Hybrid Genetic and Ant Colony Optimization Multipath Congestion-Free Routing Algorithm

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Abstract—**In response to the critical issues of link saturation and excessive latency stemming from inter-cluster coordination within partitioned Vehicular Ad-hoc Networks (VANETs), this research develops a Hybrid Genetic-Ant Colony Multipath Routing scheme (GAAC) designed for congestion-free data dissemination. By synthesizing node buffer occupancy, relative mobility patterns, and temporal constraints into a comprehensive assessment framework, the routing selection is reformulated as a multi-constrained optimization challenge. The methodology integrates Genetic Algorithm (GA) operations to conduct a broad-spectrum exploration of the solution space, thereby seeding the Ant Colony Optimization (ACO) process with superior initial pheromone distributions to bypass the traditional pitfalls of erratic searching and sluggish convergence. To further refine path acquisition, the transition rule is augmented with composite heuristic cues, while an adaptive link restoration and proactive failover protocol is implemented to uphold session persistence amidst volatile topology shifts. Performance evaluations indicate that the GAAC framework stabilizes within approximately 34 iterations, exhibiting superior convergence efficiency over decoupled GA or ACO implementations. Compared to the baseline GA configurations, the integrated approach yields a 3.66% enhancement in delivery success, shortens latency by 0.094s, and expands throughput by 73.589 Kbps. Notably, the maintenance of a 200 ms delay profile at high-velocity mobility (80 km/h) underscores the algorithm's suitability for time-sensitive vehicular multimedia applications.**

Keywords-Congestion Control, Genetic-Ant Colony Optimization, Link Stability, Multipath Routing, Vehicular Networking

I. INTRODUCTION

With the popularity of Vehicular Networking (VANETs) applications, the high-speed mobility of vehicle nodes, combined with a surge in communication demand, has led to problems such as network congestion and high delay. This has become the core bottleneck restricting the real-time performance and reliability of VANETs communications. To cope with the challenges of the network's highly dynamic nature and scalability, clustering technology has been widely adopted. However, while optimizing intra-cluster communication, this architecture shifts the performance pressure to inter-cluster routing [1]. This shift in pressure necessitates a more robust mechanism to manage the increased traffic load within the inter-cluster backbone.

In clustered VANETs, inter-cluster communication relies on a backbone network consisting of cluster heads and gateway nodes, as shown in Fig 1(a), and the main cause of congestion lies in the failure to find optimal routes in this backbone network. This problem is particularly significant in high-density or highly dynamic environments, where node-level congestion is triggered when the processing and caching capabilities of nodes on the path are insufficient,

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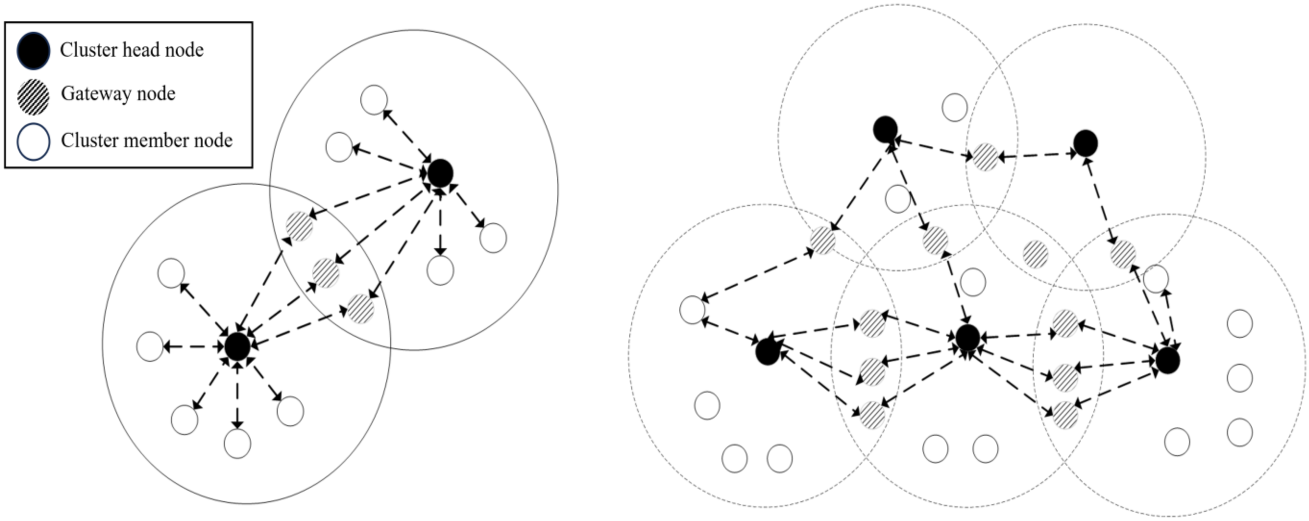
which subsequently increases the probability of packet collisions, ultimately leading to link-level congestion. As the network topology becomes more complex, as shown in Fig 1(b), the number of alternative paths increases dramatically, which makes the overhead of using an exhaustive algorithm to establish routes extremely large and difficult to apply.



(a) typical backbone structure and

(b) complex scenario with multi-path routing overhead.

Figure 1. Inter-cluster Communication Network Topology

Network congestion is mainly caused by three core factors [2][3]: the limited processing and caching capacity of nodes, the conflict and contention of shared wireless channel resources, and the dynamic topology of the network triggered stemming from the rapid displacement of vehicular nodes. Current academic consensus emphasizes the integration of heuristic intelligence for congestion awareness as a pivotal trend [4]. While prior efforts have frequently deployed Ant Colony Optimization (ACO) to mitigate these bottlenecks, such strategies typically struggle with stagnant convergence rates and diminished flexibility when confronted with the volatile fluctuations of VANET topologies[5].

To overcome these limitations, this research introduces GAAC, a hybrid multipath routing framework characterized by the synergistic fusion of Genetic Algorithms and Ant Colony systems. By constructing a multidimensional evaluation model that incorporates congestion, link stability, and delay, the algorithm transforms the routing problem into a multi-objective optimization problem, aiming to dynamically discover and maintain the optimal routing model that combines low delay, high stability, and low congestion.

In VANETs, clustering is a key technique to cope with the high dynamics of the network and improve scalability. When designing effective clustering algorithms, researchers must adhere to some basic principles [6][7], such as dynamic adaptability, low overhead, stability, and scalability. On the basis of a stable clustering architecture, efficient inter-cluster routing technology becomes the core to guaranteeing communication quality. The development of routing techniques for clustered VANETs has evolved continuously to cope with the highly dynamic nature of the network and to guarantee the reliability of communication [8].

