Communication Paths for LASER Uplink by utilizing ANT Colony Optimization Strategy

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Abstract- 164
This paper proposes a novel approach to optimize laser uplink communication paths within a network using the Ant Colony Optimization (ACO) algorithm. In laser uplink communication systems, establishing efficient paths from nodes to base nodes is crucial for minimizing signal loss and ensuring reliable data transmission. Inspired by the foraging behavior of ants, the ACO algorithm is employed to find the shortest and most optimal paths in the network topology. Ant-like agents traverse the network graph, depositing pheromone trails on paths based on their quality, and gradually converge towards the optimal solution. The proposed approach aims to enhance network performance, minimize signal degradation, and improve overall communication reliability in scenarios where line-of-sight communication is critical.
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I. INTRODUCTION

Efficient communication is vital in modern networked systems, particularly in scenarios where line-of-sight transmission, such as laser uplink communication, is essential. Laser uplink communication systems rely on establishing optimal paths from nodes to base nodes to ensure reliable data transmission with minimal signal degradation. However, determining these paths presents a complex optimization problem, especially in large-scale networks with dynamic environmental conditions.

This paper proposes a novel approach to address this challenge by leveraging the ACO algorithm, inspired by the foraging behavior of ants. The ACO algorithm offers a distributed, swarm-based optimization technique that has shown promising results in solving combinatorial optimization problems. By applying the ACO algorithm to laser uplink communication networks, we aim to find the shortest and most efficient paths for data transmission, thus enhancing network performance and reliability.

Through a combination of network graph representation, ant-like agent traversal, pheromone-based path selection, and global pheromone update mechanisms, the proposed approach seeks to optimize communication paths while adapting to dynamic network conditions. This introduction sets the stage for exploring the implementation details, experimental results and potential applications of the proposed framework in optimizing laser uplink communication paths for modern networked systems.

PROBLEM STATEMENT

In laser uplink communication systems, establishing efficient communication paths from nodes to base nodes is critical for ensuring reliable data transmission with minimal signal degradation. However, traditional path finding methods may struggle to find optimal solutions in complex network topologies or dynamic environmental conditions. The primary challenge addressed in this paper is to develop a robust optimization framework that can efficiently determine the shortest and most efficient paths for laser uplink communication within networked systems. This framework should consider factors such as network topology, signal quality, and dynamic environmental conditions while optimizing communication paths.

Furthermore, the optimization framework must be capable of adapting to changes in network configurations or environmental factors in real-time, ensuring continuous optimization and reliable communication performance. Overall, the goal is to design and implement a solution that leverages the ACO algorithm to address the complexities of path finding in laser uplink communication systems, ultimately enhancing network efficiency, reliability, and performance.

OBJECTIVES

1. Develop a robust optimization framework using the ACO algorithm to find the shortest and most efficient paths for laser uplink communication within networked systems.
2. Design the optimization framework to adapt to dynamic changes in network topologies, environmental conditions, and signal quality, ensuring continuous optimization and reliable communication performance.
3. Integrate the optimization framework seamlessly with existing network infrastructure, allowing for easy deployment and compatibility with various network configurations and protocols.
4. Implement algorithms and mechanisms that enable real-time path finding, allowing for swift adaptation to changing network conditions and minimizing communication latency.
5. Ensure that the optimization framework is scalable to handle large-scale network deployments while maintaining efficiency in path finding and resource utilization. 165

II. BACKGROUND AND MOTIVATION

A thorough analysis of machine learning approaches for Quality of Service (QoS) management in wireless networks is provided by ZHUNUSSOV A. et al. [1], who highlight the critical role that supervised and unsupervised learning techniques play in improving network performance and resource allocation. In order to anticipate QoS parameters in cloud computing environments, the study [2] explores the use of random forest algorithms. This study demonstrates the effectiveness of ensemble-based approaches in forecasting workload performance and resource availability. In the meantime, researchers in [3] investigate reinforcement learning approaches for adaptive QoS management in the context of Software-Defined Networks (SDNs), allowing for dynamic resource optimization and self-governing decision-making.

