



Evolutionary Algorithms

Muhammad Meesum Ali Qazalbash - mq06861

Syed Ibrahim Ali Haider - sh06565

March 19, 2023

CS451 - Computational Intelligence

Assignment 2

Contents

1	Abstract	3
2	Problems	4
2.1	Capacitated Vehicle Routing using ACO	4
2.1.1	External Modules	4
2.1.2	Chromosome	5
2.1.3	Initialization	6
2.1.4	Reading Input	7
2.1.5	Mathematics	8
2.1.6	Simulation	10
2.1.7	Plotting	15
2.1.8	Running	16
3	Analysis	18
3.1	Capacitated Vehicle Routing using ACO	18

Chapter 1

Abstract

The assignment focuses on swarm intelligence and provides students hands-on with Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) techniques to solve complex optimization problems.

Chapter 2

Problems

2.1 Capacitated Vehicle Routing using ACO

2.1.1 External Modules

There are three external modules used. Run the following command to download them.

```
1 pip install numpy vrplib matplotlib
```

If this does not work then use,

```
1 pip3 install numpy vrplib matplotlib
```

```
1 import numpy as np
2 import vrplib
3 from matplotlib import pyplot as plt
```

Listing 2.1: External modules for ACO

2.1.2 Chromosome

The class `Ant_t` is used to represent the chromosome. It contains routes and distance.

```
6 class Ant_t:
7     """Ant Class for the Ant Colony Optimization Algorithm"""
8
9     def __init__(self, routes: list, distance: int | float, **kwargs)
10         -> None:
11
12         """Constructor for the Ant Class
13
14         Args:
15             routes (list): Routes taken by the Ant
16             distance (int | float): Distance travelled by the Ant
17         """
18
19         self.routes = routes
20         self.distance = distance
```

Listing 2.2: Chromosome for ACO

2.1.3 Initialization

```
20 class Ant_Colony_Optimization:
21     """Ant Colony Optimization Algorithm Class"""
22
23     def __init__(self, alpha: int | float, beta: int | float,
24                 iteration: int,
25                 num_ants: int, rho: int | float, path: str, *args,
26                 **kwargs) -> None:
27
28         """Constructor for the Ant Colony Optimization Algorithm
29         Class
30
31         Args:
32             alpha (int | float): Used to control the pheromone
33             influence
34             beta (int | float): Used to control the heuristic
35             influence
36             iteration (int): Number of iterations
37             num_ants (int): Number of Ants
38             rho (int | float): Used to control the evaporation rate
39             path (str): Path to the Distance Matrix file
40
41         """
42
43         self.alpha: int | float = alpha # pheromone influence
44         self.beta: int | float = beta # heuristic influence
45         self.ITERATION: int = iteration # number of iterations
46         self.NUM_ANTS: int = num_ants # number of ants
47         self.evap_rate: float = 1.0 - rho # evaporation rate
48         self.path = path # path to the instance file
```

Listing 2.3: Initilization of ACO

2.1.4 Reading Input

Note that the `read_file` does not depends on the object that's why it is a static method. This function would work when internet is available. If you get an error about the http request then make sure that you are connected to the internet.

```
43     @staticmethod
44     def read_file(path: str, *args, **kwargs) -> dict:
45         """Reads a VRP instance file.
46
47         Args:
48             path (str): Path to the instance file.
49
50         Returns:
51             dict: A dictionary containing the instance data.
52         """
53         vrplib.download_instance(path, f"instances_CVRP/{path}.vrp")
54         return vrplib.read_instance(f"instances_CVRP/{path}.vrp")
55
56     def extract(self, *args, **kwargs) -> None:
57         """Extracts the data from the Distance Matrix file"""
58         file = self.read_file(self.path)
59         self.capacity = file["capacity"]
60         self.depot = file["depot"][0]
61         self.n = file["dimension"]
62         self.demand = file["demand"]
63         self.distances = file["edge_weight"]
64         self.min_distance = float("inf")
65         self.eta = np.reciprocal(self.distances,
66                                 out=np.zeros_like(self.distances),
```

```

67                                     where=self.distances != 0)
68     self.min_route = None
69     self.mean_distances = []
70     self.tau = np.zeros((self.n, self.n))

