Using Local Searches Algorithms with Ant Colony Optimization for the Solution of TSP Problems

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ABSTRACT

Swarm intelligence is a relatively new approach to problem solving that takes inspiration from the social behaviors of insects and other animals. Ants, in particular, have inspired a number of methods and techniques among which the most studied and successful is the general-purpose optimization technique, also known as ant colony optimization, In computer science and operations research, the ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. Ant Colony Optimization (ACO) algorithm is used to arrive at the best solution for TSP. In this article, the researcher has introduced ways to use a great deluge algorithm with the ACO algorithm to increase the ability of the ACO in finding the best tour (optimal tour). Results are given for different TSP problems by using ACO with great deluge and other local search algorithms.

KEYWORDS: Travels Salesman Problem (TSP), Ant Colony Algorithm (ACO), Great Deluge Algorithm, Optimization, opt-algorithm.

1. INTRODUCTION

Ant Colony Optimization (ACO) uses the behavior of ants for finding optimal paths for TSP problems. Adding Great Deluge algorithm to ACO increase the efficiency of ACO to get a better result in a minimum time. Great Deluge algorithm generates new tour from an old tour by finding neighbor of the cities in the tour by using local search methods, in this article we used 2-Opt algorithm and N-Shift.[1].

2.Travelling Salesman Problem (TSP)

TSP is an NP-hard problem in combinatorial optimization [1]. Given a set of cities in which every city must be visited once only and return to the starting city for completing a tour such that the length of the tour is the shortest among all possible tours [1, 2]. In general there are two different kinds of TSP, the Symmetric TSP (STSP) and the Asymmetric TSP (ATSP). the number of tours in the ATSP is (n-1)!, Whereas it is (n-1)!/2 in STSP for n

cities. Formally, the TSP is a complete weighted graph G (N, A) where N is the set of cities which must be visits, and A (i, j) is the set of arcs connecting the cities together [1]. The length between city A_i and A_j can be represented as d_{ij} . Thus the optimal (minimum length) tour to the TSP can be found as shown below.

$$Btour = \left(\sum_{i=1}^{n-1} d_{p(i) \, p(i+1)}\right) + d_{p(n) \, p(1)}$$

Where p is a probability list of cities with minimum distance between city (p_i and p_{i+1}) [2, 3].

2.1 Ant Colony Optimization (ACO) and TSP

The Ant Colony Optimization (ACO) heuristic is an inspiration of the real ant behavior to find the shortest path between the food and ant's nest [1, 2]. As shown in figure 1.

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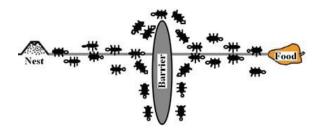


Figure (1): ACO

The behavior of each ant in nature

- First each ant randomly, laying down a pheromone trail in its path for food searching.
- If any ant founds a food, return to the nest laying down a pheromone trail
- If in a path the pheromone increased the other ant follow that path.

ACO use the same procedure to find the optimal (minimum length) path to the TSP problem, in a given set of cities at first each ant use the pheromone trail to choose a nearest city to its current position and adds cities one by one until it complete the tour by visiting all cities and back to the starting city. After each ant complete its tour ACO update the pheromone trail. ACO pseudo code is shown below.

Initialize

Loop

Each ant is positioned on a starting node

Each ant applies a state transition rule to incrementally build a solution and a local pheromone updating rule Until all ants have built a complete solution

A global pheromone updating rule is applied Until end condition

2.2 Great deluge algorithm

It is a comprehensive approach for solving optimization problems. It use local searches algorithm to find the neighbor of the current solution and compare it with the fitness of the best solution and the water level (WL) if its better it replaces common solution (New_solution) with best results (Best_solution). This action continues until stop conditions is provided [4]. Great Deluge pseudo code is shown below.

