ECM3412 – ACO Report

Question 1: Which combination of parameters produces the best results?

On the Burma dataset, the best from the standard implementation of Ant Colony Optimisation (ACO) occurs with colony size 50 and evaporation rate 0.3, the best fitness after 10,000 iterations was 3494. The other top results were 3500 and 3610 coming from Colony sizes 50 and 100 respectively at evaporation rate 0.9.

On the Brazil dataset, the parameters for the best results were with colony size 50 at evaporation rate 0.9, resulting in the fitness of 42917 after 10,000 iterations. Results are illustrated in Figures 1 & 2 and their subsequent tables.

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

For both the Burma and the larger Brazil datasets, the optimal fitness emerged with only 50 ants but at different evaporation. Brazil benefits from larger decay to encourage more exploration and less exploitation given the size of the network.

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

Concerning the optimal size of the colony, there is a preference for many ants due to their ability to go through the entire search space, eventually finding an optimal path. With a reduced colony size, striking a balance between exploration and exploitation becomes more straightforward, aiding in the discovery of diverse solutions and preventing premature convergence to suboptimal solutions. During multiple iterations of the algorithm, it was observed that using the lowest number of ants ,10, resulted in higher costs. Lack of exploration could be a seemingly obvious potential cause for this at 10 ants but with a small number of ants, the pheromone trail information may be less accurate, as it relies heavily on the paths chosen by these few ants. This can lead to less effective exploitation of promising paths.

In the algorithm's solution construction, alpha and beta parameters play a pivotal role in shaping its behaviour. Alpha dictates the weight assigned to pheromone information, with higher values emphasizing exploration through the collective knowledge of the ant colony. Conversely, beta determines the significance of heuristic information, enabling ants to prioritize shorter paths when beta is elevated. The interplay of alpha and beta in the probability calculation for selecting the next city establishes a delicate balance between exploration and exploitation. Higher alpha values encourage exploration by relying on pheromone trails, while higher beta values promote exploitation by prioritizing shorter distances.

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

The visibility heuristic is also based on the distance between cities. However, it may include additional factors [4]. The probability is defined as: $v_{ij}=1/d_{ij}^{\beta}$

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

2 variations of ACO that could improve results are the MMAS and Elitist implementations.

Elitist ACO enhances the exploration-exploitation trade-off by incorporating an elitism mechanism. Elitism ensures that the best solutions found so far are retained. This helps in preserving valuable information about high-quality paths. By exploiting these elite solutions, the algorithm is more likely to converge towards better and more promising regions of the solution space. This was seen in the Burma dataset, as the elitist ACO algorithm at elite percentage 0.1 provided the best fitness amongst the algorithms with 3323, Figure 5. There is also an improvement when applied onto the Brazil dataset of [3680,15429].

Elitism can accelerate the convergence speed of the algorithm [5]. By incorporating the best solutions into the pheromone update process, the algorithm leverages the knowledge gained from these solutions to guide the search towards regions of the solution space with higher-quality solutions. This was seen in both datasets running faster than MMAS by 42 minutes (Brazil) and 2 minutes (Burma).

Max-Min Ant System (MMAS) represents a modified version (ACO), incorporating additional mechanisms aimed at imposing a more stringent control on the levels of pheromones [6].MMAS addresses the issue of pheromone stagnation that can occur in traditional ACO. By controlling the upper and lower bounds of pheromone values, MMAS prevents stagnation and allows the algorithm to adapt to changing conditions, promoting a more dynamic search. Additionally, MMAS can be more scalable to larger problem instances such as with the Brazil dataset. MMAS was able to best the original and elitist ACO and produce the best fitness of 34259. In the Burma dataset, MMAS was also able to produce the joint optimal score of 3323, Figure 3. The only issue with this variation of the ACO how long it takes to run.

Question 6: Do you think of any other nature inspired algorithms that might have provided better results? Explain your answer.

Evolutionary algorithms (EAs) offer a powerful approach to optimization problems, such as TSP, as an alternative to ACO. Inspired by natural selection, EAs employ a population of candidate solutions that evolve over generations, gradually refining their parameters toward the optimal configuration.

