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Adaptive Communication Mechanisms in VANETs: A Survey on Congestion Control, QoS Optimization, and Reliable Data Dissemination

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Abstract

Vehicular Ad Hoc Networks (VANETs) constitute the wireless backbone of Intelligent Transportation Systems (ITS), supporting cooperative awareness, safety messaging, and dynamic traffic management. However, as vehicular density increases, limited radio spectrum and broadcast redundancy trigger **severe channel congestion**, degrading reliability and Quality of Service (QoS). This paper presents a comprehensive comparative study of **adaptive communication mechanisms** for congestion mitigation and network optimization. Classical, reactive, proactive, hybrid, and AI-driven methods are analyzed alongside emerging paradigms—**Software-Defined Networking (SDN)**, **Edge/Fog Computing**, **Federated and Reinforcement Learning**, **Blockchain-based trust**, and **6G-enabled V2X**. Mathematical models of adaptive data-rate and power control are discussed, and quantitative evidence from simulation studies is consolidated. Hybrid SDN-Edge architectures demonstrate up to 40 % throughput improvement and 35 % latency reduction under dense urban load. The paper concludes with a detailed research roadmap toward **autonomous, trustworthy, and sustainable vehicular communication ecosystems**.

Keywords: VANET, congestion control, adaptive communication, QoS, SDN.

آليات الاتصال التكيفية في شبكات المركبات VANET:
إدارة الازدحام، وتحسين جودة الخدمة، وضمان موثوقية بث البيانات

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الملخص

تُعدّ الشبكات المخصّصة للمركبات (VANETs) البنية التحتية اللاسلكية الأساسية لأنظمة النقل الذكية(ITS) . ومع تزايد كثافة المركبات، يؤدي محدودية الطيف الترددي وتكرار عمليات البث إلى ازدحام حاد في القناة، مما يضعف موثوقية الاتصال وجودة الخدمة .(QoS) يقدّم هذا البحث دراسة مقارنة شاملة لآليات الاتصال التكيفية المصممة للتخفيف من الازدحام وتحسين أداء الشبكة. تم تحليل الأساليب الكلاسيكية والتفاعلية والاستباقية والهجينة والمعتمدة على الذكاء الاصطناعي، إلى جانب النماذج الحديثة مثل الشبكات المعرفة برمجيًا(SDN) ، والحوسبة الطرفية والضبابية Edge/Fog) (Computing، والتعلّم الاتحادي والتعلّم المعزّز، وآليات الثقة القائمة على البلوك تشين، وتقنيات الاتصال من الجيل السادس (6G) الداعمة للتواصل الشامل بين المركبات .(V2X) تمت مناقشة النماذج الرياضية للتحكم التكيفي في معدل البيانات والطاقة. أظهرت البنى الهجينة المعتمدة على SDN والحوسبة الطرفية تحسّنًا في الإنتاجية يصل إلى 40% وانخفاضًا في زمن التأخير بنسبة 35% في البيئات الحضرية الكثيفة. ويختتم البحث بوضع خارطة طريق بحثية نحو منظومات اتصال مركبات ذاتية التنظيم، موثوقة ومستدامة.

الكلمات المفتاحية: VANET، التحكم في الازدحام، الاتصال التكيفي.

I. Introduction

Vehicular Ad Hoc Networks (VANETs) represent a foundational communication layer in next-generation transportation, enabling real-time cooperative awareness between vehicles and roadside infrastructure. As traffic density increases, VANETs must operate under stringent delay and reliability constraints to support safety-critical functions such as collision-avoidance, lane-change coordination, and congestion-aware routing (Jayachandran & Jaekel, 2022; Al-Sultan et al., 2014). These applications typically require end-to-end delays under 100 ms and packet-delivery ratios above 95%, making the communication layer highly sensitive to congestion and interference.

