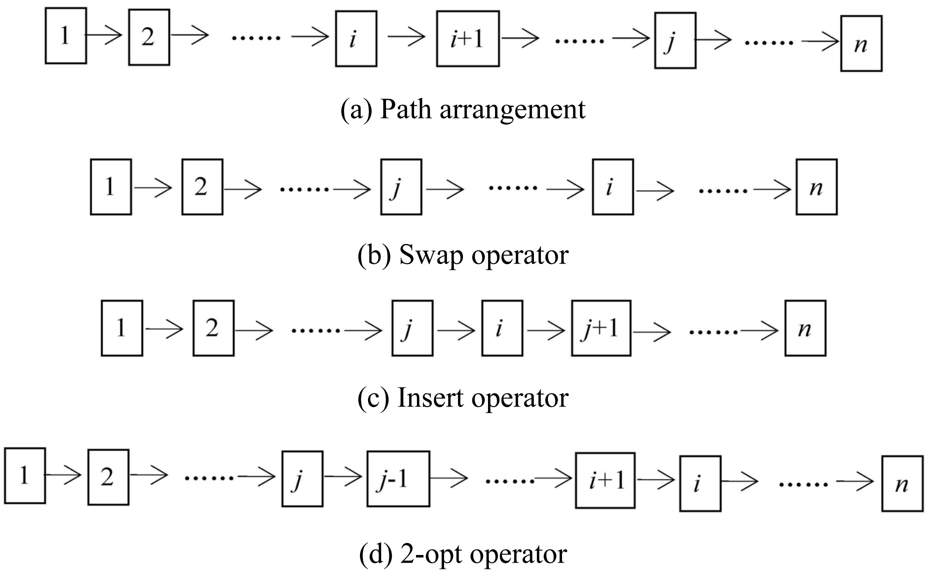
Fig. 5. The main steps of the improved TS algorithm

4.2 Improvement of Algorithm Accuracy

The accuracy of the algorithm is an important index to measure the quality of an algorithm. In TS algorithm, neighborhood search method is extended, and the tabu object is re-selected.

Extension of neighborhood search. TS algorithm is an algorithm based on neighborhood search technology, the neighborhood search method is an important step of tabu search algorithm. However, the classical TS algorithm is unreasonable in the design of encoding and tabu list, and the most important point is that the neighborhood search methods are not sufficient. The classic TS algorithm generate candidate sets by randomly exchanging two customer points, which greatly weakens the diversity of candidate sets, with the result that the breadth and depth of algorithm optimization is not enough.

In this paper, two other neighborhood search methods are added to the classical TS algorithm: the insertion method and the 2-opt method. Before the simulation test, in theory, when every neighborhood search, besides exchanging two points at random, a point in one path is also randomly inserted into another point, or invert the path between two points. As a result, it greatly enriched the content of the neighborhood search, thus improving the depth and breadth of the algorithm, so it is logical to improve the accuracy of the algorithm. The exchange operator, insertion operator and 2-opt operator is shown in Fig. 6.



(a) Path arrangement

(b) Swap operator

(c) Insert operator

(d) 2-opt operator

Fig. 6. Neighborhood search structure

Selection of tabu object. The selection of tabu objects determines tabu range, and then determines the calculation time, to a certain extent, it affects the accuracy and the searching efficiency of the algorithm. The tabu objects of the classical TS algorithm can usually choose simple solution change, change of solution vector, and change of fitness value; in the modified TS algorithm, the movement of two client nodes from one path to another is chosen as a tabu object, which can achieve a balance between the tabu range and the computing time, and the precision and the efficiency can also be taken into account.

4.3 Modified TS Algorithm for Solving VRP

According to the above ideas, the steps of the modified tabu search algorithm to solve the VRP are as follows:
Step 1. Use sequential coding to randomly generate initial solutions *x*, read the data of customers, calculate the euclidean distance between the customers, randomly generated initial solution X_{now}, set the tabu list $T = \phi$, the optimal solution for the record in the bulletin board $X_{best} = \infty$, set the termination condition *W*.
Step 2. Judge whether *W* is satisfied? If it is, end the algorithm and the output optimization results ; otherwise, step3.
Step 3. The swap operator, insert operator or 2-opt operator are randomly chosen to generate candidate set in current neighborhood set, and by means of sorting candidate set to confirm the best candidate X_{best}.
Step 4. Judge whether the candidate solution X_{best} is better than the optimal value in the bulletin board? If it is, amnesty unconditionally, replace the optimal solution in the bulletin board with the candidate solution, then update *T*.
Step 5. Judge $X_{best} \in T$? If it is not, directly put the candidate into *T*, then update *T*; otherwise, delete the candidate.
Step 6. Set *i*=*i*+1, go to the step2.