Wang, Z. & Mao, S. [4] introduce a deep learning-based methodology for traffic classification in mobile networks, facilitating

QoS differentiation and traffic prioritization based on application types and user preferences. Similarly, Zhiguo Qu et al. [5] delve into predictive analytics techniques for QoS optimization in IoT environments, leveraging historical data and machine learning algorithms to anticipate network congestion, device failures, and service disruptions. Furthermore, authors in [6] propose a QoS-aware resource allocation framework for wireless sensor networks utilizing genetic algorithms to optimize energy consumption, network coverage, and data reliability while adhering to QoS constraints.

The exploration of ensemble learning techniques for dynamic QoS management in edge computing environments is showcased in [7], demonstrating the effectiveness of combining multiple models to adaptively allocate resources and prioritize tasks. Additionally, Satheesh et al. [8] delve into machine learning-based anomaly detection methods for QoS monitoring in network security, aiming to identify abnormal behavior and potential threats to network performance and integrity.

In parallel, research [9] investigates Support Vector Machine (SVM) algorithms for QoS optimization in multimedia streaming applications, enhancing video quality, reducing latency, and enhancing user satisfaction. Nadine Hasan [10] introduces a fuzzy logic-based approach for QoS management in the Internet of Vehicles (IoV), enabling adaptive decision-making and resource allocation to ensure reliable communication and seamless connectivity.

Moreover, the integration of machine learning techniques into routing protocols for QoS-aware routing in Mobile Ad hoc Networks (MANETs) is explored by the authors in [11]. They optimize path selection based on real-time network conditions and performance metrics. Meanwhile, researchers in [12] focus on deep reinforcement learning approaches for QoS-aware task scheduling in fog computing environments, dynamically allocating computing resources and minimizing task completion time while adhering to QoS requirements.

Lynch D. [13] examines the application of evolutionary algorithms for QoS optimization in 5G networks, addressing challenges such as network slicing, resource allocation, and service orchestration to enhance end-to-end QoS guarantees. System [14] proposes a Bayesian network-based approach for QoS-aware network management, modeling dependencies between network elements and predicting QoS metrics to facilitate proactive fault detection and resource optimization. Lastly, Kumar & Naveen [15] investigate machine learning-based traffic engineering techniques for QoS improvement in data center networks, optimizing network routing, load balancing, and congestion control to enhance application performance and user experience.

The study [36] addresses the critical issue of power consumption in ad hoc and fixed networks by proposing QoS Multipath routing protocols for heterogeneous networks. It discusses various ad hoc routing protocols, including AODV and its extension AOMDV, aiming to minimize congestion and improve network lifetime. NS2 simulations demonstrate the performance analysis of AODV and AOMDV in hybrid environments, focusing on metrics such as power consumption, delay, bandwidth, routing overhead, and packet delivery ratio under varying traffic loads.

introduces a novel QoS routing algorithm for mobile ad hoc networks to address the challenge of load balancing and congestion avoidance. It classifies traffic into real-time and normal categories and routes high-priority traffic through lightly loaded links. The algorithm dynamically calculates cost metrics based on link loads, ensuring efficient routing paths for different traffic classes, thereby improving network performance.

The authors at [38] introduces EQR-RL, an energy-aware QoS routing protocol for Wireless Sensor Networks (WSNs) using reinforcement learning. It addresses the issue of premature energy depletion in nodes with the best QoS by balancing energy consumption. Comparisons with QoS-AODV and RL-QRP highlight EQR-RL's superior performance in packet delivery ratio and average end-to-end delay under varying traffic loads and node mobility in simulations.

A QoS-based routing protocol for wireless sensor networks has been introduced[39], accommodating both periodic and event-driven data. It employs geographic routing coupled with QoS support and prioritizes packets through multiple transmission queues. Next-hop selection factors in proximity to the sink, residual energy, link quality and load. Congestion control is implemented via a ring or barrier mechanism, showcased through simulations against existing approaches.

[40] introduces AODV with QoS, a routing protocol for mobile ad hoc networks, which estimates available resources based on shared channel busy ratio considering constraints like interference. Simulations using NS2 show its effectiveness in providing QoS support with low overhead, addressing challenges in resource estimation for multimedia applications.

These collective works underscore the versatility of machine learning algorithms in addressing QoS challenges across a spectrum of networking domains encompassing cloud computing, IoT, edge computing, wireless sensor networks, and data centers. Through the application of machine learning, researchers can engineer adaptive and intelligent QoS management solutions adept at optimizing network performance, resource allocation, and user satisfaction within dynamic and heterogeneous networking environments. Integrating machine learning into QoS management offers responsiveness, efficiency and proactive resource allocation, effectively addressing the complexities inherent in modern networks.

