

Multi-Objective Optimization of Airplane-to-Ground Station Data Routing Paths over North Atlantic Using Genetic Search Algorithm and Particle Swarm Optimization

```
In [1]: import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import math
```

Considering two ground stations Heathrow as LHR and Newark Liberty as EWR

```
In [2]: #LHR
X1 = -0.4543 # Longitude is given in west direction therefore we consider it as negative
Y1 = 51.4700 # Latitude
Z1 = 81.73 # Altitude

#EWR
X2 = -74.1745
Y2 = 40.6895
Z2 = 8.72
```

```
In [3]: data = pd.read_csv(r"C:\Users\Dataset.CSV")
data
```

Out[3]:

	Flight No.	Timestamp	Altitude	Latitude	Longitude
0	AA101	1530277200	39000.0	50.9	-38.7
1	AA109	1530277200	33000.0	60.3	-12.2
2	AA111	1530277200	39000.0	52.7	-18.1
3	AA113	1530277200	37000.0	43.0	-11.1
4	AA151	1530277200	36400.0	47.0	-27.7
...
211	UA971	1530277200	32000.0	60.9	-29.9
212	UA973	1530277200	33000.0	61.0	-39.3
213	UA975	1530277200	36000.0	50.5	-26.4
214	UA986	1530277200	36000.0	60.0	-32.2
215	UA988	1530277200	36100.0	52.7	-18.8

216 rows × 5 columns

```
In [4]: data.rename(columns = {'Flight No.': 'F_No'}, inplace = True)
data
```

Out[4]:

	F_No	Timestamp	Altitude	Latitude	Longitude
0	AA101	1530277200	39000.0	50.9	-38.7
1	AA109	1530277200	33000.0	60.3	-12.2
2	AA111	1530277200	39000.0	52.7	-18.1
3	AA113	1530277200	37000.0	43.0	-11.1
4	AA151	1530277200	36400.0	47.0	-27.7
...
211	UA971	1530277200	32000.0	60.9	-29.9
212	UA973	1530277200	33000.0	61.0	-39.3
213	UA975	1530277200	36000.0	50.5	-26.4
214	UA986	1530277200	36000.0	60.0	-32.2
215	UA988	1530277200	36100.0	52.7	-18.8

216 rows × 5 columns

```
In [5]: # check unique values
data['F_No'].nunique(), data['Timestamp'].nunique()
```

Out[5]: (216, 1)

```
In [6]: # Remove the time stamp column as it is not necessary
data.drop(['Timestamp'], inplace = True, axis = 1)
```

```
In [7]: data2 = {'Altitude': [81.73, 8.72],
                'Latitude': [51.4700, 40.6895],
                'Longitude': [-0.4543, -74.1745]}

index = ['LHR', 'EWR']

data_gs = pd.DataFrame(data2, index=index)
print(data_gs)
```

	Altitude	Latitude	Longitude
LHR	81.73	51.4700	-0.4543
EWR	8.72	40.6895	-74.1745

```
In [8]: # Data for the switching threshold
thresh_data = {
    'Mode k': [1, 2, 3, 4, 5, 6, 7],
    'Mode color': ['Red', 'Orange', 'Yellow', 'Green', 'Blue', 'Pink', 'Purple'],
    'Switching threshold': [500, 400, 300, 190, 90, 35, 5.56],
    'Transmission rate': [31.895, 43.505, 52.857, 63.970, 77.071, 93.854, 119.130]
}

# Creating the DataFrame
df_thresh = pd.DataFrame(thresh_data)

# Display the DataFrame
print(df_thresh)
```

