

## CCVRP optimization with Genetic and ACS

- **Problem Description:**

The Clustered capacitated vehicle routing problem (CCVRP) consist of  $n-1$  costumers with certain need and one depot with some vehicles with specific amount of capacity.

Each customer  $v_i$  ( $i \in \{1, \dots, n\}$ ) has a known nonnegative demand  $d_i$  to be delivered or collected and the depot has a fictitious demand  $d_0 = 0$ . There exist  $m$  identical vehicles, each with a capacity  $Q$  and in order to ensure feasibility we assume that  $d_i \leq Q$  for each  $i \in \{1, \dots, n\}$ .

Problem assumption:

- each route starts and ends at the depot vertex;
- once a vehicle enters a cluster, it visits all the vertices within the cluster before leaving it;
- the sum of the demands of the visited vertices by a route does not exceed the capacity of the vehicle,  $Q$ .

- **Instances Description:**

Instances are created based on CVRP instances form TSPLIB library with difference that we created new problem that is a clustered version of CVRP.

Each CVRP instance file consists of two part as **specification part** that contains information about the instance data and **data part**.

- **Algorithm Description:**

The algorithm designed base on the related paper as (*A novel two-level optimization approach for clustered vehicle routing problem*).

Our approach is obtained by decomposing the problem into two logical and natural subproblems: an upper-level (global) subproblem and a lower-level (local) subproblem. The first subproblem aims at determining the routes visiting the clusters, called global routes, using a genetic algorithm applied to the corresponding global graph (see details in Section 3) while the aim of the second subproblem is to determine the visiting order within the clusters for the above-mentioned routes. The second subproblem is solved by transforming each global route into a TSP which then is computed optimally using the Concorde TSP solver.

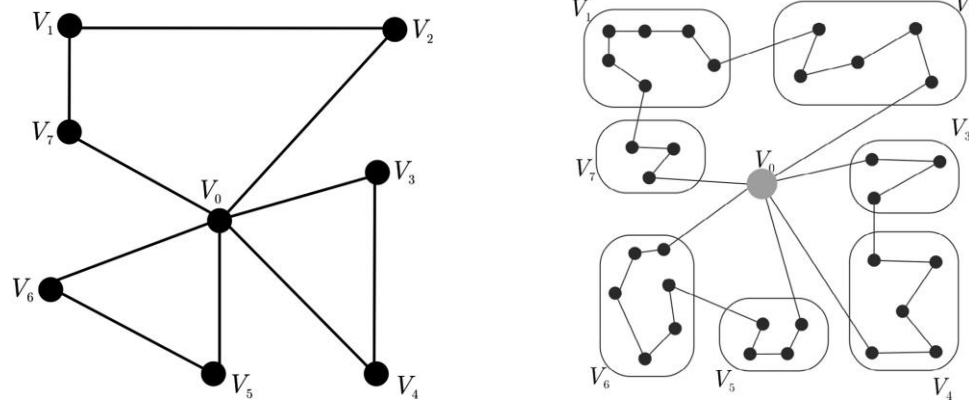
- **Global subproblem with GA:**

As mentioned, we solve this subproblem using GA, so we describe out GA as follow parts:

- **Representation:**

Global subproblem search space is consist of number of clusters  $V_i$  ( $i \in \{0, \dots, n\}$ ) witch depot node placed in  $V_0$  cluster .

So our representation would be a sequence of cluster numbers that shows our global routes toward clusters. Depot cluster would be seen repeatedly as finish each route from depot and back to it.



As images shows one feasible solution can be: (7 1 2 0 3 4 0 5 6)

For creating the chromosome, we list cluster needs in descending and trying to satisfy needs by minimum vehicle number.

- Fitness function:

The fitness function of each individual chromosome in the population is given by the total length of the best corresponding clustered routes associated to the collection of global routes specified by the chromosome. This distance also takes into account the order in which the vertices within the clusters are visited. Our aim is to minimize this total distance.

- Crossover:

Our GA uses a custom version of the two-point crossover. The crossover function takes two parent candidate solutions as input and outputs two solutions.

Cross over acts like two-point crossover but it allows repetition of depot cluster (because at the end of each route we came back to depot) as number of it was repeated in the parent chromosome.

$$P1 = (6 \ 8 \ 0 \mid 1 \ 3 \ 7 \mid 0 \ 5 \ 4 \ 2)$$

$$P2 = (7 \ 2 \ 1 \mid 6 \ 0 \ 4 \mid 3 \ 0 \ 5 \ 8)$$

$$O1 = (2 \ 6 \ 0 \ 1 \ 3 \ 7 \ 4 \ 0 \ 5 \ 8)$$

$$O2 = (8 \ 0 \ 1 \ 3 \ 6 \ 0 \ 4 \ 7 \ 5 \ 2)$$

- Mutation:

we use a swapping inter-cluster mutation operator which acts as follows: we randomly select genes (i.e. clusters) and if the genes are from different global routes, their position is exchanged.

$$(5 \ 8 \ 1 \ 0 \ 3 \ 7 \ 0 \ 6 \ 4 \ 2) \rightarrow (5 \ 6 \ 1 \ 0 \ 3 \ 7 \ 0 \ 8 \ 4 \ 2)$$

- Parent Selection:

Two parents with same chromosome size randomly selected from 30% of best population.

