

CARP Project

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1. Preliminaries

1.1. Software

For this project, I write it by python, and the extra packets I used is numpy.

This project aim to design a excellent enough solution of a Capacitated Arc Routing Problems

1.2. Algorithm

The algorithm I used is Genetic Algorithm, and I design 4 rules to do the pathscanning, design ulusoy [1], 2-opt, Merge-Split Operator to do the local-search and variation, and use a way that desribble in the paper **Memetic Algorithm with Extended Neighborhood Search for Capacitated Arc Routing Problems** [2] to do the crossover.

2. Methodology

2.1. Representation

In my code, to design the algorithm, I write it into three part:

- *pathscanning*: Do the pathscanning, get the initial solution.
- *localsearch*: For a ordered list, give a best split of it.
- *varition*: For a solution change it and apply the change if the solution can be better.
- *crossover*: Crossover two solution and generate a child solution.

2.2. Architecture

- Read data an storage:
 - Open the filename incoming as the parameter
 - Storage all the node and the cost of edge in a matrix, and this matrix in fact is the adjacency matrix of the graph.
 - Storage all the edge and its demand.
 - Storage all the edge that have demand in a set.

- Use floyd to the adjacency matrix of the graph.
- pathscanning: Random use the step below in each step.
 - maximize the distance
 - minimize the distance
 - maximize the term $dem(t)/sc(t)$
 - maximize the term $dem(t)/sc(t)$
- Choice 30 best result in the pathscanning and generate the initial population
- Do MS(Merge-Split) Operator to the population.
 - Merge and do split. Then use ulusory.
- Crossover
- Do MS Operator until the timeout.
 - Merge and do split. Then use ulusory.

2.3. Detail of Algorithm

For the detail of the algorithm, I will introduct it in some parts.

2.3.1. Read data and pretreatment. When we read Data, I read the data from the file given, and storage the graph in two matrix, both two matrices can regard as the adjacency matrix of the graph, but on matrix is for the cost and one matrix is for the demand.

Then, I will storage all the information of the edges that have demand, including the two nodes and the cost. Why we need this set? When we do pathscanning, we need know when we have satisfy all the required edges, the node is used to get the destination point and the next depot. The cost is used to calculation the final cost. Because for the required edge, we can't use the adjacency matrix after floyd. Because for the two node of the required edge, there may be other route between two nodes with less cost than the cost of the edge, then the value in the matrix will be the least coat, but we must use the cost in the edge. The last step is do floyed to the adiacency matrix.

2.3.2. pathscanning. After read data and storage, I will do the pathscanning and get the initial population. When I do the pathscanning, I will use the set that I storage the required edges. In each step, I will scan the set and choice the best edge. Firstly, I will choice the closest one, if there is many node have the least cost, I will apply four rules randomly.

algorithm 1 ReadData

Input: The path of the dat file**Output:** The information of the dataset, the matrix of map

```
1: function BUILDMAP(way)
2:   content  $\leftarrow$  open(way)
3:   DEPOT  $\leftarrow$  3rd line
4:   CAPACITY  $\leftarrow$  7th line
5:   VERTICES  $\leftarrow$  2nd line
6:   VEHICLES  $\leftarrow$  6th line
7:   while content is not end do
8:     edgeProp[]  $\leftarrow$  line.split(' ')
9:     edgeProp[0]  $\leftarrow$  1
10:    edgeProp[1]  $\leftarrow$  1
11:    matrixC[edgeProp[0], edgeProp[1]]  $\leftarrow$ 
12:    edgeProp[2]
13:    matrixD[edgeProp[0], edgeProp[1]]  $\leftarrow$ 
14:    edgeProp[3]
15:    if edgeProp[3] > 0 then
16:      arcs.add((edgeProp[0], edgeProp[1],
17:      edgeProp[2]))
18:    end if
19:  end while
20:  matrixC  $\leftarrow$  floyd(matrixC)
21:  return DEPOT, VEHICLES, VERTICES,
22:  matrixC, matrixD, arcs
23: end function
24: function FLOYD(matrixC)
25:   n  $\leftarrow$  len(matrixC)
26:   for i from 0 to n do
27:     for j from 0 to n do
28:       for k from 0 to n do
29:         if matrixC[i, j] =  $\infty$  and
30:         matrixC[i, k]  $\neq \infty$  then
31:           matrixC[k, j]  $\leftarrow$ 
32:           min(matrixC[k, j], matrixC[i, k] + matrixC[i, j])
33:           matrixC[j, k]  $\leftarrow$  matrixC[k, j]
34:         end if
35:       end for
36:     end for
37:   end for
38:   return matrixC
39: end function
```

