Enhancing Traffic Flow through Advanced ACO Mechanism

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***Abstract*—Severe traffic congestion is a significant challenge for urban areas, and improving sustainable urban development is critical, yet traditional traffic management systems often struggle to cope with dynamic real-time conditions due to their reliance on predetermined schedules and fixed control mechanisms. This paper advocates for the application of optimizing techniques, specifically an enhanced version of ant colony optimization (ACO), to alleviate this challenge. By effectively managing and enhancing vehicle movement, these approaches target the reduction of congestion, travel times, and costs while concurrently enhancing fuel efficiency. This approach can also be adapted to optimize the deployment and movement of drones in wireless communication networks, ensuring optimal coverage and resource utilization. Implementations, comparisons, and visualizations show how these approaches help improve traffic movement, thereby minimizing congestion-associated problems.**

***Index Terms*—Congestion factor, Enhanced Ant Colony Optimization, Inverted pheromones, Pheromone, Traffic Flow Optimization, Drone-assisted wireless communication.**

I. INTRODUCTION

The rapid development of vehicles and urbanization has led to a critical issue of traffic congestion [1]. Besides causing frustration, traffic congestion also leads to a loss in the economy, a rise in air pollution, and safety issues [2][3]. Just as traffic conditions in urban areas are dynamic and constantly changing, so are the communication requirements in wireless networks. This has paved the way for developing traffic flow optimization (TFO) strategies and algorithms. Traffic flow optimization involves finding better and smarter solutions to manage traffic, reduce delays, and enhance the overall efficiency of traffic flow. Unlike traditional approaches, it aims for real-time information analysis, dynamic decision-making, and optimization techniques, which depend on static traffic management systems [4][5]. This paper focuses on improving the Ant colony optimization (ACO) algorithm, proposing an enhanced approach to ACO. The techniques involved (1) the principles of artificial intelligence, (2) mimicking natural behaviors, and (3) an experience-based learning approach to optimize traffic flow. Which has a huge impact and works smoothly on the Unmanned Aerial Vehicles (UAV) [6] similar to the vehicular networks.

ACO optimizes route selection through repeated exploration and updating of pheromone levels, which is inspired by the foraging habits of ants. In the enhanced version of ACO, congestion feedback and inverted pheromones are used to discourage travel on crowded routes. The TFO traffic congestion is done by simulating congestion scenarios and visualizing optimum routes[7][8][9]. The strategies' advantages, disadvantages, and appropriateness for diverse traffic optimization problems are stated by a comparative examination of various traffic congestion optimization strategies in the literature[10][11][12][13]. These strategies require innovative approaches by simulating congestion scenarios and mapping out efficient routes to address the complex challenges of urban traffic management[14]. The aim is to provide a comprehensive understanding of how these techniques are transforming urban transportation and offering innovative solutions to the growing challenges of traffic congestion.

The organization of the paper is as follows: The related works are presented in Section II as a literature review. Section III discusses the detailed description of ACO and our proposed enhanced ACO model, including the stepwise algorithm and necessary system requirements used to implement this proposed model, which is illustrated in Section IV. Section V discusses the experimental results of the traditional ACO and the proposed enhanced ACO algorithm, followed by the performance analysis in Section VI. Finally, the paper's conclusion, along with future work, is depicted in Section VII.

II. RELATED WORK

Traffic flow optimization (TFO) has been the subject of immense research, with various algorithms proposed to address congestion issues. This literature review examines prominent algorithms, including Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Reinforcement learning (RL), and Ant Colony Optimization (ACO), highlighting their efficiency. Subsequently, the discussion focuses on the superiority of ACO and the advancements offered by enhanced ACO over the traditional ACO approach.