- Survivor Selection:

Elitism manner used in the way that only best individual of every generation moving into the next generation.

- Local subproblem:

The basic idea used in our transformation is to add an artificial cost  $M$  to all the inter-cluster edges in this way forcing the vehicle to visit all the vertices within the cluster before leaving it.

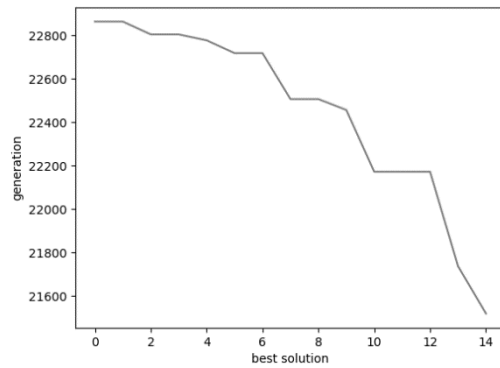
1. The set of nodes of  $G_p$  and  $G_{p'}$  are the same.
2. The entries of the cost matrix  $G_{p'}$  are defined as follows:
  - (a) if  $v_i, v_j \in V_k$  then  $c'(v_i, v_j) = c(v_i, v_j)$ ;
  - (b) if  $v_i \in V_k, v_j \in V_l$  with  $k \neq l$  then  $c'(v_i, v_j) = c(v_i, v_j) + M$ ;  
where  $M > \sum c(v_i, v_j)$ .

After that we passing the edge matrix to TSP solver with bellow configuration.

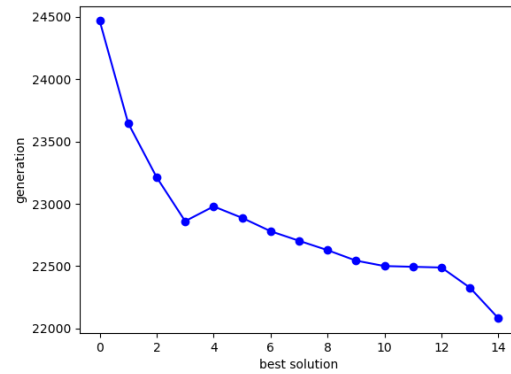
For solving local subproblem open source TSP solver used as bellow.

```
solver.read_mat(mat)
config = TwoOpt_solver(initial_tour='NN', iter_num=100)
answer = solver.get_approx_solution(config)
```

- GA learning process:



Best solution per generation



average solution per generation

- GA Results:

Because of HW limitation of execution time (1 minute per instance) bellow configuration selected.

MUTATION\_RATE = 0.2  
POPULATION\_SIZE = 40  
MAX\_GENERATION = 10  
XOVER\_METHOD = ORDER\_2POINT  
SELECTION = RANDOM  
SURVIVOR\_SEL\_TYPE = ELITISM (best will be kept)

$\rho = 10\%$											
index	clusters	vehicles	vertices	Q	BKS	Best	average	worst	variance	avg_time	avg vehicles
1	120	9	241	550	5759/25	16532.41	17153.33	17830.24	406.655	22.984	9
2	101	10	321	700	9247/92	22933.83	23503.14	24101.87	287.613	32.732	10
3	96	10	401	900	12904/6	29986.90	30851.00	31644.01	524.867	73.037	10
4	104	10	481	1000	17810/4	41385.85	42151.04	43103.16	503.638	115.14	10
5	49	5	201	900	8960/31	16526.34	17232.05	17702.95	334.257	56.114	5
6	67	7	281	900	10976/5	22204.49	22861.75	23504.54	372.046	64.244	7
7	88	9	361	900	12485/8	28235.49	28795.24	29269.60	378.717	71.651	9
8	108	11	441	900	13331/2	33223.84	34325.43	35153.69	519.279	84.987	11
9	51	15	256	1000	710/64	974.90	1022.87	1045.15	19.996	32.074	16.0

