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A Survey on Intelligent Routing in Vehicular Ad Hoc Networks Using Deep Learning and Gannet Optimization

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***Abstract*—Vehicular Ad Hoc Networks (VANETs) have emerged as an important communication technology for intelligent transportation systems, enabling vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) communication. However, high vehicle mobility, rapidly changing network topology, intermittent connectivity, congestion, limited link lifetime, and stringent latency requirements make reliable routing a challenging problem. Conventional routing protocols are often unable to adapt rapidly to these dynamic conditions. Consequently, machine learning, deep learning, metaheuristic optimization, edge computing, and federated learning have increasingly been investigated for intelligent vehicular networking. Among metaheuristic techniques, the Gannet Optimization Algorithm (GOA) has attracted attention because of its exploration and exploitation mechanisms inspired by the foraging behavior of gannets. Recent research has demonstrated the applicability of GOA to VANET routing, while deep learning techniques such as graph convolutional networks, long short-term memory networks, graph neural networks, and attention mechanisms have been used for mobility prediction, congestion estimation, and intelligent routing. This paper surveys conventional VANET routing, optimization-based routing, GOA-based optimization, deep-learning-assisted routing, and edge/federated intelligence for vehicular networks. The comparative analysis identifies the strengths and limitations of existing approaches and highlights the lack of a unified framework that jointly exploits mobility-aware graph learning and adaptive multi-objective GOA for real-time routing. Based on this gap, a future research direction integrating graph learning, adaptive Gannet optimization, and edge intelligence is proposed.**

***Index Terms*—Vehicular Ad Hoc Networks, VANET, Internet of Vehicles, Gannet Optimization Algorithm, Deep Learning, Graph Neural Network, Intelligent Routing, Edge Computing, Federated Learning, Mobility Prediction.**

I. INTRODUCTION

The rapid development of intelligent transportation systems (ITS) has resulted in increasing deployment of connected and autonomous vehicles. Vehicular Ad Hoc Networks (VANETs) provide a distributed communication environment in which vehicles communicate directly with neighboring vehicles and roadside infrastructure. Unlike conventional wireless networks, VANETs are characterized by high node mobility, rapidly changing topology, variable vehicle density, short communication durations, and geographically constrained movement. These characteristics make routing one of the most challenging problems in vehicular communication.

Early VANET research concentrated on conventional topology-based, position-based, broadcast, multicast, and hybrid routing mechanisms. Li and Wang presented an early survey of VANET routing and emphasized the importance of mobility characteristics and specialized routing mechanisms for vehicular environments [1]. Subsequent research classified routing methods according to topology, geographic position, dissemination mechanism, and cross-layer information [2], [3].

The rapid growth of connected vehicles has increased the requirement for intelligent routing mechanisms capable of predicting network conditions rather than reacting only after route degradation occurs. Machine learning (ML) and deep learning (DL) have consequently been introduced for vehicle mobility prediction, traffic forecasting, congestion detection, link-quality estimation, and routing optimization.

Metaheuristic optimization algorithms provide another promising approach. These algorithms are particularly useful when routing involves multiple conflicting objectives, such as minimizing delay and routing overhead while maximizing packet delivery ratio and route lifetime. The Gannet Optimization Algorithm (GOA), introduced by Pan et al. in 2022, is a population-based metaheuristic inspired by gannet predatory behaviour [4]. GOA employs exploration and exploitation mechanisms based on diving, sudden rotation, and random wandering behaviour.

More recently, GOA has been incorporated into VANET routing. Sahu and Tripathy proposed a multitier routing mechanism combining Bellman-Ford with Fire Hawk Optimization, Gannet Optimization, and Mayfly Optimization [5]. This demonstrates that GOA is already being investigated in vehicular routing and therefore a simple “GOA-based VANET routing” framework would have limited novelty.

At the same time, recent deep-learning research has investigated graph-based and temporal models for intelligent routing. A GCN-LSTM framework has been proposed for adaptive routing and congestion control in urban VANETs, incorporating edge-cloud cooperation [6]. More recent work has explored federated Transformer-GNN architectures for smart routing in IoV and VANET environments [7]. These developments indicate a transition from reactive routing toward predictive and learning-driven routing.

Therefore, this survey investigates the evolution from conventional VANET routing to optimization-based, deep-learning-based, and edge-intelligent routing, with particular emphasis on the role of Gannet Optimization.

II. CHARACTERISTICS AND CHALLENGES OF VANETs

VANETs are specialized mobile ad hoc networks consisting primarily of vehicles and roadside infrastructure. The major communication modes include V2V, V2I, and V2X communication.

A. High Mobility

Vehicles may move at significantly different velocities and directions. Consequently, neighboring vehicles can enter and leave communication range rapidly.

B. Dynamic Network Topology

The topology of VANETs changes continuously. A route that is optimal at one instant may become unavailable shortly afterward.

C. Short Link Lifetime

Because vehicles are moving, communication links may exist only for a limited period. Route selection must therefore consider predicted link stability rather than only current distance.