	Mode k	Mode color	Switching threshold	Transmission rate
0	1	Red	500.00	31.895
1	2	Orange	400.00	43.505
2	3	Yellow	300.00	52.857
3	4	Green	190.00	63.970
4	5	Blue	90.00	77.071
5	6	Pink	35.00	93.854
6	7	Purple	5.56	119.130

```
In [9]: def func cartesian(lati, long, alti):
        rad = 6371 * 1000 + alti # radius of earth plus altitude
        # converting to cartesian coordinates
        a = rad * math.cos(lati) * math.cos(long)
        b = rad * math.cos(lati) * math.sin(long)
        c = rad * math.sin(lati)
        return a, b, c
```

```
In [10]: from scipy import spatial
def dist(place1, place2):

    if place1 in ['LHR', 'EWR']:
        #get place1 location and convert to radians and metre
        lati1 = data_gs.Latitude[place1] * math.pi / 180
        long1 = data_gs.Longitude[place1] * math.pi / 180
        alt1 = data_gs.Altitude[place1] * 0.3048

    else:
        #get place1 location and convert to radians and metre
        lati1 = data.Latitude[place1] * math.pi / 180
        long1 = data.Longitude[place1] * math.pi / 180
        alt1 = data.Altitude[place1] * 0.3048

    if place2 in ['LHR', 'EWR']:
        #get place2 location and convert to radians and metre
        lati2 = data_gs.Latitude[place2] * math.pi / 180
        long2 = data_gs.Longitude[place2] * math.pi / 180
        alt2 = data_gs.Altitude[place2] * 0.3048

    else:
        #get place2 location and convert to radians and metre
        lati2 = data.Latitude[place2] * math.pi / 180
        long2 = data.Longitude[place2] * math.pi / 180
        alt2 = data.Altitude[place2] * 0.3048

    #Convert to cartesian
    p1 = func cartesian(lati1, long1, alt1)
    p2 = func cartesian(lati2, long2, alt2)

    # find distance
    dis = spatial.distance.euclidean(p1, p2)

    return dis
```

```
In [11]: def datarate(place1, place2):
        # Datarate depends on distance, so find distance between the locations
        dis = dist(place1, place2) / 1000

        # Define thresholds and corresponding datarates
        thresholds = [500, 400, 300, 190, 90, 35, 0]
        datarates = [500.00, 400.00, 300.00, 190.00, 90.00, 35.00, 5.56]

        # Find the appropriate threshold
        th = next(th for th in thresholds if dis > th)

        # Get the corresponding datarate
        dr = next(rate for t, rate in zip(thresholds, datarates) if t == th)

        return dr
```

```
In [12]: def pathdatarate(routing_path):
        # create a tuple with consecutive nodes
        tuple_path = [(routing_path[i], routing_path[i + 1]) for i in range(len(routing_path) - 1)]

        # calculate data rates for each link in the path and find the minimum
        dr_min = min(datarate(tup[0], tup[1]) for tup in tuple_path)

        return dr_min
```

```
In [13]: def path_latency(routing_path):  
         return (len(routing_path) - 1) * 50
```

```
In [14]: def routing_path(flights):  
         routing_paths = []  
         current_path = [flights[0]]  
  
         for i in range(1, len(flights)):  
             current_flight = current_path[-1]  
  
             # Find distance of current flight from nearest ground station  
             distance_cur_fl_lhr = dist(current_flight, 'LHR')  
             distance_cur_fl_ewr = dist(current_flight, 'EWR')  
             gs_distance_cur_fl, gs_cur_fl = (distance_cur_fl_lhr, 'LHR') if distance_cur_fl_lhr < dist  
  
             # Find distance of next flight from nearest ground station  
             distance_nxt_fl_lhr = dist(flights[i], 'LHR')  
             distance_nxt_fl_ewr = dist(flights[i], 'EWR')  
             gs_distance_nxt_fl, gs_nxt_fl = (distance_nxt_fl_lhr, 'LHR') if distance_nxt_fl_lhr < dist  
  
             # Find distance between the flights  
             distance_fl = dist(current_flight, flights[i])  
  
             # Compare the distances  
             # If both flights are nearer to GS than each other  
             if gs_distance_cur_fl < distance_fl and gs_distance_nxt_fl < distance_fl:  
                 current_path.append(gs_cur_fl)  
                 routing_paths.append(current_path)  
                 current_path = [flights[i]]  
  
             # If the next flight is nearer to GS  