Initial explorations in this field primarily migrated legacy protocols from the MANET domain into vehicular contexts. A cornerstone of this era is the AODV algorithm, introduced by Perkins et al. at the end of the last century [9]. To bolster the resilience of data transmission, subsequent refinements by Marina and Das led to the development of AOMDV in 2001 [10], a multipath extension designed to offer failover capabilities and redundant path selection. However, these early protocols mainly used the minimum hop count as the sole criterion for path selection, and they failed to fully consider the special characteristics of the VANET environment, such as link stability and network congestion conditions.

To optimize routing performance in specific scenarios, researchers have started to introduce new metrics. To address the problem of the rapidly changing topology of VANETs, some scholars proposed a geolocation-based routing protocol [11]. On this basis, in order to further improve the packet delivery rate, other scholars took the stability of links into consideration and selected more reliable paths by predicting the duration of links [12][13]. However, although these methods improved stability to a certain extent, most of them ignored the problem of network load balancing.

With the growth of network size and communication demand, the congestion problem becomes more and more prominent. To address this deficiency, researchers have started to try to apply intelligent optimization algorithms to routing. In fact, recent authoritative reviews highlight the integration of bio-inspired intelligence, particularly GA and ACO frameworks, as essential methodologies for tackling contemporary VANET obstacles [14]. A pioneering effort by Gunes et al. introduced ACO-based routing mechanisms to this field in 2002 [15]. Subsequently, various scholars have sought to refine pheromone deposition rules and path selection heuristics to facilitate faster solution discovery [5]. Nevertheless, independent ACO implementations continue to grapple with fundamental limitations, notably stagnant convergence rates and a high susceptibility to local optima entrapment, especially within the volatile mobility patterns typical of vehicular networks.

In summary, although existing inter-cluster routing algorithms have made some progress in a single dimension such as link stability or congestion awareness, they fail to construct a comprehensive evaluation model to balance multiple conflicting performance metrics, and they also fail to fundamentally solve the challenges of convergence efficiency and global optimality-seeking ability of intelligent algorithms in the VANET environment. To address these gaps, this study develops the GAAC algorithm—a hybrid multipath strategy designed for congestion-free routing. This approach capitalizes on the Genetic Algorithm's capacity for expansive global exploration to initialize the search space, which is then synergistically coupled with the ACO's precision in localized path optimization. This hybrid engine is further guided by an integrated assessment model focusing on traffic density, link persistence, and transmission delay.

II. GAAC ALGORITHM DESIGN

A. Algorithmic Architecture

The GAAC algorithm follows a hierarchical collaborative optimization architecture. The architecture is based on a comprehensive multidimensional evaluation model for decision making, path finding through a hybrid GA-ACO optimization engine, and supplemented by an active link repair mechanism to guarantee communication robustness. A structural overview of the proposed framework is depicted in Fig 2.

Central to the decision-making process is a comprehensive assessment model that transforms parameters such as traffic density, link persistence, and temporal latency into a unified path fitness metric. This derived value subsequently drives a collaborative GA-ACO optimization module. In this configuration, the Genetic Algorithm (GA) performs an expansive exploration of the network to generate high-potential path candidates, which are then utilized to initialize the pheromone field for the Ant Colony Optimization (ACO) algorithm. By doing so, the ACO component can focus on precision-based local refinement to realize the synergistic benefits of both meta-heuristics. In the final stage, an autonomous link restoration module is executed in parallel to adapt to rapid topological fluctuations, thereby safeguarding the persistence and resilience of the data sessions. This integrated approach ensures that the routing process is not only aware of the current network state but also resilient to the rapid topological transitions inherent in VANETs. By synergizing global exploration with local exploitation, the GAAC algorithm effectively balances competing performance objectives, ultimately yielding a set of congestion-free, high-stability paths that meet the stringent Quality of Service (QoS) requirements of real-time vehicular applications.