III. SYSTEM ARCHITECTURE

A major change in network management is brought about by prioritized quality of service (QoS), which dynamically allocates resources according to the significance of the traffic and particular QoS needs. Particularly in diverse situations, traditional consistent techniques frequently result in inefficiencies. By classifying traffic and allocating resources optimally for vital applications such as real-time video conferencing and financial transactions, prioritized quality of service improves user experiences. Adaptive decision-making is made possible by integrating machine learning (ML) into network architecture. [26]Devices at the edge evaluate traffic, categorize apps, and set priorities accordingly. Using machine learning, routers dynamically modify QoS parameters to improve efficiency and lessen congestion. In Software-Defined Networking (SDN), centralized controllers anticipate traffic patterns to optimize resource distribution throughout the network. Reliability is ensured via cloud-based systems that leverage machine learning (ML) for anomaly detection, provisioning, and predictive analytics. [24]ML integration makes adaptive networks possible, enabling dynamic response to changing needs. Important QoS factors like throughput, latency, packet loss, and dependability provide services priority and guarantee that modern applications and users receive sufficient performance across traffic classes.

Our suggested solution uses machine learning methods like K-Nearest Neighbours (KNN), random forests, and decision trees to create a Prioritized-Based QoS protocol for systemized networks. By allocating network resources dynamically according to traffic priority, this system improves customer happiness and performance. While random forests and decision trees capture intricate linkages and feature interactions, KNN uses local similarity for prioritization. Our approach assesses prediction accuracy, scalability, and adaptability in various network contexts by means of comprehensive experimentation. Our protocol assures effective resource utilization, reduces congestion, and optimizes QoS parameters in real time by using these techniques. With the help of intelligent and adaptable QoS management solutions made specifically for the dynamic nature of contemporary networking environments, this strategy enables network operators to satisfy changing needs.

Dataset

The QoS localization file produces a dataset that frequently contains important information on the effectiveness and dependability of a system or service across many geographical locations. This dataset often includes parameters such as packet loss, throughput, jitter, latency and other measures from multiple endpoints or nodes spread across different locations. This dataset is directly fed into the machine learning models for further analysis. By looking at this dataset we can find out more about how network performance varies with user location. This will assist us in maximizing service delivery, identifying areas in need of upkeep, and ensuring that customers receive consistently high-quality service. Additionally, this data can be used to assess network performance, identify issues with the network, and direct infrastructure upgrades to enhance overall service quality.