             elif gs_distance_cur_fl > gs_distance_nxt_fl:  
                 current_path.append(flights[i])  
  
             # If the current flight is nearer to GS  
             elif gs_distance_nxt_fl >= gs_distance_cur_fl:  
                 current_path.append(flights[i])  
                 current_path[-2], current_path[-1] = current_path[-1], current_path[-2]  
  
             # If it's the last flight  
             if i == len(flights) - 1:  
                 if current_path[-1] == current_flight:  
                     current_path.append(gs_cur_fl)  
                 else:  
                     current_path.append(gs_nxt_fl)  
                 routing_paths.append(current_path)  
  
         return routing_paths
```

```
In [15]: import numpy as np  
  
         def cost_function(flights, objective_type):  
             # get routes from flights  
             routing_paths = routing_path(flights)  
  
             # get data rate and latency for each path  
             data_rate_list = [pathdata_rate(route) for route in routing_paths]  
             latency_list = [path_latency(route) for route in routing_paths]  
  
             # single objective  
             if objective_type == 'single':  
                 cost = np.average(data_rate_list)  
  
             elif objective_type == 'multiple':  
                 cost = np.average(data_rate_list) + (1 - np.average(latency_list)) / np.average(latency_li  
  
         return cost
```

```

In [16]: import random
import matplotlib.pyplot as plt

def genetic_algorithm(flights, num_generations, population_size, selection_size, objective_type):

    # Randomly initialize population
    population = []
    for _ in range(population_size):
        population.append(random.sample(flights, len(flights)))

    # Evaluate initial population
    costs = [cost_function(individual, objective_type) for individual in population]

    max_cost = max(costs)
    best_individual = population[costs.index(max_cost)]
    cost_history = [max_cost]

    print(f'Generation 0 has maximum cost of {max_cost}')

    # Loop for generations
    for generation in range(1, num_generations + 1):

        # Parent selection using TRUNCATION SELECTION technique
        pop_costs = [cost_function(individual, objective_type) for individual in population]
        pop_cost_sort = [(pop, cost) for pop, cost in zip(population, pop_costs)]
        pop_cost_sort = sorted(pop_cost_sort, key=lambda x: x[1], reverse=True)

        # Get the best individuals up to the selection size provided
        parents = [p[0] for p in pop_cost_sort[:selection_size]]

        # Child crossover using SINGLE POINT Crossover using PERMUTATION ENCODING
        parents_tuple = [(population[k], population[k+1]) for k in range(0, len(population)-1, 2)]
        children = []

        for parent1, parent2 in parents_tuple:
            crossover_point = random.randint(0, len(parent1) - 1)
            child1 = parent1[:crossover_point] + [city for city in parent2 if city not in parent1]
            child2 = parent2[:crossover_point] + [city for city in parent1 if city not in parent2]
            children.append(child1)
            children.append(child2)

        # Mutation using ORDER CHANGING MUTATION
        for child in children:
            idx1, idx2 = random.sample(range(len(child)), 2)
            child[idx1], child[idx2] = child[idx2], child[idx1]

        # New population
        population = parents + children

        # Evaluate new population
        costs = [cost_function(individual, objective_type) for individual in population]
        new_max_cost = max(costs)

        # Update the best cost if the current is better
        if new_max_cost < max_cost:
            max_cost = new_max_cost
            best_individual = population[costs.index(max_cost)]

        cost_history.append(max_cost)
        print(f'Generation {generation} has maximum cost of {max_cost}')

    # Plot the graph
    plt.plot(cost_history)
    plt.title('Cost vs Generation')
    plt.xlabel('Generation')
    plt.ylabel('Cost')
    plt.show()

    return routing_path(best_individual)

