Ant Colony Optimisation Report

1 Which combination of parameters produces the best results?

The best combination of initial parameters on a standard ACO is to use a colony size of **75**, an evaporation rate of **0.5**, alpha value of 0.5 and a beta value of 3, as well as randomising the starting point for each ant every iteration. For the Burma dataset, this gave a best quality score of **2916** with a path of:

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The best route is:  [4, 3, 2, 13, 5, 11, 6, 12, 10, 8, 9, 1, 7, 0]
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For the Brazil dataset, this gave a best quality score of **23871** with a path of:

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The best route is:  [6, 30, 37, 41, 15, 10, 38, 54, 21, 7, 53, 1, 40, 34, 9, 51,
50, 46, 48, 16, 35, 25, 5, 18, 27, 13, 32, 44, 45, 55, 33, 14, 36, 20, 28, 2, 47,
 4, 22, 42, 26, 11, 56, 23, 57, 43, 17, 0, 29, 39, 12, 8, 24, 31, 19, 52, 49, 3]
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2 What do you think is the reason for your findings?

The colony size of **75** was found to be the optimum number of ants because it provided the best trade off between number of ant runs within an iteration and total number of iterations due to the limit of 10,000 ant runs in total. It was also because this is the greatest balance between having too many different pheromones, which would cause the effect on them to be diminished, causing slower learning, and having too few paths explored, which would cause the algorithm to fall into a local optimum.

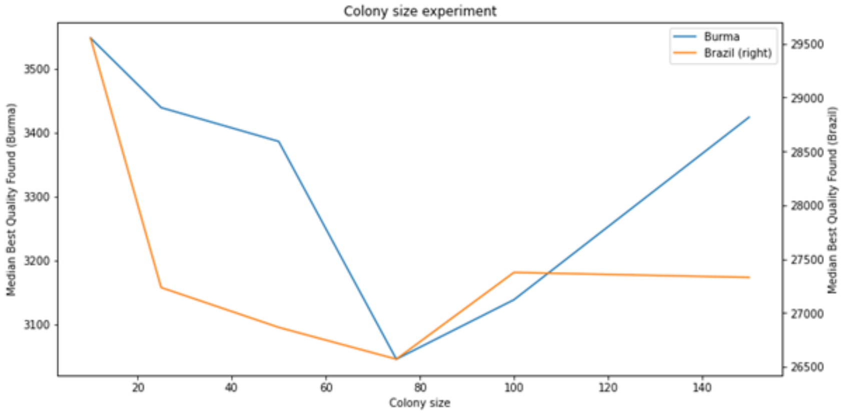
The evaporation rate of **0.5** was found to be a good balance between the algorithm being too dependent on heuristics or too even of a pheromone matrix. If it were to be too high, this would cause most pheromones to evaporate, so the pheromones that were deposited would be more impactful, but transition formula would still be much more heavily skewed by the unchanging heuristics. At the other end of the scale, if the evaporation rate were to be too low it is likely the pheromones would keep adding up and the pheromone matrix would maintain a high baseline level along with a smaller degree of differentiability between paths with high amounts of ant deposited pheromones and those with small amounts.

The alpha rate of **0.5** and beta rate of **3** likely produced the best results because this placed more emphasis on the heuristics rather than the pheromones. This meant that when calculating the probability to move to a different node, the pheromone matrix was halved, and the heuristic matrix was cubed. This meant the algorithm operated a bit like local search but with a help of pheromones to guide it away from short local paths that lead to much longer paths later on.

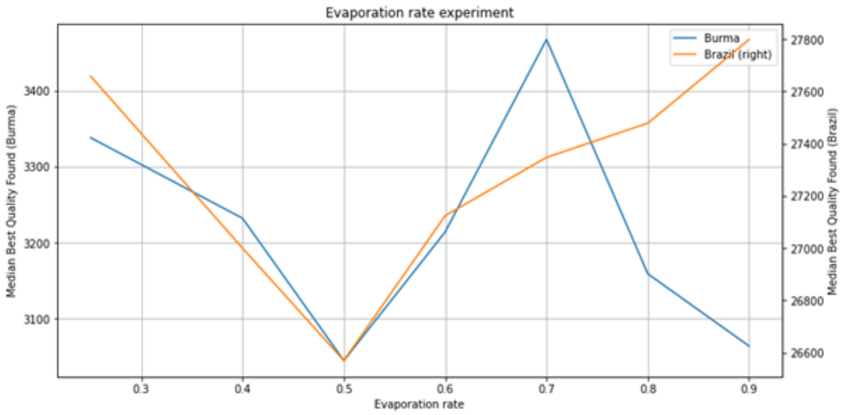
The starting point being **random for each ant every iteration** is also important as it ensures the full range of routes are explored. If the starting point is set to a specific city, then this will most likely make the best quality route the algorithm can find to be much higher. If the starting point is set randomly for each ant, then each ant will explore a different route, meaning that the majority of promising routes will most likely be traversed and tested by an ant at some point, ensuring no routes are left out. This will also ensure the algorithm doesn't stay in a local optimum as some ant will be forced to traverse new paths if they start on a node that no other iteration has started from before.

