Open Vehicle Routing Problem by Genetic Algorithm

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ABSTRACT :

Vehicle routing problem (VRP) is real-world combinatorial optimization problem which determines the optimal route of a vehicle. Generally, to provide the efficient vehicle serving to the customer through different services by visiting the number of cities or stops, the OVRP follows the Travelling Salesman Problem (TSP), in which each vehicle visits a set of cities such that every city is visited by exactly one vehicle only once. This work proposes the Genetic Algorithm Optimization.

Keywords: Vehicle routing Problem(VRP);Open Vehicle routing Problem(OVRP); Travelling Salesman Problem(TSP);

INTRODUCTION:

The School Bus Routing Problem (SBRP) is a common real-life problem, proposed in the literature by Newton and Thomas (1969), but has not been tackled that often in the field of computer science. The problem is closely related to the Vehicle Routing Problem (VRP), which has been a popular research area for the last four decades. The Vehicle Routing Problem was first described by Dantzig and Ramser (1959), and has been proved NP-hard by Lenstra and Kan (1981). Vehicle Routing Problem (VRP) is a problem which searches for the optimal routes that a vehicle travels in order to serve customers residing in a geographically dispersed area. The SBRP has the same characteristics with the Vehicle Routing Problem (VRP) in several ways. Genetic algorithms have been inspired by the natural selection mechanism introduced by Darwin. They apply certain operators to a population of solutions of the problem at hand, in such a way that the new population is improved compared with the previous one according to a prespecified criterion function. This procedure is applied for a preselected number of iterations and the output of the algorithm is the best solution found in the last population or, in some cases, the best solution found during the evolution of the algorithm. In general, the solutions of the problem at hand are coded and the operators are applied to the coded versions of the solutions. The way the solutions are coded plays an important role in the performance of a genetic algorithm. Inappropriate coding may lead to poor performance. The operators used by genetic algorithms simulate the way natural selection is carried out. The most well-known operators used are the reproduction, crossover, and mutation operators applied in that order to the current population. The reproduction operator ensures that, in probability, the better a solution in the current population is, the more (less) replicates it has in the next population. The crossover operator, which is applied to the temporary population produced after the application of the reproduction operator, selects pairs of solutions randomly, splits them at a random position, and exchanges their second parts. Finally, the mutation operator, which is applied after the application of the reproduction and crossover operators, selects randomly an element of a solution and alters it with some probability. Hence genetic algorithms provide a search technique used in computing to find true or approximate solutions to optimization and search problems.

OPEN VEHICLE ROUTING PROBLEM:

The Open vehicle routing problem (OVRP) has received in the literature relatively less attention than the VRP. The problem is first described in a paper by Schrage (1981) without any solution attempt. Bodin et al. (1983) address the express airmail distribution in the USA and solve two separate routing problems, one for the delivery and another one for the pick up using a modified Clarke-Wright saving algorithm. The open vehicle routing problem (OVRP) describes efficient routes with minimum total distance and cost for a fleet of vehicles that serve some commodity to a given number of customers.

The OVRP differs from the well-known vehicle routing problem (VRP) in that the vehicles do not necessarily return to their original locations after serving to the customers; if they do, they must follow the same path in the reverse order.

The major difference in theory between the OVRP and the VRP is that the routes in the OVRP consist of Hamiltonian paths originating at the depot and ending at one of the customer side, while the routes in the VRP are Hamiltonian cycles. In other words, the best Hamiltonian path is NP-hard, since the Hamiltonian path problem is equivalent to the traveling salesman problem, which is known to be NP-hard.

The best Hamiltonian path problem with a fixed source node must be solved for each vehicle in the OVRP, and OVRP solutions involve finding the best Hamiltonian path for each set of customers assigned to a vehicle. Consequently, the OVRP is also an NP-hard problem.

IMPLEMENTATION:

We decided to use a genetic algorithm to solve this OVRP. we can solve this problem using various methods like Tabu Search, simulated annealing, A* algorithm,Greedy Search etc.But as on real-time basis the data set for the problem could be huge so it will obviously increase time complexity and space complexity.and as genetic algorithm is well known problem for solving optimization problem considering tentative cases and then with the help of iterating, modifying, updating the candidate solution using genetic operators takes place which nearly gives is best possible solution.