4.4 The Evaluation of the Modified Algorithm

Compared with the standard tabu search algorithm, the modified algorithm has following advantages: (1) The encoding method is more directly, algorithm strategy is relatively simple and easy to understand. (2) Tabu list uses a single linked list, although the tabu list will be repeated to store the object, but the repetition will have its strengths: not only ensures that the number of tabu objects is fixed length and do not need to reduce the length of each, but also save memory. (3) The algorithm can obtain higher quality solutions by reducing unnecessary judgments, the convergence speed of the algorithm is also fast and the calculation efficiency is higher. (4) This paper constructs a TS algorithm for VRP, which has a certain reference value for solving similar combinatorial optimization problems.

5 Experiment and Analysis

In this section, analyses are conducted on the results of different algorithms in different categories, the computational efficiency and the optimal solution of the algorithm are compared with the results of the standard database. In order to test the correctness and effectiveness of the algorithm, furthermore, an open standard test case (instances benchmark) ia used to indicate that the results are comparability and persuasion. Data from the internationally recognized VRP database (http://www.branchandcut.org/). The running environment of the experiment is Inter (R) Core (TM) CPU 2.8GHz i5-4200H processor, 4.00GB memory, Windows 10 64 bit operating system, using VC++6.0 programming.

5.1 Algorithm Parameter Optimization

Before testing, make a statement of parameter setting: algorithm parameters are divided into fixed and adjustable parameters. But TS has seldom fixed parameters, the key factors are required to be adjusted according to the size of the problem *M*. Among them, the number of iterations has a great influence on the convergence of the algorithm, it is hard to get good results if the number of iterations is set too small or too large. Set iterations depending on *M*, usually, *M* is larger, the number of iterations is more increasing. In our research, when the M is not more than 200, the number of iterations is chosen 100000 times and 10000 otherwise. Similarly, tabu length and candidate set are adjusted according to M. Each experiment is tested 30 times, and finally the average value is taken.

Refer to Table 1 for the abbreviation of the parameters in the following table.

Table 1. Parameters abbreviation

parameters	abbreviation
Best Known value	BKR
Candidate Size	CS
Tabu Length	TL
Average Value	Ave V
Average Relative Deviation	Ave RD
Average Computing Time	Ave CT
Best Computing Time	Best CT
Standard Deviation	SD
Best Value	BV

As can be seen from Table 2, the size of the candidate set can not be selected careless. No matter how big or small candidate set will both affect the quality of the solution and search efficiency. From the above comparison of the different parameters of the two instances, we can see that the improved TS can achieve better results in the accuracy and the efficiency when the candidate set is about twice the size of the problem. If we blindly pursuit precision, efficiency will be decreased and vice versa. Therefore, we adapt the candidate according to the scale of the problem in following experiments, so does the tabu length.

Table 2. Experimental results of parameter setting

Instance	BKR	CS	TL	Ave V	Ave RD	Ave CT
A-n33-k5	661	44	5	666	0.0076	2.35
		54	5	664	0.0045	3.20
		64	5	662	0.0015	4.16
		74	5	668	0.0106	5.45
A-n44-k6	937	66	6	947	0.0107	4.90
		76	6	945	0.0085	6.13
		86	6	940	0.0032	7.23
		96	6	941	0.0043	8.88
B-n78-k10	1221	134	7	1249	0.0229	19.1
		144	7	1253	0.0262	21.3
		154	7	1240	0.0160	24.8
		164	7	1272	0.0418	26.4

5.2 Comparison and Analysis of the Experiment

Comparison of efficiency with the classical TS algorithm. Because of the complicated data structure and the judging process, the classic TS algorithm has not been improved in efficiency, in this section, experimental data explain that the efficiency of the algorithm has been greatly improved, the results show in Table 3.

The accuracy of the modified algorithm is much better than that of the classical algorithm, but not shown in the Table 3, mainly to compare efficiency, so do not do too much narrative, in the subsequent table will be displayed. In Table 3, while maintaining the consistency of other parameters, the modified TS algorithm is obviously much more efficient than the classical TS algorithm. Whether the customer point is very small or great many, the modified TS algorithm can be implemented in a short time, which also shows the feasibility and superiority of the modified TS algorithm.

