Comparison Of Various Mutation Operators Of Genetic Algorithm To Resolve Travelling Salesman Problem

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Abstract — The Travelling Salesman Problem (TSP) is a classic combinatorial optimization problem, which is simple to state but very difficult to solve. This problem is known to be NP-hard, and cannot be solved exactly in polynomial time. Genetic algorithms have been successfully utilized for solving NP-hard problems in the last 30 years. They can reduce the running times of NP-complete problems substantially. The main purpose of this paper is to give a brief introduction about genetic algorithm and travelling salesman problem. And we are going to discuss how genetic algorithm can be applied, especially its mutation operators to solve the TSP. In the end we will conclude that inversion mutation operator will always gives better results compared to other mutation operators.

Keywords— Genetic Algorithm, Travelling Salesman problem, Mutation Operators.

I. INTRODUCTION

The travelling salesman problem is finding a shortest possible cycle visiting every city in a map given the set of cities and pair wise distances between them. Modeling of this problem can also be done with an undirected weighted graph. The vertices of the graph are cities. The edges of the graph are distances. The travelling salesman problem is one the toughest and fundamental problems in real world application. Genetic Algorithms have proven efficient in solving the Travelling Salesman Problem in last 30 years or so. Travelling Salesman is an NP-Hard problem. In this paper we compared and concluded the solution of TSP using Exchange Mutation, Inversion Mutation and Scramble Mutation and we found that, the using of Inversion Mutation operator will always gives better solution based on our experiments.

II. GENETIC ALGORITHMS

Genetic Algorithms (or simply GAs) are powerful and widely applicable stochastic search and optimization methods based on the concepts of natural selection and natural evaluation. GAs work on a population of individuals represents candidate solutions to the optimization problem. These individual are consists of a string (called chromosomes) of genes. The genes are a practical allele (gene could be a bit, an integer number, a real value or an alphabet character,…, etc depending on the nature of the problem). GAs applying the principles of survival of the fittest, selection, reproduction, crossover (recombining), and mutation on these individuals to get, hopefully, a new butter individuals (new solutions) GAs are applied for those problems which either cannot be formulated in exact and accurate mathematical forms and may contain noisy or irregular data or it take so much time to solve or it is simply impossible to solve by the traditional computational methods.

How Genetic algorithms Work

The flowchart explains how genetic algorithms work is showing in the following figure.

Figure (1) Flowchart explains the general structure of the genetic algorithms.

Genetic algorithm maintains a population of individuals, say \( P(t) \), for generation \( t \). Each individual represents a potential solution to the problem at hand. Each individual is evaluated to give some measure of its fitness. Some individuals undergo stochastic transformations by means of genetic operations to form new individuals. There are two type of transformation:

1) Mutation, which creates new individuals by making changes in a single individual.
2) Crossover, which creates new individuals by combining parts from two individuals. The new individuals, called offspring $C(t)$, are then evaluated. A new population is formed by selecting the more fit individuals from the parent population and offspring population.

The genetic algorithm process consists of the following:

1) **Encoding**: The process of representing the solution in the form of a string that conveys the necessary information. They are classified into 2 categories:[26]
   - a. Binary Encoding
     - Chromosome A: 101100101100111001101
     - Chromosome B: 111111100000001111111
   - b. Permutation Encoding
     - Eg: TSP
     - Chromosome A: 153264798
     - Chromosome B: 856723149

2) **Selection**: The best chromosomes will be selected based on the fitness function. A fitness value is assigned to each solution depending on how close it actually is to solving the problem.

3) **Crossover**: It is the process in which two chromosomes (strings) combine their genetic material (bits) to produce a new offspring which possesses both their characteristics. The following are some of the examples for Crossover Operator applied on binary encoding.
   - a) Single Point: A cross-point is selected randomly. The parents are split at this cross over point. Children are created by exchanging tails.
     - parents
       
       
     
     

   - b) Multi Point Crossover: Multi cross over points are selected randomly.