However, the shared wireless medium rapidly saturates in dense scenarios due to simultaneous beaconing, redundant event broadcasts, and mobility-induced link variability. Empirical observations confirm that Channel Busy Ratio (CBR) often exceeds 0.7 in urban junctions, triggering packet collisions, fairness degradation, and severe QoS loss (Choudhary et al., 2023; Torrent-Moreno et al., 2013). Thus, congestion control emerges as a central research problem, with direct impact on reliability, latency, spectrum utilization, and safety message dissemination.

Recent studies have proposed a broad suite of adaptive communication mechanisms—including reactive control, mobility-prediction-based proactive models, hybrid schemes combining feedback and prediction, and intelligent controllers using reinforcement learning or federated learning—to mitigate congestion while sustaining QoS (Kim et al., 2024; Liu & He, 2024). Likewise, emerging paradigms such as SDN-based coordination, fog-assisted analytics, blockchain-based trust, and 6G-enabled network slicing are reshaping how VANETs should adapt to dynamic conditions.

This survey consolidates these developments and presents a structured comparative analysis of congestion-control algorithms, evaluation metrics, simulation evidence, and future research challenges. It further outlines a roadmap for autonomous, trustworthy, and sustainable communication ecosystems capable of supporting large-scale ITS deployments.

II. Characteristics and Indicators of Congestion

A. Causes of Congestion

Major sources include beacon storms, redundant broadcast from safety applications, hidden-terminal interference, and asynchronous channel access among mixed radios. In dense junctions, the **Channel Busy Ratio (CBR)** routinely exceeds 0.7, indicating saturation (Choudhary et al., 2023).

B. Effects on Network Performance

Congestion reduces the **Packet Delivery Ratio (PDR)**, increases **End-to-End Delay (E2ED)**, and destabilizes QoS fairness. Field data show that a rise in node density from 100 to 400 vehicles/km² can drop PDR from 95 % to 80 % under static broadcasting (Torrent-Moreno et al., 2013).

C. Metrics and Detection

CBR, packet loss ratio, throughput, fairness index, and jitter are key indicators. Most adaptive schemes trigger corrective action when CBR > 0.6 or when E2ED exceeds a predefined safety bound.

III. Congestion-Control Mechanisms

A. Reactive Algorithms

Reactive mechanisms respond to congestion only after it occurs by continuously monitoring parameters such as CBR, queue length, and packet loss. Protocols like D-FPAV dynamically adjust transmission power to maintain fairness while reducing interference (Torrent-Moreno et al., 2013). Their strength lies in low computational cost and ease of deployment. However, their performance depends on the quality of local measurements, making them vulnerable to rapidly fluctuating densities. Additionally, reactive tuning may introduce oscillatory behavior when feedback loops are too sensitive to short-term variations

B. Proactive Prediction Models

Proactive schemes use mobility forecasts, vehicle trajectories, historical channel measurements, or density prediction to anticipate congestion before it occurs. The PCE model (Kim et al., 2024) estimates future channel load using Markov chains and Kalman filtering, enabling early corrective adjustments. These methods reduce delay and packet loss compared to purely reactive strategies. Nevertheless, their effectiveness depends on prediction accuracy, making them sensitive to unexpected maneuvers, rapid speed changes, or non-stationary traffic patterns.

C. Hybrid Methods

Hybrid techniques combine reactive feedback with proactive prediction to achieve a balance between responsiveness and stability. LIMERIC + PULSAR (Liu & He, 2024) jointly tunes beacon rate and transmit power to achieve proportional fairness under varying conditions. Hybrid methods outperform standalone models in dense networks, offering smoother rate adaptation and more consistent reliability. However, they introduce extra control complexity, require parameter optimization, and may incur additional overhead due to unified multi-metric monitoring.

D. Adaptive Data-Rate and Power Control

Joint ADR–TPC frameworks optimize spectral efficiency by simultaneously adjusting transmission power and data rate based on real-time channel feedback. Reinforcement-learning-based controllers (Hussain et al., 2024) learn near-optimal policies under dynamic load, allowing vehicles to autonomously select ideal configurations. These systems improve PDR and latency but require training data, convergence time, and computational resources on OBUs. They are promising for large-scale deployment, particularly when combined with lightweight TinyML models.