10	56	18	324	1000	908/89	1243.49	1267.09	1300.11	19.571	45.193	18.0
ρ = 25%											
index	clusters	Vehicles	vertices	Q	BKS	best	average	Worst	variance	avg_time	avg_vehicles
1	40	10	241	550	6051/04	9188.307	9592.559	9899.38	166.623	52.46	10
3	38	10	401	900	13692/6	17823.20	18334.96	18584.4	210.22	50.949	10
5	19	5	201	900	9340/7	11125.28	11383.95	11579.1	140.223	41.615	5
7	34	9	361	900	12348/1	16028.19	16513.08	17077.0	301.396	45.701	9
9	51	16	256	1000	717/63	1032.50	1080.82	1128.57	31.236	34.746	16
11	63	20	400	1000	1131/84	1621.83	1688.73	1757.85	34.881	55.476	19.4
13	98	27	253	1000	1034/3	1786.37	1818.89	1872.01	26.135	20.263	28.0
15	124	36	397	1000	1667/08	2892.85	2938.43	2987.39	32.63	41.011	36.4
17	98	23	241	200	795/33	1738.09	1780.32	1823.69	26.223	20.235	23.4
19	153	33	361	200	1538/2	3619.93	3694.05	3776.65	47.559	26.072	34.7
ρ = 50%											
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time	avg_vehicles
11	37	18	400	1000	1101/51	1220.54	1285.73	1323.74	26.892	140.71	19.0
12	40	20	484	1000	1311/91	1468.56	1512.06	1538.39	20.35	160.09	20.0
13	58	28	253	1000	1053/47	1283.13	1313.73	1334.24	18.24	27.601	29.0
14	66	32	321	1000	1342/7	1690.19	1714.35	1738.92	17.303	34.624	33.0
15	73	36	397	1000	1657/22	2056.48	2088.56	2146.57	28.903	37.968	37.0
16	80	39	481	1000	2003/1	2483.53	2536.66	2574.27	31.63	41.825	40.0
17	47	24	241	200	881/66	1081.14	1101.15	1117.64	11.417	25.301	24.0
18	59	30	301	200	1199/12	1535.39	1562.26	1586.88	15.86	30.215	30.0
19	69	35	361	200	1612/33	2049.17	2102.60	2132.47	25.443	34.669	35.0
20	81	41	421	200	2278/64	2856.31	2941.40	2993.29	37.502	39.778	41.0
ρ = 75%											
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time	avg_vehicles
2	13	13	321	700	10204/3	10520.98	10520.98	10520.98	0.0	31.146	13.0
4	13	13	481	1000	17077/5	17626.74	17626.74	17626.74	0.0	48.007	13.0
6	9	9	281	900	11452/0	11847.54	11847.54	11847.54	0.0	21.714	9.0
8	14	13	441	900	13882/23	14485.70	14516.30	14644.08	57.622	42.148	13.0
10	22	21	324	1000	1000/507	1028.73	1028.73	1028.73	0.0	31.6839	22.0
12	27	26	484	1000	1475/679	1502.48	1504.87	1518.18	4.54	20.698	26.0
14	42	41	321	1000	1520/546	1540.77	1552.04	1562.49	8.058	19.034	41.0
16	51	51	481	1000	2265/537	2308.49	2308.49	2308.49	0.0	22.7072	51.0
18	38	37	301	200	1392/153	1422.93	1422.93	1422.93	0.0	22.992	39.0
20	53	52	421	200	2502/34	2599.88	2599.88	2599.88	0.0	35.1147	53.0

$\rho = 100\%$											
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time	avg_vehicles
1	9	9	241	550	6293/036	6401.09	6401.09	6401.09	0.0	28.533	9.0
2	10	10	321	700	9879/586	10187.39	10187.39	10187.39	0.0	46.259	10.0
4	10	10	481	1000	16130/39	16664.14	16664.14	16664.14	0.0	75.881	10.0
5	5	5	201	900	8394/111	8679.34	8679.34	8679.34	0.0	49.568	5.0
7	8	8	361	900	11346/11	11705.95	11705.95	11705.95	0.0	49.408	8.0
8	10	10	441	900	13188/94	13572.42	13572.42	13572.42	0.0	48.076	10.0
10	16	16	324	1000	837/516	860.64	860.64	860.64	0.0	25.972	16.0
11	18	18	400	1000	1054/133	1091.88	1091.88	1091.88	0.0	42.810	18.0
19	34	34	361	200	1667/454	1696.12	1696.12	1696.12	0.0	25.765	34.0
20	39	39	421	200	2128/597	2158.55	2158.55	2158.55	0.0	28.537	39.0

Instance name	BKS		best	average	worst	variance	avg_time	avg_vehicles
e-n10-c2.map	2016/57		2016.57	2016.57	2016.57	0.0	0.4629	2.0
a-n15-c4.map	1947/3		1961.98	1961.98	1961.98	0.0	0.3818	3.0
b-n15-c4.map	2602/56		2684.84	2933.94	3325.27	305.288	0.0462	2.4
a-n20-c5.map	2759/13		2788.79	2788.79	2788.79	0.0	0.4808	3.0
c-n20-c5.map	3028/83		3038.93	3118.86	3438.59	159.862	0.4508	4.0
d-n20-c5.map	2239/09		2239.09	2244.23	2290.48	15.419	0.5597	3.0
e-n20-c5.map	3343/34		3343.34	3343.34	3343.34	0.0	0.4799	4.0
b-n30-c6.map	3116/84		3285.15	3361.59	3514.92	83.185	0.8846	3.0

