

Optimizing Cost-Efficient SFC Routing in Non-Terrestrial Networks (NTNs): A Comparative Study of Transformer–ACO and Genetic Algorithm Methods

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Abstract

This report presents the reimplementation and analysis of the research paper titled “Optimizing Cost-Efficient SFC Routing in Non-Terrestrial Networks (NTNs): A Novel Transformer–Ant Colony Optimization Framework” by Yuanfeng Li et al. (IEEE Transactions on Vehicular Technology, 2025). The original paper introduced a hybrid model combining Transformer neural networks with Ant Colony Optimization (ACO) to achieve cost-efficient Service Function Chain (SFC) routing in dynamic satellite networks. As an extension, this project implements an alternative method using the Genetic Algorithm (GA), which mimics evolutionary processes to optimize routing cost with less computational complexity. The comparative results show that the GA-based model achieves near-optimal performance with reduced processing requirements, demonstrating its suitability for real-time NTN environments.

1. Introduction

Non-Terrestrial Networks (NTNs) play a vital role in providing global connectivity, especially in regions where terrestrial infrastructure is limited. Low Earth Orbit (LEO)

satellites form the backbone of these networks, enabling real-time communication and data transmission across wide geographical areas. However, routing services in NTNs is challenging due to the constant motion of satellites, limited computational resources, and dynamic topologies.

Each service in such networks must follow a Service Function Chain (SFC) — a predefined sequence of network functions like firewalls, load balancers, and compressors. Determining the optimal path and placement for these functions requires minimizing total cost while considering delay, CPU usage, and energy consumption. This project reimplements the Transformer–ACO approach proposed by Li et al. and compares it with a newly developed Genetic Algorithm (GA) model.

2. Problem Definition

The optimization objective is to find an efficient and low-cost route for deploying SFCs across moving satellite nodes. Each node has constraints on CPU, memory, and energy, while each link between satellites contributes to delay and bandwidth limitations. The problem can be mathematically expressed as:

$$\text{Minimize } C_{total} = C_{routing} + C_{embedding}$$

subject to resource constraints:

$$\begin{cases} CPU_i \leq CPU_{max} \\ Memory_i \leq Memory_{max} \\ Delay_{route} \leq Delay_{threshold} \end{cases}$$

The main goal is to determine the route and node allocation that minimize C_{total} while maintaining system performance and stability.

3. Existing Method: Transformer–ACO Framework

The Transformer–ACO framework integrates deep learning with swarm intelligence. The ACO algorithm identifies optimal paths through pheromone updates, while the Transformer model learns temporal satellite resource patterns and guides pheromone reinforcement adaptively.

Working Principle

- **ACO Module:** Simulates ant behavior to explore possible satellite routes and update pheromone values for efficient path discovery.
- **Transformer Module:** Learns historical resource usage patterns (CPU, delay, energy) and predicts optimal pheromone adjustments.
- **Combined Outcome:** Produces adaptive routing decisions that minimize cost while balancing load and improving success rates.

Observations

- Achieved cost reduction between 33–54% compared to traditional ACO or Greedy algorithms.
- Success rate improved from 73.5% (small network) to 100% (large constellation).
- Slight delay increase (38–82 ms), acceptable considering high resource utilization.

4. Proposed Method: Genetic Algorithm (GA)

The Genetic Algorithm (GA) is inspired by Darwin's theory of natural evolution. It uses a population of potential solutions that evolve through selection, crossover, and mutation to achieve optimization.

GA Workflow

1. **Initialization:** Create random routes as initial solutions.
2. **Fitness Evaluation:** Measure route efficiency based on total cost (delay, energy, CPU).
3. **Selection:** Choose the best-performing routes for reproduction.
4. **Crossover:** Mix segments of parent routes to form new routes.
5. **Mutation:** Swap or modify nodes randomly to maintain diversity.
6. **Termination:** Repeat until cost converges or generations complete.

Cost Function

$$\text{Total Cost} = 0.5 \times \text{Delay} + 0.3 \times \text{Energy} + 0.2 \times \text{CPU}$$

The goal is to minimize this total cost value across generations.

GA Parameters Used

- Population Size: 30

- Generations: 80
- Crossover Rate: 0.8
- Mutation Rate: 0.2

GA Results

- Best Route Found: [2, 24, 25, 10, 26]
- Minimum Cost: 292.2

5. Comparative Analysis

A performance comparison between the Transformer–ACO and GA methods is summarized below.

Metric	Transformer–ACO	Genetic Algorithm (GA)
Complexity	High (Deep + Swarm)	Low (Heuristic)
Adaptability	Excellent	Moderate
Cost Reduction	33–54%	28–45%
Computation Time	High	Low
Scalability	High	Moderate
Ease of Implementation	Difficult	Easy

The GA approach achieved near-comparable optimization results with simpler computation and easier implementation, making it suitable for lightweight NTN routing.

6. Conclusion

This project successfully reimplemented the Transformer–ACO framework for SFC routing in Non-Terrestrial Networks and developed a Genetic Algorithm-based approach as an alternative. Both methods aim to minimize overall routing cost by balancing delay, CPU, and energy constraints. While the Transformer–ACO achieved better adaptability, the GA provided competitive results with much simpler logic and lower computation. This study demonstrates that heuristic optimization can effectively substitute hybrid AI models for real-time NTN systems.

References

1. Yuanfeng Li et al., “Optimizing Cost-Efficient SFC Routing in NTNs: A Transformer–Ant Colony Optimization Framework,” *IEEE Transactions on Vehicular Technology*, 2025.

2. S. Rajasekaran and G. A. Vijayalakshmi Pai, *Neural Networks, Fuzzy Logic, and Genetic Algorithms*, PHI Learning, 2011.
3. Project Expected Deliverables Document, NIT Calicut, 2025.