ECM3412 - Coursework exercise

1) Which combination of parameters produces the best results?

Parameter	**Burma City**	**Brazil City**
ACO Approach	Rank Based Ant System (rank factor = 1)	Rank Based Ant System (rank factor = 1)
Evaporation Rate	0.2	0.8
Colony Size	100	100
Local Heuristic Function	Ranking cities	Ranking Cities
Iterations	100	100

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

The optimal ACO approach will produce the most cost-effective algorithm for the environment, the most consistently. *Figure 1* shows four approaches of the ACO algorithm.

The MMAS approach has improved performance on a smaller number of ant colony size. This is a result of the preventative measures against premature convergence and enhancing exploration. All done by limiting the pheromone values within a specified range. The implications of the MMAS model results in the optimal colony size of basic ACO being too large for the convergence measures of MMAS.

The elitist ACO approach allocates a percentage of the total ants to be selected as elite ants. The pheromone levels on paths corresponding to paths found by elite ants are updated more significantly than other non-elite ant paths. This mechanism therefore mitigates premature convergence on a percentage of the paths, preventing the algorithm from removing valuable solutions too quickly.

The rank-based ant system uses a ranking mechanism for solutions of ants in order to compare the objective function values or other measures of the algorithm. Rank Based AS produced the lowest costs consistently when compared with each other ACO approach as shown in *Figure 1&2*.

The optimal ACO approach was found to be the Rank Based Ant System as a result of the consistently lower Cost values, on top of generating this consistent low cost with fewer ants. Of which is preferred if possible. The optimal number of ants / colony size was found to be in the range of 50 to 100 *Figure 1 (Bottom Right)*. In determining which value in the range produces better results more consistently an analysis of further parameters, notably the evaporation rate, must also be taken in account for a fair judgement. The combination of the Colony size and evaporation rate can be seen in *Figure 3* where its clear that both colony sizes 50 and 100 produces statistically significant lower cost than 10 regardless of evaporation rate.

The comparison of evaporation rate (decay) represented by Greek, rho, against the colony size shown in *Figure 4* demonstrates that a Colony Size of 100 and Decay of 0.2 produce the most consistent results for low cost in Burma. Brazil benefits from larger decay to encourage more exploration and less exploitation given the size of the network.

In the Basic ACO example, the number of iterations is found to be sufficient at 100 given the plateau of Best Cost value in the range of 50 to 70 iterations. As shown in *Figure 4* the Cost plateaus at 40 iterations. Therefore, keeping the number of iterations fixed at 100 ensures the algorithm is given enough opportunity to converge on the best possible solution.

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

In determining the optimal colony size, there is a preference towards a lower number of ants in the colony as this has a greater computational efficiency with requiring less memory and processing power. The balance between exploration and exploitation is easier to determine with a smaller colony size which contributes towards discovering diverse solutions by avoiding premature convergence on suboptimal solutions. The reduced colony size also benefits from reduced pheromone maintenance overhead as a result of fewer parameters to update each iteration.

In the example of the Rank Based AS *(Figure 1).* The smallest number of 10 ants, suffers from not having enough ants and fails to converge on better local minima in optimising the network. This may be a result of premature convergence, getting stuck in local minimum. With fewer ants, the ability to explore the whole solution space in the number iterations is more limited, therefore there is an increased probability of missing better solutions.

In the example of the MMAS ACO *(Figure 1)*, the highest number of ants at 250 produces higher cost than the two lower values of ants on multiple iterations of the algorithm. Perhaps this is a result of the greater number of ants being more sensitive to parameter tuning. The pheromone evaporation and exploration-exploitation trade off by alpha and beta hyperparameters will further influence and fluctuate the cost as the number of ants rises. The greater number of ants may also be too large for the small Burma network, giving reason as to the convergence issues that is accustomed to a very high number of ants. Too many ants result in excessive exploration, preventing exploiting promising paths and converging to a better solution, thus generating higher cost.