- GA One-minute run Results:

$\rho = 10\%$				
file name	BKS	vehicles	best	vehicles
kelly01.ccvrp	5759/25	9	16751/19	9
kelly02.ccvrp	9247/92	10	22744/33	10
kelly03.ccvrp	12904/6	10	28874/64	10
kelly04.ccvrp	17810/4	10	41207/75	11
kelly05.ccvrp	8960/31	5	16768/86	5
kelly06.ccvrp	10976/5	7	22215/53	7
kelly07.ccvrp	12485/8	9	28314/09	9
kelly08.ccvrp	13331/2	11	33422/68	11
kelly09.ccvrp	710/64	15	1065/26	16

<b>kelly10.ccvrp</b>	<b>908/89</b>	<b>18</b>	<b>1287/338</b>	<b>19</b>
<b><math>\rho = 25\%</math></b>				
<b>file name</b>	<b>BKS</b>	<b>vehicles</b>	<b>best</b>	<b>vehicles</b>
kelly01.ccvrp	6051/04	10	9409/454	10
kelly03.ccvrp	13692/6	10	18045/11	10
kelly05.ccvrp	9340/7	5	11209/1	5
kelly07.ccvrp	12348/1	9	16518/23	9
kelly09.ccvrp	717/63	16	1054/309	16
kelly11.ccvrp	1131/84	20	1664/447	20
kelly13.ccvrp	1034/3	27	1772/769	30
kelly15.ccvrp	1667/08	36	2851/527	38
kelly17.ccvrp	795/33	23	1635/427	23
kelly19.ccvrp	1538/2	33	3678/73	35
<b><math>\rho = 50\%</math></b>				
<b>file name</b>	<b>BKS</b>	<b>vehicles</b>	<b>best</b>	<b>vehicles</b>
kelly11.ccvrp	1101/51	18	1263/157	19
kelly12.ccvrp	1311/92	20	1498/865	20
kelly13.ccvrp	1053/47	28	1273/728	29
kelly14.ccvrp	1342/7	32	1673/094	33
kelly15.ccvrp	1657/22	36	2041/113	37
kelly16.ccvrp	2003/1	39	2516/534	40
kelly17.ccvrp	881/66	24	1088/141	24
kelly18.ccvrp	1199/12	30	1533/102	30
kelly19.ccvrp	1612/33	35	2030/046	35
kelly20.ccvrp	2278/64	41	2939/032	41
<b><math>\rho = 75\%</math></b>				
<b>file name</b>	<b>BKS</b>	<b>vehicles</b>	<b>best</b>	<b>vehicles</b>
kelly02.ccvrp	10204/3	13	10520/98	13
kelly04.ccvrp	17077/6	13	17626/74	13
kelly06.ccvrp	11452	9	11847/54	9
kelly08.ccvrp	13882/2	13	14492/69	13
kelly10.ccvrp	1000/51	21	1023/978	21
kelly12.ccvrp	1475/68	26	1502/488	26
kelly14.ccvrp	1520/55	41	1540/777	41
kelly16.ccvrp	2265/54	51	2308/495	51
kelly18.ccvrp	1392/15	37	1401/552	37
kelly20.ccvrp	2502/34	52	2572/521	52

$\rho = 100\%$				
file name	BKS	vehicles	best	vehicles
kelly01.ccvrp	6293/04	9	6401/095	9
kelly02.ccvrp	9879/59	10	10187/4	10
kelly04.ccvrp	16130/4	10	16664/14	10
kelly05.ccvrp	8394/11	5	8679/348	5
kelly07.ccvrp	11346/1	8	11705/95	8
kelly08.ccvrp	13188/9	10	13572/43	10
kelly10.ccvrp	837/516	16	860/6491	16
kelly11.ccvrp	1054/13	18	1091/883	18
kelly19.ccvrp	1667/45	34	1696/128	34
kelly20.ccvrp	2128/6	39	2158/556	39

Instance name	BKS		best	avg vehicles
e-n10-c2.map	2016/57		2016.57	2.0
a-n15-c4.map	1947/3		1961.98	3.0
b-n15-c4.map	2602/56		2684.84	2.4
a-n20-c5.map	2759/13		2788.79	3.0
c-n20-c5.map	3028/83		3038.93	4.0
d-n20-c5.map	2239/09		2239.09	3.0
e-n20-c5.map	3343/34		3343.34	4.0
b-n30-c6.map	3116/84		3285.15	3.0

- GA Algorithm analysis:

Algorithm diversity seems to be low per some instances because of deleting non feasible solutions that could be create after Xover or mutation. Replacing parent instead of child when child isn't feasible will also decrease population diversity.