```

```

In [17]: import random
import math
import matplotlib.pyplot as plt

def simulated_annealing(flights, gen_size, temperature, cooling_percentage, objective_type='single
# random initial solution
pop = random.sample(flights, len(flights))

# evaluate cost
cost = cost_function(pop, objective_type)
max_cost = cost
best_pop = pop
graph = [max_cost]
print(f'Generation 0 has maximum cost of {max_cost}')

# copy pop to newpop
newpop = pop.copy()

# Loop for generation
for i in range(1, gen_size + 1):
    curpop = newpop.copy()

    # generate new generation using SWAP operation
    # get two points
    s1 = random.randint(0, len(curpop) - 1)
    s2 = random.randint(0, len(curpop) - 1)
    curpop[s1], curpop[s2] = curpop[s2], curpop[s1]

    # evaluate cost and if the results are better then accept and new pop
    cost = cost_function(curpop, objective_type)
    if max_cost < cost:
        max_cost = cost
        best_pop = curpop
        newpop = curpop

    # check acceptance criteria whether to take forward or not
    elif cost <= max_cost:
        # generate acceptable probability
        accept_prop = math.exp((cost - max_cost) / temperature)

        # get random probability value
        probability = random.random()

        # if probability is better
        if probability < accept_prop:
            newpop = curpop

        # if probability is too high
        elif temperature > 0:
            temperature *= (1 - cooling_percentage)

    graph.append(max_cost)
    print(f'Generation {i} has maximum cost of {max_cost}')

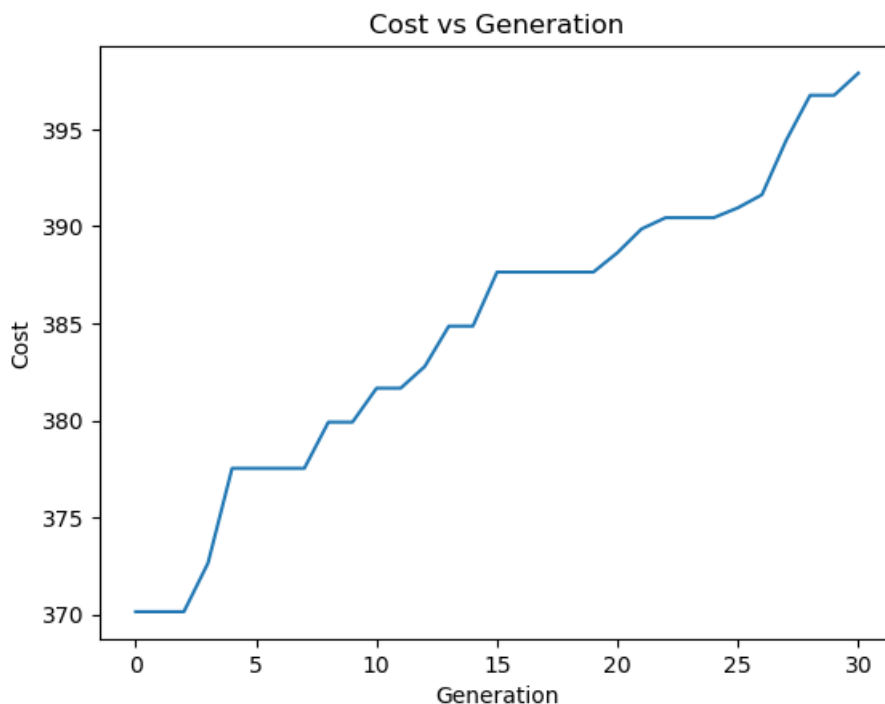
# plot the graph
plt.plot(graph)
plt.title('Cost vs Generation')
plt.xlabel('Generation')
plt.ylabel('Cost')
plt.show()

return routing_path(best_pop)