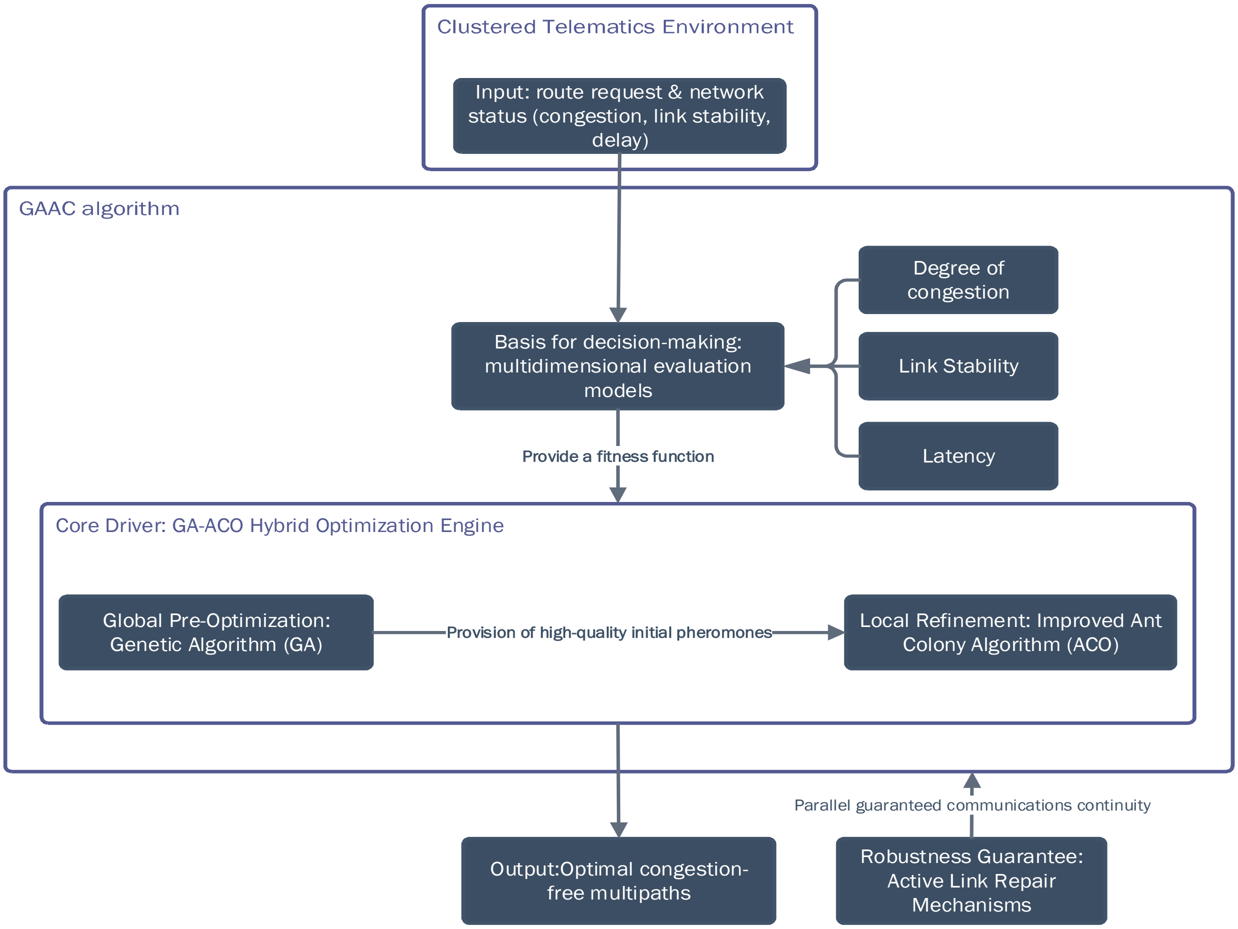


Figure 2. Algorithm Architecture Diagram

B. Routing Congestion and Stability Metrics

To overcome the limitations of traditional minimum-hop routing, this paper constructs a multidimensional evaluation model and transforms the route-finding problem into a multi-objective optimization problem.

1) Routing Congestion Metric

Node-level congestion stems from its limited forwarding and caching capacity. Therefore, in this paper, the remaining cache queue length of a node is used as a key metric to measure its congestion level (N_c) as in (1)

$$N_c(n) = \frac{q_{use}(n)}{Q_{max}} \quad (1)$$

The congestion of the whole route is then defined as the maximum value of all nodes N_c on the path as in (2)

$$F_c(R(S,D)) = \max\{N_c(n) | \ n \in R(S,D)\} \quad (2)$$

2) Link Stability Metrics

Given the volatile topological shifts inherent in VANETs, a specialized metric is formulated to quantify link reliability. By synthesizing real-time spatial coordinates, instantaneous velocities, and the effective signal coverage of paired nodes, the proposed approach characterizes their relative displacement patterns. This is operationalized through a stochastic predictive framework [16] that estimates the likelihood of sustained link connectivity across a specific temporal window. Link stability is related to the route lifetime (RLT), which refers to the duration during which a route may become interrupted. Routes in VANETs consist of multi-hop wireless links. If the link lifetime (LLT) of each segment is known, the RLT is expressed as shown in (3).

$$RLT_R = \min_{\text{link } l \in R}\left(LLT_l\right) \tag{3}$$

In this context, R represents a communication path formed by a sequence of wireless segments l, bridging the source and the target nodes. Broadly speaking, point-to-point data exchange is attainable provided that the spatial separation between a pair of vehicular units does not exceed their maximum broadcast radius TR. Within the vehicular network environment, every mobile participant utilizes an onboard navigation module to facilitate self-localization. Simultaneously, neighboring nodes periodically broadcast HELLO packets to nearby vehicles, containing their coordinates, velocity information, and timestamps. Therefore, each vehicle node can predict the remaining lifetime of each link using the HELLO packets from neighboring vehicle nodes and its own information. As shown in Fig 3, at time t, vehicle node node_i receives broadcast information from vehicle node node_j and communicates with node_j via wireless link l_{ij}.

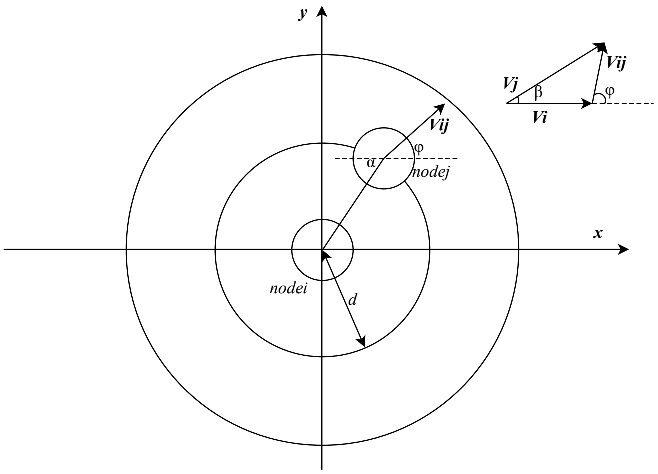


Figure 1. Vehicle Node *i* and Node *j* Spatial Relationship Diagram

The stability of the entire route is then determined by the product of the stability of all the links on the path, as in (4).

$$r_t(l) = \int_{l}^{t+T_{est}} \frac{R_{ij}}{\sigma_{\Delta v_{ij}}\sqrt{2\pi T^2}} e^{-\frac{\left(\frac{R_{ij}}{T}-X_{\Delta v_{ij}}\right)^2}{\left(2\sigma_{\Delta v_{ij}}\right)^2}} dt, T_{est} > 0 \tag{4}$$

$r_t(l)$ is the link stability of link l at time t. According to (3), the stability of the route is then shown in (5).

$$F_{LT}(R) = \min_{\text{link } l \in R}\left(r_t(l)\right) \tag{5}$$

Utilizing the aforementioned methodology, individual nodes evaluate the dependability of their immediate wireless connections. Guided by these reliability metrics, the most persistent trajectory is identified and extracted from the candidate path set provided by the underlying protocol.

The delay metric is obtained by normalizing the end-to-end delay of data transmitted by different paths.

3) *Objective Function*

Through the previous analysis, we see that the conventional routing strategies predominantly favor the shortest hop count for path determination, a practice that often triggers localized traffic hotspots and systemic congestion. To mitigate this, our study supersedes the simplistic hop-based criterion with a triad of sophisticated routing variables, effectively reframing the path discovery process as a constrained multi-objective optimization task, with the objective function shown in (6).

$$f = \omega_1 F_c - \omega_2 F_{LT} + \omega_3 F_d \tag{6}$$

In the objective function F_c denotes the route congestion, F_{LT} denotes the route stability, F_d denotes the delay metric of the route, and ω_1, ω_2, and ω_3 correspond to the weights of F_c, F_{LT}, and F_d in that order. Employing meta-heuristic frameworks, specifically GA and ACO, for accelerated route exploration necessitates a robustly formulated fitness function. This performance indicator serves as the primary benchmark for assessing candidate solutions, directing the iterative evolution of the search engine toward global optimality. The fitness function is usually converted from the objective function. The paper defines the fitness function as shown in (7).

$$FF = \frac{1}{\omega_1 F_c - \omega_2 F_{LT} + \omega_3 F_d} \tag{7}$$

C. Route Optimization Algorithm Incorporating Genetic Ant Colony

In this section, multiple metrics are considered to replace the traditional minimum hop count measure of path quality, and a genetic-ant colony fusion algorithm is designed to find congestion-free routes between cluster heads to improve network performance. The flowchart of the proposed genetic-ant colony fusion multipath congestion-free route optimization algorithm is shown in Fig 4.