Evolutionary Algorithms (EAs) are a class of optimization algorithms inspired by the process of natural evolution. These algorithms follow the principles of biological evolution, where individuals in a population undergo selection, genetic variations, and reproduction over successive generations [7]. In the context of the TSP, a chromosome might represent a possible order in which cities are visited. Genetic operations are applied to produce new orders, and the fitness is determined by the total distance travelled.

EAs could be better since they can converge faster in some cases due to the efficiency of crossover and mutation operations. ACOs, on the other hand, often require several iterations for the pheromone trails to guide the search effectively as seen in this coursework as with a large dataset ACO was running upwards of 2 hours.

References :

[4]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.

[5]Negulescu, Sorin & Oprean, Constantin & Kifor, Claudiu & Carabulea, Ilie. (2008). Elitist ant system for route allocation problem.

[6] Thomas Stützle, Holger H. Hoos,MAX–MIN Ant System,Future Generation Computer Systems,Volume 16, Issue 8,2000,Pages 889-914

[7] Conor Ryan. “Evolutionary Algorithms and Metaheuristics”. In: Encyclopedia of Physical Science and Technology (Third Edition). Ed. by Robert A. Meyers. Third Edition. New York: Academic Press, 2003, pp. 673–685.

Figures:

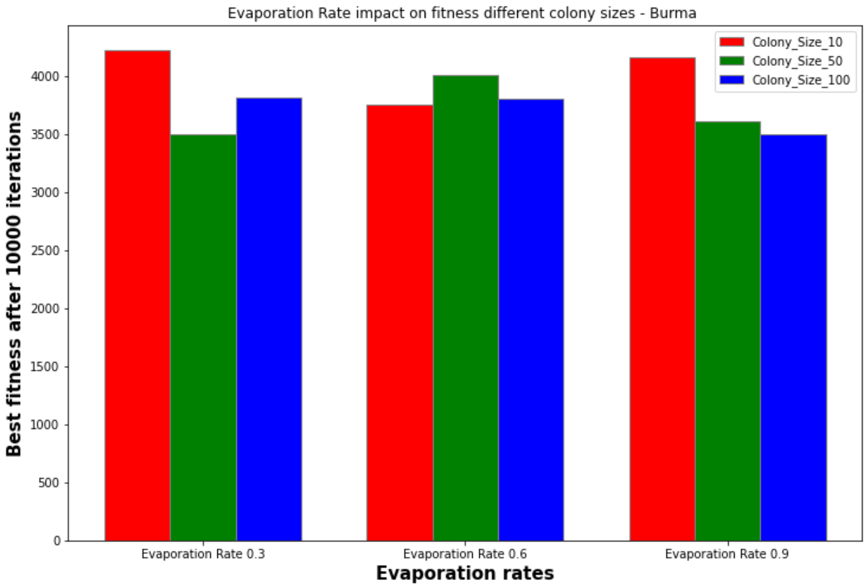


Figure 1

	Colony_Size_10	Colony_Size_50	Colony_Size_100
Evaporation Rate 0.3	4225.0	3494.0	3809.0
Evaporation Rate 0.6	3756.0	4004.0	3801.0
Evaporation Rate 0.9	4161.0	3610.0	3500.0

