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Modified Reactive Tabu Search for the Symmetric Traveling Salesman Problems

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Abstract. Reactive tabu search (RTS) is an improved method of tabu search (TS) and it dynamically adjusts tabu list size based on how the search is performed. RTS can avoid disadvantage of TS which is in the parameter tuning in tabu list size. In this paper, we proposed a modified RTS approach for solving symmetric traveling salesman problems (TSP). The tabu list size of the proposed algorithm depends on the number of iterations when the solutions do not override the aspiration level to achieve a good balance between diversification and intensification. The proposed algorithm was tested on seven chosen benchmarked problems of symmetric TSP. The performance of the proposed algorithm is compared with that of the TS by using empirical testing, benchmark solution and simple probabilistic analysis in order to validate the quality of solution. The computational results and comparisons show that the proposed algorithm provides a better quality solution than that of the TS.

Keywords: Traveling salesman problem, Reactive tabu search, Tabu search
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INTRODUCTION

Traveling salesman problem (TSP) is the most visited classical combinatorial optimization problem [1, 2]. It is often used to demonstrate the efficiency of the methods of artificial intelligence in solving problems of combinatorial optimization, which are characterized by a finite number of feasible solutions. Therefore, studies on TSP will provide rich experiences and a sound basis for combinatorial optimization problem [3].

Generally, TSP can be described as given a number of cities to visit and their distances from all other cities are known; an optimal travel route has to be found so that each city is visited once and only once with the least possible distance traveled. To discover the shortest path that reaches all the cities is the main objective of the TSP [4].

TSP is so easy to describe but it is so difficult to solve, hence it has commanded much attention of mathematicians and computer scientists [2]. The difficulty of TSP is obvious when one realizes that n-city set has a search space of $(n-1)!$. Therefore, the TSP can be concluded as a simple problem with a handful of cities but becomes complicated as the number of city increases [5].

Many algorithms for solving TSP have been developed by researchers and categorized into two branches which are exact approaches and heuristic approaches. Since the researchers realized that the exact approaches are computational infeasible to obtain the optimal solution to TSP due to excessive time or storage requirement, hence heuristic approaches are extensively used [2]. It is because heuristic approaches can produce at least feasible solutions with minimum time and storage requirement for TSP.

Over the last two decades, TSP has obtained considerable attention by many researchers and various methods were proposed to solve TSP such as simulated annealing (SA) [6], tabu search (TS) [3,7] and ant colonies (AC) [8]. However, efforts to develop good algorithms have continued because there is high importance in obtaining quick approximate solutions to large size problems. A good algorithm is also important in designing an efficient implicit enumeration method for the problem and its variants. Therefore, we propose a modified reactive tabu search (RTS) algorithm to solve a TSP in this paper, which possesses high probability to lead us to optimum solution of the TSP.

Similar work by Lim et al. [3] introduced an improved TS algorithm to solve symmetric TSPs and the improved TS algorithm is an integration of two heuristic algorithms which are TS and SA. The improved TS indicated that the quality of solution is highly influenced by the initial solution [9] and it overcame this disadvantage by using SA to enhance

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the initial solution of TS. But, the performance of the conventional TS algorithm is also highly dependent on tabu list size. However, another disadvantage of conventional TS and that of the improved TS which has not been overcome so far is involving the parameter tuning in tabu list size, which until now is hard to set [10].

As a result, in this paper we propose a modified RTS algorithm to alleviate the disadvantage of the conventional TS that is tabu list size should tuneappropriately for each target problem. The modified RTS algorithm will be used for solving symmetric TSPs, in which bi-directional distances between a pair of cities are identical. The main objective of our study is to indicate the importance of dynamic tabu list in the RTS algorithm. The modified RTS algorithm then dynamically adjusts the tabu list size based on how the search is performing to achieve a good balance diversification and intensification for the TSP. With this parameter tuning, the proposed algorithm is expected to have better performance as compared to the improved TS algorithm [3] as done in the previous study.

Subsequently, this paper is structured as follows. In the coming section, a brief description of the modified RTS is given. Then the results for the seven chosen benchmarked problems of the symmetric TSP ranging from 20 to 101 cities are presented and analyzed. Finally, the conclusions and recommendation for future study are discussed.