   - c) Uniform Crossover: In this form of cross over operator each bit from either parent is selected with a probability of 0.5 and then exchanged. A cross over mask is randomly generated. When there is 1 in the mask, the gene is copied from the first parent and if 0, the gene is copied from the second parent.

   - 4) **Mutation**: The operation of mutation allow new individual to be created. It begins by selecting an individual from the population based on its fitness. A point along the string is selected at random and the character at that point is randomly changed, the alternate individual is then copied in to the next generation of the population. Following are the some of the examples for mutation operator.
     - a) Bit-Mutation:
     - Parent
     - Child

   - b) Insert-Mutation:

5) **Recombination**: The process that determines which solutions are to be preserved and allowed to reproduce and which ones deserve to die out. The good
solution survive, while bad ones die. This process will be useful to generate new population.

These 5 steps of genetic algorithm will be repeated until it meets predefined iterations or until to get the near optimal solution.

III. TRAVELLING SALESMAN PROBLEM
The Travelling Salesman Problem (TSP) is considered to be an important combinatorial problem, because of its simplicity to define. Though TSP is easy to define but difficult to solve because it is as an NP-hard optimization problem. It consists of n cities which must be visited by a salesman, starting from one of them passing through each city only once and returning to the first city. The cost is given for the journey, which is referred to as a tour. Finally, the minimum cost is required to solve this problem.

The Travelling Salesman Problem (TSP) is determined as follows: Given N cities, known as nodes, a distance matrix where, D = [d_{ij}], consists of the distance between city i and city j. In an attempt to finding near optimal solutions for NP-hard problems; the Travelling Salesman Problem (TSP) is considered a standard benchmark problem for combinatorial methods [2]. It provides a standard optimization test bed, to find near optimum solutions to NP-hard problems [1, 4, 5, and 6]. It is to be known, that, the Travelling Salesman Problem (TSP) is called Symmetric TSP (Standard), if the cost between any two cities are equal in both directions, which means, the distance from city i-j is the same as the distance from city j-i. Two alternative approaches exist to solve the Travelling Salesman Problem (TSP). First, is to find its solution and try proving its optimality, this takes a long period of time, which might take years. The second, approach, is to find an approximate solution in a short period of time [3].

Practical Applications of TSP:

Much of the work on the TSP is motivated by its use as a platform for the study of general methods that can be applied to a wide range of discrete optimization problems. This is not to say, however, that the TSP does not find applications in many fields. Indeed, the numerous direct applications of the TSP bring life to the research area and help to direct future work.

1. Genome Sequencing
Researchers at the National Institute of Health have used Concorde's TSP solver to construct radiation hybrid maps as part of their ongoing work in genome sequencing. The TSP provides a way to integrate local maps into a single radiation hybrid map for a genome; the cities are the local maps and the cost of travel is a measure of the likelihood that one local map immediately follows another.

2. Starlight Interferometer Program

A team of engineers at Hernandez Engineering in Houston and at Brigham Young University have experimented with using Chained Lin-Kerninghan to optimize the sequence of celestial objects to be imaged in a proposed NASA Starlight space interferometer program. The goal of the study it to minimize the use of fuel in targeting and imaging maneuvers for the pair of satellites involved in the mission (the cities in the TSP are the celestial objects to be imaged, and the cost of travel is the amount of fuel needed to reposition the two satellites from one image to the next).

3. Scan Chain Optimization
A semi-conductor manufacturer has used Concorde's implementation of the Chained Lin-Kernighan heuristic in experiments to optimize scan chains in integrated circuits. Scan chains are routes included on a chip for testing purposes and it is useful to minimize their length for both timing and power reasons.

4. DNA Universal Strings
A group at AT&T used Concorde to compute DNA sequences in a genetic engineering research project. In the application, a collection of DNA strings, each of length k, were embedded in one universal string (that is, each of the target strings is contained as a substring in the universal string), with the goal of minimizing the length of the universal string. The cities of the TSP are the target strings, and the cost of travel is k minus the maximum overlap of the corresponding strings.