Genetic algorithms have been widely employed in traffic optimization because they can explore vast search spaces. Studies [1] and [2] showcased GA's effectiveness in optimizing traffic signal timings, but the limitations are observed in complex traffic scenarios regarding the solution quality [3]. Similarly, research on particle swarm optimization (PSO) demonstrated PSO's success in dynamic route planning and congestion control [4][7]. However, PSO's performance heavily relies on parameter tuning and might face scalability issues in larger traffic networks [8]. Reinforcement Learning techniques adaptively learn the traffic patterns, but challenges persist regarding training time and real-time implementation.

Although these optimization techniques present valuable contributions to traffic flow optimization, the literature review emphasizes the emergence of Ant Colony Optimization (ACO) as a powerful approach in traffic flow management. ACO stands out for its ability to model real-time traffic scenarios, dynamically update pheromone trails, and consider congestion feedback, thus effectively controlling traffic congestion compared to other optimization techniques [15].

Furthermore, Enhanced ACO extends traditional ACO by incorporating congestion feedback mechanisms and inverted pheromones to discourage travel along congested routes. This enhancement significantly reduces congestion compared to the traditional ACO approach, making Enhanced ACO a preferred choice for traffic flow optimization in urban areas.

III. Proposed Scheme

In this paper, a method called Ant Colony Optimization (ACO), which mimics the foraging behavior of ants to find optimal paths or solutions by depositing pheromones, is analyzed. An improved version of ACO, Enhanced Ant Colony Optimization, which enhances traditional ACO algorithms by incorporating additional strategies and mechanisms for improved performance, is proposed and compared.

A. System Model for Enhanced ACO

There are three main mechanisms incorporated in the Enhanced ACO system model for traffic flow optimization:

1) **Dynamic Congestion Feedback Integration:** Enhanced ACO introduces dynamic congestion feedback mechanisms within the system model to asses real-time congestion levels on traffic routes.
2) **Inverted Pheromone Implementation:** The model integrates inverted pheromones to denote congestion for less favorable routes.
3) **Adaptive Route Optimization:** Enhanced ACO focuses on dynamic route optimization strategies by combining congestion feedback and inverted pheromones to optimize traffic routes in real time.

B. Design Goal for Enhanced ACO

The primary objective set for enhanced ACO in TFO includes significant congestion reduction through the implementation of congestion feedback and inverted pheromones. The design goal emphasizes the system's real-time adaptability by dynamically responding to traffic conditions. Enhancing traffic flow efficiency is a critical goal. The objective is to optimize overall traffic flow, minimize delays, and improve the system's operational efficiency.

C. Ant Colony Optimization (ACO)

Traffic flow optimization using Ant Colony Optimization (ACO) is a technique inspired by the foraging behavior of ants to solve complex optimization problems related to traffic management. ACO is a meta-heuristic algorithm that can be used to find optimal paths. The main inspiration for ACO comes from stigmergy, which is the interaction and coordination of natural organisms by modifying the environment. It is a complex and decentralized form of communication. This is an optimizing task as ants choose the maximum amount of food source by choosing the shortest path from nest to food source, consuming the minimum amount of energy.

Ants produce a chemical called 'Pheromone' for communication to find the shortest path from their nest to the food source. Ants are more likely to choose the path with higher pheromones, and this decision-making is based on probabilities. If the distance is the same to the destination, then the ant chooses a single path and not different paths, though the paths are of the same distance, which leads to higher deposits of pheromone in one path. This path is established even if evaporation occurs. Ants are found to deposit a high amount of pheromone if the quantity of food source is large and also based on the quality of the path. Ants choose paths based on probabilities. Cost and pheromone have an impact on the probability of choosing a path.

D. ACO Process in TFO

In the context of traffic flow optimization, the road network is typically represented as a graph, where nodes are intersections and edges are road segments connecting them. Each edge has associated information such as distance, congestion level, travel time, etc. ACO simulates the pheromone deposition and path selection behavior of ants. The amount of pheromones deposited corresponds to the quality of the route; shorter paths receive more pheromones. Over time, paths with higher pheromone levels become more attractive, influencing the route selection of subsequent ants. In traffic optimization, this could relate to the speed of travel or the absence of congestion. This pheromone deposition and path selection collectively guide the ants toward efficient routes. Artificial ants are released onto the road network from different starting points. They move through the network, choosing edges based on a combination of pheromone levels and other factors like distance and traffic conditions. Edges with higher pheromone levels are more likely to be chosen, simulating the tendency of ants to follow paths with stronger pheromone traces.