RELATED WORK ON MODIFIED RTS FOR THE TSP

TS is one of the modern heuristic methods for large combinatorial optimization problems and is recognized as one of the effective approach in solving problem [11]. However, TS requires search parameters for efficient search process and generally the appropriate parameter value highly depends on the type of problems. This so because parameter tuning especially in tabu list size is often needed with the purpose of obtaining competitive results and requires either a deep knowledge of the problem structure or else, would be a time consuming and not always reproducible tinkering process [12].

For instance, when the search process diversification is too strong the algorithm converges too slowly if the tabu list size is too large. Alternatively, if the tabu list size is too small, the search intensification is too strong so that the algorithm may be trapped around local optima and fail to improve the current solution. Therefore, a good balance between diversification and intensification is very significant to the search process.

Due to the problem scenario, an advanced concept of TS which is the RTS was introduced by Battiti and Tecchiolli in 1994 [12] to recover the problem of TS in parameter tuning.

According to Battiti and Tecchiolli [12], RTS is one the reactive search methods and it employs two mechanisms which are feedback schemes and escape strategy. The feedback scheme builds an automatedtabu tenure that is maintained during the search process by a dynamic reaction to the repetitions, while the escape strategy employs that to take the search process out from its current position when too many configurations are repeated too often.

From the TS literature, beside initial solution, we also noticed that the success of TS algorithm depends highly on the parameters, especially the tabu list size. It cannot guarantee the absence of cycles and choosing the tabu list size without prior knowledge about the structure of the search space that can be generated in a given problem is difficult. By employing RTS algorithm, a good balance between diversification and intensification without lots of prior experience with the problem or lots of testing to determine appropriate parameter values for the problem can be achieved.

Generally, we can say that the RTS algorithm maintains the basic steps of TS except that the tabu list size is not static and it is adaptive to the problem and current solution of the search process. Specific for the TSP, we thus propose a modified version of RTS algorithm as developed by Battiti and Tecchiolli [12] and is identified as the modified RTS in this paper. Such algorithm is subsequently given and a more in-depth explanation is presented in the following section.

The Modified RTS

A modified RTS is introduced in this section. The distinct feature of this algorithm is the parameter tuning in tabu list size. A flexible tabu list size is helpful and has a great potential to produce a good algorithm. It is advisable to adjust the tabu list size dynamically based on the search performance.

The procedures for the modified RTS are different from the procedures of RTS that were developed by Battiti and Tecchiolli [12]. The difference is in the reactive mechanism. For the modified RTS algorithm, the tabu list size does not depend on the repetition of the configuration. Instead, it depends on the number of iterations when the solutions do not override the aspiration level. This type of modified RTS was employed because we observed that the repetitions of configurations in TSP are few as the number of cities increases. Hence, the conventional RTS algorithm is not applicable in solving the TSP.

Firstly, we use SA algorithm to generate an initial solution for the modified RTS algorithm. Next, we explore its neighborhood to select the best neighbor solution as the current solution by using the 2-option local search (2-opt) switch procedures. Meanwhile, we set the initial tabu list size based on the number of city of the problem and keep the memory on the search process. After that, the algorithm looks for the best neighbor solution as the new current solution for the next iteration and keeps updating the search process. The tabu list size will increase by 1 if the solutions do not improved for the specified number of iterations and will reset back to the initial tabu list size if it achieves a specified value for the tabu list size. The search process continues until the suggested stopping criterion is met. Figure 1 describes the steps of the modified RTS algorithm.

Step 1: Generate an initial solution by using SA.
Determine the total distance for the tour and set as aspiration level, Ca.
Initialize the tabu list and state the tabu restriction.
Set the tabu list size as 25% of the number of cities and nonimprove = 0.
Step 2: Apply a move to form a feasible new tour that is by swapping two cities.
Determine the total distance for the tour.
Repeat step 2 until no more neighbor solutions.
Step 3: Choose the best admission solution as the current solution.
Set the swapped cities as tabu and update the tabu list.
Step 4: If nonimprove ≥25,tabu list size increasing by 1 and go to step 5.
Step 5: If thetabu list size = 75% of the number of the cities, reset the tabu list size back to initial tabu list size.
Else go to step 6.
Step 6: Stop if reach the stopping criterion and set the best tour as the final solution
Else go back to step 2.