Choose an initial configuration as Old_solution and Best_solution

Choose **D** WL and WL

For n=0 to # of iterations

Generate a New_ solution from neighbor of Old_ solution

If Fitness (New_solution) <WL

If Fitness (New_solution) < (Best_solution)

Old_solution := New_solution

End If

End If

 $WL = WL - \Delta WL$

End For

2.3 Finding neighbor for Great Deluge Algorithm

In this paper two methods are used to find neighbors to be use by Great Deluge algorithm which are (N-Shift method and 2-Opt method).

2.3.1 N-Shift:

This method changes the order of cities in the current path. It chooses a city and change with all other cities in the list gradually as shown below.

Initial A=> B=> C=> D=>E=>F

Step1 B=>A=> C=> D=>E=>F

Step2 C=>B=> A=> D=>E=>F

N-Sift pseudo code is shown below for i=1 to number of cities -1

for j=i+1 to number of cities

replace the position of city(i) and city(j)

End End

2.3.2. 2-Opt algorithm

The 2-opt algorithm basically removes two edges from the tour, and reconnects the two paths in reverse order. This is often referred to as a 2-opt move [5,6,7].

The figure 2 is showing that the tour {1,2,3,4,5,6,7,8} After applying 2-opt algorithm it Become {1,2,6,5,4,3,7,8,}

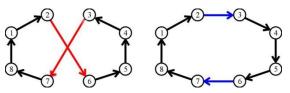


Figure (2): 2-Opt algorithm

2-Opt pseudo code is shown below.

Require: Tour T.

Let Ti ← Cluster (Ti).

for $x \leftarrow 1, 2, \dots, m-2$ do

Calculate the shortest paths along the tour T from every vertex in Ty to every vertex in Tx+1 and from every vertex in Ty+1 to every vertex in Tx for every y = x + 2, x + 3,..., $min\{m, x + m - 2\}$.

for $y \leftarrow x + 2, x + 3, ..., min\{m, x + m - 2\} do$

Construct a layered network L as in Figure 2b.

Apply CO to L to get the shortest cycle C.

if w(C) < w(T) then

Replace T with C.

Restart the whole algorithm.

2.4 Using N-Shift and 2-Opt with Great Deluge algorithm

N-Shift or 2-Opt algorithm can be used for (*Generate a New_solution from the Old_solution*) In Great Deluge algorithm. (2-Opt & N-Shift) inside Great Deluge pseudo code is shown below.

Choose an initial configuration as Old_solution and Best solution

Choose Δ WL and WL

For n=0 to # of iterations

N-Shift OR 2-Opt

If Fitness (New_solution) > WL

If Fitness (New_solution) > (Best_solution)

Old_solution := New_solution

End If

End If

 $WL = WL + \Delta WL$

End For

2.5 Inserting Great Deluge to ACO

Inserting Great Deluge algorithm to ACO make the result of ACO approaches or equal to the optimal one. Great Deluge with (N-Shift OR 2-Opt) algorithm are used either inside ACO algorithm or at the end of ACO algorithm.

2.5.1 Using Great Deluge inside ACO

When Great Deluge is used inside the ACO algorithm it tries to optimize the results of ACO at each loop. Great Deluge inside ACO pseudo code is shown below.

Initialize

Loop

Each ant is positioned on a starting node

Loop

Each ant applies a state transition—rule to incrementally build a solution and a local pheromone *updating rule* Apply Great Deluge with (N-shift OR 2-Opt) to the current tour

Until all ants have built a complete solution A global pheromone updating rule is applied Until end condition

2.5.2 Using Grete Deluge at the end of ACO

When Great Deluge is used at the end of ACO algorithm it tries to optimize the best solution found by ACO. Great Deluge at the end of ACO pseudo code is shown below.

