Dynamic Local Search Algorithm for Solving Traveling Salesman Problem

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***Abstract*— In this paper, developing a new local search approach based on 2-Opt operator and its implementation for TSP solution in SA algorithm (as a global search algorithm) is purposed. It is shown that more favorable results are expected by meaningful correlation between local search approach and global search algorithm in annealing process. In order to compare the performance of the proposed operator with the 2-Opt as a basic operator, 24 benchmarks of TSP is selected from TSPLIB and both algorithms are implemented for 20 times for solving these benchmarks. The results show the improvement of error average for about 27%.**

Keywords- TSP; Local search; 2-Opt; Global search; Simulated annealing

I. INTRODUCTION

Traveling Salesman Problem is the problem of searching the shortest closed route (shortest Hamiltonian cycle) among N cities, the cities which the traveling salesman has passed one and only one time and in the end has returned to the start point. TSP problem is one of the combinatorial optimization problems and includes all aspects of a combinatorial optimization problem in addition to a very simple definition. Needed time to solve this problem using algebraic algorithms is a non-polynomial function of the problem size [1]. This is why this problem is also categorized in NP-complete problems. Traveling sales man problem has many practical applications in science and engineering such as vehicle routing, integrated circuits design, automated guided vehicles scheduling, robot control and etc.

In recent decades, many researchers have tried to solve TSP problem using metaheuristic methods such as Neural Network (NN) [2-4], Simulated Annealing (SA) [5-12], Genetic Algorithm (GA) [13-15], Tabu Search (TS) [16-18], Ant Colony Optimization (ACO) [19-21], and Particle Swarm Optimization (PSO) [22-23]. Also, integration of these algorithms is widely used, i.e., integration of Simulated Annealing and Genetic Algorithm [6, 11], Simulated Annealing and Neural Network [7] and Simulated Annealing and Particle Swarm Optimization algorithm [23].

In this paper, solving the traveling salesman problem using modified 2-Opt [25] operator in Simulated Annealing algorithm is proposed. Consequently, a new operator for local searching is proposed. So in Section 2, basic simulated annealing algorithm is defined. In Section 3, with redefinition of 2-Opt operator, a dynamic operator is introduced according to the existing conditions in simulated annealing algorithm. Simulation results and their comparison on presented benchmarks in TSPLIB site [25] are presented in Section 4 and the authors' suggestions and conclusion are given in the final section.

II. BASIC SIMULATED ANNEALING ALGORITHM

The idea of simulated annealing was first presented by Nicholas Metropolis in 1953 as a modified Monte Carlo integration method [26]. He resembled the paper to the material which is made by cooling after heating of them. Simulated annealing for integrated optimization applications such as Travelling Salesman Problem was introduced the first time by Kirkpatrick et al. [5] in 1983 inspired from Metropolis algorithm. This algorithm is adapted from the cooling process which metal is heated to its melting point and then cools gradually. This temperature decrease is such that the system is approximately in thermodynamic equilibrium. During the process of gradual reduction of temperature, system becomes more regular and moves toward steady state with minimum energy. The main Metropolis scheme in determination of temperature and the initial energy state of thermodynamic system is that if the energy changes are negative, new structure (energy and temperature) will be accepted but if the energy changes are positive, the acceptance is subjected to the Boltzmann distribution function with $\exp(-\Delta E/\kappa_B T)$ in which κ_B is Boltzmann's constant with positive value [27]. The whole process will be repeated until the energy is minimized and the system reaches a steady state. This algorithm is suitable for solving mixed discrete problem and complicated nonlinear problem. In simulated annealing algorithm, cooling schedule parameters have role of process controlling in the search algorithm. Cooling schedule has three parameters which are:

1) Initial temperature (T_0).

2) Convergence criterion or Freezing temperature (T_F).

3) Cooling function.