After analysis for example in execution of *a-n15-c4.map* instance 30% of population was not feasible after Xover or mutation. As dimension of problem decrease diversity of population will also decrease.

Algorithm representation is another important factor of diversity.

The representation that described in the related paper cause many-to-one mapping between phenotype and genotype in the way that for example Ch1 = (6 7 0 1 2 3 0 4 5) and Ch2 = (1 2 3 0 6 7 0 4 5) have same fitness value cause they both have same global routes but the order of them is different.

Even one chromosome itself could be mapped to many members of phenotype for because representation shows only sequence of clusters to be seen and doesn't specifies node orders to be visiting in a cluster.



In compare results were reasonably close to best known solution.  
But algorithm configuration that used in this report has significantly low number of generation (10 generation) in compare with paper configuration (200 generation) and it causes less chance of getting out of local optima.

Mutation rate (20%) will shows its role of preserving diversity could not be achieved by small number of generations.

- Global and local subproblem with ACS:

- Each ant solution form would be same as GA representation.
- M ants would place randomly on graph clusters.
- Local subproblem is the same as describe in GA and use in determining the global best solution in the colony.

```

Initialize
Loop /* at this level each loop is called an iteration */
  Each ant is positioned on a starting node
  Loop /* at this level each loop is called a step */
    Each ant applies a state transition rule to incrementally build a solution
    and a local pheromone updating rule
  Until all ants have built a complete solution
  A global pheromone updating rule is applied
Until End_condition

```

- ACS state transition rule

an ant positioned on node  $r$  chooses the city  $s$  to move to by applying the rule given:

$$s = \begin{cases} \arg \max_{u \in J_k(r)} \{ [\tau(r, u)] \cdot [\eta(r, u)]^\beta \} & \text{if } q \leq q_0 \quad (\text{exploitation}) \\ S & \text{otherwise} \quad (\text{biased exploration}) \end{cases}$$

we S set as follow:

$$p_k(r, s) = \begin{cases} \frac{[\tau(r, s)] \cdot [\eta(r, s)]^\beta}{\sum_{u \in J_k(r)} [\tau(r, u)] \cdot [\eta(r, u)]^\beta} & \text{if } s \in J_k(r) \\ 0 & \text{otherwise} \end{cases}$$

- ACS local updating rule

$$\tau(r,s) \leftarrow (1-\rho) \cdot \tau(r,s) + \rho \cdot \Delta\tau(r,s)$$

where  $0 < \rho < 1$  is a parameter.

- (i) we set  $\Delta\tau(r,s) = \tau_0$ , where  $\tau_0$  is the initial pheromone level
- (ii) we set  $\Delta\tau(r,s) = 0$ .

- **ACS global updating rule**

$$\tau(r,s) \leftarrow (1-\alpha) \cdot \tau(r,s) + \alpha \cdot \Delta\tau(r,s)$$

$$\text{where } \Delta\tau(r,s) = \begin{cases} (L_{gb})^{-1} & \text{if } (r,s) \in \text{global - best - tour} \\ 0 & \text{otherwise} \end{cases}$$

$0 < \alpha < 1$  is the pheromone decay parameter, and  $L_{gb}$  is the length of the globally best tour from the beginning of the trial

- **ACS parameter settings**

$\beta=2, q_0=0.9, \alpha=\rho=0.1, \tau_0=(n \cdot L_{nn})^{-1}$ , where  $L_{nn}$  is the tour length produced by the nearest neighbor heuristic

values of the parameters were largely independent of the problem, except for  $\tau_0$  for which, as we said,  $\tau_0=(n \cdot L_{nn})^{-1}$ . The number of ants used is  $m=10$  (this choice is explained in Section IV.B). Regarding their initial positioning, ants are placed randomly, with at most one ant in each city.

- **ACS Implementation**

- **State transition:**

```
# exploitation
if q < Q0:
    s = candidates[args.index(max(args))]
# exploration
else:
    p = [arg/sum(args) for arg in args]

    # roulette wheel
    s = candidates[rouletteWheel(p)]
```

### Local update:

Update the pheromone path in both ways.

```
self.T[r][s] = (1-RHO) * self.T[r][s] + RHO * self.T0
self.T[s][r] = (1-RHO) * self.T[s][r] + RHO * self.T0
```

### Global update:

If edge(i,j) is in the best solution.set the delta as  $1/L_{gb}$ .  
And after that update edge path in both ways.

```
if i in bestSol and j in bestSol and + \
    abs(bestSol.index(i) - bestSol.index(j)) == 1:
```