Pheromone levels on all edges gradually evaporate over time to avoid convergence to a suboptimal solution. This mimics the natural process of pheromone dissipation. Edges that are not being used will have their pheromone levels reduced. As ants move through the network, they accumulate their chosen path's total cost (travel time, congestion, etc.). After a certain number of ants have completed their journeys, the pheromone levels on the edges are updated based on the quality of the solutions found. Better solutions lead to stronger pheromone reinforcement on the corresponding edges. The process of ant movement, pheromone update, and evaporation occur in multiple iterations. Over time, the algorithm converges towards a solution representing a good trade-off between path length and traffic conditions.

Algorithm 1 Ant Colony Optimization

- Define the road network as a graph: $G(V, E)$, where V is nodes (intersections), and E is edges (roads).
- Minimize $f(x)$ such as travel time or congestion.
- Set initial pheromone levels: τ_{ij}^{0}.
- Define heuristics information: η^{ij} based on road attributes.
- Ant k at node i chooses the next node based on probabilities for Ant Movement:

$$p_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{l \in \mathbb{N}} (\tau_{il})^{\alpha} \cdot (\eta_{il})^{\beta}}$$

  Ant k constructs a solution iteratively by selecting nodes j using p_{ij}^{k}.
- Continue until the stopping criterion is met.
- Evaporate pheromone for pheromone update:

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij}$$

- Deposit pheromone based on ant solutions:

$$\Delta\tau_{ij}^{k} = \frac{1}{f_k}, \text{ where } f_k \text{ is ant } k\text{'s solution quality.}$$

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k} \Delta\tau_{ij}^{k}$$

- Repeat solution construction and pheromone update for a fixed number of iterations
- Evaluate solutions using optimising objective $f(x)$ and select the best solution by ants.
- Return the best solution as an optimized traffic flow solution.

The reason to choose ACO for TFO is that ACO aligns well with the dynamic nature of TFO. It operates in a distributed manner, meaning that individual agents (ants) make decisions based on local information, which can lead to a more scalable approach when dealing with large and complex road networks. ACO also adapts to changing traffic conditions by updating the pheromone levels based on real-time data, which can be crucial to handling dynamic traffic scenarios. Also, ACO naturally balances the exploration of new routes (less explored paths) and exploring known routes (paths with higher pheromone levels).

ACO offers applications such as Route Optimization, minimizing congestion by finding optimal routes with higher pheromone levels, and Traffic Signal Timing, reducing waiting times by optimizing signal timings at intersections.

E. Enhanced Ant Colony Optimization

The enhanced version of ACO introduces improvements over the previous ACO to simulate and optimize real-time traffic situations even better by adding an inverted pheromone and the congestion factor. In the original ACO algorithm, pheromone levels on edges are increased when the ants detect shorter paths, whereas, in this version, inverted pheromone levels are introduced to decrease when ants experience congestion. The congestion factor represents the current traffic

Algorithm 2 Enhanced Ant Colony Optimization

- Initialise optimization G, nodes, and edges.
- Initialise pheromone matrix (P) and inverted pheromone matrix (Q) with ones and zeros respectively.
- Initialise heuristic matrix (H) based on road distances.
- Set ACO parameters: *num_ant*, α, β, ρ, *num_iterations*.
- For each iteration, for each ant movement: choose a random start node i_k.
- Set initial v_k(current_speed).
- While ant path not complete: Calculate congestion_factor c_k, Calculate edge selection probabilities p_{ki} for feasible neighboring nodes :

$$p_{ki} = \frac{(P_{ikj} - Q_{ikj})^{\alpha} \cdot H_{ikj}^{\beta} \cdot c_k}{\sum_{j \in \text{feasible nodes}} (P_{ikj} - Q_{ikj})^{\alpha} \cdot H_{ikj}^{\beta} \cdot c_k}$$