```

```
In [18]: flights_list = list(data.index.values)
genetic_algorithm(flights_list.copy(), 30, 8, 4, 'single')
```

Generation 0 has maximum cost of 370.15238095238095
Generation 1 has maximum cost of 370.15238095238095
Generation 2 has maximum cost of 370.15238095238095
Generation 3 has maximum cost of 372.65238095238095
Generation 4 has maximum cost of 377.53333333333333
Generation 5 has maximum cost of 377.53333333333333
Generation 6 has maximum cost of 377.53333333333333
Generation 7 has maximum cost of 377.53333333333333
Generation 8 has maximum cost of 379.91428571428565
Generation 9 has maximum cost of 379.9142857142857
Generation 10 has maximum cost of 381.66024096385536
Generation 11 has maximum cost of 381.66024096385536
Generation 12 has maximum cost of 382.7780487804878
Generation 13 has maximum cost of 384.8564705882353
Generation 14 has maximum cost of 384.8564705882353
Generation 15 has maximum cost of 387.6374683544304
Generation 16 has maximum cost of 387.6374683544304
Generation 17 has maximum cost of 387.6374683544304
Generation 18 has maximum cost of 387.6374683544304
Generation 19 has maximum cost of 387.6374683544304
Generation 20 has maximum cost of 388.63720930232563
Generation 21 has maximum cost of 389.85975903614457
Generation 22 has maximum cost of 390.43953488372097
Generation 23 has maximum cost of 390.43953488372097
Generation 24 has maximum cost of 390.43953488372097
Generation 25 has maximum cost of 390.9472727272727
Generation 26 has maximum cost of 391.6211764705883
Generation 27 has maximum cost of 394.4064367816092
Generation 28 has maximum cost of 396.7427272727273
Generation 29 has maximum cost of 396.7427272727273
Generation 30 has maximum cost of 397.8790909090909



```
Out[18]: [[140, 'LHR'],
[8, 98, 'EWR'],
[1, 167, 'LHR'],
[17, 'EWR'],
[175, 50, 15, 'LHR'],
[162, 'EWR'],
[151, 'LHR'],
[10, 23, 199, 'EWR'],
[152, 56, 12, 95, 35, 148, 2, 'LHR'],
[145, 'EWR'],
[93, 41, 109, 'LHR'],
[66, 'EWR'],
[204, 75, 59, 'LHR'],
[138, 31, 99, 'LHR'],
[180, 'EWR'],
[157, 135, 179, 197, 58, 146, 'LHR'],
[113, 44, 'EWR'],
[133, 188, 27, 100, 78, 'LHR'],
[168, 'EWR'],
[205, 61, 'LHR'],
[46, 'EWR'],
[212, 70, 28, 6, 'LHR'],
[127, 'LHR'],
[39, 'LHR'],
[134, 'EWR'],
[190, 19, 43, 91, 161, 'LHR'],
[82, 'EWR'],
[142, 139, 193, 'LHR'],
[156, 'EWR'],
[57, 77, 107, 102, 72, 51, 96, 'LHR'],
[81, 33, 'LHR'],
[208, 'EWR'],
[64, 'EWR'],
[86, 153, 185, 'LHR'],
[83, 115, 'EWR'],
[26, 'LHR'],
[9, 80, 'EWR'],
[164, 104, 166, 'LHR'],
[108, 'EWR'],
[160, 'LHR'],
[55, 105, 189, 'LHR'],
[94, 42, 'EWR'],
[191, 203, 165, 'LHR'],
[7, 118, 'EWR'],
[149, 206, 'LHR'],
[37, 186, 'EWR'],
[163, 'LHR'],
[121, 116, 'EWR'],
[74, 'LHR'],
[32, 181, 'LHR'],
[192, 16, 'EWR'],
[71, 'LHR'],
[29, 171, 'EWR'],
[154, 174, 159, 144, 36, 79, 155, 173, 87, 125, 101, 200, 195, 69, 'LHR'],
[25, 120, 'LHR'],
[97, 'LHR'],
[124, 117, 211, 172, 85, 73, 'LHR'],
[11, 'LHR'],
[63, 'LHR'],
[20, 'EWR'],
[54, 'LHR'],
[128, 89, 'LHR'],
[53, 'EWR'],
[5, 'EWR'],
[141, 0, 207, 'LHR'],
[111, 'EWR'],
[131, 38, 176, 136, 184, 178, 'LHR'],
[76, 150, 183, 137, 49, 30, 14, 214, 182, 209, 68, 201, 'LHR'],
[65, 213, 177, 122, 'LHR'],
[13, 'EWR'],
[67, 170, 60, 'LHR'],
[52, 194, 'LHR'],
[90, 45, 21, 'EWR'],
[119, 202, 'LHR'],
[18, 88, 'EWR'],
[123, 'LHR'],
```