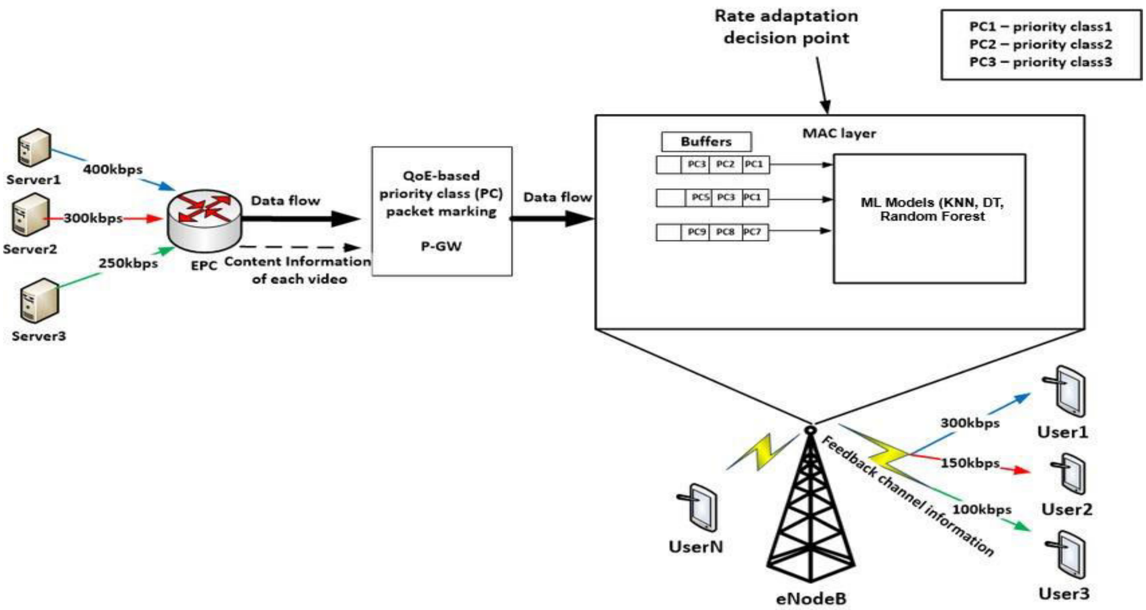

Fig. 1: System Architecture

IV. PRIORITIZATION FRAMEWORK

Machine learning models play a pivotal role in predicting and ensuring optimal resource allocation for high-priority services in network environments. [23] These models leverage historical data, learn patterns, and adapt to changing network conditions to make informed decisions, ultimately enhancing the overall QoS for critical applications.

Traffic Prediction:

Predictive Analytics: Machine learning models analyze historical network data to predict future traffic patterns. This enables the anticipation of peak usage times and the identification of trends in service demand.

Dynamic Bandwidth Allocation:

Dynamic Bandwidth Allocation (DBA) in QoS refers to the process of dynamically distributing available bandwidth among different users or traffic classes based on their QoS requirements and network conditions. [21] Unlike static bandwidth allocation, which assigns fixed bandwidth to users or applications regardless of

variations in demand, DBA adjusts bandwidth allocation in real time to optimize network performance and ensure a satisfactory user experience.

Adaptive Resource Allocation: Machine learning models can dynamically allocate bandwidth based on real-time predictions of service demands. [18]For high-priority services, these models ensure that sufficient bandwidth is allocated to meet their requirements, optimizing overall network performance.

QoS Parameter Optimization:

Latency Prediction: ML models predict potential latency issues by analyzing historical latency data and current network conditions. This proactive approach allows for the optimization of latency-sensitive services.

Jitter Reduction: To reduce jitter for high-priority applications, machine learning models can dynamically modify packet scheduling and routing based on patterns that lead to jitter.

Working of QoS in Propsoed System

Dataset Utilization: To reduce jitter for high-priority applications, machine learning models can dynamically modify packet scheduling and routing based on patterns that lead to jitter. Using the dataset gathered from the localization file is where QoS begins. This dataset includes data on several geographic areas' network performance measures (such latency, throughput, packet loss and jitter). It provides insights into the reliability and efficiency of data transmission paths in different regions.

Detection of Unsafe Channels: The network is always being monitored by QoS algorithms for possible transmission blocking caused by unsafe channels. A number of things, including hardware malfunctions, network congestion, and security concerns, might result in unsafe channels.

Redirection of Data Packets: When QoS detects an unsafe channel that can prevent data transfer, it starts to reroute data packets to other pathways. Redirection ensures that data can continue to flow over the faulty channel and reach its destination.

Shortest Path Selection: Path selection algorithms are used by QoS to choose the best route while rerouting data packets. Deciding which way is the shortest in terms of transmission time is an important consideration for path selection. This entails figuring out the method that minimises transmission delay by taking into account variables like available capacity and network latency.

Path Evaluation and Decision Making: Using performance data from past and present that is kept in the localization file, QoS assesses the paths that are accessible. To make well-informed selections about path selection, it takes into account variables like traffic load, previous dependability, and present network circumstances.

V. MACHINE LEARNING MODELS

The Ant Colony Optimization (ACO) algorithm is a nature-inspired metaheuristic optimization technique that mimics the foraging behavior of ants to solve complex combinatorial optimization problems. Developed based on observations of ant colonies' ability to find the shortest paths between their nest and food sources, ACO has been successfully applied to a wide range of optimization problems, including path finding, routing, scheduling, and resource allocation.

At its core, the ACO algorithm operates by simulating the behavior of artificial ants as they traverse a solution space, depositing and following pheromone trails to guide their search. These pheromone trails represent indirect communication among ants, conveying information about the quality of discovered solutions. The algorithm iteratively improves upon these solutions by leveraging the collective intelligence of the ant colony.

The basic steps of the ACO algorithm can be summarized as follows:

Initialization: The algorithm begins by initializing a population of artificial ants and assigning them random starting positions within the solution space.