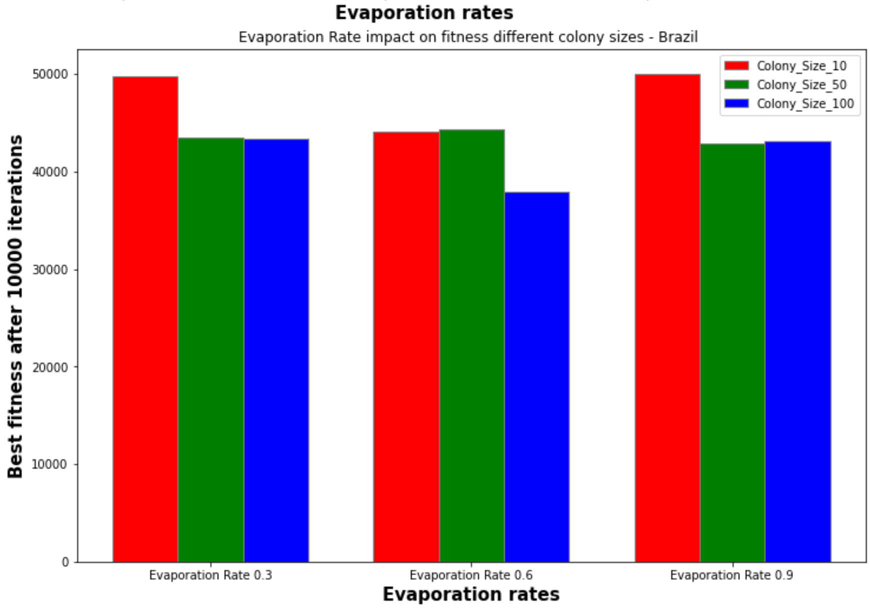
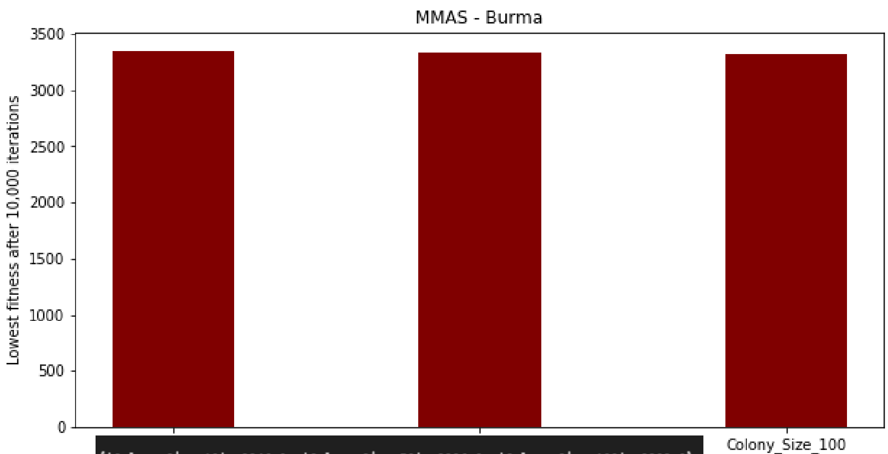


Figure 2

	Colony_Size_10	Colony_Size_50	Colony_Size_100
Evaporation Rate 0.3	4225.0	3494.0	3809.0
Evaporation Rate 0.6	3756.0	4004.0	3801.0
Evaporation Rate 0.9	4161.0	3610.0	3500.0

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{'Colony_Size_10': 3346.0, 'Colony_Size_50': 3336.0, 'Colony_Size_100': 3323.0}
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Figure 3

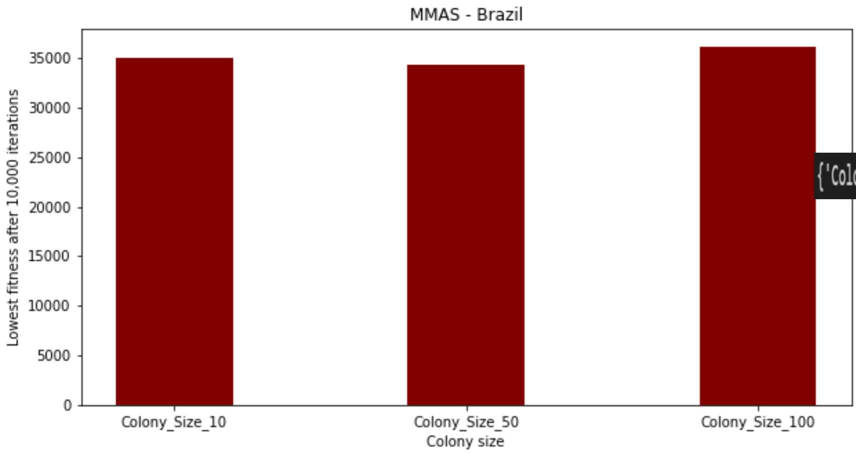

Figure 4

{'Colony_Size_10': 34992.0, 'Colony_Size_50': 34259.0, 'Colony_Size_100': 36116.0}