GENETIC ALGORITHM:

GAs generate new candidates by inheritance and recombination of solution components from two parents selected, based on their fitness. The idea is to serendipitously combine good components that occur in the two parents. In the TSP problem, the components are the individual segments in a tour, and also subtours made up a sequence of segments. For GAs to work well, one must be able to devise crossover operators that allow for such recombination. This is a somewhat difficult task, and different crossovers, and even alternate representations,have been tried. We look at a few of them here.

GA has distinct features:

- A string representation of chromosomes.
- A selection procedure for initial population and for off-spring creation.
- A cross-over method and a mutation method.
- A fitness function should be minimized.
- A replacement procedure.
- Parameters that affect GA are initial population, size of the population, selection process and fitness function.

Path Representation:

In path representation, the simple one point or multipoint crossovers defined in this chapter earlier do not work because the resulting sequences are not likely to be valid tours. For example, given two parent tours

P1 =(2, 4,7, 1,5, 9, 8, 3.6), and
P2 = (4,5, 7, 2,6, 8, 1, 9, 3)

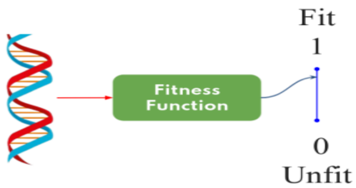
if we do a crossover after four segments, we get the two offspring:

C1 = (2, 4,7, 1,6, 8, 1,9, 3), and
C2 = (4, 5, 7, 2, 5, 9, 8, 3.6)

Neither of the two offspring is a valid tour because cities repeat in them. We need crossover operators that will retain the n cities and only introduce a different order. Some interesting crossovers that have been tried out (Michalewicz and Fogel, 2004) are as follows.

Fitness function:

The fitness function is a function that takes a gene as input and produces as output how “fit” or how “good” the solution is with respect to the problem in consideration. The fitness of a gene ranges from 0 to 1. 1 means that the gene is 100% fit.
For our problem of finding the best route, we need the route to have a minimum distance. So our fitness function will take a route, and calculate fitness as reciprocal of the total distance.



Selection:

- Selection is a procedure of picking a parent chromosome to produce off-spring.
- Types of selection:
  - Random Selection – Parents are selected randomly from the population.
  - Proportional Selection – probabilities for picking each chromosome is calculated as:

    $P(\mathbf{x}_i) = f(\mathbf{x}_i)/\Sigma f(\mathbf{x}_j)$ for all j
  - Rank Based Selection – This method uses ranks instead of absolute fitness values.

$P(\mathbf{x}_i) = (1/\beta)(1 – e^{r(\mathbf{x}_i)})$

Elitism:

Like in real life, some space is reserved in the next population for elites. Elites fill these spaces without any competition with others. We can set this reservation in advance.

Reproduction:

- Reproduction is a process of creating new chromosomes out of chromosomes in the population.
- Parents are put back into the population after reproduction.
- Cross-over and Mutation are two parts in reproduction of an off-spring.
- Cross-over : It is a process of creating one or more new individuals through the combination of genetic material randomly selected from two or parents.

Cross-over:

- Uniform cross-over : where corresponding bit positions are randomly exchanged between two parents.
- One point : random bit is selected and the entire sub-string after the bit is swapped.
- Two point : two bits are selected and the sub-string between the bits is swapped.

	Uniform Cross-over	One point Cross-over	Two point Cross-over
Parent1 Parent2	00110110 11011011	00110110 11011011	00110110 11011011
Off-spring1 Off-spring2	01110111 10011010	00111011 11010110	01011010 10110111

Mutation:

- Mutation procedures depend upon the representation schema of the chromosomes.
- This is to prevent falling all solutions in population into a local optimum.
- For a bit-vector representation:
  - random mutation : randomly negates bits
  - in-order mutation : performs random mutation between two randomly selected bit position.