```

Listing 2.4: Reading input for ACO

2.1.5 Mathematics

The mathematics for Ant Colony Optimization is implemented in the following functions.

```

72     def evaluate_tau(self, *args, **kwargs) -> list[list]:
73         """Evaluates the pheromone matrix based on the Ants' routes
74
75         Returns:
76             list[list]: Pheromone matrix
77         """
78         delta_tau = np.zeros((self.n, self.n))
79         for ant in self.ants:
80             for route in ant.routes:
81                 for path in range(len(route) - 1):
82                     u, v = route[path], route[path + 1]
83                     inverse_distance = 1 / ant.distance
84                     delta_tau[u][v] += inverse_distance
85                     delta_tau[v][u] += inverse_distance
86         return delta_tau
87
88     def evaluate_prob(self, current_city: int, potential_cities: list
89     , *args,
90
91                                     **kwargs) -> list:

```



```

90     """Evaluates the probabilities of the Ants' next move based
on the
91     pheromone, heuristic matrices, Ant's current city and
potential cities
92
93     Args:
94         current_city (int): Current city of the ant
95         potential_cities (list): Potential cities the ant can
move to
96
97     Returns:
98         list: Probabilities of the Ants' next move
99     """
100     P = list(
101         map(
102             lambda i: (self.tau[current_city][i]**self.alpha) +
103             (self.eta[current_city][i]**self.beta),
potential_cities))
104
105     normalization_factor = 1 / sum(P)
106
107     P = list(map(lambda x: x * normalization_factor, P))
108
109     pp = []
110     start = 0
111
112     for i in range(len(P)):
113         pp.append((start, start + P[i]))
114         start += P[i]
115

```

```

116         return pp
117
118     def revise_tau(self, *args, **kwargs):
119         """Updates the pheromone values"""
120         delta_tau = self.evaluate_tau()
121         self.tau = self.tau * self.evap_rate + delta_tau

```

Listing 2.5: Mathematics for ACO

2.1.6 Simulation

All the functions related to simulation are implemented in the following functions.

```

123     def get_next_city(self, current_city: int, unvisited: list,
124                       truck_capacity: int, *args, **kwargs) -> int:
125         """Gets the next city the Ant will move to
126
127         Args:
128             current_city (int): Current city of the ant
129             unvisited (list): List of unvisited cities
130             truck_capacity (int): Truck's capacity
131
132         Returns:
133             int: Next city the Ant will move to
134         """
135         potential_cities = [
136             city for city in unvisited
137             if self.demand[city] <= truck_capacity and city !=
138             current_city
139         ]

```

```

140         proportional_probabilities = self.evaluate_prob(current_city,
141
potential_cities)
142
143         p = np.random.uniform(0, 1)
144
145         for city in range(len(proportional_probabilities)):
146             if (proportional_probabilities[city][0] <= p <
147                 proportional_probabilities[city][1]):
148                 next_city = city
149                 break
150
151         return potential_cities[next_city]
152
153     def _simulate_Ants(self,
154                       initialize: bool = False,
155                       *args,
156                       **kwargs) -> Ant_t:
157         """Simulates the Ants
158
159         Args:
160             initialize (bool, optional): If True, the Ants will be
initialized
161             at the Depot and will not return to it. Defaults to False
.
162
163         Returns:
164             Ant_t: _description_
165         """
166         total_distance = 0

```

```

167         current_city = self.depot
168         truck_capacity = self.capacity
169         route = []
170         path = [current_city]
171         unvisited = list(range(self.n))
172         bound = not initialize
173
174         if initialize:
175             unvisited.pop(0)
176
177         while bound < len(unvisited):
178             if initialize:
179                 i = np.random.randint(len(unvisited))
180                 next_city = unvisited[i]
181
182                 if truck_capacity < self.demand[next_city]:
183                     total_distance += self.distances[current_city][
self.depot]
184
185                     route.append(path)
186
187                     current_city = self.depot
188                     path = [self.depot]
189
190                     truck_capacity = self.capacity
191             else:
192                 next_city = self.get_next_city(current_city,
unvisited,
193                                             truck_capacity)
194                 truck_capacity -= self.demand[next_city]