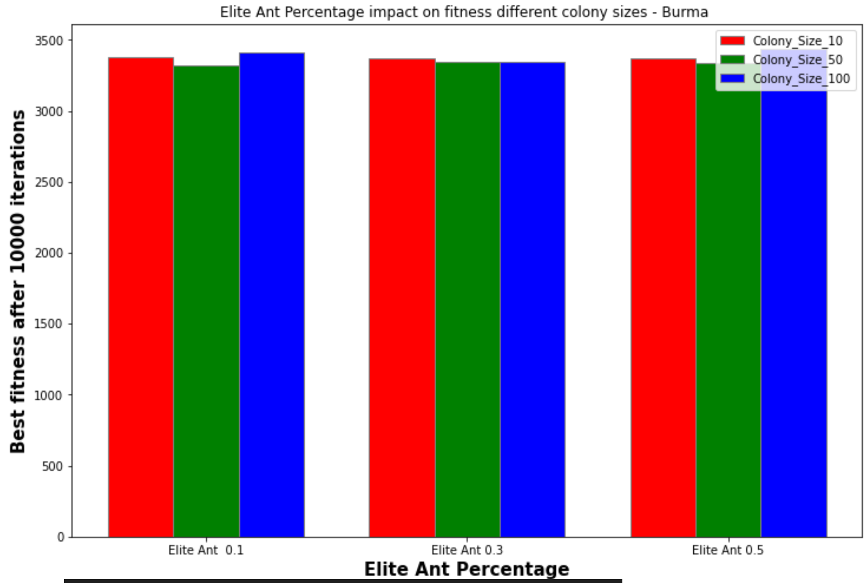

Figure 5

	Colony_Size_10	Colony_Size_50	Colony_Size_100
Elite percantage 0.1	3381.0	3323.0	3411.0
Elite percantage 0.3	3371.0	3346.0	3346.0
Elite percantage 0.5	3369.0	3336.0	3440.0

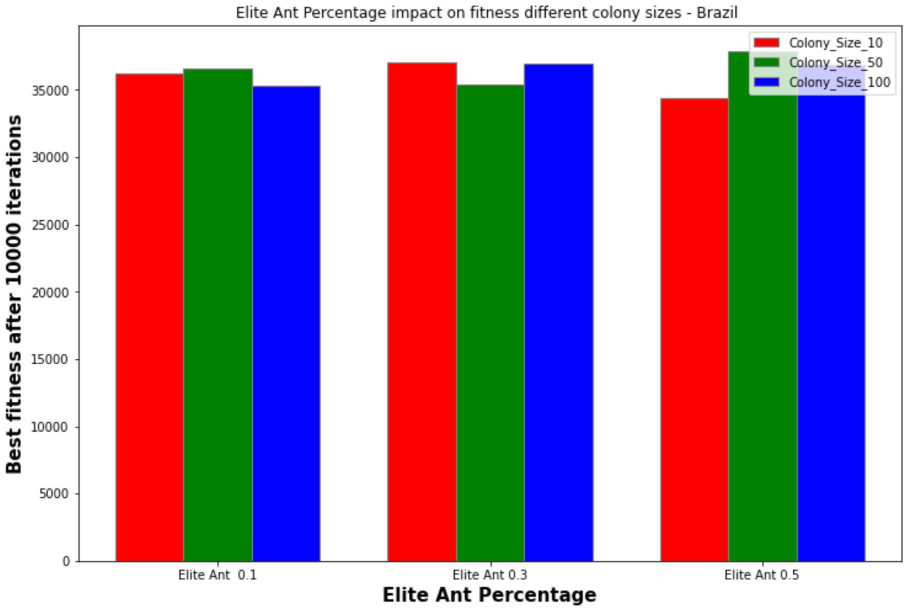

Figure 6

	Colony_Size_10	Colony_Size_50	Colony_Size_100
Elite percantage 0.1	36222.0	36546.0	35340.0
Elite percantage 0.3	37041.0	35418.0	36989.0
Elite percantage 0.5	34351.0	37901.0	36885.0