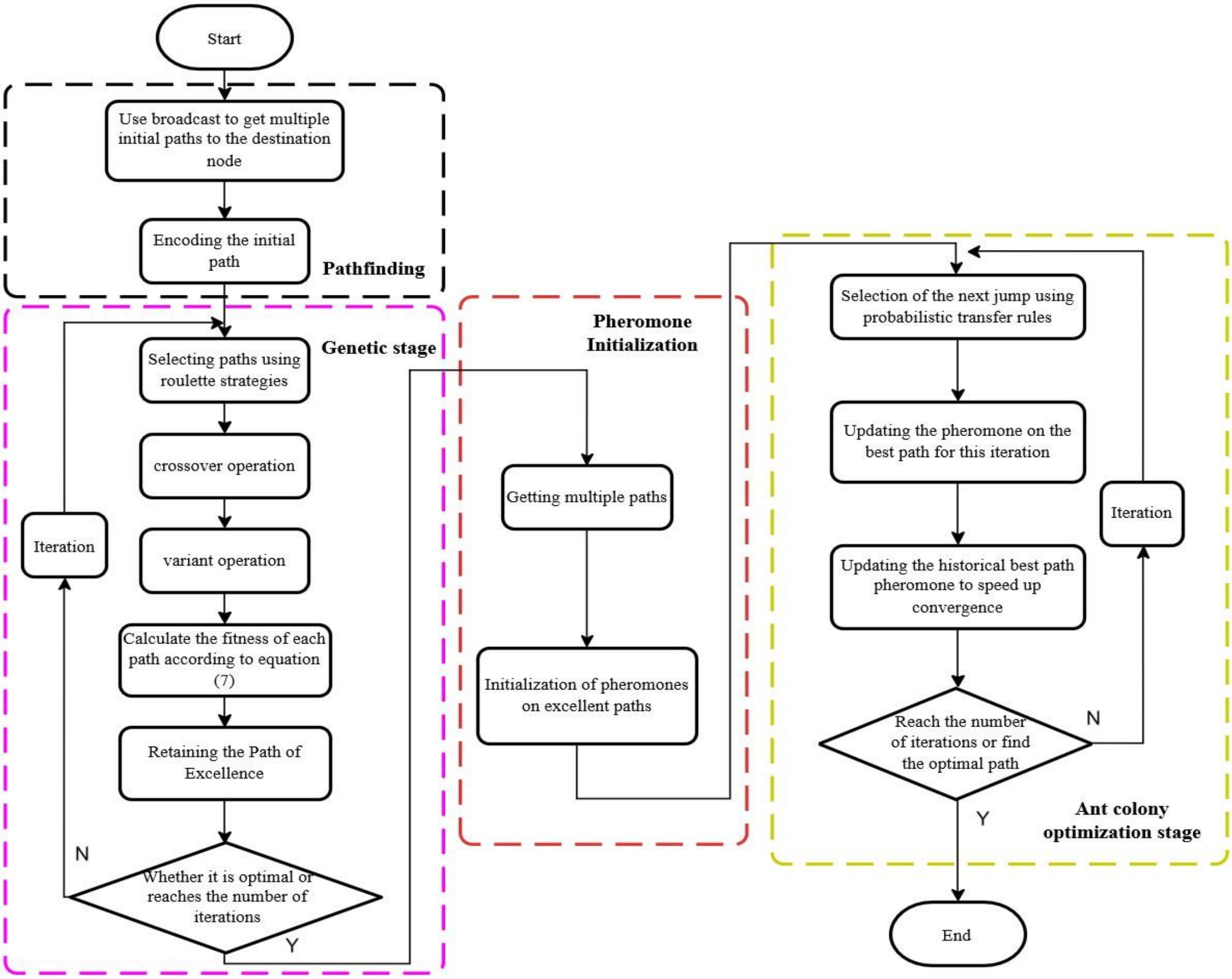


Figure 4. Flowchart of the Genetic-Ant Colony Fusion Congestion-Free Routing Algorithm

The sequential optimization logic of the GAAC framework is illustrated in the accompanying diagram. First, multiple available paths are initially discovered through the broadcast mechanism, which constitutes the initial population of the genetic algorithm. Then, the global search capability of the genetic algorithm optimizes this population and filters out paths with higher fitness. Finally, these preferred paths are used as the initial pheromone of the ant colony algorithm, which guides it to perform more efficient local search and refinement so as to quickly converge to the final optimal congestion-free route.

1) Routing Message Design

Standardized protocol formats are augmented to accommodate the integrated decision-making variables and hybrid search strategies of our model. Specifically, the Route Request (RREQ) and Route Reply (RREP) headers are expanded to include data fields for link persistence, latency, and buffer occupancy, while the HELLO broadcast is updated to encapsulate instantaneous node conditions. Furthermore, to facilitate autonomous path restoration and swarm-based intelligence, specialized control packets-including Route Request Repair (RRER), Route Error (RERR), and bi-directional ant agents (FRANT/BRANT)—are incorporated to maintain seamless data synchronization throughout the algorithmic cycles.

The main routing control packets used in the genetic ant colony fusion congestion-free multipath routing designed in this section achieve neighbor state sharing by periodically broadcasting HELLO packets, initial path establishment by RREP and RREQ, link repair by the route request repair message RRER and error message RERR, and send and receive ant messages FRANT and BRANT to update the pheromones on the path, thus realizing dynamic evaluation and selection of the network topology.

2) path discovery process

Upon the requirement for data packet delivery between vehicular units, the originating node examines its internal routing cache for pre-existing trajectories toward the destination. Should a valid route be absent, a dedicated path exploration procedure is triggered.

The exploration phase commences as the source node propagates an RREQ packet embedded with the proposed multi-criteria parameters. Upon the arrival of the initial RREQ at the destination, a brief temporal buffer is activated to aggregate various incoming requests from diverse network trajectories. After the window closes, the destination node evaluates all the collected paths based on the fitness function and returns RREP messages along a number of paths that are evaluated optimally, thus completing the establishment of multiple initial paths and providing an initial population for the subsequent genetic algorithm.

3) Genetic Algorithm to Obtain Congestion-Free Initial Routes

After obtaining the initial set of paths, GA is used to perform global pre-optimization. We encode each path as a chromosome whose fitness is determined by (7). The path population undergoes iterative evolution through the execution of classical genetic operators, encompassing elitism-based selection, recombinant crossover, and stochastic mutation. Among them, crossover prioritizes common nodes between paths, and the mutation operation tends to replace nodes in the paths that contribute the most to congestion. The goal of GA is to quickly locate high-potential regions in the solution space to provide a high-quality search starting point for subsequent ACO algorithms, thus effectively avoiding the lengthy stochastic exploration phase of ACOs.

4) Improving Ant Colony Algorithm to Obtain Multipath Routes

The GA-preferred paths are used to guide the Ant Colony Algorithm to perform a finer local search. Its core improvement is reflected in three aspects:

Pheromone initialization: To provide a clear initial search direction, we initialize the pheromones on the GA-output paths, weighting them according to their fitness, as shown in (8) and (9).

$$\tau_{ij}(0)=\begin{cases} C_i\tau_0, & i,j\in R \\ 0, & \text{else} \end{cases} \tag{8}$$

$$C_i=\frac{FF(R_i)}{\sum_{i=1}^{N} FF(R_i)} \tag{9}$$

Transfer strategy incorporating multidimensional metrics: to make the path selection smarter, the improved transfer probability formula incorporates three pieces of heuristic information: pheromone concentration, congestion, stability, and delay, to guide the ants to move to the next-hop node with better comprehensive performance. Meanwhile, as shown in (10), the stochastic search operator P_0 is introduced to balance the exploration and utilization of paths, effectively avoiding premature convergence of the algorithm.

$$P_{ij}^{k}(t)=\frac{[\tau_{ij}(t)]^{\alpha}[F_{Cij}(t)]^{-\beta}[F_{Rij}(t)]^{\gamma}[F_{dij}(t)]^{-\kappa}}{\sum_{j\in N}[\tau_{ij}(t)]^{\alpha}[F_{Cij}(t)]^{-\beta}[F_{Rij}(t)]^{\gamma}[F_{dij}(t)]^{-\kappa}} \tag{10}$$

The next hop node X_{ij} is shown in (11).

$$X_{ij}=\begin{cases}\arg\max_{j\in n_i}\{\tau_{ij}\}, & P_j<P_0\\ P_{ij}, & \text{otherwise}\end{cases} \tag{11}$$

Pheromone updating: "Local + Global" Elite Update Strategy: To further accelerate the convergence, the pheromone update adopts a dual elite strategy. After an ant moves, the local update moderately reduces the pheromone on the visited path, as shown in the following equations, to encourage the exploration of new paths.

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\rho\Delta\tau_{ij}(t) \tag{12}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{13}$$

$$\Delta\tau_{ij}^{k}=\begin{cases}\log F_R(l_{ij})+\dfrac{1}{F_C+1/F_d}, & \text{if } l_{ij}\in P_{best}\\ 0, & \text{else}\end{cases} \tag{14}$$

Where P_{best} denotes the set of links in the current optimal path.

And at the end of each round of iteration, as shown in (15), pheromone augmentation is performed only on the currently found globally optimal paths, thus reinforcing the deep mining of high-quality solutions. The pheromone augmentation $\Delta\tau_{ij}$ is directly linked to the comprehensive performance of the paths, which ensures that the algorithm efficiently converges towards the optimization of the objective function. Upon the successful transition of ant k between vertex i and vertex j, the immediate pheromone adjustment is executed according to the expression below.

$$\tau_{ij}(t+1)=(1-\delta)\tau_{ij}(t)+\delta\Delta'\tau_{ij}(t) \tag{15}$$

Where δ is the global pheromone volatilization factor.

The calculation formula for $\Delta'\tau_{ij}$ is shown in (16).

$$\Delta'\tau_{ij}=\begin{cases}\dfrac{Q}{l_{best}}, & \text{if } l_{ij}\in P_{global}\\ 0, & \text{else}\end{cases} \tag{16}$$

Where P_{global} denotes the set of links in the historically optimal path found so far, Q represents the pheromone incremental constant, and l_{best} corresponds to the cost of this optimal path. By reinforcing the pheromones on these specific links, the algorithm effectively enhances the exploitation of known superior paths while maintaining the ability to explore new ones.

D. Link Repair Algorithm

Since the rapid mobility of vehicular nodes often triggers a substantial decline in the reliability of network links, a path disconnection is inevitable when a pair of adjacent nodes along a trajectory loses their direct communication capability. In this section, a link repair algorithm is proposed for the phenomenon of link breakage, where the GAAC routing protocol can identify multiple paths and select the path with the lowest cost and highest utility as the primary path, designating other paths as alternate paths. Once a node on the primary path suffers from a broken link or a failure that prevents it from delivering information to the target node, link repair will be triggered. The operational logic of the link restoration mechanism is illustrated in Fig 5.

Guided by the diagram, the procedural execution of this algorithm is detailed below.

Upon detecting a connectivity disruption, the immediate precursor node (Npd) of the malfunctioning unit transmits an RRER (Repair Request) notification to the originating source (NS). Concurrently, Npd functions as a localized initiating node to investigate an alternative trajectory toward the destination (ND) by leveraging the GAAC framework.

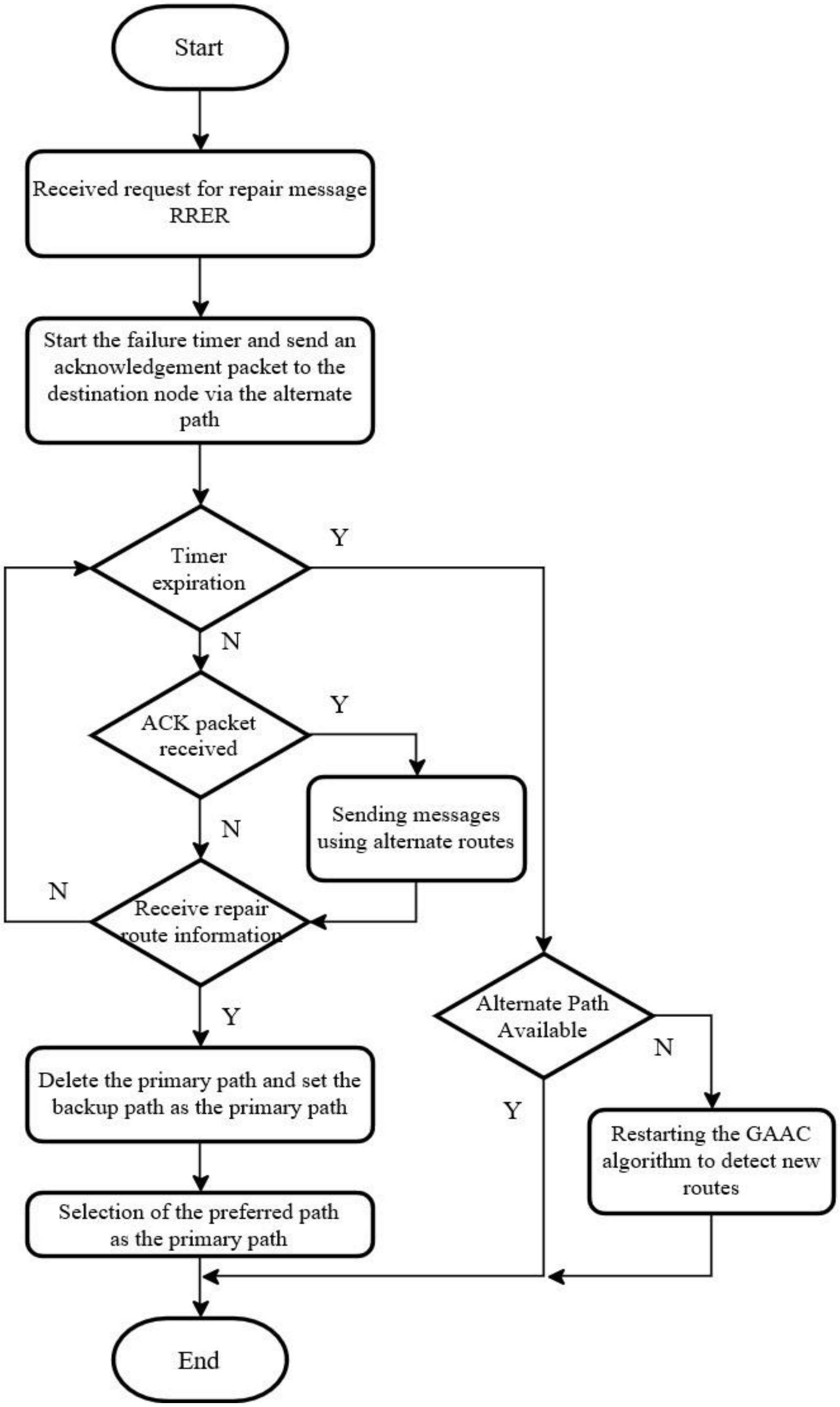


Figure 5. Link Repair Source Node Flowchart

Once the RRER alert is acknowledged, the source node (NS) initializes a failure countdown timer. Meanwhile, it designates the existing primary route as compromised and dispatches a verification packet toward the destination (ND) via a pre-established backup channel.

If it successfully receives an ACK packet from the destination node ND via the alternate path before the failure timer expires, it continues to transmit the remaining data via the alternate path.

In the event that Npd identifies a viable replacement path to ND, it dispatches a backward ant agent (BRANT) to convey the routing update to NS. Conversely, should the restoration attempt prove unsuccessful, an RERR failure notification is issued to the source node NS.

Upon receipt of the BRANT message, NS conducts a comparative analysis of the overhead between the original and redundant trajectories, opting for the more economical route to resume data flow. Should the reconstructed primary link exhibit higher costs than the existing backup, the source node designates the latter as its new primary transmission channel.

The expiration of the failure timer without an incoming ACK signals a breakdown of the standby route. Furthermore, the absence of both a BRANT update and an RERR alert confirms the total disconnection of all available paths. Under such circumstances, a complete route discovery process is re-initiated by the source node to reconnect with ND utilizing the GAAC framework.

Through this link repair mechanism, the algorithm achieves a fast response to and processing of link failures and breakage in the dynamic Vehicle Networking environment, and ensures the connectivity and reliability of data transmission.

III. EXPERIMENTATION AND ANALYSIS

To assess the proposed GAAC framework, this section details a comprehensive evaluation executed via a co-simulation environment integrating SUMO and NS-3. The performance metrics are benchmarked against legacy protocols, specifically AODV, AOMDV, and the EAA scheme[17].

A. Experimental Setup

The simulation scenario is set up as an inter-cluster backbone network consisting of 10 to 100 mobile nodes, which represent cluster heads. The nodes move in a predefined urban road environment with speed and density as key variables to be adjusted.

The core parameters of the algorithm are shown in Table I to provide a fair benchmark for comparison.

TABLE I. GENETIC-ANT COLONY FUSION ALGORITHM PARAMETERS

Parameters	**Value**
population size N	25
probability of mutation P_M	0.31
maximum number of iterations of the genetic algorithm	20
pheromone coefficients in probability transfer α	0.52
congestion metric β	0.83
link stability factor γ	0.78
latency measurement factor κ	0.84
ant colony random search probability P_0	0.5
localized pheromone volatility factor ρ	0.37
global pheromone volatilization factor δ	0.52
maximum number of iterations of ant colony algorithm	50

B. Ablation Experiment

To isolate and examine the individual contributions of the GA and ACO components, a series of ablation studies are performed. The proposed GAAC framework is benchmarked against two baseline configurations: a GA-only version for route optimization and a standalone ACO implementation utilizing a uniform initial pheromone distribution of 1/N. These variants are evaluated based on their convergence efficiency and overall network metrics, with the specific convergence data summarized in Table II.

TABLE II. COMPARISON OF ALGORITHM CONVERGENCE

	Finding the optimal solution		**30 Iterations**	
Algorithm	**Avg. Iterations**	**Avg. computing time (s)**	**Mean fitness value**	**Avg. computing time (s)**
GA	67	0.34	13.1	0.16
ACO	51	0.57	15.6	0.33
GAAC	34	0.28	17.3	0.24
GAAC	34	0.28	17.3	0.24

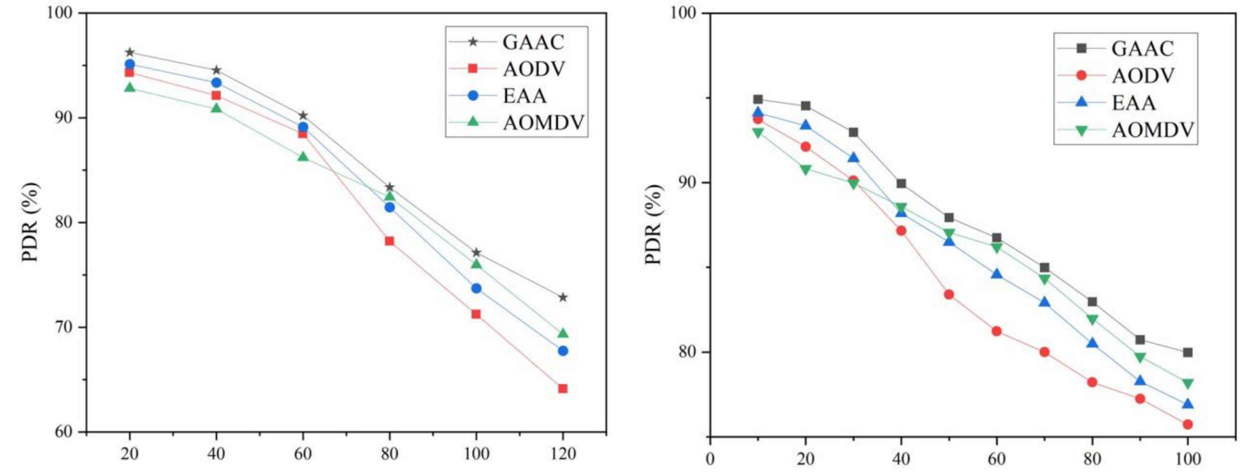
Observing the tabulated data, the GAAC framework identifies the global optimum within approximately 34 iterations on average, representing a substantial improvement in convergence efficiency over standalone GA and ACO methods. Under a constrained scenario of 30 iterations, the proposed integrated approach maintains a superior mean fitness score of 17.3, surpassing the path quality achieved by either the genetic or ant colony variants. These findings collectively underscore the GAAC algorithm's enhanced stability and faster search progression compared to its individual algorithmic components.

TABLE III. ALGORITHM NETWORK PERFORMANCE ABLATION EXPERIMENTS

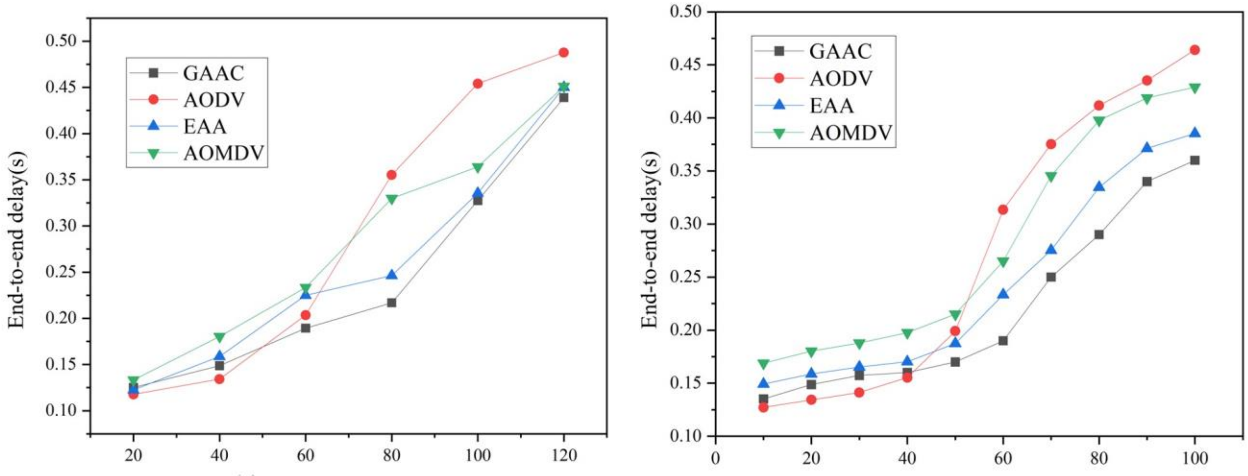
Algorithm	Packet delivery ratio	End-to-end delay (s)	Throughput （Kbps）	Routing overhead ratio
GA	79.31%	0.391	386.867	13.563%
ACO	80.49%	0.334	390.443	10.953%
GAAC	82.97%	0.297	460.456	10.720%

For the evaluation of network-wide performance through ablation studies, the simulation environment is configured with a population of 80 vehicular nodes traveling at a velocity of 40 km/h. The proposed GAAC framework undergoes a comparative assessment against standalone GA and ACO modules, focusing on critical metrics such as Packet Delivery Ratio (PDR), latency, network throughput, and standardized routing load. Upon reaching algorithmic stability, the comparative results for these performance indicators are tabulated in Table III.

As shown in the table, the routes found by the converged GAAC algorithm show significant improvements over those from the individual components. Compared to the ablation experiment using only GA, GAAC improved the packet delivery rate by 3.66%, reduced end-to-end delay by 0.094s, and increased throughput by 73.589 Kbps. Similarly, relative to the ablation experiment using only ACO, GAAC improved the packet delivery rate by 2.48%, reduced delay by 0.037s, and increased throughput by 70.013 Kbps.



(a) Vehicle speed(km/h) (b) Number of vehicles



(c) Vehicle speed(km/h) (d) Number of vehicles

Figure 6. Performance Comparison: PDR and End-to-End Delay

The experiment proves that the global search of GA provides high-quality initial solutions for ACO, while the local refinement of ACO improves the performance of the final path, and the fusion of the two achieves a synergistic effect.

C. Comparison Experiment

To evaluate the performance benefits and efficacy of the GAAC scheme, a comparative analysis is conducted against several benchmark protocols, including AODV, AOMDV, and the EAA routing framework.

The outcome of these simulations is illustrated in Fig 6 and Fig 7, which substantiate the resilient nature of the GAAC algorithm within volatile network settings.

1) Analysis of Delivery Success Ratio (PDR) and Transmission Latency

Observing the graphical data, a general decline in PDR is evident across all tested protocols as mobility and node concentration intensify; however, GAAC exhibits the most stable performance with minimal degradation. In the extreme scenarios of high dynamics (120 km/h) and high density (100 vehicles), GAAC still maintains its leading PDR, thanks to its multipath strategy and prioritization of link stability, which effectively reduces packet loss due to topology changes.

At low speed and low density, single-path protocols such as AODV showed a slight advantage due to their simplicity. However, once the network becomes more dynamic, its latency deteriorates dramatically due to frequent route disruptions and reconstruction. In contrast, GAAC, with its congestion awareness and link stability metrics, intelligently avoids congestion and unstable paths to maintain the lowest and most stable end-to-end delay even in the most complex scenarios.

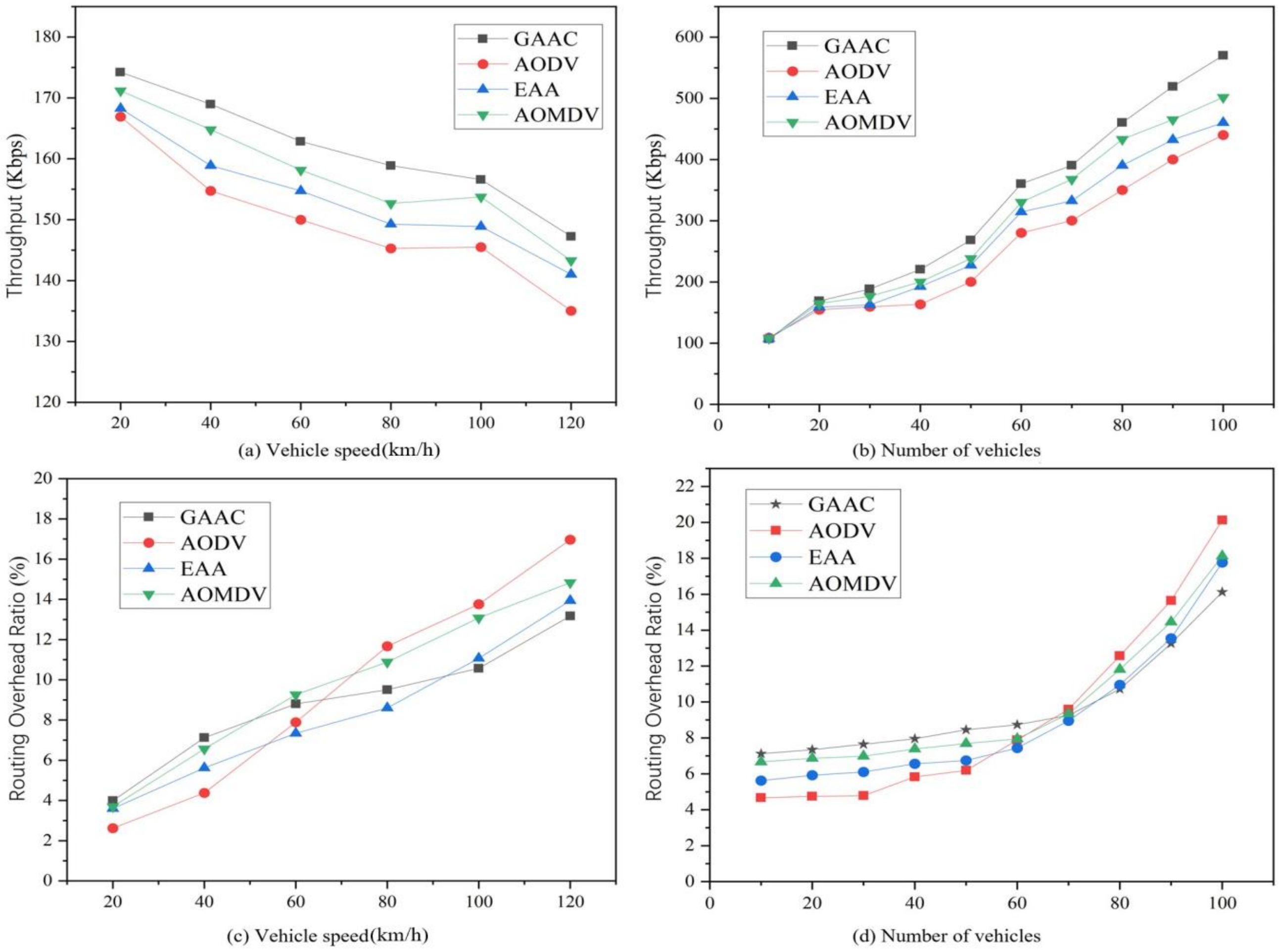


Figure 7. Performance Comparison: Throughput and Routing Overhead

2) *Throughput and Routing Overhead*

Across a spectrum of velocities and node concentrations, as illustrated by the comparative data in Fig 7(a) and Fig 7(b), the GAAC framework maintains a steady dominance in network throughput. This performance is primarily driven by its congestion-sensing logic, which adaptively reallocates data traffic toward nodes with lower utilization. Such a strategy effectively mitigates localized bottlenecks, thereby elevating the overall transmission capacity and throughput limits of the entire system.

GAAC has a relatively high overhead for establishing and maintaining multiple high-quality paths at low loads. However, as the network load, defined by the speed and number of vehicles, increases, its advantages begin to emerge. Since its routes are more stable and need to be rebuilt much less frequently than the other algorithms, its overhead grows slowly and ends up being lower than the other protocols in high load scenario. This suggests that GAAC trades a manageable upfront overhead for superior stability and scalability of the network under high load.

D. Conclusion of the Experiment

The experimental results fully demonstrate the comprehensive advantages of the GAAC algorithm. Primarily, by integrating the broad-spectrum exploration of Genetic Algorithms (GA) with the fine-grained exploitation potential of Ant Colony Optimization (ACO), the proposed framework attains superior convergence rates and enhanced network metrics compared to decoupled heuristic approaches. Furthermore, within intricate VANET environments characterized by rapid mobility and high node concentration, GAAC demonstrates significant proficiency in minimizing latency, curbing routing control traffic, and elevating both the success ratio of packet delivery and overall system throughput relative to legacy protocols. Finally, its delay performance of about 200 ms at 80 km/h aligns perfectly with the stringent temporal constraints of interactive multimedia services (e.g., audio-visual streaming requiring <400 ms), thereby confirming the industrial viability of the GAAC scheme in facilitating high-efficiency data exchange for VANET applications.

IV. CONCLUSIONS

This research introduces the GAAC protocol, a hybrid multipath solution that synthesizes Genetic Algorithms (GA) and Ant Colony Optimization (ACO) to mitigate congestion issues stemming from suboptimal inter-cluster coordination in partitioned vehicular networks. Moving beyond the simplistic minimum-hop selection logic, the proposed framework reformulates path determination as a multi-constrained optimization challenge, driven by a multidimensional assessment of link persistence, latency, and traffic density. To ensure computational efficiency, the algorithm harmonizes the broad-spectrum exploration of GA with the high-precision refinement of ACO, complemented by an adaptive link restoration protocol to manage volatile topological shifts.

Empirical evidence from extensive simulations highlights that the GAAC framework achieves a superior balance between search efficiency and operational throughput. When benchmarked against classical schemes like AODV and AOMDV, the GAAC approach demonstrates pronounced advantages in packet delivery success, latency reduction, and network capacity within demanding high-mobility and high-density environments. The resulting technical profile is robust enough to fulfill the Quality of Service (QoS) prerequisites for time-sensitive vehicular services, such as interactive multimedia traffic, thereby validating its practical utility for enhancing VANET reliability.

Although the GAAC algorithm proposed in this paper has achieved good results, there is still room for further optimization. Future research work can be carried out in two aspects: testing and validating the algorithm in more complex real traffic scenarios; and exploring the adaptive adjustment mechanism of the parameters to further enhance the robustness of the algorithm.

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