Table 3. Efficiency comparison results of TS algorithm

Instance	Classical TS			Modified approach		
	Best CT	Ave CT	SD	Best CT	Ave CT	SD
B-n31-k5	24.5	24.6	0.91	3.7	3.8	0.14
A-n33-k5	27.3	27.6	0.98	4.6	4.7	0.18
A-n44-k6	46.6	47.0	1.72	7.8	7.9	0.29
att-n48-k4	54.5	55.2	2.02	9.1	9.1	0.33
B-n56-k7	73.7	74.0	2.70	11.3	11.4	0.43
B-n64-k9	94.6	96.3	3.45	15.0	15.2	0.58
A-n65-k9	96.1	98.5	3.51	15.3	15.5	0.58
F-n72-k4	89.8	90.7	3.36	20.0	20.1	0.76
B-n78-k10	139.1	141.5	5.40	21.0	21.9	0.82
A-n80-k10	144.3	146.3	5.28	23.3	23.6	0.88
E-n101-k8	229.9	231.2	8.47	35.9	37.2	1.48
M-n101-k10	230.7	232.7	8.61	35.5	36.3	1.38
M-n121-k7	322.5	327.8	13.23	51.4	518	1.94
M-n200-k17	239.9	247.2	24.23	46.0	46.3	1.69
G-n262-k25	409.7	417.9	15.53	81.4	82.5	3.02

Comparison with solomon example of classical TS algorithm. In this section, the VRP instances of the modified TS and classical TS in the standard database is tested and compared. Under the premise of ensuring the number of vehicles as the first target, classical algorithm and modified algorithm are calculated to get the the same number of vehicles, specific results are shown in Table 4.

Table 4. Comparison results of the instance of solomon

Instance	BKV	Classical TS				Modified TS			
		BV	Ave V	Ave RD	SD	BV	Ave V	Ave RD	SD
B-n31-k5	672	676.088	688	0.024	8.28	676.088	678	0.009	2.31
A-n33-k5	661	662.110	670	0.014	8.82	662.110	662	0.002	0.22
A-n44-k6	937	938.207	945	0.009	3.88	935.181	938	0.001	0.89
B-n56-k7	707	718.602	747	0.057	36.10	710.916	718	0.016	1.76
B-n64-k9	861	871.666	948	0.101	49.27	857.126	868	0.008	5.05
A-n65-k9	1174	1201.739	1220	0.039	22.57	1181.687	1187	0.011	3.04
F-n72-k4	237	263.531	292	0.232	12.31	238.974	245	0.030	3.19
B-n78-k10	1221	1270.953	1325	0.085	41.64	1221.605	1240	0.016	10.27
A-n80-k10	1763	1819.765	1835	0.041	16.31	1766.615	1777	0.008	3.06
E-n101-k8	817	871.891	879	0.076	14.50	824.878	838	0.026	1.87
M-n101-k10	820	902.619	980	0.195	51.02	827.080	836	0.020	3.76
M-n121-k7	1034	1174.564	1247	0.206	61.03	1047.519	1078	0.043	30.09
M-n200-k17	1373	1512.536	1544	0.125	12.98	1391.383	1423	0.036	22.17
G-n262-k25	6119	6385.287	6526	0.067	69.86	5915.078	6075	-	60.30

In Table 4, several different instances are tested, and the results of the classical TS algorithm and modified TS algorithm for VRP are compared. The experiments have been made in a total of 9 cases. Through a concrete analysis of the classical TS algorithm and the modified TS algorithm for the optimal value, it shows that the modified algorithm is better than the standard algorithm not only in efficiency and accuracy, especially significant improvement in efficiency. And it can be found from the contrast, as the scale of the problem continues to expand, global optimization has been greatly enhanced. Especially in the instance M-n200-k17 and G-n262-k25. When the scale of the problem becomes larger, the best values of TS after improved are always better than classical algorithms. In addition, as can be seen from the Var, TS algorithm after modified has good robustness and the effect is obvious. All data of the modified algorithm are better than the current optimal solution, which further shows the effectiveness and feasibility of the algorithm.

5.3 Comparison and Analysis of the Experiment

A large number of test experiments are carried out and compared with the artificial bee colony algorithm in literature [27] and [28], it shows the superiority of the algorithm in solving the VRP problem, and the specific results are shown in Table 5.