	Random Mutation	In-order Mutation
Before mutation	1110010011	1110010011
After mutation	1100010111	1110011010

FUTURE SCOPE:

The multi-depot open vehicle routing problem (MDOVRP) is an extension of the conventional OVRP, in which more than one depot exists and vehicles travel an open route. Future research directions can be considered some operational constraints, such as time windows, travel distance limitations, heterogeneous fleet, and the like. Moreover, multi- criteria MDOVRPs can be considered and solved using proper multi-criteria decision making approaches. This research investigates the MDOVRP with a predetermined planning time horizon. However, a multi-period MDOVRP can be studied for future.

FLOWCHART :

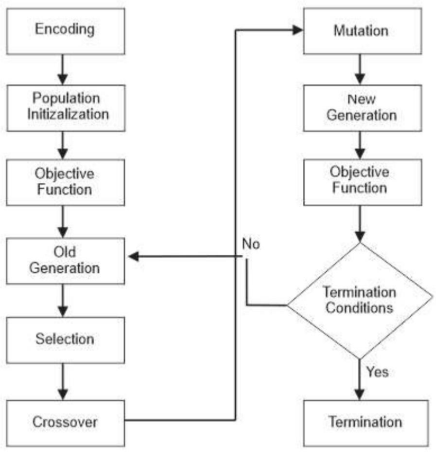
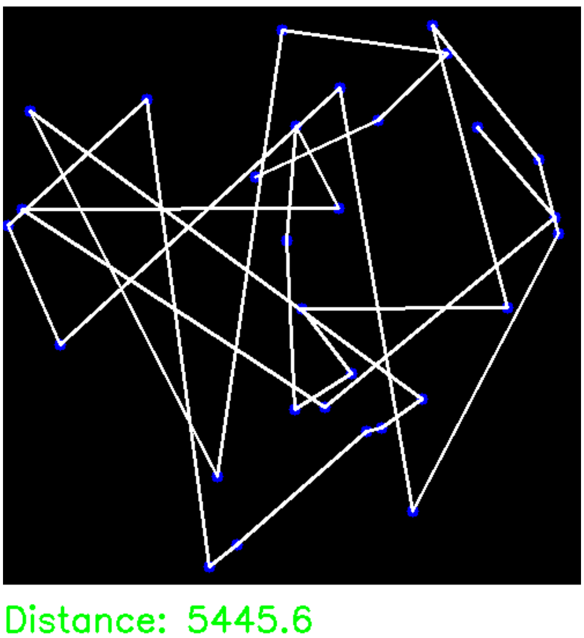


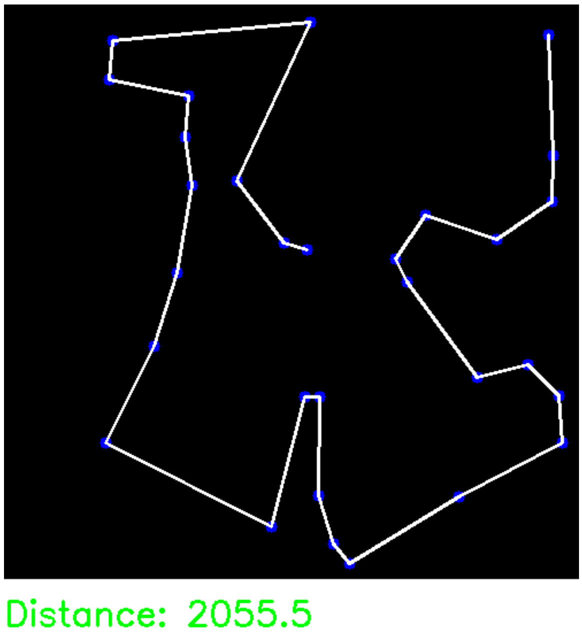
Figure 2. Genetic Algorithm Flow Diagram

OUTPUT:

Candidate route:



Route after applying GA:



ANALYSIS OF DIFFERENT HEURISTIC USED:

Heuristic	***% reduced in Total distance***
Euclidean	64.86%
Hamming	61.56%
Euclidean+Hamming	58.29%

REFERENCE:

1) [Solving the Vehicle Routing Problem using Genetic Algorithm (thesai.org)]()

2) [Open Vehicle Routing Problem by Ant Colony Optimization (thesai.org)]()

3) **Prof. khemani's First course in AI textbook.**