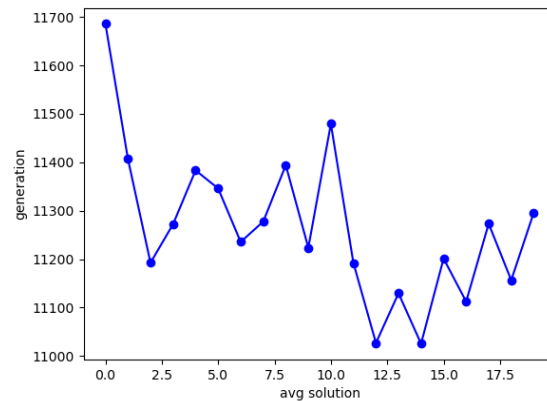
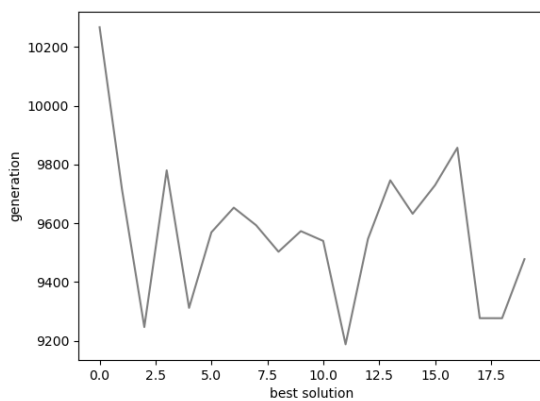
```
    deltaT = 1/self.best[1]
```

```
    self.T[i][j] = (1-ALPHA) * self.T[i][j] + \
        (ALPHA * deltaT)
```

```
    self.T[j][i] = (1-ALPHA) * self.T[j][i] + \
        (ALPHA * deltaT)
```

### ACS convergence process:

Best and average solution per iteration for instance 0.1%\_kelly01



It shows that overall, the pheromone trail leads the search to better solution during algorithm. Although exploration manner search could happen to.

• ACS Results:

iterations = 10

ALPHA = RHO = 0.2

Beta = 2

Q0 = 0.9

T0 = 0.00005 (value is based on some search results)

Ants\_num = max(Clusters\_num/10, 2)

$\rho = 10\%$										
index	clusters	vehicles	vertices	Q	BKS	Best	average	worst	variance	avg_time
1	120	9	241	550	5759/25	9311/123	9524/57	10076/36	230/952	18.097
2	101	10	321	700	9247/92	14608/26	15142/85	15540/95	279/1	26.299
3	96	10	401	900	12904/6	19725/90	20017/18	20326/97	190/524	41.711
4	104	10	481	1000	17810/4	25823/08	26967/54	27998/27	678/783	64.355
5	49	5	201	900	8960/31	13030/843	13436/76	13761/94	262/992	9.5907
6	67	7	281	900	10976/5	15562/00	16137/14	16708/44	361/586	18.995
7	88	9	361	900	12485/8	19062/93	19561/38	20021/09	332/632	35.513
8	108	11	441	900	13331/2	20047/18	21490/08	22168/08	620/596	50.363
9	51	15	256	1000	710/64	787/7316	799/3658	809/9543	6/832	4.0530
10	56	18	324	1000	908/89	989/7373	996/7994	1005/142	5/058	6.0530
$\rho = 25\%$										
index	clusters	Vehicles	vertices	Q	BKS	best	average	Worst	variance	avg_time
1	40	10	241	550	6051/04	7152/93	7324/41	7437/47	84/994	3.6489
3	38	10	401	900	13692/6	15311/51	15637/0	16007/93	199/748	9.7655
5	19	5	201	900	9340/7	10379/19	10486/2	10548/73	47/584	4.6584
7	34	9	361	900	12348/1	13918/10	14014/0	14080/33	58/941	9.4245
9	51	16	256	1000	717/63	767/8084	786/112	804/6502	10/616	3.5788
11	63	20	400	1000	1131/84	1221/950	1233/58	1246/456	9/698	8.7118
13	98	27	253	1000	1034/3	1165/701	1209/72	1233/166	20/108	5.5740
15	124	36	397	1000	1667/08	1863/173	1897/73	1923/843	15/59	13.096
17	98	23	241	200	795/33	1040/013	1070/78	1100/964	19/253	5.7340
19	153	33	361	200	1538/2	2026/525	2091/53	2131/029	25/555	19.384
$\rho = 50\%$										
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time
11	37	18	400	1000	1101/51	1132/953	1152/95	1166/500	10/472	4.5660
12	40	20	484	1000	1311/91	1352/895	1355/98	1359/790	1/995	7.4104
13	58	28	253	1000	1053/47	1069/599	1080/11	1093/557	7/775	1.9484
14	66	32	321	1000	1342/7	1370/867	1390/00	1404/544	8/793	2.8605
15	73	36	397	1000	1657/22	1692/704	1702/33	1710/727	6/215	4.6001

