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TABU SEARCH ALGORITHM BASED ON INSERTION METHOD*

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ABSTRACT

This paper presents a tabu_insertion search algorithm(TIS) based on the merits of insertion method(IM) and tabu search(TS) algorithm for solving travel salesman problem(TSP). TIS combines the good local_search ability of tabu search with the good tour_construct ability of insertion method to search the solution space and to solve the combinatorial optimization problem. In this paper, we use the classical NP hard problem TSP to test the effectiveness of TIS. Results show that TIS has the good ability to jump beyond local optimum and to obtain the global optimu.

1. INTRODUCTION

Tabu search(TS) is a metaheuristic search method originated by Glover(1986)[1,2] that has proven very effective in solving large combinatorial optimization problem. TS is based on the use of *prohibition_based* techniques and "intelligent" schemes as a complement to basic heuristic algorithms like local search, with the purpose of guiding the basic heuristic beyond local optimum. Recently, TS has widely used in Scheduling, Design, Location and Allocation, logic and artificial intelligence etc. While it has some weaknesses: 1) it's search procedure depends much on the initial point, good initial point helps the search process get the optimum fast while poor initial point always get poor result or get the optimum very difficult[3]; 2) The search process is sequential, not parallel.

Insertion Methods(IM) are a class of algorithms, proposed by Rosenkrantz, Stearns and Lewis for constructing a tour visiting a set V of points in a metric space M. The performance guarantee $PG_A(n)$ of an algorithm A is the supremum over all instances with n vertices of the cost of the tour produced by A divided by the cost of the optimal tour; Rosenkrantz *et al* proved that the performance guarantee of every insertion method, given a worst_case point ordering, is at most $\lceil \log n \rceil + 1$ it always no more than 4[4]; Vineet Bafna *et al* proved that some insertion methods have a performance guarantee of $\Omega(\log n/\log\log n)$[5]; while Yossi Azar proved that the $PG_A=\Omega(\log\log n/\log\log\log n)$ with random insertion method[6]. Obviously using insertion method to construct the initial point in TS has the advantages.

According to the characteristics of the two algorithm, we combine the merits of them and proposed a TIS algorithm to overcome the first weakness of TS. We use the classical Combinatorial optimization problem TSP to test the effectiveness of TIS. Computational results show that TIS has the good ability to solve the reliance problem. Data come out of [7, 8].

2. TIS ALGORITHM

Because of the good tour_construct ability of Insertion Methods and the good local search ability of TS, TIS uses IM to construct a tour first, then TS uses this tour as the start point to begin search, it must accelerate the search process. Intensification and diversification search are two important strategies, diversification is especially important in some situations. Since TS always construct neighborhood by 2-opt or 3-opt, it only can move 2 or 3 cities and product one solution every time. Although TS has the good local search ability, it will have much difficulty to jump beyond the local optimum when it trapped in a very poor local optimum even by a fastidious turning of the parameters. So in order to overcome the first weakness of TS and to enforce the diversification search of TS, we combined the merits of IM and TS and

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designed TIS algorithm as follows:

2.1. TS[9]

2.2. Insertion Method

1) Select two cities v_i, v_k randomly from $V=\{v_1,v_2,\ldots,v_n\}$, $T=\{v_i, v_k, v_i\}$;
2) If $T=V$, stop; else determine v_j ($v_j \notin T$), and two consecutive vertices v_i,v_k($v_i,v_k \in T$) such that ($d_{ij}+d_{jk}-d_{ik}$) is minimal;
3) Insert v_j between v_i,v_k, and get a new tour $T=\{\ldots,v_i,v_j,v_k,\ldots\}$, repeat step2)

2.3. TIS

1) Construct a tour x^{now} using Insertion Methods;
2) TS starts search begin with x^{now}, when the iteration steps(best_num) of current optimal x^{best} that don't descend attains the preliminary times, select Cn vertices from x^{now}, and subtract these vertices from x^{now}, the remaining vertices construct a tour T in the previous sequence; Using the second and third step of Insertion Methods to insert the Cn vertices into T, and obtain a new tour x^{new}, $x^{now}=x^{new}$, best_num=0;
3) Repeat step 2, stop when it satisfies the stop rules.