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

The first experiment I did was to determine the optimum **colony size**. I had a set of control values using a standard ACO, with an evaporation rate of 0.5, a local heuristic function of 1/d, an alpha value of 1, and a beta value of 2. I experimented with colony sizes ranging from 10 to 150 and ran these for 5 separate runs each, recording the median best route. I did this for both the Burma and Brazil datasets. I found that the optimum colony size was **75** for both datasets, with algorithm quality dropping when this value was increased or decreased from 75. This resulted in a median best quality of **3045** for Burma and **26570** for Brazil. When it was too low, the quality was likely to have decreased as less paths were being explored, increasing the chance of falling into a local optimum. When it was too high, the quality was likely to have decreased because more node connections were being explored each iteration, causing pheromone deposits by the best ants to have a lesser effect, and also due to less overall iterations, meaning less frequent pheromone updates.



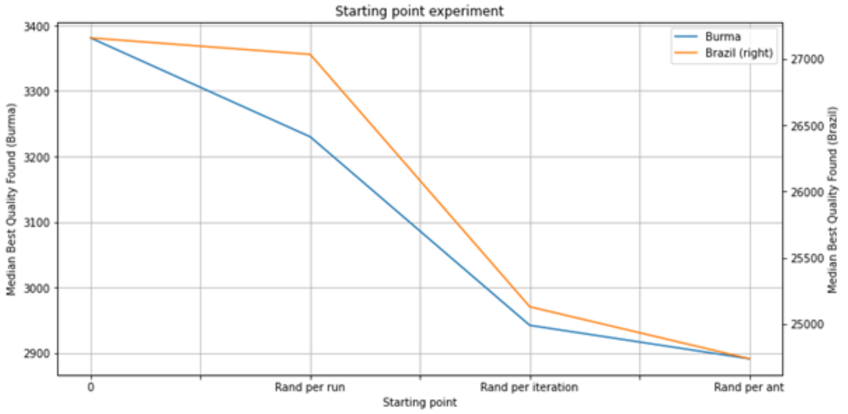
I then experimented with the **evaporation rate**. I set the control values using a standard ACO, with a colony size of 75, a local heuristic function of 1/d, an alpha value of 1, and a beta value of 2. I experimented on both datasets with evaporation rates ranging from 0.25 to 0.9. I ran each of these tests 5 separate times, recording the median best routes given. I found that the optimum value for evaporation rate was **0.5** for both datasets, with a median best quality of **3045** for Burma and **26570** for Brazil. This is most likely due to the best balance between heuristics and deposited pheromones. Lower evaporation rates greatly decreased performance, and higher rates do decrease performance for the most part. However, when the evaporation rate reaches a very high value (0.8 and higher), the performance does start to improve, this is due to the algorithm then mostly disregarding pheromones, meaning the algorithm will tend to take the shorter paths but won't be able to find the most optimum overall path as it does not take into account pheromones, which can help to distinguish how good of a choice a certain node connection is.



Next, I experimented with adjusting the **alpha** and **beta** values used in the transition formula. I had a set of control values using a standard ACO, with a colony size of 75, an evaporation rate of 0.5, and a heuristic function of 1/d. I experimented with 3 different values for alpha and beta, one of which being the standard values used previously. I tested these on both datasets and recorded the median best of 5 runs. I found that the optimum values were **0.5** for alpha and **3** for beta, resulting in a median best quality of **3199** for Burma and **26539** for Brazil. This shows that the pheromones being less important can increase the quality of the algorithm and results. The original values did only perform slightly worse, but when I swapped them around and used 2 for alpha and 1 for beta, the performance drastically decreased. This was most likely because the algorithm then became even more dependent on pheromones rather than heuristics, meaning it was even more likely to fall into a local optimum due to the greatly increased probability of choosing a path that an ant has already taken. This is due to the ants placing more importance on pheromone values rather than the actual cost of a node connection.