Table 5. Comparison with other algorithms

Instance	Best Result		ABC [27]		ABC [28]		Modified TS	
	vehicles	BKV	vehicles	Ave V	vehicles	Ave V	vehicles	Ave V
A-n33-k5	5	661	5	680	5	678	5	662
A-n45-k7	7	1146	7	1215	7	1265	7	1155
A-n55-k9	9	1073	9	1145	9	1132	9	1083
A-n65-k9	9	1174	9	1223	9	1223	9	1203
A-n80-k10	10	1763	10	1934	10	1864	10	1817
E-n101-k8	8	817	8	889	8	859	8	854

As can be seen from Table 5, for these different scales, comparing with the other ABC algorithms, the modified algorithm always obtains the best-known solutions. The optimal solution of ABC in the literature [28] is better than that in the literature [27], but worse than that in the modified algorithm, which shows the effectiveness of the modified algorithm. When the scale of the problem is small, the deviation of the three algorithms is relatively small; however, the problem size becomes larger, the modified algorithm is more close to the best known solution. For the best known solution, it is usually the results of several heuristic algorithms that are nested and even with the help of some classical algorithms, but this paper only through an algorithm can find a good solution, which means that TS has a good effect on the VRP. In addition, TS is better than the bee colony algorithm for solving relatively large-scale VRP, that can also be further research and demonstration in the future.

This paper also makes a comparison with other intelligent optimization algorithms, the specific data are shown in Table 6.

Table 6. Comparison with other algorithms

algorithm	Ave V	Ave RT	Optimal path
AACAIE [29]	398.0906	29.4	The first vehicle: 1-40-39-38-36-32-33-34-37-35-1 The second vehicle: 1-14-1 8-19-20-16-17-15-13-12-l The third vehicle: 1-2-3-5-4-6-8-7-10-9-11-24-23-22-1 The forth vehicle: 1-44-48-50-47-46-45-41-42-43-49-51-30-28-25-1 The fifth vehicle: 1-21-26-31-29-27-1
DLACADC [30]	390.8920	25.6	The first vehicle: 1-14-18-19-20-16-17-15-13-12-l The second vehicle: 1-33-34-35-37-40-39-38-36-32-l The third vehicle: 1-48-50-49-46-45-41-42-43-44-47-51-30-31-29-27-24-1 The forth vehicle: 1-2-3-5-4-6-8-7-10-9-11-23-22-1 The fifth vehicle: 1-28-26-25-2-1
Modified TS	385.5974	12.2	The first vehicle: 1-11-12-14-16-15-19-18-17-13-1 The second vehicle: 1-20-22-24-47-49-50-48-45-46-44-40-41-42-43-1 The third vehicle: 1-32-33-31-35-37-38-39-36-34-1 The forth vehicle: 1-5-7-3-1-2-4-6-9-8-10-21-1 The fifth vehicle: 1-25-27-29-30-28-26-23-1

The results of this algorithm are compared with those of other algorithms, as shown in table 6. From the results of the solution, the improved TS algorithm is better than other two AC algorithm in solving the time and the quality of the optimal solution, Especially the computing time is almost twice as fast. Besides, the customer nodes of the example has the distribution characteristics of cluster classes, the modified TS algorithm still has a good solution to VRP.

6 Conclusion

In this paper, we improve the classical TS algorithm to solve VRP, through making the improvement of the neighborhood structure, tabu list and the whole flow of the algorithm. Experiment results show that the modified TS algorithm is feasible, so TS algorithm can be used as a simple, effective and feasible method to solve such problems. And also carried out on various instances indicate that the algorithm outperforms some heuristic algorithms. However, the stability of the algorithm remains to be improved in the follow-up work.

The future research work mainly focuses on more numerical experiments to further verify the performance of the algorithm such as extendibility and robustness. In addition, large scale VRP, more different types of VRP, such as multi-depot vehicle routing problems, heterogeneous vehicle routing problem, and even more application problems can be considered.

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References

[1] G. Dantzig, J. Ramser, The truck dispatching problem, Management Science 6(1)(1959) 80-91.

[2] M.-Y. Li, L.-P. Liang, Y.-X. Lu, A model of vehicle routing problem based on improved tabu search algorithm, Journal of Highway and Transportation Research and Development 34(10)(2017) 108-113.

[3] C.-H. Fu, F. Zhuo, An improved tabu search algorithm with adjacent information for capacitated Vehicle Routing problem, Journal of Systems Engineering 28(5)(2010) 81-84.

[4] M.-X. Lang, S.-J. Hu, Study on the Tabu Search Algorithm for Vehicle Routing Problem, Journal of Industrial Engineering and Engineering Management 18(1)(2004) 81-84.

[5] D. Mu, C. Wang, F. Zhao, et al, Solving vehicle routing problem with simultaneous pickup and delivery using parallel simulated annealing algorithm, International Journal of Shipping and Transport Logistics 8(1)(2016) 81-106.