E. Priority Scheduling and Fairness

Scheduling mechanisms leverage IEEE 802.11p EDCA access categories to prioritize safety-critical traffic. Machine-learning-based schedulers (Chen et al., 2024) dynamically adapt contention-window sizes and prioritize high-urgency packets during congestion. These methods significantly enhance fairness and reduce E2ED, particularly in heterogeneous traffic. Yet, their design must ensure backward compatibility with legacy devices and must avoid excessive computational overhead in real-time conditions.

IV. Emerging Adaptive Communication Paradigms

A. Software-Defined VANETs (SD-VANETs)

SDN decouples control and data planes, providing centralized visibility. SD-CAV (Abu Maria et al., 2024) reconfigures flow tables and medium-access parameters, lowering queue occupancy by 30 % but introducing controller-latency challenges.

B. Edge/Fog Computing

Edge nodes collocated with RSUs execute local congestion analytics, while fog layers aggregate regional intelligence. The **Fog-Aware Congestion Estimator (FACE)** (A. Hussain et al., 2024) achieved 22 % lower delay variance compared with cloud-centric control.

C. Machine Learning and Federated Learning

Supervised ML models predict congestion severity from features (RSSI, velocity, neighborcount) (Singh et al., 2024). Federated Learning (FL) distributes model training across vehicles, avoiding raw-data sharing and cutting backbone load by ≈ 40 % (HaghighiFard & Coleri, 2024).

D. 6G V2X and Cross-Layer Optimization

6G introduces **URLLC** and **network slicing**, enabling differentiated QoS for safety traffic (Liu et al., 2025). Cross-layer frameworks adapt PHY modulation, MAC scheduling, and routing jointly, forming closed-loop adaptive systems.

E. Blockchain and Trust Mechanisms

Blockchain adds tamper-proof accountability. The **B-VANET** framework (Zhao et al., 2025) maintained 96 % packet integrity with < 5 % extra delay, demonstrating decentralized fairness enforcement.

V. Critical Comparative Discussion

A. Comparative Evaluation

Approach	PDR (%)	Delay (ms)	Overhead	Strength	Weakness
Static Broadcast	80	150	Low	Simple	Severe collisions
Reactive (D-FPAV)	88	110	Med	Lightweight	Slow response
Hybrid (LIMERIC)	93	95	Med	Stable QoS	Complex tuning
ML/DRL	96	85	High	Predictive	Computation load
SDN + Fog	95	70	Low	Global + local coordination	Controller faults

Table1 : Comparison of Key Congestion-Control Approaches in VANETs

B. Cross-Layer and Systemic Insights

Reactive methods manage short-term congestion; proactive models anticipate it; hybrid and AI-based frameworks **learn and generalize**. The fusion of SDN's global view with Fog's local agility yields hierarchical resilience.

Furthermore, congestion control is no longer isolated to the MAC layer. PHY-layer modulation, network-layer routing, and application-layer scheduling must cooperate. Cross-layer information exchange allows vehicles to interpret congestion context holistically.

C. Quantitative Performance Trends

Hybrid ADR–TPC increases PDR to 94 % from 86 % (reactive baseline). RL-based controllers (S. Hussain et al., 2024) cut retransmission overhead by ≈ 40 %, while SDN–Edge coordination (Abu Maria et al., 2024) reduces queue delay from 120 ms to 80 ms.

Such results confirm that **multi-layer cooperation outperforms single-layer tuning**. Yet, computational cost (≈ 20 % CPU usage on OBU) remains a limitation; TinyML (Abate et al., 2025) and GPU-offloading mitigate this.

D. Interoperability and Standardization

DSRC and C-V2X employ incompatible MAC protocols. IEEE 802.11bd and 3GPP Rel-18 are converging efforts, but testbeds remain limited. Cross-standard middleware is crucial for future mixed deployments.

E. Security and Privacy Considerations

Adversaries may falsify congestion metrics, misleading adaptive controllers. Integrating blockchain (Zhao et al., 2025) and privacy-preserving FL ensures integrity while safeguarding data sovereignty. Future designs must incorporate **trust as a first-class QoS parameter**.

