<u>ECM3412 – Ant Colony Coursework Report</u>

Question1: Which combination of parameters produces the best results?

To answer this question, I ran 3 different experiments on our parameters Q in the formula Q/Fitness , the evaporation rate, and the number of ants. For each experiment I tested 5 values for Q these are [1,2,3,4,5], for the evaporation the values were [0.9,0.7,0.5,0.3,0.1] and for number of ants these were [10,25,50,75,100]. For each experiment I varied the respective value being tested and used the middle value for the other 2 parameters so we could see what happens as we change one parameter. To ensure the results I ran the ant colony multiple times taking the average best cost between all the runs and the overall best cost. For the Burma data set I ran the ant colony 10 times and for the Brazil data it was run 5 times as the data set is larger. The results of these tests can be seen in the tables below and the result of each individual ant colony run these can be found in the text files with the code.

Q Value Test Results:

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
1	3441.0	3470.9	637.8	26907.0	27460.6	1352.6
2	3451.0	3463.9	696.7	26523.0	27255.2	1301.8
3	3441.0	3467.4	550.7	26952.0	27202.0	1480.2
4	3429.0	3451.4	598.5	27029.0	27277.8	1234.0
5	3406.0	3464.0	608.0	26740.0	27100.8	1068.6

Evaporation Rate Test Results:

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
0.9	3451.0	3486.1	259.5	26936.0	27922.0	639.0
0.7	3451.0	3471.9	431.3	26756.0	27654.8	735.4
0.5	3451.0	3462.6	706.3	26435.0	27084.0	1303.2
0.3	3429.0	3447.8	974.6	26183.0	26887.0	2098.6
0.1	3429.0	3446.8	1542.7	26407.0	26824.0	6508.6

Number of Ants Test Results:

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
10	3451.0	3581.4	159.5	28140.0	29021.6	297.4
25	3429.0	3481.3	270.2	26997.0	27814.6	735.0
50	3451.0	3472.0	615.3	26956.0	27375.2	1179.2
75	3441.0	3457.0	809.9	26348.0	26680.0	1834.2
100	3429.0	3454.0	993.3	26313.0	27144.4	2713.2

Looking at the results we can find the best combination of parameters by taking the best value for each parameter. For Q this is 5 as it finds the shortest path overall for both Burma and Brazil and for Brazil has the shortest average path. For the evaporation rate the best parameter is 0.1 as it finds the shortest overall and shortest average path. For number of ants, it is 100 for the same reasons as before. Using these parameters with the ant colony gets the results below. The individual results can be found in “best parameters test data.txt”.

Burma			Brazil		
Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
3406.0	3442.5	4260.5	26313.0	26837.0	9233.8

Comparing these results to our tests above this combination of parameters is better than any used within the tests.

Question 2: What do you think is the reason for your findings in Question 1?

The reason that we get these results is because for all our parameters chosen, they are the ones with the highest convergence number. This means that they won't be cutting off the potential better paths earlier on and is still searching for longer. If we then take all the parameters which have this attribute and put them together it should give the ant colony the best option to find paths and will search the space longer before converging than other sets of parameters. If we look at the Average Convergence for Brazil data set, we see that it is 9233.8 which is very close to our limit of 10,000 potential if we increased this number there could be more improvements with these parameters.

Question 3: How does each of the parameter settings influence the performance of the algorithm?

For the evaporation rate we see that the larger the rate the worse the performance. This is likely because with larger evaporation rates potentially better paths are being cut off too quickly when evaporating the pheromones. Meaning for the best evaporation rate of 0.1 more path variations can be explored which also explains why the average convergence rate decreases as we decrease the value of the evaporation rate.

For the number of ants, we find that as we increase the number of ants within an iteration of the ant colony that we get better solutions. This is most likely because more paths are being explored so variations of paths have the opportunity to be explored before we can cut them off through updating the pheromones. This means that for a lower number of ants the algorithm would have to randomly pick a near optimal path for the solution to be optimal while with a larger number of ants there is a higher chance of this. As we increase the number of ants convergence rate decreases which means that it is searching for a solution for longer.

For the Q value we chose to use values between 1-5 but in theory the value could go up higher. We find that as we increase the value of Q, we are increasing the influence of the pheromones on the chosen path which promotes better exploration. This can also be seen as the convergence rate decreases as we increase Q. To see what happens if we increase the value of Q past 5, I ran a test with Q being 10, the number of ants 50 and the evaporation rate being 0.5 to keep consistent with previous results. The results are below, and the individual results can be found in "Q Value 10 test data.txt".

Burma			Brazil		
Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
3451.0	3466.1	627.3	26719.0	27389.8	1075.8

Comparing these results to when Q is 5, we see that there aren't any significant increases in performance and in some cases does worse. If we increase Q any further likely the results won't improve.

Question 4: Can you think of a local heuristic function to add?

For this question I tested two different variations of the local heuristic function. The default heuristic function is 1/d where d is the distance between cities. When using this function with ant number 50 , evaporation rate 0.5 and Q value of 3 we get the below results.

Burma			Brazil		
Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
3451.0	3478.8	523.1	26915.0	27440.4	1239.4

The first variation I tested for the heuristic function was Q/d where Q is the same value used in the formula Q/fitness. As we did before I ran this test for values of Q 1,2,3,4,5 to see if varying Q changes the results. The same values parameters were used as the above test. The results for this test are in the table below and individual runs are in “q over d heuristic test data.txt”.