Constructive Solution Construction: Each ant constructs a solution by iteratively selecting components from the solution space, guided by both heuristic information and pheromone trails. Heuristic information helps ants make informed decisions based on their knowledge of the problem domain, while pheromone trails bias their choices towards promising solution components.

Pheromone Update: After all ants have constructed solutions, pheromone trails are updated based on the quality of the solutions found. Ants deposit pheromone along the paths they traverse, with the amount of pheromone proportional to the quality of the solution. Evaporation is also applied to pheromone trails to prevent stagnation and encourage exploration of alternative solutions.

Global Pheromone Update: In addition to local pheromone updates, a global pheromone update mechanism is employed to reinforce high-quality solutions discovered by the entire ant colony. This global update ensures that promising paths are reinforced over time, leading to convergence towards optimal solutions.

Termination Criterion: The algorithm iterates through the construction and pheromone update steps until a termination criterion is met, such as a maximum number of iterations or convergence to a satisfactory solution.

Through this iterative process of solution construction and pheromone update, the ACO algorithm efficiently explores the solution space, gradually converging towards high-quality solutions. By leveraging the collective intelligence and decentralized nature of ant colonies, ACO offers a powerful optimization technique for solving complex problems in various domains. Its adaptability, scalability, and ability to handle dynamic environments make it a popular choice for addressing real-world optimization challenges.

VI. RESULTS AND DISCUSSION

```
Enter number of nodes : 6
**************************************************
*****************Nodes List***********************
**************************************************
Node h1 has been created
Node h1 has been started
Node h2 has been created
Node h2 has been started
Node h3 has been created
Node h3 has been started
Node h4 has been created
Node h4 has been started
Node h5 has been created
Node h5 has been started
Node h6 has been created
Node h6 has been started
**************************************************
****************Anchor Nodes List******************
**************************************************
Anchor A1 has been created
Anchor A2 has been created
Anchor A3 has been created
Anchor A4 has been created
**************************************************
****************Anchor Mapping******************
**************************************************
(h1,A3)
(h2,A2)
(h3,A4)
(h4,A1)
(h5,A1)
(h6,A1)
```

Fig. 2: Nodes and Anchor Nodes Creation

Using the NS3 simulation, we have generated 6 nodes in the above diagram, including 4 anchor nodes that will remain constant during the application process. Following their creation, the anchor nodes and the nodes map to one another and are prepared for data transfer.

```
****************Request Generation****************
**************************************************
29.109.19.187
222.214.35.44
46.217.30.123
114.31.203.63
113.23.68.25
214.73.60.148
92.52.96.157
49.32.30.190
254.218.160.105
232.185.153.238
**************************************************
****************Ipaddress List********************
**************************************************
29.109.19.187
222.214.35.44
46.217.30.123
114.31.203.63
113.23.68.25
214.73.60.148
92.52.96.157
49.32.30.190
254.218.160.105
232.185.153.238
**************************************************
****************Anchor Nodes List*****************
**************************************************
92.52.96.157
49.32.30.190
254.218.160.105
232.185.153.238
**************************************************
**************************************************
114.31.203.63--------------->46.217.30.123
114.31.203.63--------------->222.214.35.44
232.185.153.238--------------->113.23.68.25
254.218.160.105--------------->49.32.30.190
214.73.60.148--------------->49.32.30.190
113.23.68.25--------------->232.185.153.238
222.214.35.44--------------->222.214.35.44
254.218.160.105--------------->92.52.96.157
46.217.30.123--------------->214.73.60.148
46.217.30.123--------------->49.32.30.190
92.52.96.157--------------->29.109.19.187
222.214.35.44--------------->254.218.160.105
232.185.153.238--------------->214.73.60.148
```

Fig. 3: Nodes Mapping

The nodes are mapped to one another as seen above; each node will have a unique IP address. The IP address will determine how anchor nodes and noes are mapped.

```
**********************************************
********Anchor Collections*******************
**********************************************
13.23.68.25--------------->92.52.96.157
22.214.35.44--------------->222.214.35.44
14.73.60.148--------------->46.217.30.123
14.31.203.63--------------->29.109.19.187
14.31.203.63--------------->222.214.35.44
14.73.60.148--------------->49.32.30.190
```

Fig. 4: Anchor Collections

Anchor collections play a crucial role in QoS by acting as points of reference for effective and efficient network management. Anchor collections provide as storage for important data in QoS. Various datasets from different network components and monitoring systems, such as routers, switches, probes, and traffic analyzers, are frequently included in these collections. Moreover, anchor collections form the basis for sophisticated QoS techniques like traffic engineering, congestion management, and dynamic routing, enabling network managers to plan traffic patterns and resource allocations wisely in order to achieve predetermined QoS goals.