In this algorithm, if initial and final temperature are appropriately defined and temperature reduction is selected so that the slope of temperature reduction curve is less than the slope of $T_{K+1}=T_0/(1+\log(k+1))$, then simulated annealing algorithm will converge to the absolute minimum when the number of iterations (k) tends to infinity [28] but the temperature reduction based on this slope requires a lot of computational times. So faster cooling functions are used such as $T_{K+1}=\alpha.T_K$ in which $0.8<\alpha<1$ or $T_{K+1}=T_K/(1+\log(k+1))$. The number of temperature change steps from melting temperature to freezing point will have a considerable reduction using these functions and subsequently the probability of passing through suitable temperature range for optimum search will also decrease.

Therefore, in each temperature, it is tried to give sufficient search time to the algorithm in suitable temperature range by defining several iterations in inner search loop including new generation, evaluation and decision making. In the algorithm, the number of repetitive frequencies in a constant temperature is named Markov Chain Length. What distinguishes this algorithm in discrete or continuous problems is how it generates a new generation based on the current generation. In continuous problems, some definitions such as neighborhood radius are used for production of new generation in a neighborhood of the current generation, so that the next generation will be produced by determination of random changes around the variables of the current generation with value of the neighborhood radius. In simulated annealing process, neighborhood radius is reduced proportional to temperature reduction in order to increase convergence speed. The same production of new generation is performed in discrete problems using some operators which generate the next generation implicit in a radius of the neighborhood of current generation. These operators are also called Move Set. Some of the effective operators in generation of discrete problems such as Traveling salesman are the following. In a TSP problem we need a means of representing the tour. Each tour can be described by a permuted list of the numbers 1 to N, which represents the cities in TSP.

1) Switching: Randomly selects two nodes from tour and replaces with each other.

2) Translation: randomly selects a portion of a tour and enters between another randomly selected node.

3) Inversion: Or 2-Opt which is a state of k-Opt operator. In 2-Opt move, the tour is broken into 2 parts, then the 2 parts are reconnects in the other possible way.

4) Lin-Kernigan, which is a kind of variable-Opt, was presented in 1973 [29] and many researchers have tried for efficient implementation of this operator. One of the most efficient LK operators is proposed by Helsguan [30], which employs a number of important innovations including sequential 5-opt moves and the use of sensitivity analysis to direct the search.

In fact, these operators are used as local search approaches in global search approaches such as Tabu search, Simulated annealing and Genetic algorithm.

III. DYNAMIC 2-OPT

In this paper, a new operator inspired by 2-Opt and the neighborhood radius concept in generation of continuous problems is developed. 2-Opt is used as the base operator in definition of this operator but in this new definition, the operator's behavior will change dynamically according to the behavior of algorithm in search process. Kirkpatrick et al. [5] have emphasized that simulated annealing algorithm will show a more efficient behavior in its intelligent search process in the temperature range of the annealing process, called as intermediate temperatures. With this explanation, it will be seen in TSP problem solving that the algorithm is not able to do direct search in initial stages of algorithm and initial temperatures, and will make mistake in its orientation. But over time and its entrance to the algorithm intermediate temperature range, it will have a suitable orientation for achieving the global minimum in addition to have the probability of passing through local minimums and hill-climbing ability. After temperature reduction and passing through intermediate range it will be seen that in the simulated annealing algorithm is only able to perform minor changes in TSP problem solving to improve goal function. In definition of the new operator, different steps of the search algorithm has been considered and change ranges of the 2-Opt operator is restricted according to each step and proportional to its requirements.

In this method, 2-Opt operator starts dynamically from its local search behavior at the beginning of the algorithm and with reduction of effective amplitude in its inversing operation performs a better search according to the algorithm progress and temperature reduction in comparison with its normal operation. In fact, the idea of such definition from local search operator of SA algorithm is how this algorithm converges to the absolute minimum in its search process. In SA algorithm, hilling up possibility is reduced by passing time. In fact searching with long steps in the search space of a problem has less chance for acceptance. Thus, acceptance chance and convergence to the improved results have been provided by reduction of inversion amplitude in 2-Opt operator.

