

Project Carp Report

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Abstract—This is the second project of class SUSTech CS303, Artificial Intelligence. This project requires us to implement an algorithm to solve the CARP problem, which is a sufficient-researched filed. Each student's program will be upload to an online platform to fight against others'.

I. PRELIMINARIES

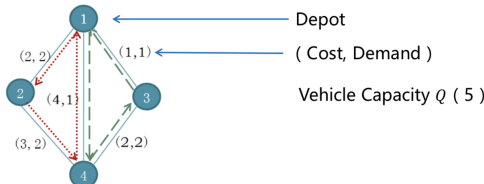
A. Problem Description

CARP(Capacitated Arc Routing Problem) can be described as follows: consider an undirected connected graph $G = (V, E)$, with a vertex set V and an edge set E and a set of required edges(tasks) $T \subseteq E$. A fleet of identical vehicles, each of capacity Q , is based at a designated depot vertex $v \in V$. Each edge $e \in E$ incurs a cost $c(e)$ whenever a vehicle travels over it or serves it (if it is a task). Each required edge(task) $\tau \subseteq T$ has a demand $d(\tau) > 0$ associated with it.

The objective of CARP is to determine a set of routes for the vehicles to serve all the tasks with minimal costs while satisfying: a)Each routes must start and end at v_0 ; b)The total demand serviced on each must not exceed Q ; c)Each task must be served exactly once(but the corresponding edge can be traversed more than once) This part describes the representation, the more detail of algorithm and the architecture I used in the codes.

B. Applications

The ARC routing problem is a classic problem with many applications in the world, such as urban waste collection, post deliver, sanding and salting the streets. CARP problem is a very classic example for ARC problem which is about urban waste collection. Since CARP is NP-hard [4], exact methods are only applicable to small-size instances. As a result, heuristics and meta- heuristics are often considered in the literature. For example, Augment-Merge, Path-Scanning, the "route first-cluster second" type heuristic proposed in, and Ulusoy's Heuristic are typical heuristic methods.[1]



C. Software

This project is written by python 3.6 using IDE pycharm. The library include numpy, random, functools, copy, operator, sys, time.

D. Algorithm

This project mainly use MEANS[1].

II. METHODOLOGY

A. Model Design

This problem is mainly solved by MEANS algorithm. Before that, I first implements Floyd algorithm to obtain the minCost matrix. MEANS algorithm is a modified genetic algorithm. Firstly, I use randomly path scanning to get a initial population of size 1000. And for each generation, I produce 5 children using crossover , and mutates according to the probability. For every generation, we maintain same population 1000 which are the best 1000 ones.

- **CrossOver:** Given two parent solutions S1 and S2, CrossOver randomly selects two routes R1 and R2 from them, respectively. Then, both R1 and R2 are further randomly split into two subroutes, say R1 = (R11, R12) and R2 = (R21, R22). After that, a new route is obtained by replacing R12 with R22.[1]
- **localSearch:** the single insertion, double insertion, and swap, are separately applied to the individual to conduct a best improvement local search. That is, for each move operator, all solutions that can be reached by it from Sx are examined, and the current solution will only be updated when a better solution has been found. After that, the MS operator is applied to this local optimal solution, forming the second stage of local search.
- **How to judge a solution :** here I make some simplification of the method provided by the paper as in my implementation, I removed all invalid solution(the one that exceeds capacity) The fomula is provided following:

$$value = \sum_{n=1}^N cost\ of\ route_i \quad (1)$$

B. Data and data structure

Here I mainly use dict and list in python.

C. Representation

To represent the chess in Gomoku , we define some rules:

- **minCost:** it is a matrix representing the min cost from one place to another place
- **allDemands:** it is a matrix representing the demand from one place to another place
- **alldemandedge:** it is a dict that contains all task as format "(a,b):demand"
- **psize:** size of initial population

- *opsize*: the amount of children of each generation
- *ubtrial*: the max time to find a solution each time
- P_{ls} : the probability to perform a local search

D. Architecture

Here is some functions in the program :

- **pathScanning**: It is the method that used to construct initial solution using path scanning method
- **crossOver**: It is the method to achieve cross over between two parent solution
- **MS**: It is the Merge-Split operator in MEANS algorithm
- **localSearch**: It is the local search algorithm
- **MEANS**: It is the main algorithm for MEANS.