In the parameters alpha and beta are key determinants in shaping the algorithm's behaviour during solution construction. Alpha influences the weight assigned to pheromone information, with higher values prioritizing exploration by emphasizing the collective knowledge of the ant colony. Conversely, beta governs the importance of heuristic information, allowing ants to favour shorter paths when beta is high. The interplay of alpha and beta in the probability calculation for choosing the next city strikes a balance between exploration and exploitation. High alpha encourages exploration by relying on pheromone trails, while high beta promotes exploitation by prioritizing shorter distances.

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

Visibility: The visibility heuristic is also based on the distance between cities. However, it may include additional factors (Shahadat, Akhand and Kamal, 2022). The probability is defined as:

$$v_{ij} = 1/d_{ij}^{\beta},$$

5) Can you think if any variation for this algorithm to improve your results? Explain your answer.

Rank-Based Ant System with Memory (RAS-M) as it achieves fast convergence to high quality solutions and outperforms $AS\ Rank$, MMAS and ACS, for most instances of the benchmark (Pérez-Carabaza, Gálvez and Iglesias, 2022).

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

Particle Swarm Optimization, PSO, is known for its exploration capabilities and quick convergence, while ACO is praised for its robustness, ability to balance exploration and exploitation, and applicability to a wide range of TSP instances (Chaudhari and Thakkar, 2019).