D. Variable Vehicle Density

Urban environments can experience high vehicle density during peak periods, whereas highways and rural areas may have sparse connectivity.

E. Congestion

High traffic density can increase channel contention, queue length, packet loss, and communication delay.

F. Real-Time Requirements

Safety applications such as collision warning and emergency notification require low-latency and highly reliable communication.

G. Security and Privacy

Vehicular networks are vulnerable to false-message injection, Sybil attacks, impersonation, denial-of-service attacks, and privacy violations.

These characteristics demonstrate why routing protocols designed for relatively stable MANET environments cannot always be directly applied to VANETs.

III. CLASSIFICATION OF VANET ROUTING APPROACHES

VANET routing mechanisms can broadly be classified as follows:

A. Topology-Based Routing

Topology-based routing maintains information about neighboring nodes and network paths.

Examples include:

AODV,DSR,OLSR

These approaches are relatively simple but can experience significant routing overhead when topology changes rapidly.

B. Position-Based Routing

Position-based routing uses geographical information obtained through GPS or similar positioning systems.

Examples include:

GPSR,GSR,GPCR

Position-based approaches are particularly attractive for VANETs because vehicles have predictable geographical movement constraints.

C. Broadcast-Based Routing

Broadcast approaches are commonly used for safety messages, emergency notifications, traffic information, and cooperative awareness.

D. Cluster-Based Routing

Vehicles are grouped into clusters, and selected cluster heads manage communication within or between clusters.

E. Hybrid Routing

Hybrid methods combine multiple routing strategies to adapt to different network conditions.

F. Intelligent and Learning-Based Routing

Recent approaches use machine learning, deep learning, reinforcement learning, graph learning, and federated learning to predict traffic and network behaviour.

A comprehensive 2023 survey classified VANET routing according to topology, position, dissemination mechanism, and application characteristics and highlighted persistent challenges caused by mobility, sparse connectivity, obstacles, and limited roadside infrastructure [3].

IV. METAHEURISTIC OPTIMIZATION FOR VANET ROUTING

Routing can be formulated as a multi-objective optimization problem. A route may need to simultaneously minimize delay, packet loss, congestion, and routing overhead while maximizing reliability and link lifetime.

A generalized routing fitness function can be represented as:

where:

$D(R)$= end-to-end delay,

$C(R)$= congestion,

$L(R)$= link instability,

$O(R)$= routing overhead,

$PDR(R)$= packet delivery ratio,

w_i= weighting coefficients.
Metaheuristic algorithms are useful because conventional deterministic methods can become computationally expensive when the search space is large and network conditions change continuously.

Commonly investigated optimization algorithms include:
Particle Swarm Optimization (PSO)
Genetic Algorithm (GA)
Ant Colony Optimization (ACO)
Grey Wolf Optimization (GWO)
Firefly Algorithm
Mayfly Optimization
Fire Hawk Optimization
Gannet Optimization Algorithm

However, the effectiveness of an optimization algorithm depends strongly on the selection of the objective function and the quality of network-state information supplied to it.

V. GANNET OPTIMIZATION ALGORITHM

A. Background

The Gannet Optimization Algorithm was introduced by Pan et al. in 2022 [4]. It models the predatory behaviour of gannets and uses two major phases:
Exploration
Exploitation

The exploration mechanism incorporates U-shaped and V-shaped diving behaviour, whereas exploitation includes sudden rotation and random wandering mechanisms [4].
The original GOA was evaluated using 28 benchmark functions and five engineering optimization problems. The study reported competitive optimization performance compared with several existing metaheuristics [4].

B. Relevance to VANET

GOA is potentially suitable for VANET routing because routing involves a large and dynamic search space.
A gannet population can represent candidate routes:
where each candidate represents a possible routing solution.
The fitness of each candidate route can be evaluated according to:
The optimal gannet position corresponds to the best route according to the selected objective function.

VI. GOA-BASED VANET ROUTING: EXISTING RESEARCH

One of the most directly relevant studies was presented by Sahu and Tripathy. Their work combines Bellman-Ford routing with Fire Hawk Optimization, Gannet Optimization, and Mayfly Optimization in a multitier framework for VANET routing [5].

The study considered traffic densities ranging from 500 to 5000 and evaluated latency, data delivery rate, throughput, and energy efficiency. At the highest reported traffic density, the framework achieved a latency of 3.88 ms, data delivery rate of 0.944, throughput of 2.94 Mbps, and energy efficiency of 97.14% [5].

This study is important because it establishes that GOA has already been applied to VANET routing.

Therefore:

GOA + VANET routing alone should not be claimed as a novel contribution.

A new study must provide additional innovation, such as mobility prediction, adaptive parameter control, multi-objective optimization, graph learning, federated learning, or edge intelligence.

VII. DEEP LEARNING FOR VANET ROUTING

Deep learning provides the ability to learn complex relationships between vehicle mobility, traffic conditions, network topology, and routing decisions.

A. CNN-Based Approaches

CNN models can extract spatial features from transformed traffic or network representations. However, conventional CNNs may not naturally represent dynamic relationships between individual vehicles.