16	80	39	481	1000	2003/1	2048/210	2067/94	2088/451	11/053	7.1417
17	47	24	241	200	881/66	899/0229	909/308	921/2504	5/69	1.2698
18	59	30	301	200	1199/12	1245/925	1255/40	1264/584	6/151	2.1820
19	69	35	361	200	1612/33	1666/086	1673/89	1679/125	4/428	3.0638
20	81	41	421	200	2278/64	2345/878	2362/97	2378/723	10/285	4.6380
$\rho = 75\%$										
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time
2	13	13	321	700	10204/3	10204/3	10520/983	10520/983	10520/983	0
4	13	13	481	1000	17077/5	17077/59	17626/743	17626/743	17626/743	0
6	9	9	281	900	11452/0	11452/01	11847/545	11847/545	11847/545	0
8	14	13	441	900	13882/23	13882/23	14485/703	14491/99	14492/689	2/096
10	22	21	324	1000	1000/507	1000/507	1023/9781	1027/308	1028/7352	2/18
12	27	26	484	1000	1475/679	1475/679	1502/488	1517/308	1542/4236	16/796
14	42	41	321	1000	1520/546	1520/546	1540/7771	1542/4697	1546/4192	2/586
16	51	51	481	1000	2265/537	2265/537	2308/4947	2308/4947	2308/4947	0
18	38	37	301	200	1392/153	1392/153	1401/5521	1403/69	1422/931	6/414
20	53	52	421	200	2502/34	2502/34	2586/0475	2594/3502	2599/8854	6/779
$\rho = 100\%$										
index	clusters	vehicles	vertices	Q	BKS	best	average	worst	variance	avg_time
1	9	9	241	550	6293/036	6401/0949	6401/0949	6401/0949	0	1.9407
2	10	10	321	700	9879/586	10187/397	10187/397	10187/397	0	4.2388
4	10	10	481	1000	16130/39	16664/141	16664/141	16664/141	0	9.1544
5	5	5	201	900	8394/111	8679/3478	8679/3478	8679/3478	0	3.2554
7	8	8	361	900	11346/11	11705/953	11705/953	11705/953	0	5.3053
8	10	10	441	900	13188/94	13572/426	13572/426	13572/426	0	7.3177
10	16	16	324	1000	837/516	860/64914	860/64914	860/64914	0	2.9047
11	18	18	400	1000	1054/133	1091/8828	1091/8828	1091/8828	0	3.9081
19	34	34	361	200	1667/454	1696/1283	1696/1283	1696/1283	0	1.4732
20	39	39	421	200	2128/597	2158/5557	2158/5557	2158/5557	0	1.9021

Instance name	BKS		best	average	worst	variance	avg_time
e-n10-c2.map	2016/57		2016.571	2016.571	2016.571	0	0.0123
a-n15-c4.map	1947/3		1961/9887	1961/9887	1961/9887	0	0.0153
b-n15-c4.map	2602/56		2684.840	2684.840	2684.840	0	0.0206
a-n20-c5.map	2759/13		2788.78	2788.78	2788.78	0	0.0283
c-n20-c5.map	3028/83		3038.936	3038.936	3038.936	0	0.0224
d-n20-c5.map	2239/09		2239.09	2239.09	2239.09	0	0.0288
e-n20-c5.map	3343/34		3343.3399	3343.3399	3343.3399	0	0.0263
b-n30-c6.map	3116/84		3125.264	3125.264	3125.264	0	0.0550

- ACS One-minute run Results:

<b><math>\rho = 10\%</math></b>			
<b>file name</b>	<b>BKS</b>		<b>best</b>
kelly01.ccvrp	5759/25		9580/8395
kelly02.ccvrp	9247/92		15034/384
kelly03.ccvrp	12904/6		19805/949
kelly04.ccvrp	17810/4		27206/636
kelly05.ccvrp	8960/31		12710/506
kelly06.ccvrp	10976/5		16211/253
kelly07.ccvrp	12485/8		19635/97
kelly08.ccvrp	13331/2		20358/169
kelly09.ccvrp	710/64		796/07424
kelly10.ccvrp	908/89		978/17974
<b><math>\rho = 25\%</math></b>			
<b>file name</b>	<b>BKS</b>		<b>best</b>
kelly01.ccvrp	6051/04		7162/3492
kelly03.ccvrp	13692/6		15173/437
kelly05.ccvrp	9340/7		10379/19
kelly07.ccvrp	12348/1		13591/408
kelly09.ccvrp	717/63		776/39522
kelly11.ccvrp	1131/84		1229/9866
kelly13.ccvrp	1034/3		1207/9695
kelly15.ccvrp	1667/08		1872/9098
kelly17.ccvrp	795/33		1027/5664
kelly19.ccvrp	1538/2		2054/3725
<b><math>\rho = 50\%</math></b>			
<b>file name</b>	<b>BKS</b>		<b>best</b>
kelly11.ccvrp	1101/51		1136/72
kelly12.ccvrp	1311/92		1354/43
kelly13.ccvrp	1053/47		1067/8632
kelly14.ccvrp	1342/7		1374/37
kelly15.ccvrp	1657/22		1692/8696
kelly16.ccvrp	2003/1		2044/8591
kelly17.ccvrp	881/66		901/4698
kelly18.ccvrp	1199/12		1233/3751
kelly19.ccvrp	1612/33		1654/4038
kelly20.ccvrp	2278/64		2353/2575

