

# Capacitated Arc Routing Problem (CARP) Report

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## 1. Preliminaries

The capacitated arc routing problem (CARP) has attracted much attention during the last few years due to its wide applications in real life. Since CARP is NP-hard and exact methods are only applicable to small instances, heuristic and metaheuristic methods are widely adopted when solving CARP[1]. In this project, I used Genetic Algorithm to solve this NP-hard problem.

### 1.1. Software

In this project, I used Pycharm mainly and Sublime Text 3 cosmetically. I wrote this project in Python3.

### 1.2. Algorithm

I used genetic algorithm to solve this problem. At first, I used Path-Scanning algorithm to get some initial results. I wrote 5 rules to decide which edge should be chosen when some edges have the same distance from my current position. Then I wrote 5 operators to make crossover and mutation of the initial results. I choose about 300 optimal results every time and continue mutation until time over.

## 2. Methodology

### 2.1. Representation

There are several variables in my python file.

- **args**: Lists of command-line arguments
- **co**: NumPy 2D adjacent matrix
- **required\_edges\_num**: Number of required edges
- **vertices\_num**: Number of vertices
- **depot\_num**: Depot of this dataset
- **capacity**: Capacity of each vehicle

### 2.2. Architecture

There are also several methods in my file.

- **floyd**: Using Floyd algorithm to calculate distances between points and points

- **path\_scanning**: To produce initial solutions of this problem
- **better**: Choose edge when multiple edges are equal distances from the current point using following 5 rules

- maximize the distance from the task to the depot;
- minimize the distance from the task to the depot;
- maximize the term  $\text{dem}(t)/\text{sc}(t)$ , where  $\text{dem}(t)$  and  $\text{sc}(t)$  are demand and serving cost of task  $t$ , respectively;
- minimize the term  $\text{dem}(t)/\text{sc}(t)$ ;
- use rule 1) if the vehicle is less than half-full, otherwise use rule 2)

- **select**: Select the 300 optimal routes.
- **print\_list**: Print the routes in given format
- **cal\_path\_cost**: Calculate the cost of a route
- **check\_route**: check if the route is legal
- **mutation**: change the routes by following 5 methods

- **single insertion**
- **double insertion**
- **swap**
- **2opt**
- **better 2opt**

- **solve\_CARP**: Calculate the cost of a route

### 2.3. Detail of Algorithm

At first, I use Path-Scanning algorithm to produce initial solution.

```

1.  $k \leftarrow 0$ 
2. copy all required arcs in a list  $free$ 
3. repeat
4.    $k \leftarrow k + 1$ ;  $R_k \leftarrow \emptyset$ ;  $load(k), cost(k) \leftarrow 0$ ;  $i \leftarrow 1$ 
5.   repeat
6.      $\bar{d} \leftarrow \infty$ 
7.     for each  $u \in free \mid load(k) + q_u \leq Q$  do
8.       if  $d_{i,beg(u)} < \bar{d}$  then
9.          $\bar{d} \leftarrow d_{i,beg(u)}$ 
10.         $\tilde{u} \leftarrow u$ 
11.       else if  $(d_{i,beg(u)} = \bar{d})$  and  $better(u, \tilde{u}, rule)$ 
12.          $\tilde{u} \leftarrow u$ 
13.       endif
14.     endfor
15.     add  $\tilde{u}$  at the end of route  $R_k$ 
16.     remove arc  $\tilde{u}$  and its opposite  $\tilde{u} + m$  from  $free$ 
17.      $load(k) \leftarrow load(k) + q_{\tilde{u}}$ 
18.      $cost(k) \leftarrow cost(k) + \bar{d} + c_{\tilde{u}}$ 
19.      $i \leftarrow end(\tilde{u})$ 
20.   until  $(free = \emptyset)$  or  $(\bar{d} = \infty)$ 
21.    $cost(k) \leftarrow cost(k) + d_{i1}$ 
22. until  $free = \emptyset$ 