2.3.3. Local Search. In the local search, I use ulusory split algorithm to do it. In this part, I will ignore the limitation of the capacity and let the solution be an ordered list. Then, I build a tree to storage each possible case of the split, to decrease the time of search, I will confine that it will split just when the car is half-full or provide more demand. And by this way, I will get the best split scheme of this ordered list.

2.3.4. Merge-Split Operator. In the Merge-Split Operator, it's a variation algorithm to a solution. In this algorithm, it will pop some route randomly, and merge them in an unordered task list. For this unordered task list, I will do a pathscanning for it again and insert them back to the

algorithm 2 Do pathScanning

```
1: function DOSCANNING(matrixC, arcs, matrixD,
2:   CAPACITY, DEPOT)
3:   while arc is not empty do
4:     for edge in arcs do
5:       type  $\leftarrow$  random.randint(0, 3)
6:       if type == 0 then
7:         use rule: maximize the term dem(t)/sc(t)
8:       else if type == 1 then
9:         use rule: minimize the term dem(t)/sc(t)
10:      else if type == 2 then
11:        use rule: maximize the distance
12:      else if type == 3 then
13:        use rule: minimize the distance
14:      end if
15:    end for
16:    if The car is not full: then
17:      route[carNo - 1].append(edge)
18:    else
19:      carNum  $\leftarrow$  carNum + 1
20:      route.append([])
21:    end if
22:  end while
23:  return route
24: end function
```

algorithm 3 Local Search

```
1: function ULUSOY(trip, matrixC, matrixD, index, cost,
2:   CAPACITY, route, DEPOT, carNum, VEHICLES,
3:   rr)
4:   cap = 0
5:   for i from index to len(trip) do
6:     cap  $\leftarrow$  cap + matrixD[trip[i][0], trip[i][1]]
7:     if cap > CAPACITY//2 and cap <
8:     CAPACITY then
9:       if i == len(trip) - 1 then
10:        rr.append((cost, route)) break
11:      end if
12:      if carNum < VEHICLES then
13:        cost_t  $\leftarrow$  matrixC[DEPOT, trip[i][1]]
14:        + matrixC[DEPOT, trip[i + 1][0]] + cost -
15:        matrixC[trip[i][1], trip[i + 1][0]]
16:        ulusory(trip, matrixC, matrixD, i +
17:        1, cost, CAPACITY, route, DEPOT, carNum +
18:        1, VEHICLES, rr)
19:      end if
20:    end for
21:  return rr
22: end function
```

solution, and then do a local search for it. Then I can get a best solution for this Merge-Split Operation. This Operator has a big step-size, so one main advantage of the MS operator is its capability of generating new solutions that are significantly different from the current solution.

algorithm 4 Merge-Split Operator

```

1: function MS(routein, matrixC, matrixD, CAPACITY,
   DEPOT, outputni, costni)
2:   tripChoice = []
3:   size ← random.randint(len(routein)/2, 2 *
   len(routein))/3
4:   for i from 0 to size do
5:     index ← random.randint(0, len(routein) -
   1)
6:     tripChoice.append(routein.pop(index))
7:   end for
8:   route_PS = doScanning() for tripChoice
9:   routeFinal = localsearch() for route_PS
10:  return routeFinal
11: end function

```

2.3.5. Crossover. In the crossover, I choice two solution s1, s2 in the populition as the parents randomly. Then, pop two routes r1 from s1, r2 from s2 and split both of them in two part r11, r12 and r21, r22. The second step is compare r22 and r12, choice the task that r22 have but not in r12, them delete these task in the s1 and r11. Then, joint r11 and r22 and insert into s1. The third step is compare r22 and r12, choice the tasks that r12 have but not in r22, insert these task into s1 one by one, and each task should insert into the location that make the cost be least. The last step is do local search for the s1 and get the best solution for the ordered list in the s1. s1 is the child in this crossover.