In definition of 2-Opt operator, two random numbers (i, j) are produced which their generation amplitude is the number of cities in TSP. then the tour sequence is reversed between these 2 nodes. In fact, in Dynamic 2-Opt both nodes are not selected randomly. i is a random number and j is a random number in neighborhood radius of i. Using this technique, both indices for reversing operation will have correlation with each other in addition to randomly selection.

This correlation quantity increases with temperature reduction. At the beginning of the SA algorithm when the temperature is high, neighborhood radius is equal to half number of cities (N/2) in Traveling Salesman problem and the behavior of 2-Opt operator is like normal condition.

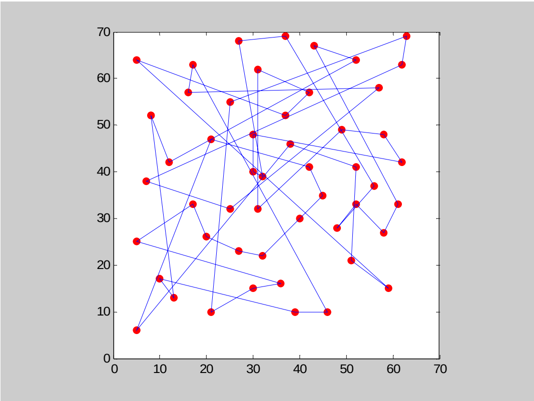

Figure 1. Sample Tour for *eil*51 at the beginning of SA algorithm

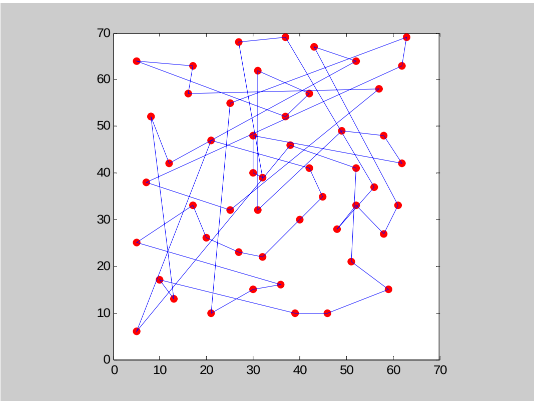

Figure 2. Improved by Dynamic 2-Opt in one operation

But with temperature decrease in next steps, this neighborhood radius will reduce with a multiplication of 0.9. Dynamic 2-Opt operator Pseudo-Matlab code is illustrated as follows.

```
NewTour =  Tour;
i = round(rand*N + 0.5);
j = round((rem((rand*(N/2)*NR + i) , N)) + 0.5);
2-Opt_Index = (min([ i ; j]):max([ i ; j]));
NewTour(2-Opt_Index) = fliplr(Tour(2-Opt_Index));
```

Where:

N = Number of cities in Traveling Salesman problem.

NR = Neighborhood Radius.

With this method in lower temperatures *j* will be generated in nearer radius to *i* and will have a narrower search space. Therefore, the operator's behavior will be dependent to the algorithm's temperature and will change dynamically during the search process based on the algorithm‘s condition. In other words, with this operator a correlation is developed between local search algorithm and global search algorithm which will result in a more intellectual search.

For instance, Figure 1 illustrates *eil*51 TSP benchmark. In this figure there is a Tour at the beginning of the SA algorithm. Figure 2 shows the results of Dynamic 2-Opt when operates in Tour which is shown in Figure 1. By this move set, the tour length is improved by 10% in one operation (Tour length in Figure 1 is 1123, which is improved to 1016 in Figure 2).