5. Whizzkids '96 Vehicle Routing
A modified version of Concorde was used to solve the Whizzkids'96 vehicle routing problem, demonstrating that the winning solution in the 1996 competition was in fact optimal. The problem consists of finding the best collection of routes for 4 newsboys to deliver papers to their 120 customers. The team of David Applegate, William Cook, Sanjeeb Dash, and Andre Rohe received a 5,000 Gulden prize for their solution in February 2001 from the information technology firm CMG.

6. Touring Airports
Concorde is currently being incorporated into the Worldwide Airport Path Finder web site to find shortest routes through selections of airports in the world. The author of the site writes that users of the path-finding tools are equally split between real pilots and those using flight simulators.

7. Designing Sonet Rings: An early version of Concorde's tour finding procedures was used in
a tool for designing fiber optical networks at Bell Communications Research (now Telcordia). The TSP aspect of the problem arises in the routing of sonet rings, which provide communications links through a set of sites organized in a ring. The ring structure provides a backup mechanism in case of a link failure, since traffic can be rerouted in the opposite direction on the ring.

IV. SOLVING TSP USING GA MUTATION OPERATOR: A PROPOSED WORK:

A genetic algorithm [7] can be used to find a solution in much less time. Although it might not find the best solution, it can find a near perfect solution for a 100 city tour in less than a minute.

To solve the traveling salesman problem, we need a list of city locations and distances, or cost, between each of them. The following are basic steps of our proposed work.

Step 1: Encoding

Permutation encoding will be used to solve TSP. We represented every city by an integer. For example, Consider 6 Indian cities: Mumbai, Nagpur, Calcutta, Delhi, Bangalore and Chennai and assign a number to each.

<table>
<thead>
<tr>
<th>City</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mumbai</td>
<td>1</td>
</tr>
<tr>
<td>Nagpur</td>
<td>2</td>
</tr>
<tr>
<td>Calcutta</td>
<td>3</td>
</tr>
<tr>
<td>Delhi</td>
<td>4</td>
</tr>
<tr>
<td>Bangalore</td>
<td>5</td>
</tr>
<tr>
<td>Chennai</td>
<td>6</td>
</tr>
</tbody>
</table>

After representing the cities in the form of integer, we will initialize the population. i.e., for the above cities, in total 6! Different possible paths are available, out of which to choose the best one decreases as the number of cities increases; hence we consider few paths for TSP solution randomly.

Step 2: Distance Matrix/ Cost Matrix

Distance Matrix is an NxN matrix of point to point distances/costs. For example, consider the following distance matrix for above 6 cities.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>863</td>
<td>1987</td>
<td>1407</td>
<td>998</td>
<td>1369</td>
</tr>
<tr>
<td>2</td>
<td>863</td>
<td>0</td>
<td>1124</td>
<td>1012</td>
<td>1049</td>
<td>1083</td>
</tr>
<tr>
<td>3</td>
<td>1987</td>
<td>1124</td>
<td>0</td>
<td>1461</td>
<td>1881</td>
<td>1676</td>
</tr>
<tr>
<td>4</td>
<td>1407</td>
<td>1012</td>
<td>1461</td>
<td>0</td>
<td>2061</td>
<td>2095</td>
</tr>
<tr>
<td>5</td>
<td>998</td>
<td>1049</td>
<td>1881</td>
<td>2061</td>
<td>0</td>
<td>331</td>
</tr>
<tr>
<td>6</td>
<td>1369</td>
<td>1083</td>
<td>1676</td>
<td>2095</td>
<td>331</td>
<td>0</td>
</tr>
</tbody>
</table>

Step 3: Selection Based on Fitness Function

The fitness function will be the total cost of the tour represented by each chromosome. This can be calculated as the sum of the distances traversed in each travel segment. \( \text{The Lesser The Sum, The Fitter The Solution Represented By That Chromosome[7].} \)

So, for a chromosome \([4 \ 1 \ 3 \ 2 \ 5 \ 6]\), the total cost of travel or fitness will be calculated as shown below

\[
\text{Fitness} = 1407 + 1987 + 1124 + 1049 + 331 + 2095 = 7993 \text{ kms.}
\]

Since TSP deals with round trip, i.e., we are also supposed to add the distance between city 6 to city 4. Therefore \(\text{Fitness}= 7993+2095 = 10088 \text{ kms} \)

Since our objective is to minimize the distance, the lesser the total distance, the fitter the solution.