FIGURE 1. The Modified RTS algorithm.

The Improved TS

We use the improved TS algorithm that was introduced by Lim et al. [3] to do a comparative analysis with the modified RTS algorithm. In the improved TS algorithm, the steps of the algorithm are almost the same as that of the modified RTS algorithm, except the aspect of parameter tuning in tabu list size. The memory on the search process was not kept and the tabu list size is static based on the number of city of the problem.

IMPLEMENTATION AND RESULTS

Implementation

We implemented the modified RTS algorithm and the improved TS on seven chosen benchmarked problems of the symmetric TSP. These algorithms were developed using Microsoft Visual C++ 2008 and ran on an Intel ® Core™ i3M390@2.67 GHz CPU.

We conducted experiments on seven symmetric TSPs range in size from 20 cities to 101 cities, which codes are hagaregn20, wi29, dj38, eil51, st70, eil76 and eil101. These data sets were obtained via three different open access websites. Hagaregn20 is generated using hagaregn applet [13] while wi29 and dj38 are the TSP instances taken from the National TSPs [14]. Wi29 represents 29 cities in Western Sahara, North Africa and dj38 represents 38 cities in Republic of Djibouti, Horn of Africa. The rest of the symmetric TSPs are taken from TSPLIB library [15].According to these symmetric TSPs, the location of the cities is displayed in node coordinates. Meanwhile,the distance between two cities is computed by using Euclidean distance equation

$$d = \sqrt{(x_1 - x_2)^2 - (y_1 - y_2)^2}. \qquad (1)$$

Then Equation (1) is round off to integer numbers.

TABLE 1. Parameter settings of the modified RTS.

Parameters	Improved TS
Initial solution	Generate by using SA algorithm. Parameter set for SA: 1. Initial temperature: 10000 2. Cooling rate: 0.9999 3. Maximum iteration: 1000000
Neighborhood structure	2-opt switch procedure that is a swap of two cities
Attribute	Both swapped cities are tabued
Tabu list, Ts	Decrease tabu tenure by 1 after one iteration performed
Selection strategy	Forbidding strategy: |Ts|> 0 Freeing strategy: |Ts|≤ 0
Tabu list size	• Dynamic • Initially set as 25% of the number of cities [16]. • Increase by 1 if 25 iterations pass without finding a new best distance and continues increasing by 1 until satisfies the following conditions. • Reset to initial if a new solution was found or reaches 75% of the number of cities.
Aspiration criteria	Two aspiration criteria 1. Aspiration by objective current distance < Ca 2. Aspiration by default that is free the least distance move.
Stopping criterion	Maximum iteration: 1000.

In this paper, each problem has been solved by a number of independent runs and each runs consist of thirty trials, where in each trial a tour is determined by the modified RTS and the improved TS. The parameters of SA in initial solution generation that we used on these algorithms were determined through the empirical testing on hagaregn20. Table 1 shows the parameter settings for the modified RTS algorithm.

Results

We computed results of the relative difference of the average solution and the best solution to the optimum solution given in the websites for each algorithm to assess the performance of the modified RTS algorithm. The relative difference of the average solution to the optimum solution, *RDav* and the relative difference of the best found solution to the optimum solution, *RDbs* are expressed as in (2) and (3).

$$RDav = \frac{\text{average solution} - \text{optimum solution}}{\text{optimum solution}}. \quad (2)$$

$$RDbs = \frac{\text{best found solution} - \text{optimum solution}}{\text{optimum solution}}. \quad (3)$$

These relative differences are chosen as index performance in percentage for comparison between the modified RTS and improved TS. The smaller value of the index indicates the better performance of the algorithm. When the algorithm results in optimum solution, the value of the performance index will be zero.

The results of the relative difference for the problem are shown in Table 2. In Table 2, Opt. column shows the benchmark solutions as reported in literature. Based on the performance index, we can evaluate the quality of solutions of the modified RTS when compared to the improved TS.