B. LSTM-Based Approaches

LSTM networks are useful for modeling temporal sequences such as:

Vehicle speed
Position
Traffic density
Link quality
Congestion

However, LSTM models alone may not adequately represent the graph structure of vehicular networks.

C. GCN-Based Approaches

Graph Convolutional Networks model vehicles as graph nodes and communication relationships as graph edges. This makes GCNs particularly suitable for VANETs.

D. GCN-LSTM Hybrid Models

Recent work has combined GCN and LSTM to capture both spatial and temporal dependencies. A 2026 study reported a GCN-LSTM framework for adaptive routing and congestion control in urban VANETs, with edge-cloud cooperation for real-time processing [6].

The reported framework achieved a packet delivery ratio of approximately 95% and routing latency of 38.13 ms in its reported experimental configuration [6].

E. Transformer-GNN Models

Recent work has moved toward Transformer-GNN combinations. FL-TrafficNet integrates federated learning, Transformer encoders, GNNs, and dual attention for routing in IoV and VANET environments [7].

The combination captures:

Spatial vehicle relationships using GNNs

Temporal variations using Transformers

Distributed training using federated learning

This represents an important recent direction in intelligent vehicular networking.

VIII. GANNET OPTIMIZATION AND DEEP LEARNING

GOA has also been combined with deep learning in non-VANET domains.

Rajakani et al. proposed a GOA-based attention deep-learning intrusion detection system for IoT networks [8]. Their framework used GOA for feature selection and attention-LSTM for intrusion detection.

Another recent study introduced an improved GOA for feature weighting in an IoT intrusion detection framework using deep learning [9].

These studies demonstrate that GOA can effectively complement deep learning by performing:

Feature selection

Feature weighting

Hyperparameter optimization

Search-space optimization

However, these approaches are primarily focused on IoT security rather than dynamic vehicular routing.

This creates an opportunity to investigate how GOA can interact with mobility-aware graph learning in VANETs.

IX. EDGE AND FEDERATED LEARNING IN VEHICULAR NETWORKS

Cloud computing provides high computational capacity but may introduce communication latency when real-time routing decisions are required.

Edge computing moves computation closer to vehicles through roadside units and edge servers.

A representative architecture is:
Vehicle → RSU → Edge Server → Cloud
The edge layer can perform:
Mobility prediction
Link-quality prediction
Congestion estimation
Route optimization
Security analysis
Recent GCN-LSTM research has demonstrated the usefulness of edge-cloud cooperation for adaptive routing in urban VANETs [16].
Federated learning provides an additional advantage by allowing vehicles or RSUs to train local models while sharing model parameters rather than raw vehicle data.
The 2026 FL-TrafficNet framework combines federated learning with Transformer-GNN architectures for intelligent routing in IoV/VANET environments [7].
A separate 2026 study proposed an attention-based deep-learning routing framework with federated learning for privacy-preserving route prediction in urban vehicular networks [10].
These developments indicate that future VANET routing systems are likely to become increasingly: Distributed , Predictive, Privacy-aware, Edge-assisted, AI-driven

X. COMPARATIVE ANALYSIS

The table shows that existing methods generally emphasize either optimization or learning. A unified framework that performs mobility prediction followed by adaptive multi-objective route optimization remains a promising research direction.

XI. CONCLUSION

This survey gives an insight about the development of intelligent routing approaches for Vehicular Ad Hoc Networks, with particular emphasis on metaheuristic optimization, Gannet Optimization, deep learning, edge computing, and federated learning. Traditional VANET routing approaches are challenged by high mobility, rapid topology changes, congestion, intermittent connectivity, and stringent latency requirements. Metaheuristic algorithms provide effective search capabilities for complex routing problems, while the Gannet Optimization Algorithm offers a promising optimization mechanism based on exploration and exploitation behaviours. However, existing research has already applied GOA to VANET routing, indicating that GOA alone is insufficient to establish strong novelty.
Deep learning approaches, particularly GCN-LSTM, GNN, Transformer-GNN, and federated learning, provide predictive capabilities that are valuable for dynamic vehicular environments. Recent research demonstrates a clear movement toward spatial-temporal learning, privacy-preserving intelligence, and edge-cloud cooperation.

TABLE 1. COMPARATIVE ANALYSIS OF VANET ROUTING APPROACHES

Approach	Mobility Awareness	Optimization	Deep Learning	Edge Support	Major Limitation
AODV	Low	No	No	No	Frequent route breakage
GPSR	Medium	No	No	No	Position dependency
PSO Routing	Medium	Yes	No	Possible	Parameter sensitivity
GWO Routing	Medium	Yes	No	Possible	May converge prematurely
GOA Routing	Medium	Yes	No	Possible	Limited mobility prediction
Multi-metaheuristic GOA	High	Yes	No	Possible	Increased complexity
GCN-LSTM	High	Limited	Yes	Yes	Training/inference cost
Transformer-GNN	High	Limited	Yes	Yes	High computational demand
Federated DL	High	Limited	Yes	Yes	Communication/training overhead
GAT + Adaptive GOA	High	Yes	Yes	Yes	Research direction

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