Step 3: Generating random numbers equal to population size.

Step 4: Dividing random numbers into intervals of 2.

Step 5: According to sequence of random numbers selecting routes from population size.

Step 6: Best of 2 routes will be chosen using Tournament selection to apply Mutation.

[ Note: In our experiment we haven’t considered the crossover operator due to the following reason.

Problems here:

- City 1 repeated in Child 1
- City 5 repeated in Child 2

The above situations does not satisfy the rule of TSP. Though many researchers are invented new crossover techniques for permutation encoding, we are not considering it, we have considered only mutation. ]

Step 7: Best route from each group of 2 will be chosen and applied mutation operators; they are, Inversion Mutation, Exchange Mutation and Scramble Mutation.

Inversion Mutation:
Exchange Mutation:

1 2 3 4 5 6 7 8 9

Scramble Mutation:

1 2 3 4 5 6 7 8 9

Step 8: Next generation of population size will be generated.

Step 9: Process will undergo predefined iterations.

Step 10: After the final iteration the smallest distance from the population size will be displayed as result.

V. RESULTS

The following are the results obtained for each mutation operator we have used. Consider the following the following table which shows that Inversion mutation will always gives better results.

<table>
<thead>
<tr>
<th>NUMBER OF CITIES</th>
<th>ITERATION</th>
<th>POP_SIZE</th>
<th>GA(Inversion)</th>
<th>GA(Exchange)</th>
<th>GA(Scramble)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>2000</td>
<td>20</td>
<td>33.7464</td>
<td>33.7464</td>
<td>33.7464</td>
</tr>
<tr>
<td>20</td>
<td>4000</td>
<td>40</td>
<td>33.9979</td>
<td>36.2076</td>
<td>37.2417</td>
</tr>
<tr>
<td>30</td>
<td>6000</td>
<td>60</td>
<td>43.3578</td>
<td>50.8858</td>
<td>49.7778</td>
</tr>
<tr>
<td>40</td>
<td>8000</td>
<td>80</td>
<td>49.3478</td>
<td>65.5511</td>
<td>61.5754</td>
</tr>
<tr>
<td>50</td>
<td>10000</td>
<td>100</td>
<td>56.902</td>
<td>66.1469</td>
<td>66.1501</td>
</tr>
<tr>
<td>60</td>
<td>12000</td>
<td>120</td>
<td>68.023</td>
<td>81.2718</td>
<td>72.9509</td>
</tr>
<tr>
<td>70</td>
<td>14000</td>
<td>140</td>
<td>70.6605</td>
<td>84.1625</td>
<td>78.3081</td>
</tr>
<tr>
<td>80</td>
<td>16000</td>
<td>160</td>
<td>72.2052</td>
<td>105.7127</td>
<td>82.3256</td>
</tr>
<tr>
<td>90</td>
<td>18000</td>
<td>180</td>
<td>76.8693</td>
<td>112.0468</td>
<td>99.595</td>
</tr>
<tr>
<td>100</td>
<td>20000</td>
<td>200</td>
<td>87.272</td>
<td>127.9681</td>
<td>112.3647</td>
</tr>
</tbody>
</table>

It is very clear from the above table that, as the number of cities increases, the inversion mutation operator will always gives the better results. Thus from the above experimental results we conclude that Inversion mutation operator is better than rest two and also Exchange mutation operator gives worst results than rest two.

VI. CONCLUSION

Genetic algorithms appear to search good solutions for the traveling salesman problem, however it depends very much on the way the problem is encoded and which crossover and mutation methods are used. So our sincere efforts to decide which mutation operator will always gives result to tackle most of the real life applications of travelling salesman problem. As a future work we want continue the same procedure different other crossover and mutation operator to give better solution to a travelling salesman problem.

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BIOGRAPHY

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