Nature Inspired Computing: Optimizing Travel Routes Using Ant Colony Optimization

James Calnan

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1 Introduction

The Traveling Salesman Problem (TSP) is a classical combinatorial optimization problem with extensive logistics and network design applications. This report explores the application of the Ant Colony Optimization (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 analyze their effects on the algorithm's performance. The results are expected to enhance the understanding of bio-inspired algorithms and their capability to solve complex optimization tasks effectively.

2 Experiment Design

My experiment was designed to analyze the Ant Colony Optimization (ACO) algorithm's performance on the Traveling Salesman Problem (TSP), with a particular focus on parameter tuning and algorithm variations. In implementing the ACO algorithm, I used an 'elitist weight' variable, 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 aimed 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.

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

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

average path cost. Additionally, I experimented with using a Tabu Search mechanism; this increased execution time significantly, so it was decided against using it.

The introduction of the ‘elitist_weight‘ parameter was aimed at examining whether additional emphasis on the best-found paths could yield better solutions.

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 Optimization (ACO) algorithm, represented in Figure 1c.

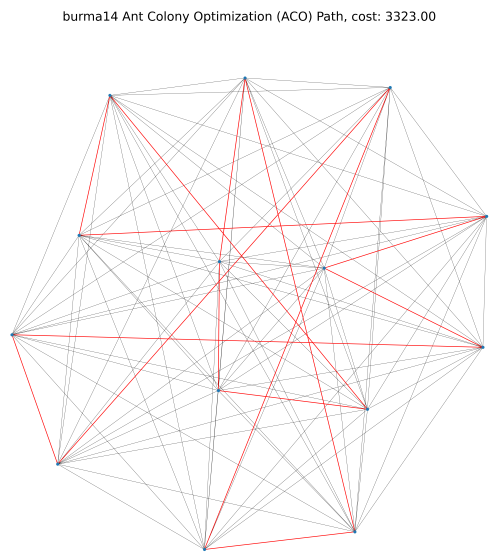
The **Best Cost Evolution** graph indicates that higher Q values lead to a steeper descent in cost, signifying an aggressive exploration that quickly stabilizes. In contrast, lower Q values demonstrate a gradual convergence, potentially due to weaker pheromone trails. In the **Average Pheromone Level** plot, the sharp decline and subsequent plateau across all Q values suggest a transition from exploration to exploitation, with lower plateaus for smaller Q values indicating subtler pheromone trails for guiding the ants.

Path Convergence displays an initial sharp increase and jittery plateau, with higher Q values achieving lower scores, implying a broader consensus on path selection among ants, contrary to the focused trails at lower Q values.

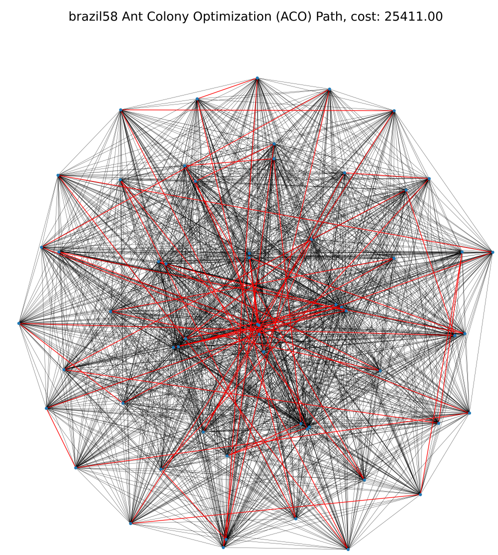
The **Pheromone Intensity** metric illustrates the spread of pheromone trails, with higher Q values dispersing pheromones more broadly, reflected by a greater standard deviation.

Iteration Improvement shows significant early improvements that level off, suggesting that the algorithm's efficiency is front-loaded into the initial iterations.