- Choose next node j_k probabilistically based on p_{ki}.
- Update current_speed v_k based on speed_limit of current edge and previous node.
- Update i_k to j_k.
- If ant path complete: Update pheromone matrix P and inverted pheromone matrix Q based on distance and negative congestion_factor.
- Update pheromone matrix P using evaporation rate ρ:

$$P_{ij} = (1 - \rho) \cdot P_{ij}$$

- Initialise best_path with start node (0) and v_{best}
- While the best_path is not complete
- Choose the next node v_{best} based on P without considering congestion.
- Update v_{best} based on the speed_limit of the current edge and previous node.
- Update current_node to j_{best}

congestion. By reducing pheromone levels on congested roads, the algorithm adapts to dynamic traffic conditions.

F. Enhanced ACO Process in TFO

In the context of TFO, congestion can occur when many vehicles are directed towards the same route, leading to slower vehicle movement and longer travel time. The traditional ACO approach may reinforce this congestion by directing more ants (vehicles) towards already popular routes with high pheromone levels. Inverted pheromones reduce the attractiveness of certain routes, helping to spread traffic across the road network and reduce congestion.

This version includes a ‘simulate_congestion’ function, which generates a congestion factor to simulate the impact of real-time traffic on the road. This factor influences the probabilities of ant movement, making it less likely for the ants to choose congested paths; this shows the dynamic nature of traffic, where congestion affects route choices. The ‘ant_move’ function now considers both static road conditions (pheromones and speed limits) and dynamic traffic conditions (congestion factor) when ants choose their next nodes, which allows ants to adapt to the changing traffic scenarios and select less congested paths.

In this improved version, pheromone updates are based on time and distance. Pheromone levels are increased in inverse proportion to the distance traveled on the road and the time taken to travel. This dual updating strategy ensures that the algorithm prefers the shortest distance and the shortest time when optimizing the traffic flow.

Then, the inverted pheromones are updated iteratively while ensuring they remain non-negative. This mechanism prevents inverted pheromones from becoming excessively negative and allows them to adapt to changing traffic conditions over multiple iterations. After optimization, the best path is calculated by considering both the shortest distance and the shortest time by the algorithm. These improvements make the enhanced ACO more suitable for optimizing traffic flow in real-time road networks. It considers the physical attributes of the roads and the dynamic nature of traffic congestion. This adaptation to changing traffic conditions and selecting routes that minimize both distance and time, the enhanced version of ACO, leads to more efficient traffic flow and reduced travel times, ultimately improving the overall quality of transportation in the network. Similarly, in wireless communication networks, drones can be utilized to establish efficient communication routes, especially in areas with poor infrastructure.

The equation stated in the algorithm calculates the probability p_{ki} for ant k to select edge i_kj based on the combination of pheromone levels (P and inverted Q), heuristic information (H), and congestion factor (k). The probabilities are then normalized to ensure they sum up to 1, and the next node j_k is chosen probabilistically based on these probabilities.

This equation-based approach allows ants to consider both positive and negative influences when selecting edges, promoting the avoidance of congested paths while still taking advantage of the attractiveness of less congested paths. It involves ant movement, pheromone updates, congestion avoidance with inverted pheromones, evaporation, and best path selection. The algorithm helps ants find optimized routes while avoiding congestion-prone roads.