$\rho = 75\%$			
file name	BKS		best
kelly02.ccvrp	10204/3		10520/983
kelly04.ccvrp	17077/6		17626/743
kelly06.ccvrp	11452		11847/545
kelly08.ccvrp	13882/2		14492/689
kelly10.ccvrp	1000/51		1023/9781
kelly12.ccvrp	1475/68		1502/488
kelly14.ccvrp	1520/55		1540/7771
kelly16.ccvrp	2265/54		2308/4947
kelly18.ccvrp	1392/15		1401/5521
kelly20.ccvrp	2502/34		2572/5211
$\rho = 100\%$			
file name	BKS		best
kelly01.ccvrp	6293/04		6401/0949
kelly02.ccvrp	9879/59		10187/397
kelly04.ccvrp	16130/4		16664/141
kelly05.ccvrp	8394/11		8679/3478
kelly07.ccvrp	11346/1		11705/953
kelly08.ccvrp	13188/9		13572/426
kelly10.ccvrp	837/516		860/64914
kelly11.ccvrp	1054/13		1091/8828
kelly19.ccvrp	1667/45		1696/1283
kelly20.ccvrp	2128/6		2158/5557

Instance name	BKS		best
e-n10-c2.map	2016/57		2016.571
a-n15-c4.map	1947/3		1961/9887
b-n15-c4.map	2602/56		2684.840
a-n20-c5.map	2759/13		2788.78
c-n20-c5.map	3028/83		3038.936
d-n20-c5.map	2239/09		2239.09
e-n20-c5.map	3343/34		3343.3399
b-n30-c6.map	3116/84		3125.264

- Comparing GA and ACS Results:

<b><math>\rho = 10\%</math></b>						
<b>file name</b>	<b>BKS</b>		<b>GA best</b>	<b>GA avg time</b>	<b>ACS best</b>	<b>ACS avg time</b>
<b>kelly08.ccvrp</b>	13331/2		33422/68	84.987	20047/18	50.363
<b>kelly10.ccvrp</b>	908/89		1287/338	45.193	989/7373	6.0530
<b><math>\rho = 25\%</math></b>						
<b>file name</b>	<b>BKS</b>		<b>GA best</b>	<b>GA avg time</b>	<b>ACS best</b>	<b>ACS avg time</b>
<b>kelly11.ccvrp</b>	1131/84		1664/447	55.476	1221/950	8.7118
<b>kelly19.ccvrp</b>	1538/2		3678/73	26.072	2026/525	19.384
<b><math>\rho = 50\%</math></b>						
<b>file name</b>	<b>BKS</b>		<b>GA best</b>	<b>GA avg time</b>	<b>ACS best</b>	<b>ACS avg time</b>
<b>kelly19.ccvrp</b>	1612/33		2030/046	34.669	1666/086	4/428
<b>kelly20.ccvrp</b>	2278/64		2939/032	39.778	2345/878	10/285
<b><math>\rho = 75\%</math></b>						
<b>file name</b>	<b>BKS</b>		<b>GA best</b>	<b>GA avg time</b>	<b>ACS best</b>	<b>ACS avg time</b>
<b>kelly10.ccvrp</b>	1000/51		1023/978	31.6839	1000/507	2/18
<b>kelly20.ccvrp</b>	2502/34		2572/521	35.1147	2502/34	6/779
<b><math>\rho = 100\%</math></b>						
<b>file name</b>	<b>BKS</b>		<b>GA best</b>	<b>GA avg time</b>	<b>ACS best</b>	<b>ACS avg time</b>
<b>kelly08.ccvrp</b>	13188/9		13572/43	48.076	13572/426	7.3177
<b>kelly19.ccvrp</b>	1667/45		1696/128	25.765	1696/1283	1.4732

As result shows ACS perform better in solution quality and algorithm time but the initial heuristic version of computing  $\tau_0 = (n \cdot L_{mn})^{-1}$  take much more time than GA (which I skipped that because of lacking of time), so time comparing of algorithms would not be much fair in this case.

In compare with GA we have both exploitation and exploration mechanism in ACS but instead of creating new solutions from parents in GA and select the better solutions based on pressure degree of the xOver and mutation result ,we choose constructive manner that creating the solution step by step based on some heuristic and collective information of colony(pheromone).

So, it seems that in this way search would be more targeted in compare with GA.