Figure 3 shows a sample condition near the end of SA algorithm which is improved by Dynamic 2-Opt in Figure 4. In these four figures, we explain the requirement of SA algorithm to improve the tours according to the algorithm's progress. In other words, the SA algorithm needs to have a long step in 2-Opt operator to improve the search results but during the algorithm progress it is required to reduce the neighborhood radius in generation of 2-opt index in order to improve the local cross. At the beginning of search process, when the neighborhood radius is N/2, the possible amplitude for generation of *j* is such that all other nodes are possible to be selected. But by passing time in search process, the amplitude of generation of node *j* (second selection) will decrease proportional to temperature reduction and will make inversion possible in smaller range. This matter is provable in discussion of the algorithm's behavior in TSP problem solving in such a way that at the beginning of the algorithm, the inversion operation with wide change ranges is efficient in passing through local minimums and proper orientation in optimal tour selection and also the reduction in inversion change range in operator will provide the possibility of minor changes at the end of the process.

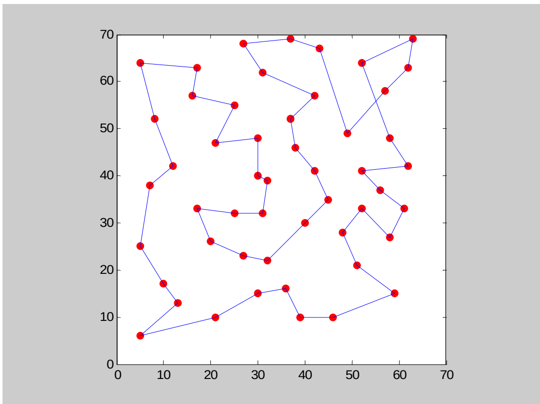

Figure 3. Sample Tour for *eil*51 near the end of SA algorithm

The results obtained by this operator are compared with 2-Opt normal performance in the next section, which declares the acceptable performance of this operator in SA algorithm.

IV. Result and Comparison

In this section, performance of two operators "2-Opt" and "Dynamic 2-Opt" is compared in simulated annealing

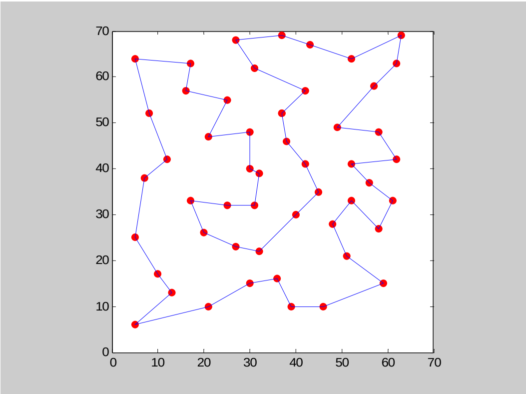

Figure 4. Figure 3 improved by Dynamic 2-Opt in one operation

algorithm process under the same conditions. The initial temperature is defined so that the initial acceptance rate in a first Markov chain is about 50%. Final temperature is defined in a condition that the acceptance condition in internal loop will not be concluded for any variable during two consecutive Markov Chain. Also the cooling function $T_{k+1}=\alpha^*T_k$ is used in this algorithm so that $\alpha=0.9$. The proposed algorithm is implemented for two operators of 2-Opt and Dynamic 2-Opt for 24 benchmarks listed in TSPLIB [46] for 20 times and the results are compared in Table I with [7] and [9].

It is quite easy to realize that using the new operator (Dynamic 2-Opt) has improved performance of SA significantly. The optimal values given by the TSBLIB site, for each case are listed in the second column of the table. We have compared the best, the worst and the average of the error in the results obtained by the new approach with other results given by other works (if the best and/or the worst cases are available). The error percentage is calculated by:

$$\delta = 100\,(E - E^*) / E^*$$

where E* is the optimal (minimum) energy.

The first method chosen for comparison is the Constructive Optimizing Neural Network (CONN) proposed in [2], for which it is claimed that all runs has led to the same results, so that the best, the worst and the average of the solutions are the same. We have compared our results with the best and the average error percentages of the results given in [4] for its memetic neural network.