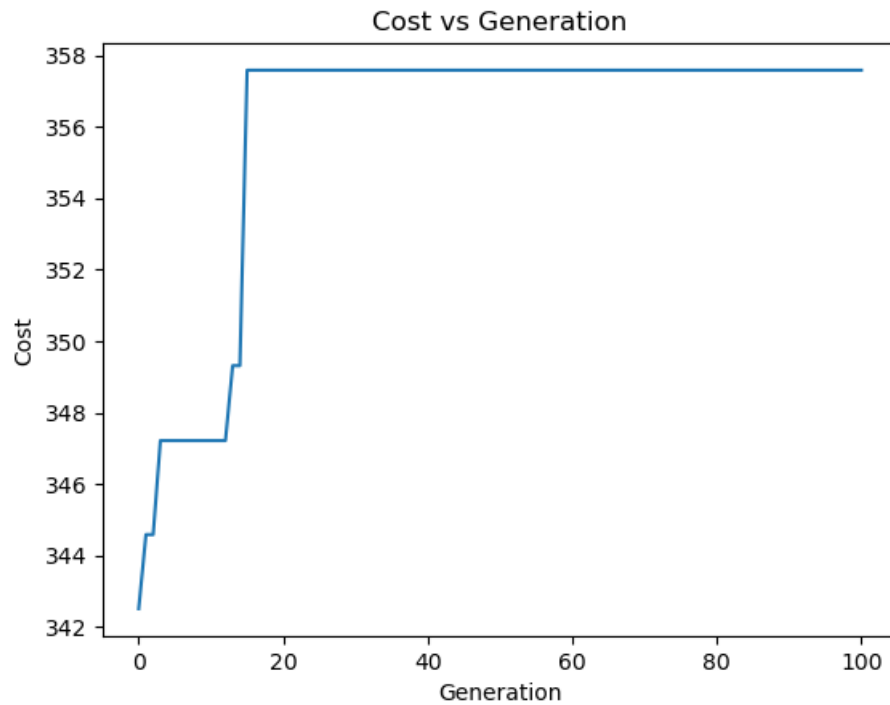


```
[130, 'EWR'],  
[187, 132, 'LHR'],  
[34, 'LHR'],  
[143, 'EWR'],  
[110, 126, 47, 'LHR'],  
[210, 'EWR'],  
[3, 'LHR'],  
[106, 158, 198, 112, 169, 215, 24, 'LHR'],  
[114, 48, 103, 92, 4, 'LHR'],  
[196, 62, 'EWR'],  
[40, 147, 129, 84, 'LHR'],  
[22, 'EWR']]
```

```
In [19]: flights_list = list(data.index.values)
sim_single = simulated_annealing(flights_list.copy(), 100, 12, 6, 'single')
```

