Nature Inspired Computing: Optimising Travel Routes Using Ant Colony Optimisation

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1 Introduction

The Traveling Salesman Problem (TSP) is a classical combinatorial optimisation problem with extensive logistics and network design applications. This report explores the application of the Ant Colony Optimisation (ACO) algorithm to the TSP. Inspired by ants' pheromone behaviours, ACO offers an innovative approach to identifying near-optimal routes. It uses a pheromone trail matrix to guide probabilistic path selection based on pheromone concentration (τ) and heuristic distance information (η), with pheromone evaporation ensuring a balance between exploration and exploitation.

This study aims to implement ACO, systematically vary its key parameters (number of ants, evaporation rate, pheromone (α) and heuristic (β) influences, pheromone deposit (Q), and local heuristic ($local\_heuristic$)) and analyse their effects on the algorithm's performance.

2 Experiment Design

The experiment was designed to analyse the Ant Colony Optimisation (ACO) algorithm's performance on the Traveling Salesman Problem (TSP), focusing on parameter tuning and algorithm variations. In implementing the ACO algorithm, an 'elitist weight' variable was used, enhancing the pheromone contribution of the most successful paths, reinforcing effective routes, and potentially accelerating convergence.

The experimental methodologies included:

1. **Grid Search**: An extensive exploration across diverse ACO parameters to find the most efficient combinations for optimal route solutions. These parameters can be seen in Table 1.

2. **Focused Search**: A deeper investigation into the most promising parameter sets identified from the grid search, providing further insights into their impact on ACO performance.

Parameter	Options
Number of Ants	10, 20, 50, 100, 200, 500, 1000
Evaporation Rate	0.1, 0.5, 0.9
Pheromone Influence (α)	1, 2, 3
Heuristic Influence (β)	1, 2, 3
Pheromone Deposit (Q)	10, 50, 100
Local Heuristic	1, 50, 100
Number of Runs	3

Table 1: Parameter Sets for ACO Grid Search

A Min-Max Ant System approach (MMAS) was tried, which involved setting upper ($\tau_{\max} = 1.0$) and lower ($\tau_{\min} = 0.1$) pheromone limits and modifying the pheromone update process to be based solely on the best ant's path. However, compared to an elitist approach, this led to an increased average path cost. Additionally, using a Tabu Search mechanism was tried; however, this increased execution time significantly, so it was decided against using it.

3 Results and Analysis

Data	# Ants	Evap. Rate	α	β	Q	Local Heuristic	Min Cost	Avg Cost (1000 runs)
Burma	10	0.1	1	1	50	100	**3323**	3326.301
Brazil	23	0.15	1	2	50	1	**25411**	25815.463

Table 2: Optimal Parameter Sets and Min Costs

These results highlight the significance of parameter tuning in ACO. Figures 1a and 1b visually represent the solutions for Burma and Brazil, respectively. The performance metrics of the Ant Colony Optimisation algorithm with varying parameter values can be seen in Figure 1c.

A low **Q** value resulted in a slower convergence on the path, indicating that weaker pheromone trails necessitate more iterations for pathfinding. Conversely, a high **evaporation rate** accelerated the path convergence process but led to minimal iterative improvements, often culminating in a suboptimal solution. This suggests that excessive pheromone volatility may impede the algorithm's ability to refine its search. On the other hand, a low **evaporation rate** was associated with a gradual reduction in average pheromone levels and a moderate pace of path convergence. However, it tended to yield a more optimal solution, implying that persistent pheromone trails provide more reliable guidance to the ants over successive iterations.

Parameters that consistently found the optimal path encompassed **high beta influence**, indicating an emphasis on heuristic cues for shorter initial paths, and high and very high **local heuristic** values, which likely enhanced decision-making quality from the outset. Settings characterized by low α influence, low β, and low **evaporation rate** were marked by slow and suboptimal convergence, highlighting the necessity of a careful balance between exploration and exploitation. Parameter sets with very high and high **evaporation rates**, along with high α values, demonstrated high path stability. However the solutions were not always optimal, potentially due to premature convergence on less-than-ideal paths. In contrast, low **evaporation rate** and low β configurations exhibited iterative improvements throughout the simulation, suggesting a sustained optimization process.

Furthermore, pheromone intensity levels for low **evaporation** and high **local heuristic** remained robust, underscoring the importance of durable pheromone trails in guiding the ants. In comparison, other parameters declined, with some maintaining higher intensity levels than others. A particularly low α value was detrimental to path cost efficiency. At the same time, a high β influence was marginally better, reinforcing the significance of striking an optimal balance between pheromone and heuristic influences in the ACO algorithm.