```

```

195         total_distance += self.distances[current_city][next_city]
196
197         current_city = next_city
198         path.append(current_city)
199
200         if initialize:
201             unvisited.pop(i)
202         elif current_city == self.depot:
203             truck_capacity = self.capacity
204             route.append(path)
205             path = [self.depot]
206         else:
207             unvisited.remove(current_city)
208
209         path.append(self.depot)
210         total_distance += self.distances[current_city][self.depot]
211         route.append(path)
212
213         if total_distance < self.min_distance:
214             self.min_distance = total_distance
215             self.min_route = route
216
217         self.mean_distances.append(total_distance)
218         return Ant_t(route, total_distance)
219
220     def _Ant_Colony_Simulation(self,
221                                initialize: bool = False,
222                                *args,
223                                **kwargs) -> None:
224         """Simulates the Ant Colony Optimization Algorithm

```

```

225
226     Args:
227         initialize (bool, optional): If True, the Ants will be
initialized
228         at the Depot and will not return to it. Defaults to False
.
229     """
230     self.ants = list(
231         map(lambda x: self._simulate_Ants(initialize),
232             range(self.NUM_ANTS)))
233
234     def run_simulation(self, initialize: bool = True, *args, **kwargs
) -> None:
235         """Runs the Ant Colony Optimization Algorithm"""
236
237         self.extract()
238
239         min_list = []
240         mean_list = []
241
242         self._Ant_Colony_Simulation(initialize)
243
244         self.tau = self.evaluate_tau()
245
246         for _ in range(self.ITERATION):
247
248             self._Ant_Colony_Simulation(False)
249             self.revise_tau()
250
251             min_list.append(self.min_distance)

```

```

252         mean_list.append(np.average(self.mean_distances))
253
254     return min_list, mean_list

```

Listing 2.6: Simulation for ACO

2.1.7 Plotting

The plotting is done using the `matplotlib` library. The following function is used to plot the results.

```

256     def plot_results(self, show: bool = False, save: bool = False) ->
        None:
257         """Plots the results of the simulation
258
259         Args:
260             show (bool, optional): If true shows the plot. Defaults
        to False.
261             save (bool, optional): If true saves the plot. Defaults
        to False.
262         """
263         min_list, mean_list = self.run_simulation(self.path)
264
265         min_fitness = round(min_list[-1], 2)
266         mean_fitness = round(mean_list[-1], 2)
267
268         plt.plot(range(1, ITERATION + 1), min_list, label="minimum")
269         plt.plot(range(1, ITERATION + 1), mean_list, label="mean")
270         plt.axhline(y=min_fitness,
271                     color="r",
272                     linestyle="--",

```

```

273         label=f"min fitness: {min_fitness}")
274     plt.axhline(y=mean_fitness,
275                 color="g",
276                 linestyle="--",
277                 label=f"mean fitness: {mean_fitness}")
278     plt.xlabel("Number of iteration")
279     plt.ylabel("Fitness")
280     plt.tight_layout()
281     plt.legend()
282     plt.grid(True)
283     if save:
284         plt.savefig(
285             f"plots/{self.path}-{self.ITERATION}-{self.NUM_ANTS}.
png")
286     if show:
287         plt.show()
288     plt.close()

```

Listing 2.7: Plotting for ACO

2.1.8 Running

The following piece of code is used to run the program.

```
291 if __name__ == "__main__":
292     ITERATION: int = 30
293     NUM_ANTS: int = 30
294     ALPHA: float = 4.0
295     BETA: float = 4.0
296     INITIALIZATION: bool = True
297     RHO: float = 0.5
298
299     files = ["A-n32-k5", "A-n44-k6", "A-n60-k9", "A-n80-k10"]
300
301     ACO = Ant_Colony_Optimization(ALPHA, BETA, ITERATION, NUM_ANTS,
302     RHO, None)
303     for file in files:
304         ACO.path = file
305         ACO.plot_results(show=False, save=True)
```

Listing 2.8: Running ACO

Chapter 3

Analysis

3.1 Capacitated Vehicle Routing using ACO

The analysis is done by varying the number of ants and the number of iterations. The results are shown in the following figures. In each grid number of ants are changing from 20 to 30 horizontally and number of iterations are changing from 20 to 30 vertically. Other parameters are $\alpha = 4$, $\beta = 4$, and $\rho = 0.5$.