```

Then, I run this methods thousands of times and sort by cost to get initial solutions

```

1 costList = list()
2 for i in range(20):
3     costList.append(path_scanning(rt,
4     cost_matrix, 1))
5     costList.append(path_scanning(rt,
6     cost_matrix, 2))
7     costList.append(path_scanning(rt,
8     cost_matrix, 3))
9     costList.append(path_scanning(rt,
10    cost_matrix, 4))
11    costList = select(costList, 300)
12    for i in range(2500):
13        costList.append(path_scanning(rt,
14        cost_matrix, 5))
15        costList = select(costList, 300)

```

initial-solution

Next, I use mutation method to change the initial solutions to get better solution.

```

1 def mutation(cost_matrix, paths):
2     rule = random.randint(1, 5)
3     if rule == 1:
4         return single_insertion(cost_matrix, paths)
5     if rule == 2:
6         return double_insertion(cost_matrix, paths)
7     if rule == 3:
8         return swap(cost_matrix, paths)
9     if rule == 4:
10        return _2opt(cost_matrix, paths)
11    if rule == 5:
12        return better_2opt(cost_matrix, paths)

```

mutation

```

1 for i in range(0, len(costList) - 1):
2     tm = mutation(cost_matrix, costList[i])
3     if tm:
4         costList.extend(tm)
5         # print(costList)
6         costList = select(costList, 250)

```

mutation-main

Before each mutation, I will check whether the population is mature or not. If it have matured, I will use 2opt method and better 2opt method to jump out of the convergence state!

```

1 if sum(costList[0][1]) == sum(costList[int((len(costList) - 1) * 0.9)[1])]:
2     costList = select(costList, 20)
3     for i in range(0, len(costList) - 1):
4         tm = better_2opt(cost_matrix, costList[i])
5         if tm:
6             costList.extend(tm)
7         tm = _2opt(cost_matrix, costList[i])
8         if tm:
9             costList.extend(tm)

```

check-mature-main

After that, I will sort the population by cost and print the least cost route.

What's more, I use multiprocessing in this project. I run 8 times at the same time. Then I choose the best solution to print.

```

1 worker = []
2 worker_num = 8
3 seed = int(sys.argv[5])
4 create_worker(worker_num)
5 Task = [seed + i + random.randint(60, 300) for i in range(0, 24, 3)]
6 # print('Task', Task)
7 for i, t in enumerate(Task):
8     worker[i % worker_num].inQ.put(t)
9 result = []
10 for i, t in enumerate(Task):
11     result.append(worker[i % worker_num].outQ.get())
12 result = sorted(result, key=lambda x: sum(x[1]))
13 print_list(result[0])
14 # print_list(result[7])
15 finish_worker()

```

multiprocessing-main

## 3. Empirical Verification

### 3.1. Design

Since CARP is NP-hard and exact methods are only applicable to small instances, heuristic and metaheuristic methods are widely adopted when solving CARP.[1]

### 3.2. Data and data structure

Data: Data is the 7 given datasets. For example, "gdb10.dat", "egl-s1-A.dat", "egl-e1-A.dat", "val7A.dat", "val4A.dat" and so on.

Data Structure: I used list, 2D NumPy matrix, dict, tuple and so on.

### 3.3. Performance

The time complexity is  $O(n^3)$  and it mainly results from floyd algorithm.

### 3.4. Result

I got a good result in CARP OJ system and this is my results.

RunTime(s)	Cost	Dataset
119.04	5313	egl-s1-A
59.51	279	val7A

RunTime(s)	Cost	Dataset
59.44	402	val4A
118.82	3687	egl-e1-A
58.80	275	gdb10
59.20	173	val1A
58.80	316	gdb1

### 3.5. Analysis

This project is an application of genetic algorithm. Through this project, I have a better understanding of genetic algorithm and I gained a lot by reading relative papers.

### Acknowledgments

### References

- [1] K. Tang, Y. Mei and X. Yao, "Memetic Algorithm With Extended Neighborhood Search for Capacitated Arc Routing Problems", IEEE Transactions on Evolutionary Computation, vol. 13, no. 5, pp. 1151-1166, 2009.