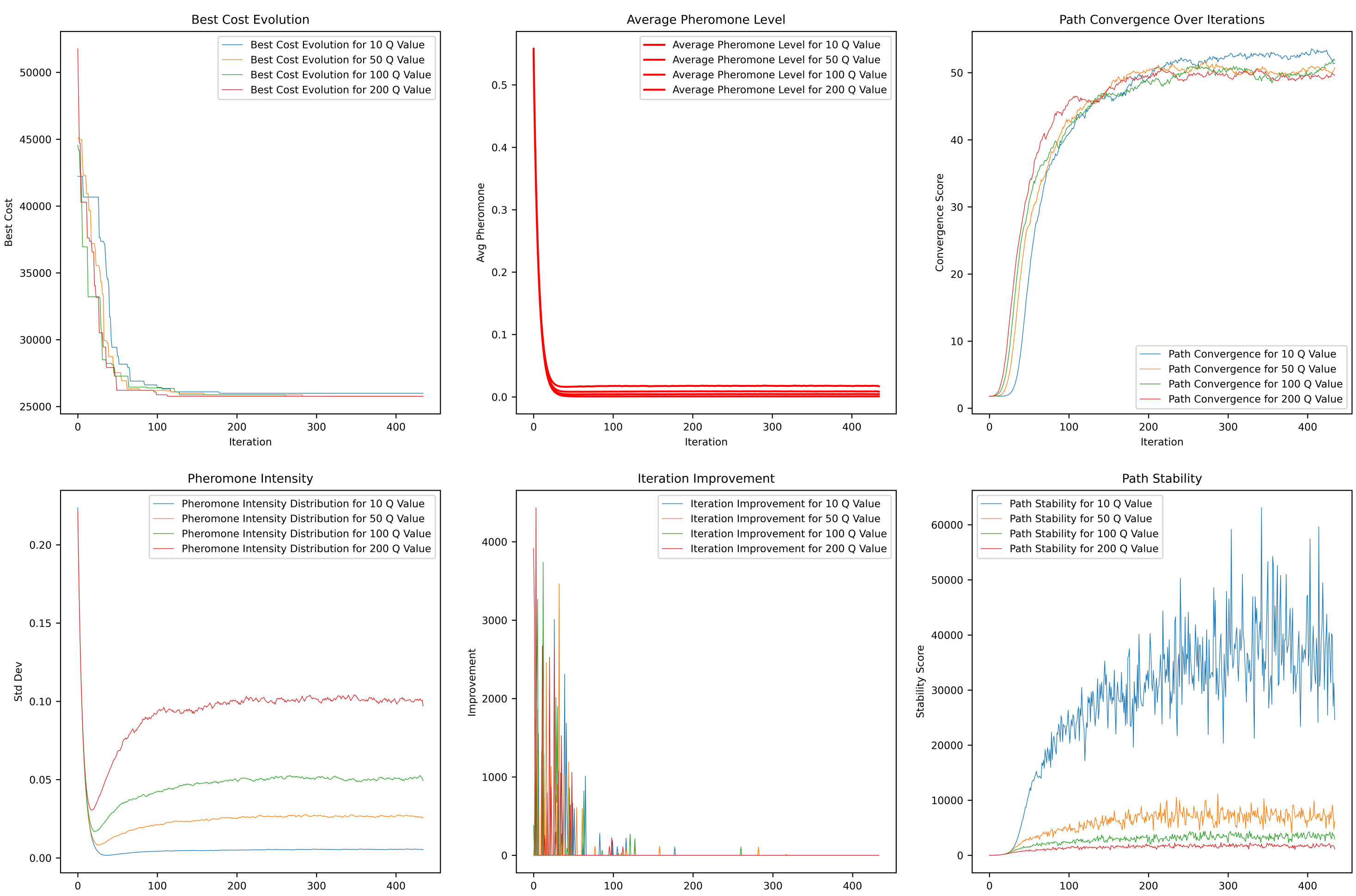
Finally, the **Path Stability** metric reveals that paths become more stable quicker with higher Q values, while lower Q values exhibit large fluctuations, indicating ongoing exploration and path adjustments.



(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.

4 Discussion of Specific Questions

1. **Which combination of parameters produces the best results?**
   The optimal parameters can be seen in Table 2. These were found by executing the grid search and then the focused grid search for more granularity. With the Burmese dataset the parameters didn't matter as much as the ACO almost always found 3323 as the answer. Due to the heuristic nature of the algorithm, when running ACO on the bigger dataset, brazil58, even with optimal parameters the best score, **25411**, was only found after extensively running the ACO roughly 10,000 times.

2. **What do you think is the reason for your findings in Question 1?**
   The effectiveness of these parameter sets is attributed to their balanced approach to pheromone and heuristic influences, which facilitated efficient pathfinding. The specific values for Q and *local_heuristic* enhanced the ants' ability to discover and reinforce optimal routes, demonstrating the critical role of fine-tuning in ACO. This balance between the various parameters enabled the ants to effectively explore the search space and converge on optimal solutions.

3. **How does each of the parameter settings influence the performance of the algorithm?**
   The number of ants influenced parallel solution exploration, with an optimal count avoiding redundancy. The Evaporation rate was pivotal in maintaining useful pheromone trails, with lower rates favoring exploitation. The balance between α and β was key, as disproportionate emphasis led to suboptimal paths. Q and *local_heuristic* were instrumental in guiding ants, especially in the initial stages of exploration.

4. **Can you think of a local heuristic function to add?**
   A dynamic local heuristic function that adapts based on path usage frequency could be beneficial. This approach would encourage the exploration of less-travelled paths, potentially uncovering new efficient routes. The function could be designed to adjust the heuristic information with each iteration of the algorithm, allowing for continuous improvement of the search strategy.

5. **Can you think of any variation for this algorithm to improve your results? Explain your answer.**
   An adaptive ACO variant, where key parameters like α, β, and *evaporation_rate* are dynamically adjusted in response to real-time performance, could yield improvements. This adaptation would enable the algorithm to fine-tune its search strategy based on ongoing results, potentially enhancing solution quality. The adaptive approach would also allow the algorithm to respond to changes in the problem space or search environment, improving its ability to converge on optimal solutions.

6. **Do you think of any other nature-inspired algorithms that might have provided better results? Explain your answer.**
   Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) could offer competitive results. GA's mechanisms for genetic diversity might excel in exploring varied solution spaces, while PSO's agent collaboration could effectively converge on optimal solutions. However, their relative effectiveness would depend on the specific TSP instance and implementation details.