Table I demonstrates an enhancement in the results of SA algorithm implemented by "Dynamic 2-Opt" operator rather than regular "2-Opt" operator. As it's clear to see, the results of implementing the "Dynamic 2-Opt", has gotten 0.35 percentage improvement in the average error of the best results, 0.49 percentage improvement in the average error of the average results and finally 1.1 percentage improvement in the average error of the worst results.

Also Table I states that the results of SA algorithm with regular 2-Opt operator have obtained 2.14 percentage improvement in the average error of the average results (for 24 benchmarks) in comparison with CONN method, which indicates the high ability of SA algorithm for solving these kind of problems. As well, the 2.71 percentage improvement in implementing the SA algorithm with Dynamic 2-Opt operator toward CONN method, predicates the possibility of enhancement in SA algorithm.

As well, Table I includes the comparison between "memetic neural network" results [4] and SA algorithm results implemented by "2-Opt" and "Dynamic 2-Opt" operators that respectively indicates 1.41 and 1.88 percentage improvements in the average error of the best results and 1.76 and 2.41 percentage improvements in the average error of the average results.

To accomplish our comparison, we have added another set of methods from [11], in which 11 methods are run on 24 benchmarks from lin105 to rat783. For brevity purpose, the problems are categorized into 3 groups, namely: small, medium and large size benchmarks. The results are given in Table II, where the average of the average error in each group is shown. For detailed explanation of each method see [11].

In [10], the result of ABD (Annealed Bounded Demon) algorithm is better than the results of other SA algorithm's family. In this paper, the SA algorithm with implementing "2-Opt" and "Dynamic 2-Opt" operators respectively has obtained 1.05 and 1.28 percentage improvements in the average error of the average results for small size problems.

In medium size problems, the SA algorithm with "2-Opt" operator shows weaker results than ABD algorithm (0.41 percentage error more) but with using the "Dynamic 2-Opt" operator, the amount of improvement in the average error of the average results has reached 0.44 percentage that it's an evidence of good performance of proposed algorithm.

For solving this problem a PIV computer with 1.8GHz CPU and 512MB RAM is used in MATLAB7.7 environment.

As it shown in Table II, with definition of Dynamic 2-Opt the average of SA algorithm results are improved 27% which shows the effect of the redefinition of 2-opt operator in this paper on efficiency of SA algorithm.

V. Conclusion

In this paper, a new definition of 2-Opt operator was presented, which will result in correlation of local search approach and global search algorithm. Using Simulated Annealing algorithm and proportional with temperature reduction in this algorithm, a new operator is designed for generation of new generation in neighborhood of current generation, so that its operation is variable during search process and will orient the local search method according to temperature reduction and the algorithm's correlation. This algorithm is implemented on 24 benchmarks of TSPLIB site for 20 times and its results are categorized in order to be compared with the base algorithm and other algorithms' results. The obtained results show the improvement of SA algorithm efficiency up to 27% which proved the performance of this operator.

Application of this operator in global search algorithms such as Ant colony or Genetic algorithm may have a good effect on their efficiency. Also since recent researches are focused on integrated metaheuristic methods, an integration of this method with others may result in better conclusions.

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TABLE I. COMPARISON BETWEEN D2-OPT AND OTHER METHODS FOR 24 BENCHMARKS
(THE AVERAGE Δ OF THE AVERAGE ERROR IN 20 RUNS)