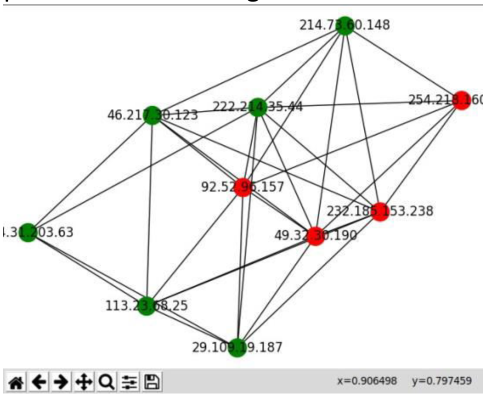

Fig. 5: Packets Transmission Simulation

In order to optimize resource allocation, minimize latency, and guarantee a satisfying user experience for key applications, the framework prioritizes some classes of traffic over others based on their significance and specific QoS requirements. Networks can more effectively deploy bandwidth, computing power and other resources thanks to this prioritization, which lowers congestion and boosts throughput overall. Furthermore, the framework improves network resilience and fault tolerance by distinguishing between high-priority and low-priority traffic, guaranteeing that critical services are given precedence during times of network failure or congestion. In the end, a more robust and resilient network infrastructure that can satisfy the various demands of contemporary applications and users is produced by the prioritized QoS architecture, which also helps to improve responsiveness, dependability and user happiness.

VII. EVALUATION METRICS

The above table shows the accuracy achieved by the different algorithms on different parameters. The table also contains the dataset split ratio which shows that random forest has the best accuracy compared to others.

Accuracy: Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome. You can calculate accuracy by dividing the number of correct predictions by the total number of predictions.

accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision: In the confusion matrix in the preceding illustration, these metrics are calculated in the following way:

Precision = TP ÷ (TP + FP)

Recall: Represents the number of positive instances correctly identified by the model.

Recall = TP ÷ (TP + FN)

The counts of true positive (TP), false positive (FP), false negative (FN), and true negative (TN) ground truths and inferences are essential for summarizing model performance. These metrics are the building blocks of many other metrics, including accuracy, precision, and recall. Metric.

VIII. CONCLUSION AND FUTURE DIRECTIONS

In conclusion, the ACO algorithm offers a powerful and versatile approach to solving complex optimization problems by emulating the foraging behavior of ants. Through the iterative construction of solutions and the updating of pheromone trails, ACO efficiently explores solution spaces and converges towards high-quality solutions. In the context of laser uplink communication optimization, ACO presents a promising solution for finding the shortest and most efficient communication paths within networked systems. By adapting to dynamic network conditions and environmental factors, ACO can continuously optimize communication paths, leading to improved network efficiency, reliability, and performance.

The integration of ACO into laser uplink communication systems has the potential to enhance their capabilities, making them more resilient and adaptable to changing operational requirements. By leveraging the collective intelligence of artificial ants, ACO enables the discovery of optimal communication paths in complex network topologies, thus addressing key challenges in laser uplink communication optimization.

Future enhancements for laser uplink communication systems using the Ant Colony Optimization (ACO) algorithm could focus on several key areas to further improve performance and adaptability. Firstly, the development of advanced ACO variants, such as Ant Colony System (ACS) or MAX-MIN Ant System (MMAS), could offer enhanced exploration and exploitation capabilities, leading to better convergence towards optimal solutions. Secondly, integrating machine learning techniques, such as reinforcement learning or neural networks, with ACO could enable the algorithm to learn and adapt to changing network dynamics more effectively. This could include dynamically adjusting pheromone evaporation rates, exploring alternative solution construction strategies, or adapting to varying environmental conditions.

Furthermore, exploring hybrid approaches that combine ACO with other optimization algorithms, such as genetic algorithms or particle swarm optimization, could leverage the strengths of each technique to achieve superior performance in optimizing communication paths.

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