Initialize

Loop

Each ant is positioned on a starting node

Loop

Each ant applies a state transition rule to incrementally build a solution

and a local pheromone updating rule

Until all ants have built a complete solution

A global pheromone updating rule is applied

Until end condition

Apply Great Deluge with (N-shift OR 2-Opt) to the best tour found by ACO

3. Implementation and Results

This section presents the performance of adapting great deluge algorithm and other local search (N-Shift, 2-Opt) algorithms to the (ACO) algorithm which are thus classified into three different table of results, the first table for the results of ACO algorithm before adding any other algorithm to it and two other tables, a table for the results of Great Deluge and 2-Opt (inside & at the end of) ACO while the other table shows the results of Great Deluge and N-Shift (inside & at the end of) ACO. The results are shown for different TSP problem from (TSPLIB95).

3.1ACO results

Initial ACO results before inserting any other algorithms to it.

Table (1): ACO results

| TSP problem | Optimal Solution | ACO result in 200 iteration | ACO result in 500 iteration |
|-------------|-------------------------|-----------------------------|-----------------------------|
| Att48 | 10628 | Fitness 11753 | Fitness 11753 |
| ch130 | 6110 | Fitness 6941.6 | Fitness 6941.6 |
| berlin52 | 7542 | Fitness 8092 | Fitness 8072 |
| ch150 | 6528 | Fitness 6871 | Fitness 6871 |
| eil51 | 426 | Fitness 472 | Fitness 472 |
| st70 | 675 | Fitness 746 | Fitness 746 |

I.Result of ACO with Great Deluge and N-Shift algorithm

N-Shift is used in two different ways (inside ACO & at the end of ACO) which gives different results. For (att48) the best solution for Great deluge and N-shift inside ACO is (11483) while it was (11904) when great deluge and N-shift are at the end of ACO.

Table (2): Result of ACO with Great Deluge and N-Shift algorithm

| TSP Problem | Optimal Solution | N-shift and great deluge # Iteration=10 inside ACO- TSP # iteration =10 | N-shift and great deluge # Iteration=10 at the end of ACO- TSP # iteration =10 |
|----------------|---------------------|---|---|
| Att48 | 10628 | Best tour Fitness 11483 Elapsed time 179.967442 Evaluation function 32486881 | Best tour Fitness 11904 Elapsed time 5.188908 Evaluation function 11760 |
| ch130 | 6110 | Best tour Fitness 6839 Evaluation function = 654031301 Elapsed time 4887.513595 seconds | Best tour Fitness 6906 Evaluation function = 85150 Elapsed time 30.899352 seconds |
| berlin52 | 7542 | Best tour Fitness 8035 Elapsed time 235.027542 seconds Evaluation function 41371721 | Best tour Fitness 8087 Elapsed time 7.219683 seconds Evaluation function 13780 |
| ch150 | 6528 | Best tour Fitness 6858 Elapsed time 8025.759414 seconds Evaluation function 1.0058e+009 | Best tour Fitness 6954 Elapsed time 40.799448seconds Evaluation function 113250 |
| eil51 | 426 | Best tour Fitness 444 Elapsed time 221.497929 second Evaluation function 39015511 | Best tour Fitness 461 Elapsed time 5.615070 second Evaluation function 13260 |
| st70 | 675 | Best tour Fitness 700 Elapsed time 607.734886 seconds Evaluation function 101430701 | Best tour Fitness 716 Elapsed time 9.443444 seconds Evaluation function 24850 |

II.Result of ACO with Great Deluge and 2-Opt algorithm

2-Opt algorithm as N-Shift also is used (inside ACO & at the end of ACO) which gives different results. For (att48) the best solution for Great deluge and 2-Opt inside ACO is (10798) while it was (11154) when great deluge and 2-Opt are at the end of ACO.