TSP Benchmark	Optimal Solution	With 2-Opt			With Dynamic 2-Opt			CONN [7]			Memetic neural network [9]	
		Best δ	Average δ	Worst δ	Best δ	Average δ	Worst δ	Best δ	Average δ	Worst δ	Best δ	Average δ
lin105	14379	0	0.9	2.55	0	0.18	0.87	0.38	0.38	0.38	0	0.34
pr107	44303	0.05	0.51	1.51	0	0.3	0.71	2.77	2.77	2.77	0.14	0.67
pr124	59030	0	0.68	2.22	0	0.29	0.88	1.74	1.74	1.74	0.26	1.52
pr136	96772	0.67	1.98	3.53	0.37	1.42	2.33	2.27	2.27	2.27	0.73	3.1
pr144	58537	0	0.94	4.02	0	0.93	4.15	2.34	2.34	2.34	-	-
pr152	73682	0.21	0.85	2.15	0	0.91	3.93	0.79	0.79	0.79	1.57	2.6
u159	42080	0	1.62	3.8	0	2.38	6.34	-	-	-	-	-
rat195	2323	1.76	3.18	4.69	0.6	2.04	3.18	5.64	5.64	5.64	4.69	6.89
d198	15780	0.2	0.86	1.66	0.37	1.22	2.64	4.16	4.16	4.16	-	-
pr226	80369	0.99	1.68	4.62	0.58	1.31	1.94	1.93	1.93	1.93	-	-
gil262	2378	1.35	2.34	3.24	0.92	1.98	2.94	-	-	-	-	-
pr264	49135	0.54	2.3	5.45	0	2.11	5.62	3.58	3.58	3.58	-	-
pr299	48191	0.5	1.92	4.32	0.6	1.69	3.92	4.8	4.8	4.8	-	-
lin318	42029	1.32	2.77	4.23	1.2	2.45	3.05	-	-	-	3.63	5.51
rd400	15281	1.26	2.66	4.25	0.84	2.13	3.30	5.77	5.77	5.77	-	-
pr439	107217	1.06	3.44	7.31	1.05	1.78	3.24	6.03	6.03	6.03	-	-
Pcb442	50778	2.06	4.68	7.00	1.86	2.81	3.68	5.77	5.77	5.77	3.57	6.08
d493	35002	1.58	2.47	5.07	1.21	2.10	2.82	5.83	5.83	5.83	-	-
u574	36905	1.86	2.75	4.46	1.40	2.04	3.03	5.90	5.90	5.90	4.09	5.08
rat575	6773	3.47	3.94	6.84	1.89	2.91	4.08	6.72	6.72	6.72	4.31	5.47
p654	34643	0.67	1.81	5.94	0.80	1.70	3.48	4.13	4.13	4.13	2.51	5.13
d657	48912	2.59	3.36	4.15	1.82	2.50	3.32	7.58	7.58	7.58	3.97	5.02
u724	41910	3.16	3.62	4.07	1.93	2.44	3.11	6.97	6.97	6.97	4.64	5.36
rat783	8806	2.12	3.05	5.59	1.45	2.87	3.70	7.59	7.59	7.59	5.46	5.95
Average		1.14	2.26	4.28	0.79	1.77	3.18	4.41	4.41	4.41	2.83	4.19
With 2-Opt		-	-	-	1.14	2.26	4.28	1.18	2.27	4.35	1.42	2.43
With D2-Opt		0.79	1.77	3.18	-	-	-	0.80	1.70	3.04	0.95	1.78

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TABLE II. COMPARISON OF D2-OPT WITH OTHER METHODS GIVEN IN [10] (THE AVERAGE OF THE AVERAGE ERROR IN 20 RUNS)

Algorithms in [10]	Average Error in Small Size			Average Error in Medium Size		
SA (Simulated Annealing)	2.76			3.25		
TA (Threshold Accepting)	5.37			4.18		
RRT (Record-to-Record Travel)	4.22			6.79		
BD (Bounded Demon)	5.26			4.44		
RBD (Randomized Bounded Demon)	4.33			9.38		
AD (Annealed Demon)	3.24			3.27		
RAD (Randomized Annealed Demon)	2.82			4.38		
ABD (Annealed Bounded Demon)	2.65			2.77		
RABD (Randomized Annealed Bounded Demon)	2.63			3.64		
ADH (Annealed Demon Hybrid)	2.97			2.95		
ABDH (Annealed Bounded Demon Hybrid)	2.69			2.89		
MSSA (the proposed method)	Min.	Ave.	Max.	Min.	Ave.	Max
With 2-Opt	0.54	1.60	3.42	1.98	3.18	5.47
With D2-Opt	0.33	1.37	3.04	1.43	2.33	3.38

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