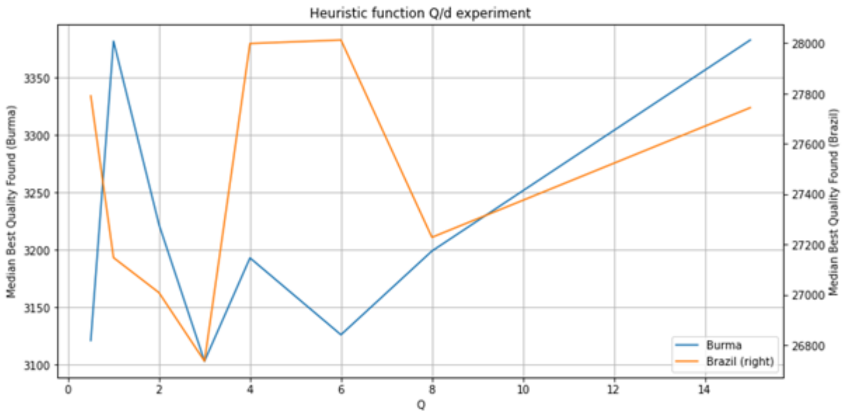
The next parameter I experimented on was the **starting point** used. For this a used a set of control values with a standard ACO, using a colony size of 75, an evaporation rate of 0.5, a local heuristic function of 3/d, an alpha value of

0.5, and a beta value of 3. I found that the best option for the starting point was to **randomise it for every ant**, each iteration, producing results with a median of **2891** for Burma, and **24738** for Brazil. The starting point of 0 limited the algorithm to the best possible route available that starts with 0. The same goes for randomising it for each run, as it will be limited to whatever the best performing route is starting from that particular node. Randomising per ant is better performing than per iteration as it means each ant within an iteration will explore more of the possible paths, increasing the scope, and decreasing the chance of falling into a local optimum.



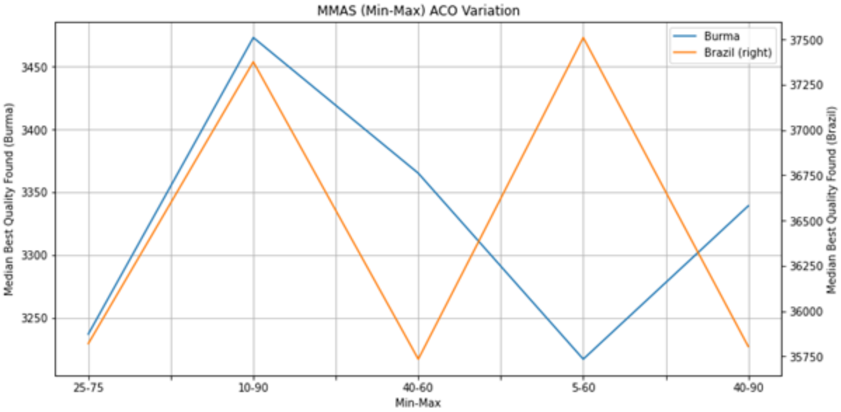
4 Can you think of a local heuristic function to add?

I experimented with a multitude of different heuristic functions, replacing the Q in the heuristic function **Q/d** with a range of values. I used a set of control values with a standard ACO, using a colony size of 75, an evaporation rate of 0.5, an alpha value of 1, and a beta value of 2. I tested a range of values from 1 to 15, once again recording the median of 5 runs on both datasets. I found the best value of q to be **3**, producing a median of **3103** for Burma, and **26737** for Brazil. This is most likely because using 3/d increases the difference in the heuristic of a connection node with a short distance compared to one with a large distance, making an ant more likely to pick a path with a cheaper cost, thereby increasing the overall cost on average, if used properly with pheromones. The Burma dataset differed from the Brazil one when the heuristic function was 1/d, this may be due to the smaller difference in distances in the Burma dataset compared to the Brazil one. Also, larger values of Q result in a worse performing algorithm because this would result in a heuristic matrix which is far too biased, meaning a local optima is quickly reached as the ants would be far more likely to choose a node with high heuristic rather than a one with a balance of heuristics and pheromone values.



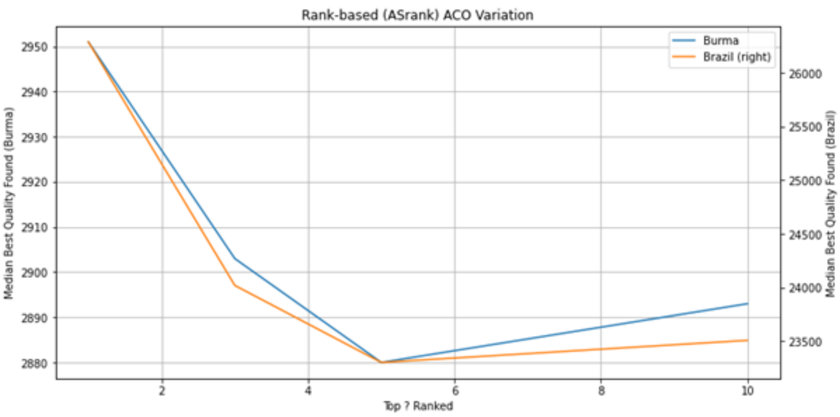
5 Can you think of any variation for this algorithm to improve your results?