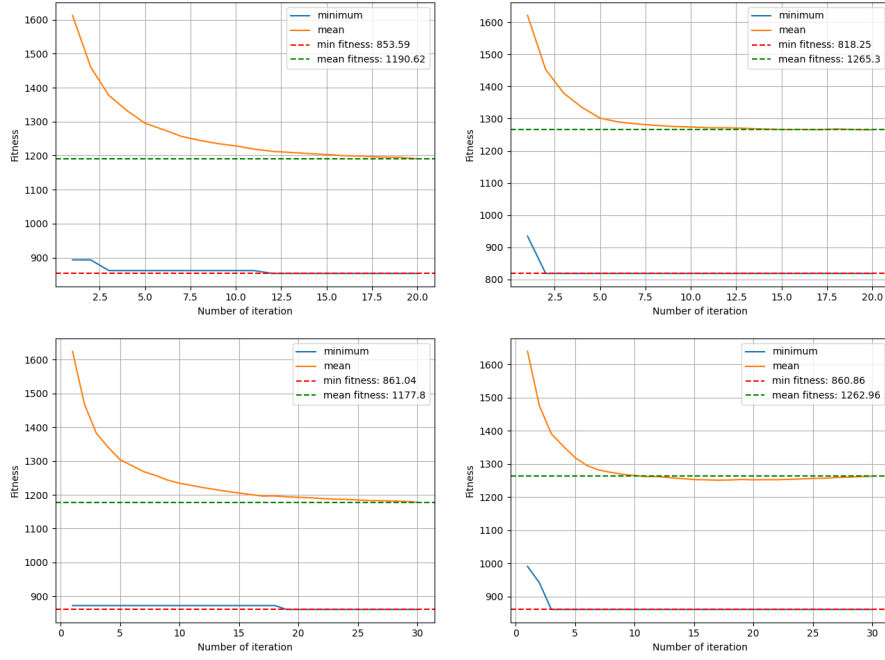


Figure 3.1: Dataset: A-n32-k5

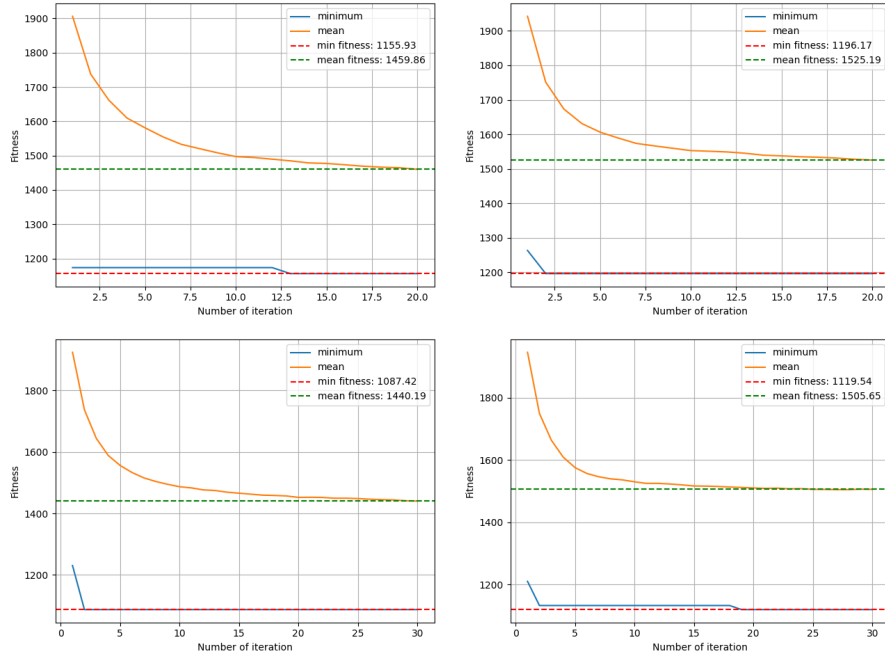


Figure 3.2: Dataset: A-n44-k6