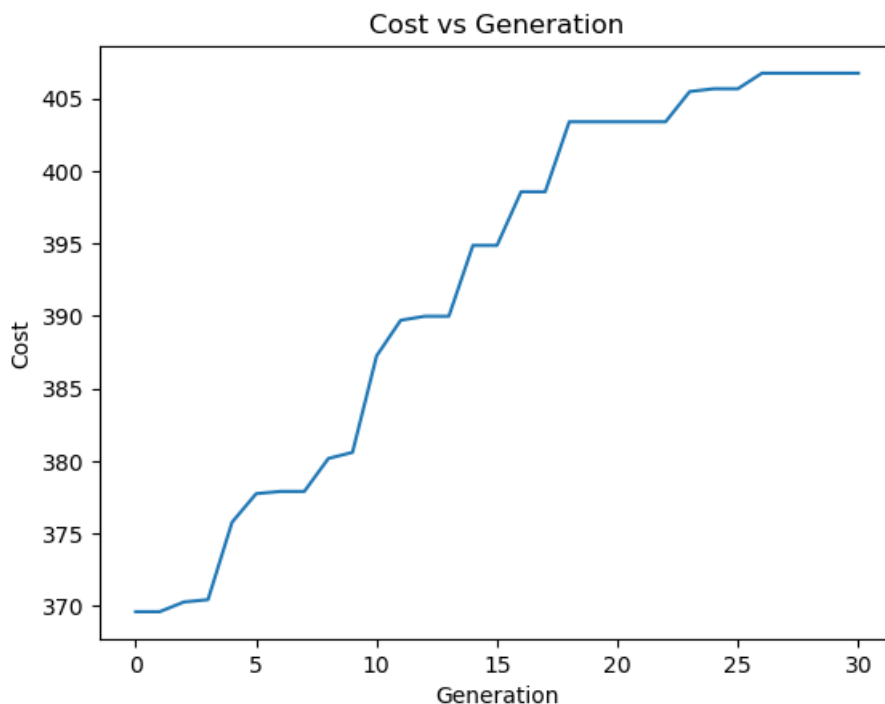
[illegible]

Generation 76 has maximum cost of 357.5781333333337
Generation 77 has maximum cost of 357.5781333333337
Generation 78 has maximum cost of 357.5781333333337
Generation 79 has maximum cost of 357.5781333333337
Generation 80 has maximum cost of 357.5781333333337
Generation 81 has maximum cost of 357.5781333333337
Generation 82 has maximum cost of 357.5781333333337
Generation 83 has maximum cost of 357.5781333333337
Generation 84 has maximum cost of 357.5781333333337
Generation 85 has maximum cost of 357.5781333333337
Generation 86 has maximum cost of 357.5781333333337
Generation 87 has maximum cost of 357.5781333333337
Generation 88 has maximum cost of 357.5781333333337
Generation 89 has maximum cost of 357.5781333333337
Generation 90 has maximum cost of 357.5781333333337
Generation 91 has maximum cost of 357.5781333333337
Generation 92 has maximum cost of 357.5781333333337
Generation 93 has maximum cost of 357.5781333333337
Generation 94 has maximum cost of 357.5781333333337
Generation 95 has maximum cost of 357.5781333333337
Generation 96 has maximum cost of 357.5781333333337
Generation 97 has maximum cost of 357.5781333333337
Generation 98 has maximum cost of 357.5781333333337
Generation 99 has maximum cost of 357.5781333333337
Generation 100 has maximum cost of 357.5781333333337



```
In [20]: flights_list = list(data.index.values)
gen_multiple = genetic_algorithm(flights_list.copy(), 30, 8, 4, 'multiple')
```