First, I experimented with a **MMAS** (Min-Max Ant System), whereby the pheromone values are limited by minimum and maximum values. I used a set of control values with a colony size of 75, an evaporation rate of 0.5, a local heuristic of 3/d, an alpha value of 1, and a beta value of 2. I experimented with a range of minimum and maximum values on both datasets, recording the median of 5 separate runs. I found the best performing algorithm for both datasets to have a minimum value of **0.25** and a maximum of **0.75**, giving a quality of **3237** for Burma and **35734** for Brazil. The best performing for Burma used 0.05 and 0.6 values, giving a median quality of **3217**, whereas the best performing for Brazil was **35734** using values 0.4 and 0.6. These are so different because the algorithm benefits from limited pheromone differences for Brazil using 0.4 and 0.6 as the increased importance of distance values enable the ants to learn more quickly. Whereas in the Burma dataset, its distances are more similar, therefore, it benefits more from having a pheromone matrix which is quite limited with a low maximum and minimum that barely keeps the pheromones relevant. The 0.25 and 0.75 values strike a balance between the two, enabling a greater performance for both datasets. However, this variation is worse than a standard ACO and would be more difficult to find the best route while it is in use.



Next I experimented with an **Elitist** variation, this is where only the global best ant path that has been traversed so far is allowed to lay pheromones. Using a set of control values with a colony size of 75, an evaporation rate of 0.5, a local heuristic of 3/d, an alpha value of 0.5, and a beta value of 3, as well as using a randomised starting point per ant for each iteration. I tested this on both datasets, with Burma having a quality of **2951** and **26292** for Brazil. This is a much greater improvement than MMAS but still leaves room for improvement as because of the elitism, it will quickly fall into a local optima, with ants following the best known path a lot more often, discovering unexplored better paths much less frequently.

I also experimented with a **rank based (ASrank)** variation of the ACO, this a where only a set number of best ants from a single iteration are allowed to lay pheromones at the end of the iteration, this aims to reduce the chances of falling into local optimums caused by elitism. Using the same control values, I tested this on both datasets and found that this was by far the superior algorithm, while taking the **top 5** of every iteration. This resulted in a median value for Burma of **2880**, which is also the best possible value, and a median value for Brazil of **23299**. This algorithm is such a high quality because it only allows the best to lay pheromones, but still makes sure there is a variation among this sub-population. This ensures there is a still a wide range of paths with pheromones on that new ants are all pretty equally likely to take, but that those paths are already very good. The more elitist this algorithm gets (by adjusting the number of top ants), the worse quality it becomes. However, if this value is increased too high, the quality begins to diminish because lower quality ants are laying pheromones, decreasing the overall quality of the pheromone matrix.



I ran this rank-based algorithm for a number of time sand I believe I have found the best routes for both datasets, with the quality of the **best route for Burma being 2880**, and possibly **best for Brazil being 22559**

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The best route is:  [4, 3, 2, 13, 11, 5, 6, 12, 7, 10, 8, 9, 1, 0]
Cost =  2880
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The best route is:  [6, 30, 37, 41, 15, 10, 38, 2, 28, 35, 16, 25, 5, 18, 27, 13, 36, 33, 14, 55, 45, 44, 32, 20, 47, 54, 53, 1, 4
0, 34, 9, 51, 50, 46, 48, 42, 26, 11, 56, 22, 4, 7, 21, 3, 49, 52, 19, 31, 8, 24, 39, 12, 29, 0, 43, 17, 57, 23]
Cost =  22559
```

6 Can you think of any any other nature inspired algorithms that might have provided better results?

A neural network could be used to provide better results, this should eventually learn to look further ahead in its path, rather than just taking the local path costs into account. It could end up combining small sets of connections with the shortest total costs. Due to the nature of deep learning, this should be able to extract more knowledge from failed attempts and may be able to discern some kind of pattern. However, this will likely not lead to any results better than the ones produced by ACO. Another option could be evolutionary algorithms using spanning trees. With the algorithm improving with mutations, it could make gradual progress, but this would be a much less efficient algorithm to use as it will learn very slowly and may be likely to fall into a local optimum.