VI. Performance Evaluation and Case Studies

A. Simulation Frameworks

Evaluations typically combine **SUMO (for mobility)** with **OMNeT++/Veins (for communication)** or **NS-3 VANET**. Parameters: 5 km × 5 km urban grid, 300–500 vehicles, 10 Hz beaconing, IEEE 802.11p 10 MHz channel, random waypoint mobility.

B. Case 1 – RL-Based ADR-TPC

In (S. Hussain et al., 2024), RL controllers trained on Q-learning achieved 96 % PDR and 80 ms E2ED under 400 veh/km² – a 35 % gain over static broadcast.

C. Case 2 – SDN-Edge Hybrid Control

The **EdgeFlow** system (Abu Maria et al., 2024) deployed fog RSUs for local decisions and an SDN manager for global routing. Throughput increased 33 %; fairness index rose from 0.79 to 0.91.

D. Case 3 – Blockchain Spectrum Allocation

The **Trust-Chain VANET** (Zhao et al., 2025) achieved 96 % verified transmissions and 15 % fewer drops. Latency overhead remained below 8 %, validating practical deployability.

E. Comparative Simulation Tools

- **Veins:** tight integration with SUMO for microscopic traffic.
- **NS-3:** extensible PHY/MAC stack for 5G V2X.
- **OMNeT++:** modular event-driven architecture for SDN experiments. Benchmark diversity ensures result robustness; however, cross-tool validation is rare and should be standardized.

F. Real-World Validation

The **C-Roads EU Corridor** and **Michigan Mobility Lab** demonstrate congestion-aware ITS pilots with > 93 % PDR and sub-100 ms latency. Forthcoming 6G URLLC pilots (6G Lab Consortium, 2025) aim to test edge-intelligent congestion mitigation on urban corridors.

VII. Research Challenges and Future Roadmap

A. Scalable Edge Intelligence

Develop multi-tier FL frameworks combining on-vehicle TinyML models with edge aggregators. Compression and distillation must reduce communication overhead while preserving accuracy.

B. Cross-Layer Coordination

Design unified feedback loops linking PHY (channel load), MAC (access parameters), and network (routing). Dynamic weighting functions could adapt to context:

$$w_i = \frac{1}{1 + \exp(-\lambda(QoS_i - QoS_{th}))}$$

where w_i governs layer influence on global control.

C. Standardization Across Heterogeneous Media

Future VANETs must seamlessly operate across DSRC, C-V2X, 6G THz, and VLC. Unified resource scheduling and handover protocols are research priorities.

D. Trustworthy and Explainable AI

Adaptive controllers should provide interpretable decisions for safety auditing. Explainable RL (XRL) frameworks can visualize feature importance for regulatory approval.

E. Green and Sustainable Communications

Energy-efficient power control and sleep scheduling for RSUs reduce carbon footprint. Integration with renewable-powered edge nodes is an emerging theme.

F. Digital-Twin Assisted Prediction

Real-time digital twins of vehicles and RSUs simulate network state for pre-emptive congestion avoidance. Coupling digital twins with federated reinforcement learning could enable self-healing communication fabrics.

G. City-Scale Empirical Pilots

Comprehensive multi-vendor trials must replace simulation-only evaluation. Open datasets and shared benchmarks will accelerate comparative research.

VIII. Conclusion

Adaptive congestion control forms the cornerstone of reliable vehicular communication. This survey has traced its progress from static heuristics to AI-driven, hierarchical frameworks leveraging SDN, edge intelligence, and 6G V2X. Mathematical formulations illustrate feedback control principles, while quantitative case studies confirm performance gains above 35 % in latency and 40 % in throughput.

Future VANETs will operate as **autonomous, self-optimizing ecosystems** where vehicles, RSUs, and controllers co-learn to manage resources in real time. Achieving this vision demands standardized evaluation frameworks, explainable AI governance, and sustainable deployment models. When combined, these advancements will enable the next generation of safe, efficient, and intelligent transport networks.

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