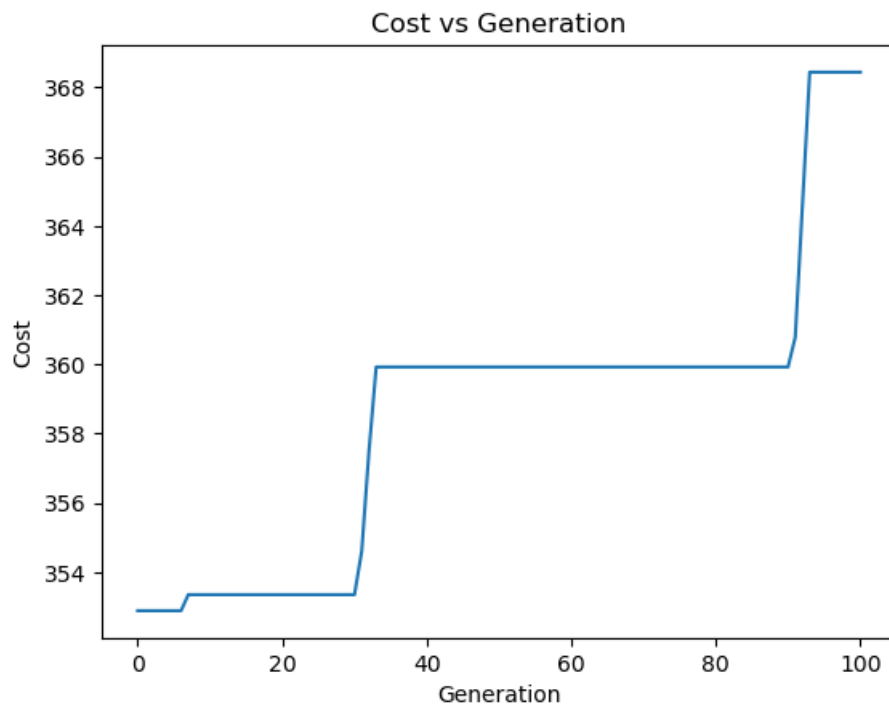
Generation 0 has maximum cost of 369.6213888888889
Generation 1 has maximum cost of 369.6213888888889
Generation 2 has maximum cost of 370.2899663299663
Generation 3 has maximum cost of 370.450487931752
Generation 4 has maximum cost of 375.78756658343735
Generation 5 has maximum cost of 377.75441756272403
Generation 6 has maximum cost of 377.9099663299664
Generation 7 has maximum cost of 377.9099663299664
Generation 8 has maximum cost of 380.18269360269363
Generation 9 has maximum cost of 380.60122222222225
Generation 10 has maximum cost of 387.24824074074075
Generation 11 has maximum cost of 389.70468966218965
Generation 12 has maximum cost of 389.98321323799047
Generation 13 has maximum cost of 389.98321323799047
Generation 14 has maximum cost of 394.86777777777775
Generation 15 has maximum cost of 394.86777777777775
Generation 16 has maximum cost of 398.5636350762527
Generation 17 has maximum cost of 398.5636350762527
Generation 18 has maximum cost of 403.3871644880174
Generation 19 has maximum cost of 403.3871644880174
Generation 20 has maximum cost of 403.3871644880174
Generation 21 has maximum cost of 403.3871644880174
Generation 22 has maximum cost of 403.3871644880174
Generation 23 has maximum cost of 405.4705842911876
Generation 24 has maximum cost of 405.661916451335
Generation 25 has maximum cost of 405.661916451335
Generation 26 has maximum cost of 406.73495210727964
Generation 27 has maximum cost of 406.73495210727964
Generation 28 has maximum cost of 406.73495210727964
Generation 29 has maximum cost of 406.73495210727964
Generation 30 has maximum cost of 406.73495210727964



```
In [21]: flights_list = list(data.index.values)
sim_multiple = simulated_annealing(flights_list.copy(), 100, 12, 6, 'multiple')
```

[illegible]

Generation 76 has maximum cost of 359.92587777777777
Generation 77 has maximum cost of 359.92587777777777
Generation 78 has maximum cost of 359.92587777777777
Generation 79 has maximum cost of 359.92587777777777
Generation 80 has maximum cost of 359.92587777777777
Generation 81 has maximum cost of 359.92587777777777
Generation 82 has maximum cost of 359.92587777777777
Generation 83 has maximum cost of 359.92587777777777
Generation 84 has maximum cost of 359.92587777777777
Generation 85 has maximum cost of 359.92587777777777
Generation 86 has maximum cost of 359.92587777777777
Generation 87 has maximum cost of 359.92587777777777
Generation 88 has maximum cost of 359.92587777777777
Generation 89 has maximum cost of 359.92587777777777
Generation 90 has maximum cost of 359.92587777777777
Generation 91 has maximum cost of 360.78429012345674
Generation 92 has maximum cost of 364.61145061728394
Generation 93 has maximum cost of 368.43861111111111
Generation 94 has maximum cost of 368.43861111111111
Generation 95 has maximum cost of 368.43861111111111
Generation 96 has maximum cost of 368.43861111111111
Generation 97 has maximum cost of 368.43861111111111
Generation 98 has maximum cost of 368.43861111111111
Generation 99 has maximum cost of 368.43861111111111
Generation 100 has maximum cost of 368.43861111111111



In []: