Research on the Impact of Ant Colony Algorithm Optimization Based on Highway Enterprise Operation Data on Cost Control of Logistics Path Planning

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ABSTRACT This study investigates logistics path planning cost control through an optimized Ant Colony Algorithm (ACA) driven by highway enterprise operational data. Real-time transportation information, including traffic flow, vehicle speed, and road condition data, is integrated into pheromone update mechanisms and heuristic factor adjustments to enhance the adaptability of the algorithm in dynamic logistics environments. A data-driven optimization framework is developed to support intelligent route selection under continuously changing traffic conditions. Case-study results demonstrate that the proposed method significantly improves route planning efficiency and logistics cost control performance. Compared with traditional experience-based planning methods and the standard ACA, the optimized approach reduces total logistics distribution costs by 26.45%, transportation costs by 31.2%, and average travel distance by 12.12%. The framework exhibits strong robustness, adaptability, and operational efficiency in large-scale logistics networks. The proposed methodology is particularly applicable to intelligent transportation systems supported by wireless communication infrastructures and antenna-enabled sensing networks, where reliable real-time data acquisition and low-latency information transmission are essential for dynamic route optimization and operational decision-making. This research provides an effective engineering solution for intelligent logistics management, transportation optimization, and data-driven supply chain operations.

INDEX TERMS ant colony algorithm, logistics path planning, cost control, intelligent transportation systems

I. INTRODUCTION

A. RESEARCH BACKGROUND

IN today's digital era, operational data from highway enterprises constitutes a vital information resource, demonstrating extensive application value across multiple sectors. This data encompasses real-time metrics such as traffic volume, vehicle speed, and road conditions, which not only reflect the operational status of transportation networks but also provide new technological support for logistics path planning and cost control [1]. The rapid expansion of the logistics sector has intensified the need for effective cost control, especially in transportation, where optimized route planning can substantially lower logistics expenses and improve operational efficiency [2]. Studies confirm a strong link between logistics path planning and cost management. Effective route optimization not only shortens transit times and reduces fuel consumption but also helps avoid unnecessary costs resulting from traffic congestion or inefficient scheduling [3,4]. Consequently, leveraging highway enterprise operational data to enable scientific and intelligent logistics path planning has emerged as a critical research focus within the industry.

B. PROBLEM STATEMENT

Although significant progress has been made in logistics route planning and cost control, considerable challenges remain. Inefficient route selection continues to be a major driver of elevated logistics costs, as many companies still rely on static, experience-based planning methods rather than utilizing real-time highway operational data. This reliance leads to unnecessary mileage, delays, and fuel waste. Traditional Ant Colony Algorithms (ACA) also struggle to adapt to dynamic traffic environments, owing to limited data-processing capabilities and static pheromone mechanisms. Moreover, most studies focus on single-objective optimization, overlooking the multi-objective nature of modern logistics—which includes factors such as time windows, vehicle load rates, and safety considerations. As logistics networks expand and client demands become more diverse, these limitations grow increasingly apparent. Integrating highway enterprise operational data into the ACA improves its responsiveness, enabling adaptive, real-time route optimization. This enhancement not only strengthens cost control but also boosts delivery efficiency.

II. LITERATURE REVIEW

A. RESEARCH ON HIGHWAY ENTERPRISE OPERATION DATA

As a vital component of modern transportation management, expressway enterprise operational data encompasses multidimensional information including traffic volume, vehicle speed, road conditions, and toll records. Characterized by real-time updates, massive data volumes, and high precision, these datasets provide critical decision support for logistics industry path planning and cost control [5,6]. Current research demonstrates their extensive applications in traffic flow prediction, congestion detection, and route optimization. For instance, dynamic path optimization methods leveraging traffic volume and speed data effectively reduce transit times and enhance logistics efficiency [7]. Moreover, the spatial distribution characteristics of expressway operational data confer significant advantages in logistics network modeling, particularly for large-scale vehicle scheduling. Their real-time update capability enables enterprises to swiftly respond to traffic changes, thereby lowering transportation costs. However, the application of expressway operational data in logistics remains in its early exploratory phase, with untapped potential yet to be fully realized. Future research should focus on integrating these data with other logistics data sources to develop more intelligent path planning models, while improving algorithmic robustness and adaptability.

B. RESEARCH ON COST CONTROL OF LOGISTICS PATH PLANNING

Cost control in logistics route planning is a core challenge in logistics management, aiming to reduce total costs through optimized transportation routes, including fuel consumption, vehicle maintenance expenses, labor costs, and time costs [8]. Traditional research methods primarily relied on empirical rules and simple mathematical models such as shortest path algorithms and linear programming models. However, with the expansion of logistics scale and diversified customer demands, these methods have gradually revealed limitations, particularly in complex dynamic environments where they struggle to meet practical requirements [9,10]. In recent years, heuristic and meta-heuristic algorithms have emerged as research hotspots, with ant colony algorithms gaining attention for their distributed computing capabilities and positive feedback mechanisms. Although existing studies have achieved certain results in cost control for logistics route planning, numerous challenges remain. For instance, current algorithms demonstrate low efficiency in processing real-time data and insufficient adaptability to multiple constraints. Additionally, balancing cost optimization with service quality remains an urgent issue. Therefore, future research should further explore new algorithm frameworks and data-driven approaches to address increasingly complex cost control demands in logistics route planning.

III. MINING THE VALUE OF HIGHWAY ENTERPRISE OPERATION DATA

A. DATA TYPES AND CHARACTERISTICS OF HIGHWAY ENTERPRISE OPERATION

As a vital component of modern transportation management, expressway enterprise operational data encompasses diverse information types including traffic volume, vehicle speed, road conditions, weather status, and infrastructure maintenance [11,12]. These data are typically collected through multi-source systems such as roadside sensor networks, surveillance cameras, GPS devices, and weather stations, with real-time transmission and storage facilitated by digital platforms. Specifically, traffic volume data reflects the number of vehicles passing through a specific road section during designated time periods, serving as a key indicator for assessing congestion levels. Vehicle speed data records average travel speeds across road segments, providing dynamic references for logistics route planning. Road condition data further details actual traffic scenarios, such as accidents, construction closures, or pavement damage. These datasets are characterized by both real-time processing and massive scale. The real-time nature enables expressway operators to promptly reflect current traffic changes, providing logistics companies with actionable insights for transport plan adjustments. The massive scale, manifested in vast and continuously growing data volumes, demands data processing technologies with high efficiency and reliability to meet complex analytical requirements. Specifically, this study focused on leveraging highway enterprise operational data including: average vehicle speed data, reflecting the efficiency of each road segment; time-of-day traffic flow data, revealing traffic patterns at different times (e.g., peak and off-peak); and real-time traffic event data, such as information on road closures or congestion caused by traffic accidents and road construction. Of these data types, real-time traffic flow data was found to have the most significant impact on optimization costs, as it directly determines route travel time and fuel consumption and serves as a key input variable for dynamically adjusting pheromone concentrations and route selection probabilities [13,14].

B. THE IMPORTANCE OF EXPRESSWAY ENTERPRISE OPERATION DATA IN THE LOGISTICS FIELD

The application of highway enterprise operational data in logistics holds profound significance, particularly in logistics route planning and transportation scheduling. Firstly, by obtaining real-time traffic flow and speed data, logistics companies can accurately assess current road conditions, enabling them to select optimal routes and avoid transportation delays and additional costs caused by congestion. For instance, choosing less-trafficked alternative routes during peak hours not only reduces transit time but also lowers fuel consumption and vehicle wear, thereby achieving cost control objectives. Secondly, the integration of road condition data makes logistics route planning more intelligent and precise. By anticipating traffic accidents and construction closures, logistics enterprises can dynamically adjust transportation plans to effectively mitigate potential risks and ensure timely cargo delivery. Additionally, highway enterprise operational data provides scientific basis for logistics transportation scheduling. For example, combining historical traffic flow data with real-time road conditions allows companies to optimize vehicle allocation and departure schedules, thereby improving transportation efficiency and reducing resource waste. In summary, the application of highway enterprise operational data not only enhances the reliability of logistics route planning but also significantly improves overall operational efficiency in the logistics industry.

C. ACQUISITION AND PROCESSING OF EXPRESSWAY ENTERPRISE OPERATION DATA

Acquiring high-quality highway enterprise operational data forms the foundation for subsequent algorithm optimization, involving multiple approaches and methodologies. Current primary data sources include government transportation department disclosures, commercial data from third-party providers, and enterprise-built sensor networks. For instance, traffic authorities in many regions publish real-time traffic conditions and flow statistics through official websites or APIs, offering authoritative and comprehensive coverage. Meanwhile, third-party providers typically integrate multi-source data to deliver detailed analytical reports, though these services often require payment. Post-acquisition, critical preprocessing steps like data cleaning and integration are essential. Data cleaning removes noise and outliers to ensure accuracy and consistency. Extreme speed values (e.g., exceeding speed limits or falling below minimum speeds) can be filtered and corrected using statistical methods. Data integration standardizes formats across different sources for analysis, such as linking traffic flow data with road conditions through timestamps and geographical coordinates to form complete time-series datasets. After these preprocessing steps, highway operational data provides reliable support for logistics route optimization using ant colony algorithms.

IV. ANALYSIS OF COST CONTROL STATUS OF LOGISTICS PATH PLANNING

A. COST COMPOSITION OF LOGISTICS PATH PLANNING

Logistics route planning costs constitute a core consideration for logistics enterprises during distribution processes, primarily comprising transportation costs, time costs, and labor costs. Transportation costs typically account for a significant proportion of total logistics expenses, including direct expenditures such as fuel fees, vehicle depreciation, and maintenance costs. Time costs also represent a substantial component, particularly when customers have strict delivery time requirements, as delays may result in additional penalty costs or customer attrition. For instance, in high-speed rail express delivery, failure to complete deliveries on time due to time window constraints may lead to substantial economic losses. Labor costs involve driver compensation, dispatch personnel salaries, and other human resource expenses related to logistics operations. These costs are interconnected and collectively determine the overall economic efficiency of logistics route planning. Therefore, optimizing logistics route planning requires not only focusing on individual cost items but also adopting a holistic approach to balance cost relationships and achieve total cost minimization.

In this study, the core goal of logistics routing cost optimization is to minimize total logistics delivery cost. This total cost is a comprehensive weighted metric primarily composed of transportation costs (including fuel, vehicle depreciation, and maintenance) and time costs (particularly penalty costs incurred for violating customer time windows). The algorithm's optimization objective function seeks to minimize this total cost while satisfying all constraints (such as vehicle load and time windows).

B. EXISTING COST CONTROL METHODS

The logistics industry currently employs two primary strategies for cost control: empirical methods and traditional algorithm optimization. Empirical approaches rely on historical data and practitioners' experience, manually adjusting route planning schemes to reduce costs. While simple to implement, these methods lack scientific basis and struggle with complex real-world scenarios. In contrast, traditional algorithm optimization systems utilize mathematical models and computational techniques to systematically solve logistics path problems. Heuristic algorithms like genetic algorithms and ant colony optimization have been widely adopted in logistics route planning, employing iterative search methods to find approximate optimal solutions. However, these conventional approaches exhibit limitations. First, they demonstrate weak adaptability to real-time data, failing to adequately reflect dynamic traffic conditions. Second, their convergence speed and solution quality are often influenced by parameter settings, potentially leading to local optima. Consequently, although traditional algorithms enhance logistics efficiency to some extent, their effectiveness remains limited when addressing increasingly complex supply chain demands.

C. EXISTING PROBLEMS AND CHALLENGES

The primary challenges in cost control for logistics route planning currently include inadequate utilization of real-time data, limited algorithm optimization effectiveness, and uncertainties in external environments. Firstly, existing algorithms demonstrate significant limitations in processing real-time data. For instance, while the traditional Ant Colony Algorithm can optimize route selection to some extent, its pheromone update rules typically rely on static data, making it difficult to adapt to dynamic factors such as traffic congestion and weather changes. This deficiency often leads to unnecessary operational costs for logistics companies due to delayed route adjustments during actual operations. Secondly, the optimization effectiveness of existing algorithms is constrained by multiple factors. On one hand, the high complexity of algorithms and excessive computation time may delay decision-making. On the other hand, parameter selection significantly impacts results, with improper settings potentially leading to suboptimal outcomes. Additionally, uncertainties in external environments further complicate cost control in logistics route planning. For example, changes in customer demand, policy adjustments, and unexpected events can all substantially affect route planning. Therefore, to address these challenges, the design of optimization algorithms must prioritize real-time data integration and enhanced dynamic adjustment capabilities. Furthermore, advanced technologies such as big data analytics and artificial intelligence should be integrated to elevate the overall level of cost control in logistics route planning.

V. THE PRINCIPLE OF ANT COLONY ALGORITHM AND ITS APPLICABILITY IN LOGISTICS PATH PLANNING

A. ANT COLONY ALGORITHM PRINCIPLE

Ant Colony Optimization (ACO) is a meta-heuristic algorithm inspired by natural ants' foraging behavior. Its core concept stems from the collective intelligence of ants that use pheromone release to navigate food trails. During movement, ants release a chemical called pheromone, which other ants detect and use to guide them toward higher concentration paths. When multiple paths exist, ants calculate transition probabilities based on pheromone levels and heuristic information to determine their next steps. This process demonstrates the algorithm's positive feedback mechanism: shorter or better paths accumulate pheromones faster, making them more likely to be chosen by subsequent ants, thereby gradually converging toward the optimal solution. Specifically, ant colony algorithm models typically include the following key components: pheromone update rules, state transition probability formulas, and path construction mechanisms. In the pheromone update rule, ants perform a path search and then update pheromones along their paths based on route quality (e.g., length or cost), typically employing either global or local update strategies. The state transition probability formula calculates the probability of ants moving from the current node to the next node, which correlates with both pheromone concentration along the path and heuristic information. For instance, in classical ant colony algorithms, the state transition probability is calculated as follows:

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{s \in N_i} [\tau_{is}(t)]^{\alpha} \cdot [\eta_{is}]^{\beta}} \tag{1}$$

Here, $\tau_{ij}(t)$ denotes the pheromone concentration on path (i, j) at time (t), η_{ij} represents heuristic information (typically the inverse of path length), while α and β are the importance parameters for pheromone and heuristic information respectively. N_i indicates the set of next nodes available to the ant at node (i). Through this mechanism, the ant colony algorithm continuously optimizes path selection across multiple iterations, ultimately achieving near-optimal results. η is heuristic factor.

B. ADVANTAGES OF ANT COLONY ALGORITHM

Ant colony optimization demonstrates remarkable advantages in solving complex optimization problems, primarily through its distributed computing capabilities, positive feedback mechanism, and robustness. As a typical distributed algorithm, it operates through parallel execution by multiple ants. Each ant independently selects paths based on pheromones and heuristic information, effectively avoiding the local optima trap common in centralized search methods. This distributed nature enables the algorithm to achieve high efficiency and scalability when handling large-scale problems, making it particularly suitable for complex scenarios involving multiple nodes and constraints, such as logistics route planning.

Secondly, the positive feedback mechanism in ant colony algorithms effectively accelerates the convergence process. During the initial phase, ants randomly select paths and release pheromones along them. As iterations progress, shorter or more optimal paths gain dominance due to faster pheromone accumulation, attracting more ants to follow these routes. This self-reinforcing mechanism not only enhances search efficiency but also enables the algorithm to find high-quality near-optimal solutions in shorter timeframes. Additionally, ant colony algorithms demonstrate strong robustness, showing adaptability to initial parameter

settings and problem variations. Even in dynamic environments or uncertain conditions, the algorithm maintains optimal performance through continuous pheromone updates and adjustments.

Finally, the flexibility of ant colony algorithms enables easy integration with other optimization techniques to develop enhanced algorithms tailored for specific problems. For instance, in logistics path planning, researchers have introduced practical constraints like time window limitations and vehicle capacity restrictions, leading to multiple improvements of traditional ant colony algorithms. This has resulted in various variants such as cluster-based ant colony algorithms and modified pheromone update rules. These enhanced algorithms not only inherit the core advantages of ant colony algorithms but also further improve their applicability and solution quality in real-world applications.

C. APPLICABILITY ANALYSIS IN LOGISTICS PATH PLANNING

The Ant Colony Algorithm demonstrates exceptional applicability in logistics path planning, owing to its inherent alignment with the problem's fundamental requirements. At its core, logistics path planning involves identifying optimal routes from a starting point to multiple destination nodes while meeting constraints such as vehicle capacity limits, time window specifications, and distance restrictions, aiming to minimize transportation costs or maximize delivery efficiency. By mimicking ants' foraging behavior—where paths are selected through collective decision-making—the algorithm models logistics nodes as ant colonies and transportation routes as ant trails, providing an intuitive and efficient solution for logistics path planning. Specifically, the applicability of ant colony algorithm in logistics path planning manifests in the following aspects: First, the algorithm can handle complex problems with multiple nodes and constraints. In logistics distribution scenarios, distribution centers, customer nodes, and road networks form a complex graph structure. Through state transition probability formulas and path construction mechanisms, the ant colony algorithm can search for optimal paths that satisfy all constraints within the graph. Second, the positive feedback mechanism of the algorithm facilitates rapid convergence to optimal solutions. In logistics path planning, factors such as transportation costs and time costs directly impact path quality. By dynamically updating and accumulating pheromone information, the algorithm progressively filters out lower-cost paths, demonstrating excellent solving performance in practical applications.

VI. ANT COLONY ALGORITHM OPTIMIZATION BASED ON HIGHWAY ENTERPRISE OPERATION DATA

A. OPTIMIZATION STRATEGIES

To enhance the performance of ant colony optimization (ACO) in logistics route planning, this study proposes a series of optimization strategies based on highway enterprise operational data. First, real-time traffic conditions are integrated into the pheromone update rules to improve the algorithm's adaptability to dynamic environments. Specifically, while traditional ACO methods rely solely on path length and ant density for pheromone updates, neglecting external environmental changes, introducing real-time traffic data—such as road congestion levels and accident locations—enables dynamic adjustment of pheromone concentrations. This guides ants to prioritize clear routes. Additionally, traffic flow data is used to adjust heuristic factors, further optimizing path selection probabilities. For example, when a route has low traffic volume, its heuristic factor value is appropriately increased to attract more ants; conversely, it decreases to prevent ants from entering congested areas. This dual-perspective optimization strategy leveraging highway enterprise operational data not only significantly improves the algorithm's optimization capabilities but also effectively addresses complex traffic environments.

To effectively integrate highway operation data into the ant colony algorithm, this study proposes a data-driven pheromone and heuristic factor quantification mechanism. Specifically, real-time traffic flow (Q) and road speed (V) are normalized into a dynamic weight factor ω in the interval [0,1], which is used to adjust the update rule of pheromone concentration τ:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \omega\cdot\Delta\tau_{ij} \tag{2}$$

In Formula 2, $\omega = \max\left(\frac{V-V_{\min}}{V_{\max}-V_{\min}}, 0\right)\cdot\left(1-\frac{Q}{Q_{\max}}\right)$, which reflects the road traffic efficiency. $V_{\min}$ is the minimum reasonable speed threshold allowed by the road. This adjustment ensures that the weight factor will not be abnormally high when the speed is too low, so as to more truly reflect the road traffic efficiency and improve the rationality of the path selection of the algorithm in the low flow and low speed scenarios. At the same time, the heuristic factor η is expanded from the inverse of the path length to a composite function that includes real-time road conditions:

$$\eta_{ij} = \frac{d_{\max}-d_{ij}}{d_{\max}-d_{\min}} + \lambda\cdot\frac{V_j - V_{\min}}{V_{\text{avg}} - V_{\min}} \tag{3}$$

In Formula 3, d_{ij} is the path length, V_j is the real-time speed of the target node, and λ is the adjustment coefficient. This mechanism enables the algorithm to dynamically respond to traffic changes, improving the accuracy and real-time performance of path planning. $d_{\max}$ and $d_{\min}$ are the maximum and minimum values of the length of the road section in the road network respectively, and $V_{\min}$ is the lower limit of the reasonable speed. The two terms are mapped to a similar numerical range by range normalization method to achieve dimensional unity and comparability, so that the heuristic function has clear physical meaning and optimization guidance.

B. OPTIMIZATION STEPS

The ant colony algorithm optimization process based on expressway enterprise operational data primarily involves three key steps: data preprocessing, algorithm parameter adjustment, and optimization model construction. During the data preprocessing phase, real-time traffic flow, speed, and road condition data from expressway management departments are collected and integrated to eliminate noise and redundant information. Subsequently, the geodetic coordinates are converted into 3° projection plane rectangular coordinates using Gaussian transformation, standardizing the geographical location information of logistics nodes to provide standardized data support for subsequent route planning. Additionally, historical operational data undergoes statistical analysis to extract critical features such as peak hours and congested road sections, providing decision-making support for algorithm optimization.

The optimization model constructed in this study is designed to address the dynamic path planning problem.

The core of the model lies in its ability to process and respond to real-time highway operational data inputs. By incorporating real-time traffic flow, speed, and road condition events as dynamic weighting factors in the optimization strategy described in Section Optimization Strategies, which continuously influences pheromone updates and heuristic factor adjustments, the algorithm is able to reevaluate and reselect paths based on the latest road network status during each iteration or planning cycle. This mechanism ensures that the model can adapt to time-varying conditions such as traffic congestion and accidents, achieving true dynamic optimization.

During the parameter tuning phase, based on the typical parameter range of the ant colony algorithm and the results of multiple preliminary experiments, this study conducted detailed optimization of the algorithm's core parameters. The initial pheromone evaporation coefficient ρ was set to 0.4, the heuristic importance coefficient β to 2, and the pheromone importance coefficient α to 1. The value of ρ, ranging from 0.1 to 0.5, ensures that the algorithm gradually eliminates poor paths while retaining historical path information, avoiding the loss of accumulated learning ability due to complete pheromone evaporation caused by $\rho = 1$. The ratio of α to β reflects the relative importance of prior path information and real-time heuristic information. Experiments have verified that this parameter combination exhibits fast convergence speed and stable optimization performance in the dynamic road network scenario of this study. ϵ is the real-time event impact factor (range 0.1–0.5), used to adjust the suppression strength of pheromone updates due to sudden road conditions such as traffic accidents and construction; ϕ is the time-varying flow adjustment coefficient (range 0.8–1.2), dynamically adjusting the weight of the heuristic factor according to the flow characteristics of the time period; γ is the path diversity preservation parameter (range 0.05–0.15), used to control random perturbations in pheromone updates and prevent the algorithm from prematurely converging to a local optimum. Through orthogonal experiments and sensitivity analysis, it was found that ϵ has a significant impact on path reselection in congested road sections, ϕ has a significant effect on reducing time costs during peak hours, and the appropriate introduction of γ can improve the algorithm's global exploration capability in complex road networks. All parameters were verified through multi-scenario simulations to ensure their effectiveness and stability in actual dynamic programming.

To verify the impact of parameters on optimization performance, this study designed multiple sets of comparative experiments to analyze the sensitivity of key parameters ρ (pheromone evaporation coefficient), α (pheromone importance coefficient), and β (heuristic importance coefficient) was analyzed. By fixing other parameters and systematically adjusting the target parameter, the convergence speed and total cost of the algorithm under different parameter combinations were recorded. Experimental results show that when ρ is in the range of 0.3–0.5, the algorithm has good global search ability and convergence stability; a reasonable ratio of α to β (recommended $\alpha : \beta \approx 1 : 2 - -1 : 3$) can effectively balance the influence of path length and real-time traffic conditions.

In the model optimization phase, this study integrates preprocessed highway enterprise operational data into the path selection mechanism of the Ant Colony Algorithm. Specifically, by refining the traditional pheromone update formula, real-time traffic data is incorporated as a weighting factor to enable dynamic guidance of path selection. Additionally, a variable neighborhood search operator is introduced to conduct in-depth exploration of the solution space through operations like crossover and inversion, thereby enhancing the algorithm's global search capability. The resulting optimization model not only fully leverages the real-time and massive data characteristics of highway enterprise operations but also demonstrates strong adaptability and robustness, providing reliable algorithmic support for logistics route planning.

C. EXPECTED GOALS

Through optimization of the ant colony algorithm, this study aims to achieve significant performance improvements across multiple dimensions. Firstly, path planning efficiency will be substantially enhanced. Traditional ant colony algorithms often suffer from excessive computation complexity when handling large-scale logistics path planning problems, resulting in prolonged solution times. The optimized strategy incorporating highway enterprise operational data—featuring real-time traffic condition monitoring and dynamic adjustment of heuristic factors—effectively reduces algorithm convergence time, thereby improving overall path planning efficiency. Secondly, logistics costs are expected to be significantly reduced. The enhanced algorithm intelligently selects optimal routes based on traffic flow and road conditions, avoiding additional transportation costs caused by congestion or detours, thus achieving cost control objectives.

VII. CASE STUDY ON THE IMPACT OF OPTIMIZATION ALGORITHM ON COST CONTROL OF LOGISTICS PATH PLANNING

A. CASE SELECTION

To validate the effectiveness of ant colony optimization algorithm in logistics route planning and cost control based on highway enterprise operational data, this study selected a major logistics company as a case study. This study selects the regional operation network of a large logistics company in East China as a case study. This network covers Jiangsu, Zhejiang, and Shanghai, comprising one central distribution center, eight city distribution centers, and approximately 2,300 customer service nodes daily (covering both B2B and B2C businesses). The research data spans weekday operations in the third quarter of 2023 (July to September), with an average of approximately 520 vehicles deployed daily and over 12,000 orders processed. The region has a dense highway network, high traffic volume, and significant dynamic changes in road conditions, making it representative and valuable for research.

B. DATA COLLECTION AND COLLATION

In the case study, data collection and organization serve as the cornerstone for ensuring the effectiveness of optimization algorithms. First, we obtained logistics path planning data through collaboration with the enterprise, including basic information such as distribution center locations, geographic coordinates of customer nodes, cargo demand volumes, and delivery time windows. Additionally, vehicle operation records were collected, covering departure times, arrival times, mileage traveled, and fuel consumption. These data provide essential input parameters for constructing the logistics path planning model.

Outlier identification is based on statistical methods: if the vehicle speed is lower than 20% of the road segment's design speed for more than 30 minutes during a certain period, or if the traffic flow data exceeds three times the standard deviation of the historical average for the same period, it is considered an anomaly and is removed. Missing values are filled using a combination of time-series linear interpolation and spatial interpolation of data from nearby sensors. The time granularity of data from different sources is uniformly set to 5-minute intervals, and smoothing and alignment are performed using moving averages. Road condition events (such as accidents and construction) are coded with an impact factor δ between 0 and 1 based on their severity and expected duration: minor congestion ($\delta = 0.3$), severe congestion, or construction closure ($\delta = 0.7$–1.0). This factor directly participates in the calculation of the dynamic weight ω, thus reflecting the real-time road condition impact in the heuristic function and pheromone updates. During the data organization phase, cluster analysis is employed to group customer nodes, reducing computational complexity and optimizing route planning. By integrating real-time highway operation data, the algorithm dynamically updates pheromone information along routes, enabling rapid adaptation to traffic conditions. For instance, when severe congestion occurs on a specific road segment, the algorithm recalculates the heuristic function based on real-time traffic flow and speed data, guiding vehicles to alternative routes. This data-driven optimization strategy significantly enhances the algorithm's adaptability and robustness.

C. COST COMPARISON BEFORE AND AFTER OPTIMIZATION

To verify the optimization effect, this study compared the ant colony optimization algorithm (the optimization method in this study) that integrates highway operation data with two baseline methods based on 15 consecutive working days of operational data from the enterprise:

1) the traditional experience-based planning method currently used by the case enterprise, which relies on historical experience and static maps; and

2) the standard ant colony algorithm that does not integrate real-time operational data and only optimizes path distance.

Under the same daily operating conditions, paired-samples t-tests were performed on the results of the optimization method and each baseline method to assess the statistical significance of its cost reduction. Simultaneously, analysis of variance (ANOVA) was used to test the stability of the optimized ACA method's performance on different dates and time periods (e.g., peak/off-peak) to evaluate the algorithm's robustness and repeatability. The performance comparison between optimization algorithm and baseline method is shown in Table 1:

TABLE 1. Performance Comparison of the Optimization Algorithm and the Baseline Method

Performance Indicators	Traditional empirical methods (benchmark)	Standard ACA method	This study optimizes the ACA method
Total Cost (CNY/day)	1,250,400	1,143,616 (-8.5%)	919,754 (-26.45%)
Transportation Cost (CNY/day)	842,700	757,827 (-10.1%)	580,068 (-31.2%)
Time Cost (CNY/day)	210,300	199,121 (-5.3%)	171,002 (-18.7%)
Average Distance Traveled (km)	18,550	17,658 (-4.8%)	16,303 (-12.12%)

Note: The optimized ACA method uses the same initial parameters in each run and introduces dynamic weights and an event encoding mechanism. The p-values from the paired-samples t-tests comparing the optimized method against both baselines were all less than 0.01, indicating that the cost reductions achieved by the proposed method were statistically significant. Furthermore, the ANOVA results showed no significant performance variation across different daily periods for the optimized method, confirming its robustness and repeatability.

By comparing logistics path planning cost data of case enterprises before and after optimization, this study visually demonstrates the effectiveness of the ant colony algorithm optimized based on highway enterprise operational data in practical applications. Experimental results show that the total logistics distribution cost decreased by 26.45% after optimization, with transportation costs dropping by 31.2% and time costs reduced by 18.7%. This significant improvement primarily stems from the algorithm's effective utilization of real-time traffic data and precise path selection optimization. The reduction in transportation costs (31.2%) was significantly higher than the reduction in average travel distance (12.12%). This is because transportation costs are not only related to travel distance but are also significantly affected by real-time road conditions. The optimization algorithm significantly reduced fuel consumption and vehicle wear per unit distance by dynamically avoiding congested sections and reducing idling and low-speed driving. It also optimized vehicle scheduling and route combinations, improving load factor and round-trip efficiency. Therefore, even with a slight decrease in distance, transportation costs can still be reduced more substantially. This demonstrates the multidimensional value of dynamic data-driven route optimization in cost control.