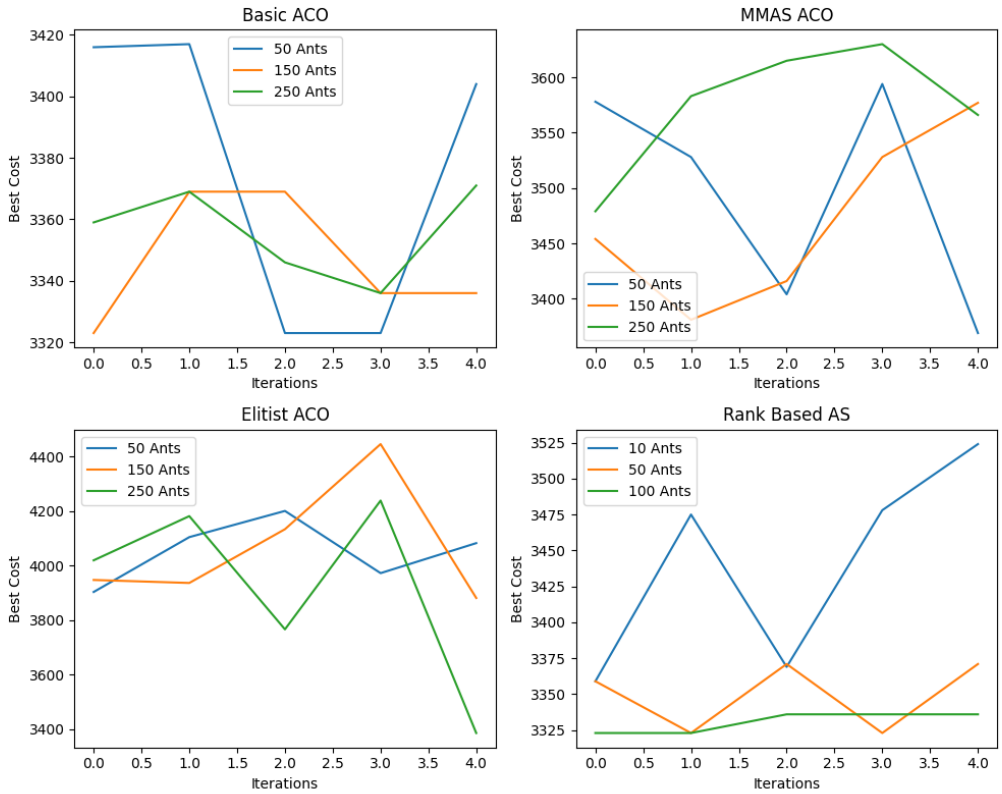

Figure 1: Competing Burma ACO Approaches

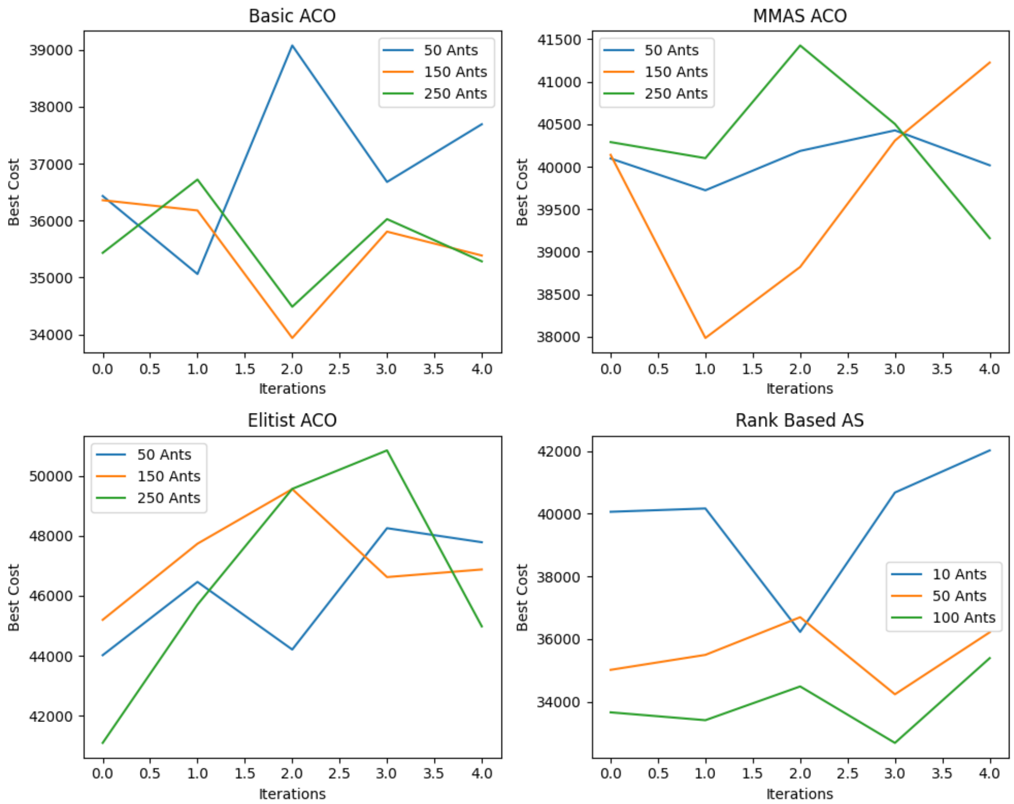

Figure 2: Competing Brazil ACO Approaches

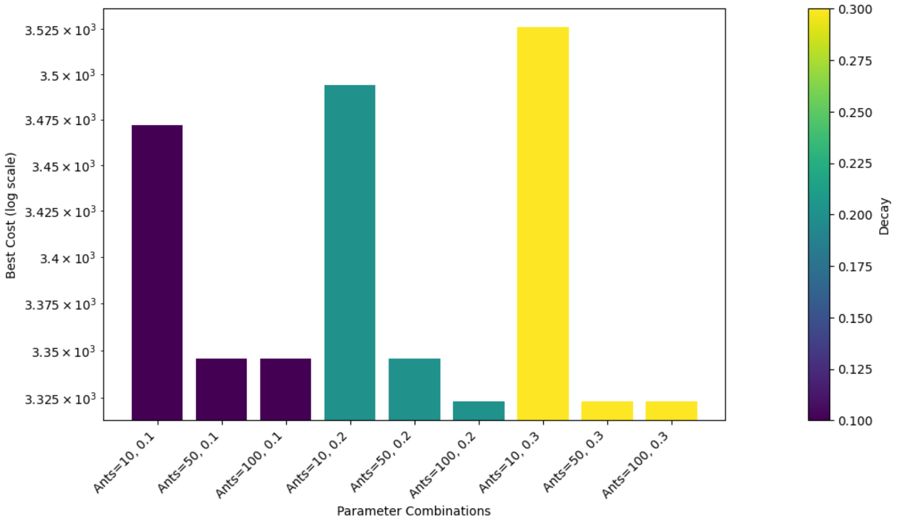

Figure 3: Rank Based AS Colony Range Comparison

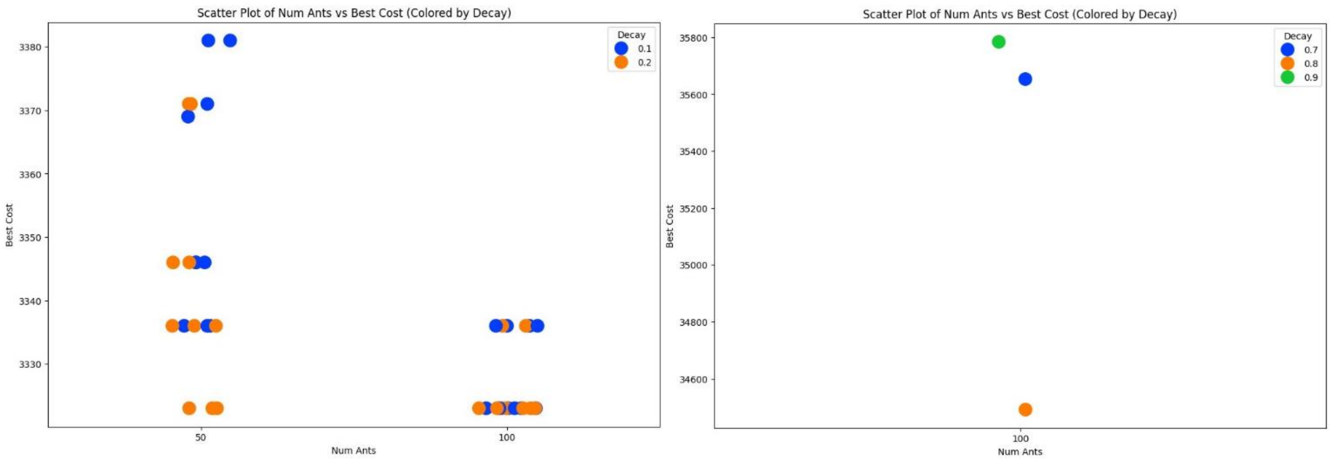

Figure 4: Rank Based AS Parameter Analysis Burma (left) and Brazil (right)

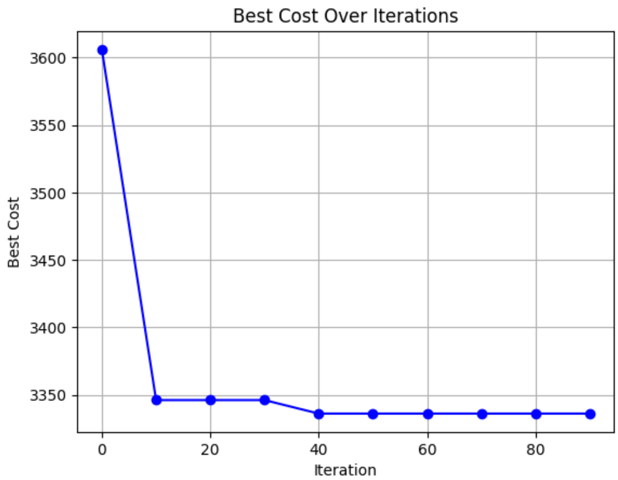

Figure 5: Iterations plateau Burma

References:

Pérez-Carabaza, S., Gálvez, A. and Iglesias, A. (2022). Rank-Based Ant System with Originality Reinforcement and Pheromone Smoothing. *Applied Sciences*, 12(21), p.11219. doi:https://doi.org/10.3390/app122111219.

Shahadat, A.S.B., Akhand, M.A.H. and Kamal, M.A.S. (2022). Visibility Adaptation in Ant Colony Optimization for Solving Traveling Salesman Problem. *Mathematics*, 10(14), p.2448. doi:https://doi.org/10.3390/math10142448.

Chaudhari, K. and Thakkar, A. (2019). Travelling Salesman Problem: An Empirical Comparison Between ACO, PSO, ABC, FA and GA. *Advances in intelligent systems and computing*, pp.397–405. doi:https://doi.org/10.1007/978-981-13-6001-5_32.