IV. SIMULATION SETTINGS

The simulation parameters for assessing Ant Colony Optimization (ACO) and Enhanced ACO in traffic flow optimization were set up in the Python environment using libraries like Matplotlib to visualize simulation results, NetworkX to perform graph-based operations, and NumPy to perform effective array computations. By combining SUMO (Simulation of Urban Mobility) with NetworkX, traffic scenarios, and road networks can be simulated to produce a wide range of traffic circumstances, fluctuating degrees of congestion, and intricate road architecture. Pheromone update rates, ant population size, convergence criteria, and heuristic data for route selection were among the specific ACO parameters that were set up. Traffic congestion levels were measured using metrics including average queue length, vehicle density, and average delay time; route efficiency was evaluated using journey time, distance traveled, and route utilization. The simulations were conducted on a MacBook Air (M1, 2020) running macOS Monterey (Version 12.0.1) equipped with an Apple M1 chip and 8 GB of memory.

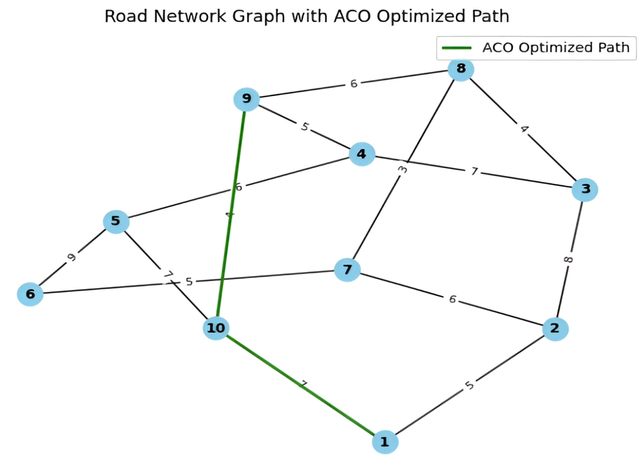

Fig. 1. ACO optimized path.

V. EXPERIMENTAL RESULTS

Ant Colony Optimization (ACO) provides good solutions for various combinatorial problems and mainly relies on pheromone updating and heuristics. Enhanced ACO offers improved solutions compared to basic ACO and incorporates additional heuristics and strategies.

A. Road Network graph with an optimized path using ACO

In Ant Colony Optimization (ACO), the parameters alpha (α) and beta (β) are used to control the influence of pheromone levels and heuristic information, respectively, on the ants' decision-making process when selecting the next node to move to. These parameters are crucial in balancing exploration and exploitation within the optimization process. Alpha (α) indicates pheromone information and higher α indicates more weight to pheromone levels, meaning it is likely to select paths with stronger trails based on successful paths in the past. Beta (β) controls the importance of heuristics (problem-specific, like distance). Higher β favors shorter paths if the heuristic is distance, aiding in escaping local optima. Experimenting with different values of α and β for traffic flow optimization is essential for real-world implementation.

The road network graph in Fig. 1. shows an optimized path using ACO from node 1 to node 9. Ant Colony Optimization (ACO) is a powerful meta-heuristic algorithm, but like any method, it has limitations. ACO can struggle with high-dimensional and complex search spaces, which are common in traffic flow optimization problems with numerous intersections, roads, and dynamic conditions. During optimization, it assumes constant road attributes (e.g., speed limits, distances),

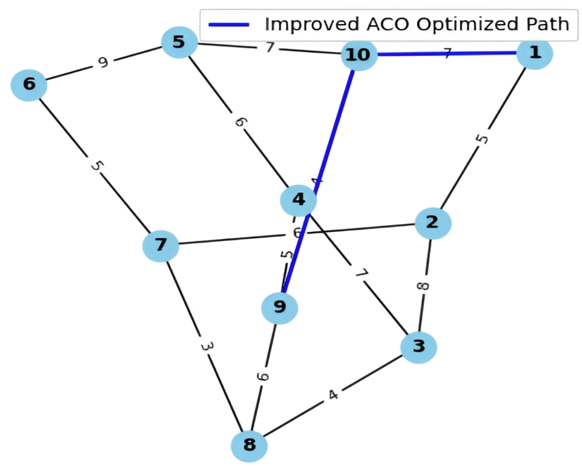

Fig. 2. Enhanced ACO optimized path.

which might not reflect real-world dynamics such as changing traffic patterns or road closures. ACO's performance is sensitive to parameter settings (e.g., α, β, evaporation rate) that can significantly impact solutions' convergence rate and quality. Parameter tuning can be time-consuming. ACO might face scalability issues when dealing with large road networks due to the combinatorial explosion of possible paths.