E. Detail of Algorithm

Here describe the detail of algorithm in some vital functions. For some unimportant and well-known algorithm like "Floyd Algorithm", "singleInsertion operator", they will not be presented below.

- MEANS: It is the main part of the MEANS algorithm.

```

1: function MEANS(psize, opsize, ubtrial,  $P_{ls}$ )
2:   //Initialization.
3:   Set the current population  $pop = \emptyset$ 
4:   while  $|pop| < psize$  do
5:     Set the trial counter  $ntrial = 0$ ;
6:      $ntrial = ntrial + 1$ 
7:     while  $S_{init}$  is not a clone of any solution  $S \in pop$  do
8:       Generate an initial solution  $S_{init}$  ;
9:        $ntrial = ntrial + 1$ 
10:    end while
11:    if  $S_{init}$  is a clone of any solution  $S \in pop$  then
12:      break;
13:    end if
14:    update  $his\_max$  and  $his\_values$ 
15:  end while
16:   $psize = |pop|$ 
17:  //Main Loop:
18:  while stopping criterion is not met do
19:    Set an intermediate population  $pop_t = pop$ 
20:    for  $i$  from 1 to opsize do
21:      Randomly select two different solutions  $S_1$ 
22:      and  $S_2$  as the parents from  $pop$ ;
23:      Apply the crossover operator to  $S_1$  and  $S_2$ 
24:      to generate  $S_x$  ;
25:      Sample a random number  $r$  from the uni-
26:      form distribution between 0 and 1;
27:      if  $r < P_{ls}$  then Apply local search to  $S_x$ 
28:      to generate  $S_{ls}$ ;
29:      if  $S_{ls}$  is not a clone of any  $S \in pop_t$  then
30:         $pop_t = pop_t \cup S_{ls}$ 
31:      else
32:        if  $S_x$  is not a clone of any  $S \in pop_t$ 
33:        then
34:           $pop_t = pop_t \cup S_x$ 
35:        end if
36:      end if
37:    end for
38:  end while

```

```

32:  else
33:    if  $S_x$  is not a clone of any  $S \in pop_t$  then
34:       $pop_t = pop_t \cup S_x$ 
35:    end if
36:  end if
37: end for
38: Sort the solutions in  $pop_t$  using stochastic
39: ranking;
40: Set  $pop =$  the best psize solutions in  $pop_t$  ;
41: end while return the best feasible solution  $S_{bf}$  in
42:  $pop$ ;
43: end function

```

- pathScanning : we use it to generate a list of initial solutions

```

1: function PATHSCANNING(method, alldemandege)
2:   $tempt =$  copy of alldemandege
3:  while  $tempt$ 's length  $\neq 0$  do
4:     $\emptyset \Rightarrow routes$ ;
5:     $capacity \Rightarrow leftCap$ ;
6:     $depot \Rightarrow start$ ;
7:    while  $leftCap > 0$  do
8:       $IFINITY \Rightarrow mincost$ ;
9:       $\emptyset \Rightarrow closet$ ;
10:     for all task(a,b) in  $tempt$  do
11:       if  $minCost[start][a] == mincost$  then
12:          $closet.add(task)$ ;
13:       end if
14:       if  $minCost[start][a] < mincost$  then
15:          $\emptyset \Rightarrow closet$ ;
16:          $closet.add(task)$ ;
17:         refresh  $mincost$ ;
18:       end if
19:     end for
20:   end while
21:   for all task in  $closet$  do
22:     if it's load exceeds the  $leftCap$  then
23:       remove task from  $closet$ ;
24:     end if
25:   end for
26:   if  $len(closet) == 0$  then
27:     break;
28:   end if
29:   if  $len(closet) == 1$  then
30:      $result = closet[0]$ ;
31:   else
32:     if method == 1 then
33:        $result =$  the task that maximize the
34:       distance to the depot;
35:     end if
36:     if method == 2 then
37:        $result =$  the task that minimize the
38:       distance to the depot;
39:     end if
40:     if method == 3 then
41:        $result =$  the task that maximize the term
42:       (load)/(serve cost);
43:     end if
44:     if method == 4 then
45:        $result =$  the task that minimize the term
46:       (load)/(serve cost);