TABLE 2. Results of the relative differences for the TSP.

Problem	**Opt.**	**Modified RTS**		**Improved TS**	
		***RDav* (%)**	***RDbs* (%)**	***RDav* (%)**	***RDbs* (%)**
hagaregn20	1508	0.30	0.00	2.22	0.00
wi29	27603	1.14	0.00	3.77	0.00
dj38	6656	11.86	0.00	21.41	3.34
eil51	426	6.88	2.58	8.90	4.69
st70	675	17.24	7.85	**25.69**	**16.44**
eil76	538	10.71	6.51	12.53	8.36
eil101	629	**17.86**	**10.33**	21.20	13.99

Beside descriptive statistics as calculated in Table 2, we also employed the inferential statistical test via IBM SPSS Statistics 19 which is two independent samples test to predict the efficiency of the performance of the proposed algorithm. There are two kinds of independent samples test based on the normality assumption of the data. The parametric test which is *t*-test will be used when the normality assumption is met. Alternatively, if the normality assumption is violated, then we use the nonparametric test which is the Mann-Whitney test.

We conducted the Shapiro-Wilk normality test on the thirty trials data for each problem and each algorithm. Table 3 shows results of the normality test. We identified that only the seventh TSP problem which is eil101 has fulfilled the assumption of normality since the probability value (*P*-value) for both algorithms are greater than 0.05 from Table 3. Therefore, we implemented the *t*-test for eil101 problem, while the rest of the TSP problems were tested using Mann-Whitney test. Results of the two independent samples test are shown in Table 4.

TABLE 3. Results of the normality test.

Problem	**Algorithm**	**Shapiro-Wilk (*P*-value)**
hagaregn20	Improved TS	0.002
	Modified RTS	0.000
wi29	Improved TS	0.035
	Modified RTS	0.004
dj38	Improved TS	0.932
	Modified RTS	0.004
eil51	Improved TS	0.017
	Modified RTS	0.457
st70	Improved TS	0.030
	Modified RTS	0.143
eil76	Improved TS	0.089
	Modified RTS	0.034
eil101	Improved TS	0.722
	Modified RTS	0.1499

TABLE 4. Results of two independent samples test.

Problem	**Statistical test**	**(*P*-value)**
hagaregn20	Mann-Whitney test	<0.0001
wi29		0.0005
dj38		<0.0001
eil51		0.0025
st70		<0.0001
eil76		0.0125
eil101	t-test	<0.0001

Moreover, based on the descriptive statistics in Table 2, it is clear that all the performance index of modified RTS, for both *RDav* and *RDbs*, are relatively smaller than the index performance of the improved TS. Meanwhile, based on inferential statistics in Table 4, we can conclude that the modified RTS is much better than the improved TS for each tested problem. It is because all the *P*-values for each problem are small and less than 0.05 which showed that the modified RTS algorithm is significantly better than improved TS algorithm.

As has been shown, the efficiency of modified RTS algorithm is validated via statistical approaches.

CONCLUSIONS AND RECOMMENDATION

Conclusions

In this paper, we present a modified RTS algorithm to solve symmetric TSPs. The main aim of this proposed algorithm is adjusting the tabu list size dynamically based on how the search is performing and then enhance the quality of solutions. The computational results and comparisons completely merits of modified RTS algorithm. From the statistical approaches, it has been proven that the modified RTS algorithm provides good quality of solutions in term of performance index when compared with the improved TS algorithm. As a conclusion, we can infer that the modified RTS algorithm has better performance than that of the improved TS.

Recommendation

For the purpose of enhancing the proposed algorithm, we have several suggestionsforfuture consideration. Firstly, instead of the static stopping criterion, a dynamic one may be applied with the purpose of increasing the efficiency of the algorithm. Next, it is potentially suitable to use different move procedures such as the 3-opt or multi-opt switch procedures to construct the neighborhood structure. This alternativeis able to drive the search process faster to convergence and thus, lowering the computational time. Last but not least, a diversification aspect such as multi-start may be applied to improve the quality of solutions.

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