4 Discussion of Specific Questions

1. **Which combination of parameters produces the best results?**
   The most successful parameter combinations are detailed in Table 2, determined through a grid and focused grid search. While the parameter impact was somewhat uniform for the Burmese dataset, consistently achieving a cost of **3323**, the larger Brazilian dataset exhibited more variability. The best score of **25,411** for brazil58 was achieved after extensive experimentation, indicating a nuanced interaction between the algorithm's heuristic nature and the dataset's complexity. These optimal parameters facilitated a balanced trade-off between exploration and exploitation, enabling the algorithm to navigate and converge on promising solutions efficiently. This balance was crucial in consistently reaching the best solutions, especially for the

more complex brazil58 dataset, where algorithmic adaptability played a significant role. The detailed path and parameters for these results are accessible in the `/results/` directory.

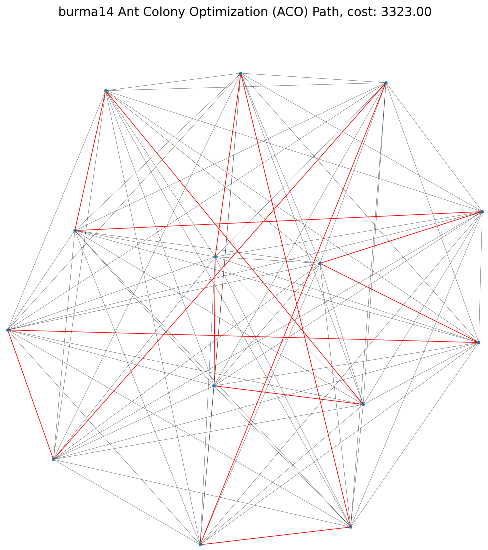
2. **What do you think is the reason for your findings in Question 1?**
The superior performance of these parameter sets stems from their strategic balance between pheromone concentration (τ) and heuristic information (η), pivotal in efficient route discovery and optimisation. Specifically, the chosen values for Q (pheromone deposit) significantly influenced the intensity and persistence of pheromone trails, directly affecting the ants' pathfinding and decision-making processes. By offering dynamic feedback based on the ants' experiences, the *local_heuristic* parameter contributed to more informed and adaptive choices at each step. This relationship between pheromone trail intensity and heuristic guidance enabled the ants to effectively explore diverse routes while gradually converging towards the most promising solutions. Consequently, this fine-tuned balance ensured an optimal blend of exploration and exploitation, crucial for navigating the complexities of the TSP landscapes.

3. **How does each of the parameter settings influence the performance of the algorithm?**
The number of ants plays a crucial role in parallel solution exploration. An optimal count promotes a diverse range of paths without leading to excessive overlap or redundancy in search efforts. The evaporation rate, governing how quickly pheromones fade is vital balancing between retaining valuable trail information and avoiding premature convergence; lower rates typically foster more thorough exploitation of known good paths. The interaction between pheromone influence (α) and heuristic influence (β) is critical for the algorithm's efficiency. A well-balanced α and β ensure that neither the pheromone trails nor the heuristic distance overly dominate the decision-making process, which might otherwise lead to either overly conservative or erratic path selection. The parameter Q, determining the intensity of the pheromone deposit, directly impacts the attractiveness of the paths to subsequent ants, influencing the rapidity and strength of the convergence on solutions. Finally, the *local_heuristic*, a measure of the perceived desirability of paths, provides crucial guidance in the initial exploratory phase, helping ants to make informed decisions when less pheromone information is available.

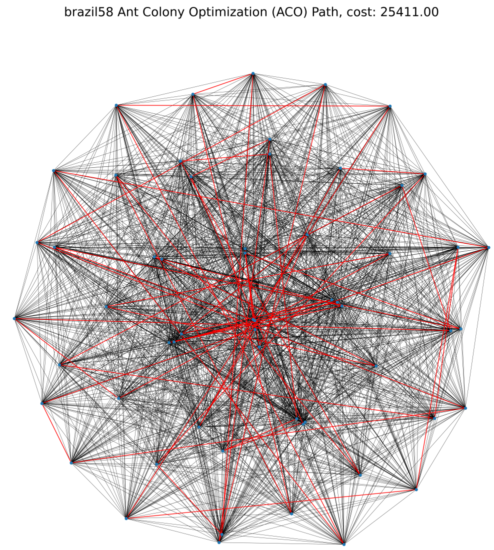
4. **Can you think of a local heuristic function to add?**
An changing local heuristic function that evolves according to the frequency and success of chosen paths offers promise. This function can diversify the search process by incrementally increasing the heuristic value of less-travelled routes, potentially revealing more efficient paths. It could recalibrate heuristic values after each iteration, incorporating recent findings to refine the ants' decision-making, thus fostering a more dynamic and responsive exploration strategy in the ACO algorithm.

5. **Can you think of any variation for this algorithm to improve your results? Explain your answer.**
An adaptive ACO algorithm is a promising variation, where parameters like α, β, and *evaporation_rate* are dynamically modified based on current iteration performance feedback. For instance, increasing α in response to stagnation can promote exploration, while reducing the *evaporation_rate* when optimal paths are emerging can reinforce beneficial trails. This responsive tuning allows the algorithm to adapt its strategy to the evolving search landscape, potentially leading to more robust and efficient solutions and enhancing its ability to converge on optimal routes consistently.