```

```

43:         end if
44:         if method == 5 then
45:             if current capacity <= 0.5capacity then
46:                 use method1;
47:             else
48:                 use method2;
49:             end if
50:         end if
51:         if method == 6 then
52:             result = random choose one from clos-
est;
53:         end if
54:     end if
55:     routes.append(result);
56:     remove result from tempt;
57:     finalresult.append(routes);
58: end while return finalresult
59: end function

```

- **crossover** : In this method , we achieved crossover part of the algorithm

```

1: function CROSSOVER(S1, S2)
2:   R1 ← randomly choose one route from S1;
3:   R2 ← randomly choose one route from S2;
4:   R11, R12 ← randomly split R1;
5:   R21, R22 ← randomly split R2;
6:   R1loss ← the one that is in R12 and not in R22;
7:   R22 ← remove the task in R22 that have appeared
in R1 except R12;
8:   R1new ← R11 + R22;
9:   for task in R1loss do
10:     insert task into R1new at the position that will
minimize total cost;
11:   end for
12:   if R1new is better than R1 then
13:     remove R1 from S1;
14:     insert R1new into S1;
15:   end if return S1
16: end function

```

- **localSearch** : We achieve local search part in this method

```

1: function LOCALSEARCH( $S_x$ )
2:   newsol1 ← using singleInsertion operator to gener-
ate a new solution that better or equal to  $S_x$ ;
3:   newsol2 ← using doubleInsertion operator to gener-
ate a new solution that better or equal to  $S_x$ ;
4:   newsol3 ← using swap operator to generate a new
solution that better or equal to  $S_x$ ;
5:   Sls ← the best one of newsol1, newsol2, newsol3;
6:   Sls ← using MS operator to generate a new solution
that better or equal to  $S_x$ ; return Sls;
7: end function

```

III. EMPIRICAL VERIFICATION

A. Dataset

Expect for the dataset provided by the carp platform provided, I also use some eglese dataset from reference of the textbook. Here is the name of the dataset: egl-e1-B.dat, egl-e1-C.dat, egl-e3-B.dat, egl-e3-C.dat

B. Hyperparameters

Here, the parameters that are needed to test is the input for MEANS function.

In the paper, the autho assigns following values to them:

psize	opsize	ubtrial	P_{ls}
30	180	50	0.3

However, I modify the parameter to the following. For the reason that our calculating resouce is limited and the most contributing part is Initialization, I increase the size of initial population and decrease the number of childrens for each generation.

psize	opsize	ubtrial	P_{ls}
1000	10	50	0.3

C. Performance Measurement

Here as this program always run until the end few second of the restricted time, it means nothing here to measure the program using time. Therefore, I use the total cost of the final solution to measure the performance of the program.

D. Experimental Results

Here is the performance of the dataset provided by the platform.

	egl-e1-A	val4A	gdb1	val7A	egl-s1-A
Cost	3785	412	316	285	5361

Here is the performance of the dataset from the reference.

	egl-e1-B.dat	egl-e1-C.dat	egl-e3-B.dat	egl-e3-C.dat
Cost	4662	6256	8246	10822

E. Conclusion

Actually, the performance is quite ok. As the size of initial population is large enough, it can get a result that closest to optimal solution at an early stage. However, it also has some defects. For example, it can not always find out the optimal solution. For this, I think it is might because that there are not enough generations as I didn't implements multithreads.

IV. ACKNOWLEDGEMENTS

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REFERENCES

- [1] Tang, K., Mei, Y. and Yao, X. (2009). Memetic Algorithm With Extended Neighborhood Search for Capacitated Arc Routing Problems. IEEE Transactions on Evolutionary Computation, 13(5), pp.1151-1166.