Table (3): Result of ACO with Great Deluge and 2-Opt algorithm

| Problem Optimal Solution # Iteration=10 inside ACO-TSP # Iteration=10 insideal insideal inside ACO-TSP # Iteration=10 insi | | | 2-Opt and great deluge | 2-Opt and great deluge |
|---|----------|----------|----------------------------|-----------------------------------|
| Solution TSP | Problem | Optimal | # Iteration=10 inside ACO- | # Iteration=10 at the end of ACO- |
| Best tour Fitness 11154 | | Solution | TSP | TSP |
| 10628 | | | | # iteration =10 |
| Best tour Fitness | | | Best tour Fitness | Best tour Fitness |
| ### 10628 ### 22.2277778 ### 5.999922 seconds. Evaluation function | | 10628 | 10798 | 11154 |
| A 22.2277775 5.999922 seconds. | - 44.40 | | Elapsed time | Elapsed time |
| Ch130 | att40 | | 422.227777s | 5.999922 seconds. |
| Ch130 | | | Evaluation function | Evaluation function |
| Ch130 | | | 24141096 | 32941 |
| Evaluation function | | | Best tour Fitness | Best tour Fitness |
| Elapsed time | | | 6347 | 6629 |
| S07978272 228404 | ch130 | 6110 | Evaluation function = | Evaluation function = |
| Best tour Fitness | CHISO | 6110 | 507978272 | 228404 |
| Best tour Fitness | | | Elapsed time | Elapsed time |
| $\begin{array}{c ccccccccccccccccccccccccccccccccccc$ | | | 8876.979989 seconds | 31.515636 seconds |
| Elapsed time | | 7542 | Best tour Fitness | Best tour Fitness |
| Serlin52 | | | 7717 | 7884 |
| Ch150 | 1 1: 50 | | Elapsed time | Elapsed time |
| $\begin{array}{c} & 35654729 & 45617 \\ & Best tour Fitness & Best tour Fitness \\ & 6622 & 6752 \\ \hline & Elapsed time & Elapsed time \\ & 9050.060806 seconds & 47.200332 seconds \\ \hline & Evaluation function & Evaluation function \\ & 836202248 & 366145 \\ \hline & Best tour Fitness & Best tour Fitness \\ & 433 & 460 \\ \hline & Elapsed time & Elapsed time \\ & 555.017500 seconds & 6.966547 seconds \\ \hline & Evaluation function & Evaluation function \\ & 29675501 & 38054 \\ \hline & Best tour Fitness & Best tour Fitness \\ & 696 & 742 \\ \hline & Elapsed time & Elapsed time \\ & 1433.249165 seconds & 9.354369 seconds \\ \hline & Evaluation function & Evaluation function \\ \hline & Evaluation function & Evaluation function \\ \hline & Elapsed time & Elapsed time \\ & 1433.249165 seconds & 9.354369 seconds \\ \hline & Evaluation function & Evaluation function \\ \hline \end{array}$ | berlin52 | | 647.569437 seconds | 6.764293 seconds. |
| Best tour Fitness | | | Evaluation function | Evaluation function |
| ch150 6528 Elapsed time 9050.060806 seconds 47.200332seconds 47.200332seconds 47.200332seconds Evaluation function 836202248 Evaluation function 366145 Best tour Fitness 433 Best tour Fitness 460 Elapsed time 555.017500 seconds 555.017500 seconds 6.966547 seconds 6.966547 seconds 5742 Evaluation function 29675501 38054 Best tour Fitness 696 Best tour Fitness 742 Elapsed time 1433.249165 seconds 59.354369 seconds 59.354369 seconds 59.354369 seconds 59.354369 seconds 59.354369 seconds 675 | | | 35654729 | 45617 |
| ch150 Elapsed time Elapsed time 9050.060806 seconds 47.200332seconds Evaluation function Evaluation function 836202248 366145 Best tour Fitness Best tour Fitness 433 460 Elapsed time Elapsed time 555.017500 seconds 6.966547 seconds Evaluation function Evaluation function 29675501 38054 Best tour Fitness Best tour Fitness 696 742 Elapsed time Elapsed time 1433.249165 seconds 9.354369 seconds Evaluation function Evaluation function | | 6528 | Best tour Fitness | Best tour Fitness |
| Section Property Property | | | 6622 | 6752 |
| Second | -1-1F0 | | Elapsed time | Elapsed time |
| eil51 836202248 366145 Best tour Fitness Best tour Fitness Best tour Fitness 433 460 Elapsed time Elapsed time 555.017500 seconds 6.966547 seconds Evaluation function Evaluation function 29675501 38054 Best tour Fitness Best tour Fitness 696 742 Elapsed time Elapsed time 1433.249165 seconds 9.354369 seconds Evaluation function Evaluation function | ch150 | | 9050.060806 seconds | 47.200332seconds |
| eil51 426 433 460 Elapsed time Elapsed time $555.017500 \text{ seconds}$ 6.966547 seconds Evaluation function 29675501 38054 Best tour Fitness 696 742 Elapsed time Elapsed time $1433.249165 \text{ seconds}$ 9.354369 seconds Evaluation function | | | Evaluation function | Evaluation function |
| eil51 $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$ | | | 836202248 | 366145 |
| eil51 426 Elapsed time 555.017500 seconds 6.966547 seconds 6.966547 seconds Evaluation function 29675501 Evaluation function 38054 Best tour Fitness 696 Best tour Fitness 742 Elapsed time 1433.249165 seconds 5.354369 seconds Evaluation function 5.354369 seconds Evaluation function Evaluation function | | 426 | Best tour Fitness | Best tour Fitness |
| ### ### ############################## | | | 433 | 460 |
| St70 Seconds 6.966547 seconds Evaluation function Evaluation function 29675501 38054 | a:1E1 | | Elapsed time | Elapsed time |
| st70 29675501 38054 Best tour Fitness Best tour Fitness 696 742 Elapsed time Elapsed time 1433.249165 seconds 9.354369 seconds Evaluation function Evaluation function | e1151 | | 555.017500 seconds | 6.966547 seconds |
| st70 Best tour Fitness 696 742 Elapsed time 1433.249165 seconds Evaluation function Best tour Fitness 696 742 Elapsed time 9.354369 seconds Evaluation function | | | Evaluation function | Evaluation function |
| st70 | | | 29675501 | 38054 |
| st70 Elapsed time Elapsed time 1433.249165 seconds Evaluation function Evaluation function | st70 | 675 | Best tour Fitness | Best tour Fitness |
| st70 675 1433.249165 seconds 9.354369 seconds Evaluation function Evaluation function | | | 696 | 742 |
| Evaluation function Evaluation function Evaluation function | | | Elapsed time | Elapsed time |
| | | | 1433.249165 seconds | 9.354369 seconds |
| 75327200 63593 | | | Evaluation function | Evaluation function |
| | | | 75327200 | 63593 |