3. Empirical Verification

3.1. Design

For the Design of the Verification, I implement a program of this algorithm and test it effect of the case. For the detail of the parameter of the program:

- pathScanning
 - The rule of pathscanning is random choice when decide which task next.
- localsearch
 - The car must be between half-full and full when Split the tasks.
- Merge-Split Operator
 - The number of the routes we choice to add in the unordered list should between $1/2$ to $\frac{2}{3}$ of the total

algorithm 5 Crossover

```

1: function CROSSOVER(matrixC, matrixD, CAPACITY,
   DEPOT, s1, s2)
2:   r1 ← s1[randint(0, len(s1) - 1)]
3:   r2 ← s2[randint(0, len(s2) - 1)]
4:   i1 ← randint(0, len(r1) - 1)
5:   i2 ← randint(0, len(r2) - 1)
6:   r11, r12 ← r1[: i1], r1[i1 :]
7:   r21, r22 ← r2[: i2], r2[i2 :]
8:   for i in r22 do
9:     if i not in r12 then
10:      Delete i from s1
11:     end if
12:   end for
13:   for i in r12 do
14:     if i not in r22 then
15:       needAdd.append(i)
16:     end if
17:   end for
18:   r1 ← r11 + r22
19:   for i in needAdd do
20:     Insert i in s1 let cost least
21:   end for
22:   localsearch() for s1
23:   return s1
24: end function

```

- The subsolution should be added into the end of the solution without the routes choiced and then do the local Search

- Crossover

- The two solutions is select randomly in the population
- The routes to merge and the index to split is also randomly choice.
- After crossover, the Child solution will add into the population if there is any solution worse than it and pop that solution.

3.2. Performance

The test was do in a *Intel 6200U 2@2.8GHz* with 12GB memaory Computer. And the test result of the dataset not in the platform is On the table behind. For the case in gdb and val, I run the program 60 seconds, and for the case in the egl, I run the program 120 seconds. And run each case 5 time.

TABLE 1. RESULT OF TEST CASE

Case	Vertices	Req Edges	best Cost	Ave Cost	Theory Cost
gdb20	11	22	121	121	121
gdb5	13	26	383	383	377
val1c	24	39	250	253.8	245
val7a	40	66	279	280	279
egl-e2-A	77	72	5210	5286	5018
egl-s1-C	190	75	9521	9548	8518

3.3. Result

For the test, the result is good and can not much higher than the theory best cost. But if the dataset is big, the algorithm need more time to get the best solution it can get.

3.4. Analysis

My algorithm can have great effect in small dataset, can get a great result and calculate fast. But if in a big dataset, it will be convergence so fast and calculate so slowly.

The reason of the convergence is that the MS operator can't import big difference to a solution getted, but the crossover is so slowly and can't do many times in the time limit. And why it will calculate slowly when use in a big dataset is that local search use much time to get a best solution of a ordered list. And the time used will increase in exponent!

References

- [1] G. Ulusoy, "The fleet size and mix problem for capacitated arc routing," *European Journal of Operational Research*, vol. 22, no. 3, pp. 329–337, 1985.
- [2] 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.
- [3] P. Lacomme, C. Prins, and W. Ramdane-Chérif, "A genetic algorithm for the capacitated arc routing problem and its extensions," in *Workshops on Applications of Evolutionary Computation*. Springer, 2001, pp. 473–483.
- [4] M. Dror, *Arc routing: theory, solutions and applications*. Springer Science & Business Media, 2012.

[2] [3] [4] [1]