[6] C.-J. Liao, C.-H. Lee, W.-Y. Chen, A hybrid tabu search algorithm for the variable periodic vehicle routing problem, Arabian Journal for Science and Engineering (2017) 1-23.

[7] R. Goel, R. Maini, A hybrid of ant colony and firefly algorithms (hafa) for solving vehicle routing problems, Journal of Computational Science 25(2018) 28-37.

[8] R.-M. Karp, R.-E. Miller, Parallel program schemata: a mathematical model for parallel computation, in: Proc. Conference Record. IEEE 8th Annual Symposium on Switching and Automata Theory, 1967.

[9] M.-L. Fisher, A polynomial algorithm for the degree-constrained minimum K-tree problem, Operations Research 42(4)(1994)

775-779.

[10] R. Bai, N. Xue, J. Chen, G.W. Roberts, A set-covering model for a bidirectional multi-shift full truckload vehicle routing problem, Transportation Research Part B 79(2015) 134-148.

[11] S.-W. Zhou, T.-H. Jiang, R.-H. Zhang, Improved genetic algorithm for VRP, Computer Simulation 30(12)(2013) 140-143.

[12] X. Liu, H. Qi, Research of dynamic vehicle routing problem based on tabu search algorithm, Journal of Wuhan University of Technology 32(2)(2010) 293-296.

[13] J.-Q. Yuan, Hybrid tabu search algorithm for solving dynamic vehicle scheduling, Computer Applications and Software 29(4)(2012) 148-150.

[14] S.C. Ho, D. Haugland, A tabu search heuristic for the vehicle routing problem with time windows and split deliveries, Computers and Operations Research 31(2004) 1947-1964.

[15] M. Gendreau, G. Laporte, A tabu search heuristic for the vehicle routing problem with stochastic demand and customers, Operations Research 44(3)(1996) 469-477.

[16] X. Liu, H. Qi, Research of dynamic vehicle routing problem based on tabu search algorithm, Journal of Wuhan University of Technology 32(2)(2010) 293-296.

[17] X. Liu, G.-G. He, Study on tabu search algorithm for stochastic vehicle routing problem, Computer Engineering and Applications 43(24)(2007) 179-180.

[18] D.S.W. Lai, O.-C. Demirag, J.M.Y. Leung, A tabu search heuristic for the heterogeneous vehicle routing problem on a multigraph, Transportation Research Part E Logistics and Transportation Review 86(2016) 32-52.

[19] S.-B. Li, Research on open vehicle routing problem based on tabu search algorithm, [dissertation] Zhengzhou: Zhengzhou University, 2010.

[20] J. Wang, B. Li, Multi-objective tabu search algorithm for vehicle routing problem with fuzzy due-time, Computer Integrated Manufacturing System 17(4)(2011) 858-866.

[21] H. Jia, Y. Li, B. Dong, H. Ya, An improved tabu search approach to vehicle routing problem, Social and Behavioral Sciences (96)(2013) 1208-1217.

[22] J.Y. Potvin, A tabu search heuristic for the vehicle routing problem with time windows; part I: tabu search, Informs J on Computing 8(1996).

[23] H. Jia, Y. Li, B. Dong, H. Ya, An improved tabu search approach to vehicle routing problem, Social and Behavioral Sciences (96)(2013) 1208-1217.

[24] H.-H. Li, Z.-Y. Xu, F.-F. Zhou, A study on vehicle routing problem with fuzzy demands based on improved tabu search, Fourth International Conference on Computational and Information Sciences 713(3)(2012) 160-164.

[25] K.M. BJ, J. Mezei, A fuzzy tabu search approach to solve a vehicle routing problem, International Conference on Artificial Neural Networks (2013) 210-217.

[26] G.-Z. Cui, Y.-Y. Niu, Y.-F. Wang, X.-C. Zhang, L.-Q. Pan, A new approach based on PSO algorithm to find good computational encoding sequences, Progress in Natural Science 17(6)(2007) 712-716.

[27] J. Yang, L. Ma, Wasp colony algorithm for vehicle routing problem, Computer Engineering and Applications 46(5)(2010) 214-216.

[28] Z.-G. Wang, H.-M. Xia, An artificial bee colony algorithm for the vehicle routing problem, Computer Engineering and Science 36(6)(2014) 1088-1093.

[29] J. Xiao, L.-P. Li, Adaptive ant colony algorithm based on information entropy, Computer Engineering and Design, 2010.

[30] J.-S. Zhang, Research on Vehicle Routing Problems of Logistics Distribution based on ant colony algorithm, [dissertation] Liaoning: Liaoning Technical University, 2014.