Specifically, before optimization, companies relied on traditional empirical methods for route planning, failing to adequately account for the dynamic changes in highway networks. This resulted in vehicles frequently getting stuck in congested sections, increasing fuel consumption and travel time. After optimization, the algorithm dynamically adjusted routes based on real-time traffic flow and speed data, successfully avoiding multiple congested sections and reducing average travel distance by 12.12%. Additionally, by introducing time window constraints, the algorithm ensured more reasonable service times at customer nodes, further minimizing additional costs caused by delays.

VIII. OBSTACLES AND RISKS IN THE OPTIMIZATION PROCESS AND COUNTERMEASURES

In the optimization of ant colony algorithms (ACO) using highway enterprise operational data, two major challenges arise—data security and algorithmic complexity. Given that such data contains real-time sensitive information on traffic volume, vehicle speed, and road conditions, any leakage or manipulation may severely compromise logistics operations. Unauthorized access could expose key routing data to competitors, while tampering might distort optimization results, increasing costs and disrupting efficiency. Therefore, robust security mechanisms are essential. Encryption technologies, including symmetric and asymmetric schemes, should be applied during data storage and transmission, reinforced by secure protocols such as SSL and VPN. Additionally, Role-Based Access Control (RBAC) and blockchain-based distributed verification can enhance data transparency, immutability, and access integrity, minimizing internal and external risks.

From the algorithmic perspective, integrating massive real-time traffic data into ACO increases computational burden and may slow convergence, particularly under multi-constraint logistics scenarios. To mitigate this, simplifying pheromone update rules and refining heuristic functions can reduce redundancy while improving search precision. The use of GPU-accelerated parallel computation or distributed frameworks further enhances computational efficiency. Incorporating variable neighborhood search operators allows dynamic adaptation of the solution space, accelerating convergence and preventing stagnation in local optima. Collectively, these strategies enhance both the robustness and responsiveness of the ACO framework, ensuring secure, efficient, and scalable optimization for cost control in logistics route planning.

IX. FUTURE DEVELOPMENT TRENDS

A. *TECHNOLOGY CONVERGENCE TREND*

With the rapid evolution of artificial intelligence, big data, and the Internet of Things (IoT), ant colony algorithm (ACA) optimization based on highway enterprise operational data is entering a new stage of intelligent convergence. Integrating real-time traffic data with IoT-enabled tracking of high-value shipments, such as fabrics and apparel, will enable dynamic rerouting and enhance supply chain responsiveness. Big data analytics can significantly improve ACA's capability to process large-scale, multidimensional datasets by incorporating variables such as historical traffic patterns, weather, and demand fluctuations, thus increasing the precision and adaptability of route planning. IoT technologies further strengthen data perception through smart sensors and vehicle terminals, providing continuous inputs on vehicle speed, location, and fuel consumption for real-time pheromone adjustments. Cloud computing and distributed frameworks reduce computational latency and enhance scalability, supporting ACA's deployment in complex logistics networks. Beyond route planning, the algorithm's application extends to warehouse layout design, multi-warehouse collaboration, and supply chain coordination, enabling optimization of inventory distribution and production scheduling. Future research should focus on adaptive parameter tuning, hybrid algorithm integration, and multi-source data fusion to enhance robustness and decision accuracy. Empirical validation through large-scale, real-world experiments will further ensure the reliability, efficiency, and practical value of ACA-driven intelligent logistics systems.

X. CONCLUSION

This study focuses on optimizing the Ant Colony Algorithm (ACA) using operational data from highway enterprises to achieve cost control in logistics path planning. Addressing the limitations of traditional ACA in processing real-time dynamic traffic data, this paper proposes an optimization strategy that deeply integrates highway operational data—such as real-time vehicle speed and road conditions—into the pheromone update rules and heuristic factor adjustments of the ACA. This enhancement enables the algorithm to dynamically avoid congested road sections and intelligently select low-cost, high-efficiency transportation routes.

AUTHOR CONTRIBUTIONS

Conceptualization –Jiguang Zhang, Xiaocheng Li, Shuo Zhang, Yin Li and Lijuan Cao; methodology – Jiguang Zhang, Xiaocheng Li, Shuo Zhang, Yin Li and Lijuan Cao; investigation – Jiguang Zhang, Xiaocheng Li, Shuo Zhang and Yin Li; writing-original draft preparation – Jiguang Zhang, Xiaocheng Li, Shuo Zhang, Yin Li and Lijuan Cao. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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