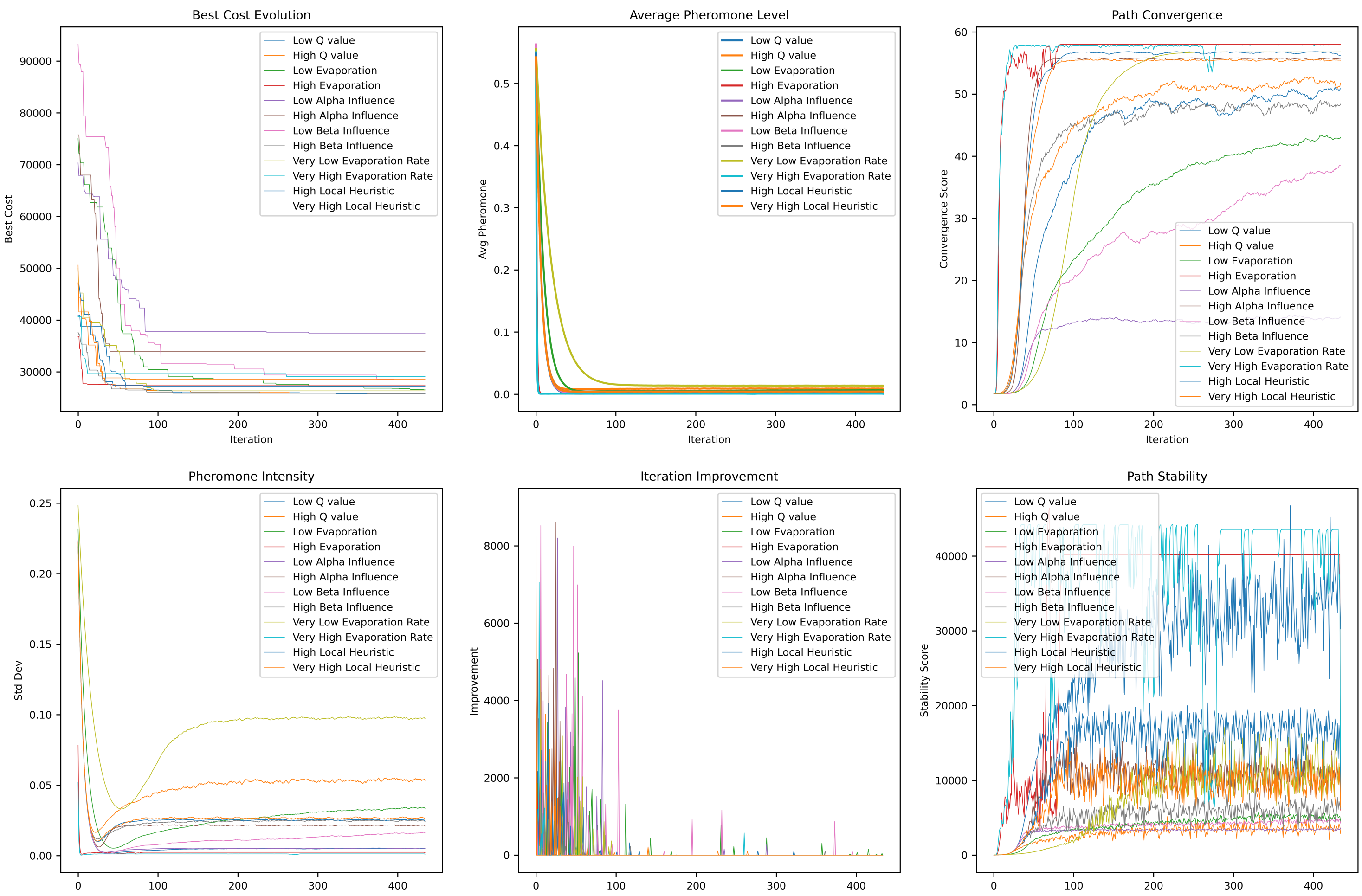
6. **Do you think of any other nature-inspired algorithms that might have provided better results? Explain your answer.**
Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) are two alternatives that could offer competitive results in specific TSP scenarios. With its crossover and mutation mechanisms, GA excels at maintaining genetic diversity and avoiding local optima, which can be advantageous in exploring complex solution spaces with multiple local minima. By leveraging global and local best solutions, PSO facilitates effective convergence by balancing individual exploration and social learning among agents. This can lead to more rapid identification of optimal paths in certain TSP configurations. However, the effectiveness of GA and PSO would vary depending on the particular characteristics of the TSP instance and the nuances of their implementation.



(a) Optimal TSP Route for Burma



(b) Optimal TSP Route for Brazil



(c) Performance Metrics of the ACO Algorithm

Figure 1: Graphical representation of the optimal routes in Burma and Brazil, and the performance metrics of the ACO algorithm.