3. RESULTS

3.1. Influences of the initial tour produced by IM

Using Insertion Methods to construct a tour, the supremum of $PG_{A=\lceil \log n \rceil+1}$ It is always less than 4. So we use the results of Insertion Methods as the starting point for TS, Computational results shows that it has the good effectiveness. The fastest searching process of gr17 is 3 steps and the fastest searching process of bays29 is 29 steps. Figure 1 and Figure 2 show the processes.

3.2. The Ability of TIS for Searching optimum

TIS has the good ability to search for the optimum. We take five problems gr17, bays29, ctsp (China Travel salesman problem), Swiss42, Berlin52 as examples. The maximum iteration steps of gr17 is 10000, the other's 20000. Results shown in table 1. In table 1 the scale of problems is from 17 to 52, TIS all obtain the best solutions published. In Berlin52, the result of TIS is 7544, that is bigger than 7542; this is because of the difference between the rounding methods, our tour sequence is same

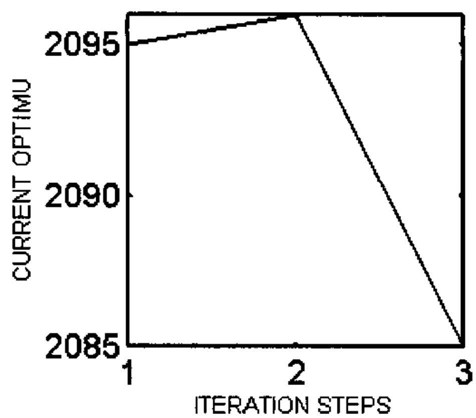

Figure 1: Best Search Procedure for gr17

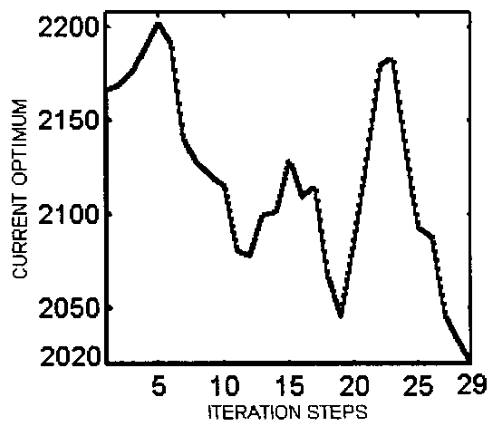

Figure 2: Best Search Procedure for bays29

as the tour provided by[7]. So combine Insertion methods and TS is feasible.

3.3. Comparison Between TIS and TS

We produced 100 tours with Insertion Methods as the initial points. TIS and TS started with these points independently to search the optimum. Results are shown as Table 2.

From table 2, we can see that TIS is superior to TS. The two methods start with the same points, TIS always can obtain the best solution published in the given steps while TS can not. Shown as Figure 3 the two algorithm begin with the same start point, when the search process fall into a local Optimum, TIS used IM to help jump beyond the local optimum. When the new starting points is constructed, the process can changes it's searching directions and starts searching from another directions. Diversification is enforced at these times. TIS obtained the optimum at the 237 iteration steps, while common TS

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Table 1: The Ability of TIS for Searching Optimal Solution

Problem	size	Best solution published	Best solution TIS	Experiment times	Probability of obtain the optimum	The best Convergence Speed (Iteration steps)
gr17	17	2085	2085	100	100%	3
bays29	29	2020	2020	100	100%	29
Ctsp	31	15404	15404	100	100%	60
Swiss42	42	1273	1273	25	100%	455
Berlin52	52	7542	7544	5	80%	1819

Table 2: Comparison of the solutions produced with TIS and TS

Problem	Problem Size	Best olution published	Method	Probability of Obtain the Optimum	Convergence Speed (Iteration steps)		
					min	max	Average
Gr17	17	2085	TIS	100%	5	3406	1372.8
			TS	6%	5	2740	1080.3
Bays29	29	2020	TIS	100%	29	8764	2196.6
			TS	49%	29	9678	3206.4
ctsp	31	15404	TIS	100%	60	11907	2706
			TS	95%	60	16904	3933.7