Also, real-world traffic systems involve intricate factors such as traffic signals, turning lanes, one-way streets, and pedestrian crossings, which can challenge ACO's ability to model and optimize effectively.

B. Road Network graph with an optimized path using Enhanced ACO

Though the enhanced version of ACO has greater optimization capabilities, restrictions still need to be considered when using it in actual traffic situations. The parameters greatly influence the algorithm's performance, including alpha, beta, evaporation rate, and the number of ants demonstrating sensitivity. It can be challenging to determine the best values for various traffic networks. As this algorithm is currently based on static road information, it might not precisely reflect the state of the road network at any given moment. The road network graph in Fig. 2. shows an optimized path using enhanced ACO from node 1 to node 9.

The algorithm's scalability is also constrained. The amount of processing time and resources needed for optimization rises considerably with the size and complexity of the traffic network. Lastly, while introducing inverted pheromones is a novel concept to address congestion, it may not fully capture the intricacies of traffic dynamics. Real-world traffic congestion depends on various factors, including traffic signal timing, lane closures, and driver behavior, which are not considered in the simplified congestion model used in this algorithm.

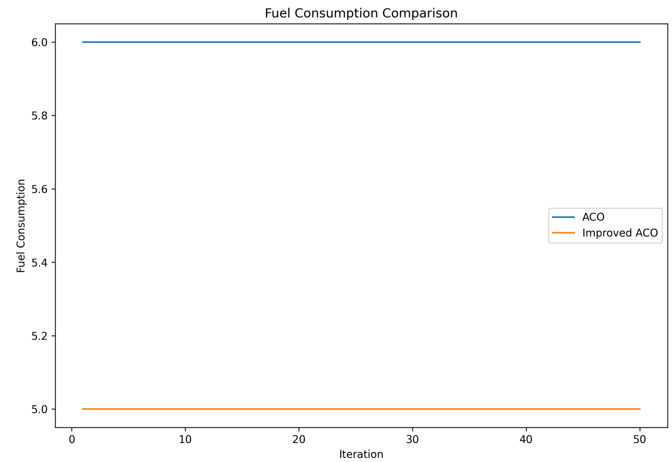

Fig. 3. Fuel Consumption Comparison of ACO and Enhanced ACO.