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
1	3429.0	3472.1	622.1	26682.0	27133.4	1530.2
2	3451.0	3466.1	656.3	26822.0	27484.6	1789.2
3	3441.0	3467.4	631.4	26183.0	27172.4	1407.6
4	3451.0	3463.8	580.1	26394.0	27405.2	1478.6
5	3406.0	3460.5	525.6	27116.0	27266.2	1403.8

As you can see the heuristic function Q/d outperforms 1/d by a significant margin for both the Burma and Brazil datasets. Interestingly the results between the Burma and Brazil datasets vary with Q being 5 being the best performance for Burma while Q being 3 is the best for Brazil after which increasing the value decreases the performance of the algorithm. With this new heuristic function convergence takes longer which is likely because more paths are being explored.

The other alternative heuristic function tested was 1/d^n where we tested for n values of 1,2,3,4,5 to see if there was any improvement. The same parameters were used as the above tests. The results are in the table below and the individual results are in “1 over d power n test data.txt”.

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
1	3441.0	3449.0	623.1	27136.0	27963.6	1145.0
2	3451.0	3516.2	227.7	27150.0	27647.8	829.6
3	3451.0	3531.3	173.4	27397.0	27539.2	687.4
4	3474.0	3673.7	172.4	27187.0	27418.6	461.2
5	3665.0	3821.2	138.6	27288.0	27412.6	495.2

As you can see from the table this heuristic function does not perform as well as the others. The best value for n is 1 which is just the heuristic function 1/d. As we increase the value of n the fitness of the paths decreases and the rate of convergence increases causing our solutions to get worse.

Overall, the best heuristic function was Q/d where the value of Q may change for the problem size. The default heuristic function 1/d gives decent results and paired with good parameters can still be effective while the worst heuristic function was 1/d^n which was not effective for our problem but could in other problem types be effective.

Question 5: Can you think of any variation for this algorithm to improve your results? Explain your answer.

The two variations of the ant colony algorithm that I tested were elitism ant colony and the min max ant colony. For the elitism ant colony when updating the pheromones, it adds pheromones to the currently best-found path in each iteration. For the min max algorithm when updating the pheromones, we use a function to ensure that the pheromones stay between a minimum and maximum value to keep the potential for exploration open and to stop one path from being to biased towards. The tests were run with our best parameters found in question 1. The results for the tests are in the table below and for the individual runs the results can be found in the text files "Best Parameters Test Data.txt", "elitism ant colony test data.txt" and "min max ant colony test data.txt".

	Burma			Brazil		
	Best Cost	Average Cost	Average Convergence	Best Cost	Average Cost	Average Convergence
Regular	3406.0	3442.5	4260.5	26313.0	26837.0	9233.8
Elitism	3406.0	3443.5	3222.6	26302.0	26302.0	7973.0
Min Max	3451.0	3459.2	4925.7	35589.0	37019.2	4743.6

For the min max ant colony, we can see that this algorithm is not as effective as the regular or elitism ant colony. Likely this is because of the min max values used in the experiment which were 0.1 for min and 2 for max. If these values were tuned better for the problem sets this algorithm could in theory be more effective than the regular ant colony.

For the elitism ant colony on the Burma data set the results for the cost are almost identical with the shortest path costing 3406.0 and their averages difference being 1. Where the elitism ant colony is better is that its average convergence is greatly improved. For the Brazil dataset the elitism ant colony finds a shorter path than regular ant colony with a cost of 26302.0 and has a better average cost by over 500. On top of this it also has a better convergence rate making the elitism ant colony far superior to the regular on the larger data set. This is likely because some bias is put towards the current best-found path meaning that it explores more around this path finding more optimal solutions quicker.

Question 6: Do you think any other nature inspired algorithms might have provided better results?

One nature inspired algorithm that we could use to solve this problem is a genetic algorithm which is inspired by natural selection. In a genetic algorithm we evolve our population of solutions through selection , crossover, and mutation operators to find optimal solutions. For the travelling salesman problem, we apply these to our solutions to find variations in path which would lead to finding an optimal solution. In a study carried out in 2013 comparing ant colony and genetic algorithms for the travelling salesman problem the genetic algorithm was found to be more effective than the ant colony at finding optimal solutions [1]. This maybe because the search space is better explored with genetic algorithms than ant colony through random mutations and crossover.

Another alternative is a firefly algorithm which simulates the flashing behaviour of fireflies. It uses that fact that fireflies attract other fireflies using their flashing which we can model by an objective function value. If we model our paths as the fireflies with a heuristic of brightness, we can use this to find our solutions. Fireflies are attracted to brighter ones which in these cases are better solutions which lead to convergence. This allows us to effectively explore the search space. In a study carried out in 2014 a comparison was done with ant colony optimisation, and it was found that the Firefly algorithm is more effective.[2]

References:

[1] Kumbharana, N. and Pandey, G.M., 2013. A comparative study of ACO, GA and SA for solving travelling salesman problem. *International Journal of Societal Applications of Computer Science*, *2*(2), pp.224-228.

[2] Ariyaratne, M.K.A. and Fernando, T.G.I., 2014. A comparative study on nature inspired algorithms with firefly algorithm. *International Journal of Engineering and Technology*, *4*(10), pp.611-617.