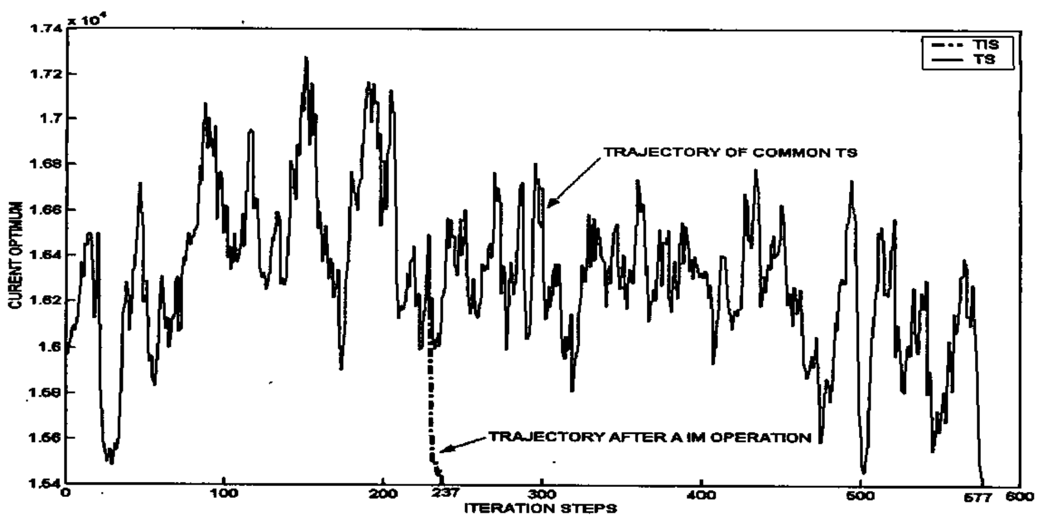

Figure 3: Comparison between TIS and TS for CTSP

need 577 steps. The probability of obtaining optimum of TIS is bigger than TS, especially when there is a very poor

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Table 3: Influence of the size of Cn for finding optimum in TIS

Problem	Size	Best solution published	Rn (Cn/n)	Experiment times	Probability of obtain the optimum	Convergence speed (Iteration steps)		
						min	max	average
gr17	17	2085	30%	100	74%	5	9859	3380
			50%	100	100%	5	6953	962.5
			70%	100	100%	3	4479	905.7
			100%	100	95%	3	9464	2672.2
bays29	29	2020	30%	100	100%	32	14773	2879.1
			50%	100	100%	29	12892	2647.8
			70%	100	100%	29	12728	2477.5
			100%	100	95%	50	15420	5473.1

local optimum such as 2090 in gr17.

3.4. Influence of the size of Cn to TIS

Cn vertices selected from the x^{now} to construct a new starting point at the time the searching process trapped in a poor local optimum. The size of Cn must have some influences to the search process. Shown as Table 3. Cn should not be too small or too large. If the Rn(Rn=Cn/n) is 100%, that is, the new start tour constructed has nothing with the previous search, we can see that the results are not very good. So TIS has some dependence on the history records in some degree. If we want to get a very fastidious value of Cn, it is not easy, while it is very easy to get a good value. In bays29, the value of Rn is 30%~70%, TIS all can get the optimum with the probability of 100%. So TIS has fewer dependences on the parameters.

4. CONCLUSIONS AND FUTURE WORK

We have presented a new search algorithm that combines Tabu Search(TS) and Insertion Methods(IM). TIS has less reliance on the initial points than TS. IM can enforce the diversification of TS and accelerate the convergence speed of the search. The average speed of TIS is faster than TS. The size of our problem is from 17 to 52 , TIS can all obtain the best solutions published. From above, we can see that TIS is a good algorithm to solve combinatorial optimization problem similar to TSP.

The future work of the author is to use TIS to solve large scale TSP with cities over 100. These work may help for demonstrating the effectiveness of the method better.

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