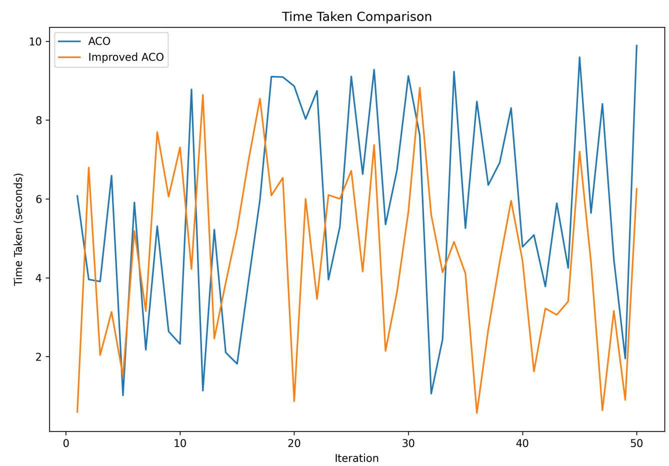

Fig. 4. Time Consumption Comparison of ACO and Enhanced ACO

VI. Performance Analysis

The key improvements in enhanced ACO include the use of an inverted pheromone matrix (Q) to avoid congested routes, the introduction of the concept of congestion factor, which affects the ant's choice of edges, considering real-time traffic conditions, the calculation of edge selection probabilities considering both pheromone levels and congestion factors and the updating of current speed based on speed limits to ensure that selected paths by the ants adhere to legal speed limits. The output emphasizes the strengths of improved ACO in reducing fuel consumption while maintaining comparable performance in other aspects of route optimization. The line graph in Fig. 3. illustrates the consistent reduction in fuel consumption achieved by improved ACO compared to ACO. Here, the fuel consumption is measured in liters per kilometer. This suggests that improved ACO is highly effective in optimizing routes for fuel efficiency.

The time taken comparison graph in Fig. 4. shows that the improved ACO has better performance in terms of route

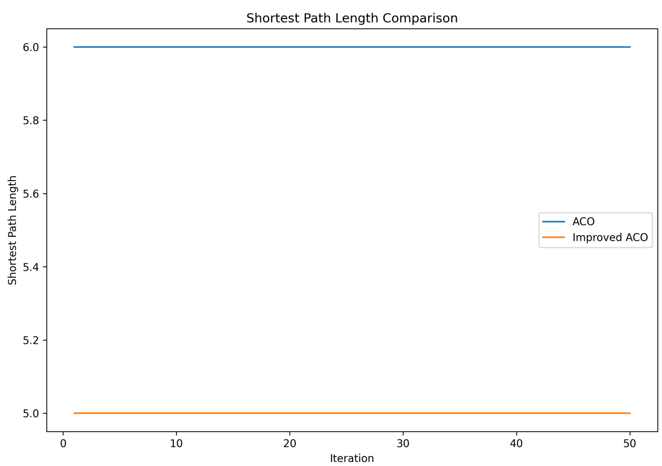

Fig. 5. Shortest path length comparison of ACO and Enhanced ACO

optimization time, where the average time taken by ACO is 4.04625450356326 seconds and the Improved ACO average time taken is 1.143631899245381 seconds for 50 iterations. This indicates that the enhancements in Improved ACO impact computational time.

The graph in Fig. 5. compares the lengths of the shortest paths found by both algorithms and demonstrates that improved ACO gives shorter path lengths comparatively. Improved ACO is effective in finding optimal or near-optimal routes. The shortest path length is measured in kilometers, representing the distance traveled along the path in the simulated road network.

Practically, it is replaced by simulated congestion with real traffic data and more complex scenarios. The code used to generate the above graphs assumes a basic road network and simulated congestion levels for illustration purposes.

VII. CONCLUSION AND FUTURE WORKS

Enhanced ACO represents a significant advancement over the basic ACO algorithm, offering faster convergence to optimal or near-optimal solutions, particularly beneficial for large-scale problems and resource-constrained scenarios. The application's specific objectives should guide the choice between ACO and enhanced ACO, with the latter being recommended for scenarios prioritizing fuel efficiency and shorter path lengths.

One avenue for future research involves exploring reinforcement learning (RL) techniques by integrating sophisticated algorithms like Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Actor-Critic methods. By integrating such techniques, the hybrid ACO-RL approach can be expected to demonstrate improved convergence rates and optimized route recommendations.

Furthermore, incorporating real-time traffic data and predictive analytics by integrating data from GPS devices and traffic cameras could provide up-to-date information on traffic congestion and road conditions. Integrating this data to dynamically update pheromone levels or adjust RL agent decisions could enhance the accuracy of route recommendations. Similarly, in drone-assisted wireless communications, drones can collaborate to optimize network performance.

In conclusion, the ACO-RL hybrid approach presents a promising framework for traffic flow optimization, offering adaptability and effectiveness in real-world scenarios. While the improved ACO version presents valuable enhancements for traffic flow optimization, addressing its limitations, such as parameter sensitivity and reliance on static data, and incorporating real-time data sources can further enhance its applicability to complex traffic scenarios

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