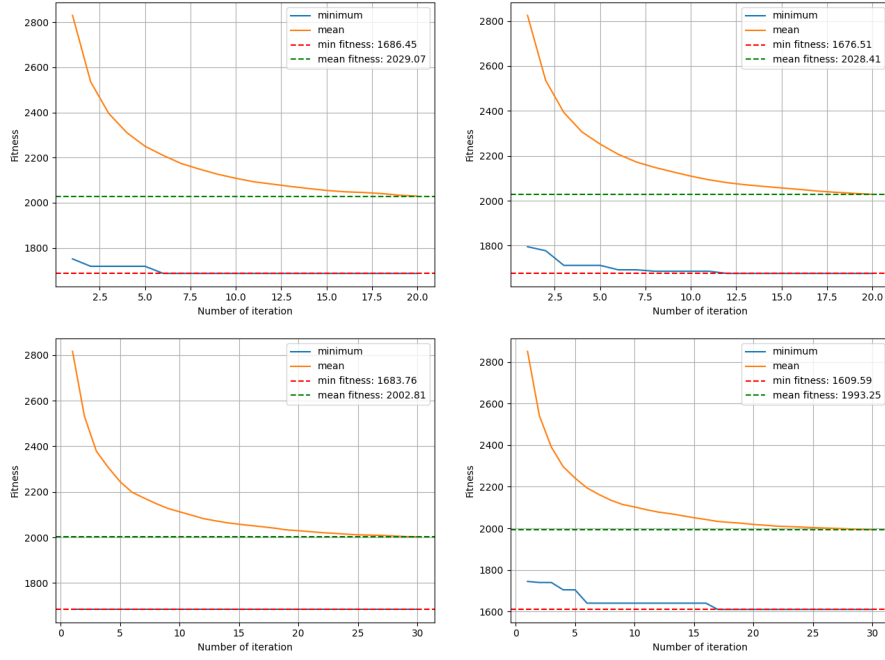


Figure 3.3: Dataset: A-n60-k9

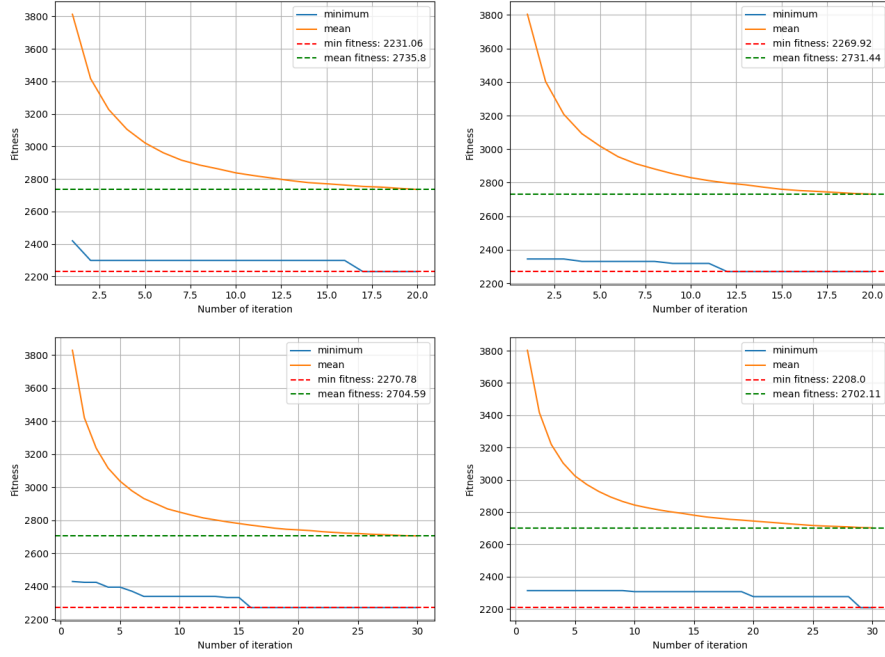


Figure 3.4: Dataset: A-n80-k10