6.Conclusions

From the results, its noted that when Great Deluge and 2-Opt are used inside ACO algorithm best tour is almost close to the optimal solution and its better than the other methods. But it need more time and evaluation functions than the other methods.

In general, using Great Deluge and 2-Opt with ACO is much more efficient than using Great Deluge and N-Shift with ACO.

References

- 1. Almufti, Saman Mohammed. (2015), "U-Turning Ant Colony Algorithm powered by Great Deluge Algorithm for the solution of TSP Problem.".
- 2. Marco Dorigo, Thomas Stu" tzle", (2004), Ant Colony Optimization
- 3. Federico Greco, (2008), Travelling Salesman Problem

- 4. J. Basic. Appl. Sci. Res., 2(3)2336-2341, (2012), A New Hybrid Algorithm for Optimization Using PSO and GDA
- 5. D. Karapetyan, G. Gutin, (2012), Efficient Local Search Algorithms for Known and New Neighborhoods for the Generalized Traveling Salesman Problem
- 6. Andrej Kazakov, (2009), Travelling Salesman Problem: Local Search and Divide and Conquer working together
- 7. Alfonsas misevičius, armantas ostreika, antanas šimaitis, vilius žilevičius, (2007), vol.36, no.2, improving local search for the traveling salesman problem.
- 8.Almufti, S. Mohammed (2017), "Using Swarm Intelligence for solving NP-Hard Problems", Academic Journal of Nawroz University, doi

(<u>https://doi.org/10.25007/ajnu.v6n3a78</u>).