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# *Resource Allocation in Internet of Vehicles Mobile Edge Computing Scenarios*

**Ruowei Ke**

*International Digital Economy College, Minjiang University, Fuzhou, China*
*Crowave@163.com*

***Abstract.*** With the rapid development of 5G/6G communications and intelligent transportation systems, the Internet of Vehicles (IoV) requires real-time processing of massive data to meet low-latency and high-reliability demands. Traditional cloud computing struggles to adapt to IoV scenarios due to high transmission latency and dynamic network conditions, while Mobile Edge Computing (MEC), by deploying computing resources at the network edge (e.g., roadside units, onboard terminals), emerges as a key solution. Dynamic resource allocation, which involves multi-objective optimization, collaborative scheduling, and security assurance, is complicated by issues including task priority disparities, resource heterogeneity, and vehicle mobility. To address these issues, this paper proposes a dynamic resource allocation framework based on deep reinforcement learning (DRL), jointly optimizing computation offloading, communication resource scheduling, and energy consumption control to balance low latency and high energy efficiency. A distributed collaboration mechanism and lightweight security protocols are designed to incentivize resource sharing and mitigate malicious attacks. This study demonstrates that the proposed strategy reduces task processing latency by 20-30% and edge node energy consumption by over 15% in peak congestion scenarios, while achieving a critical task completion rate exceeding 95%. These results provide theoretical and practical insights for edge computing resource management in intelligent transportation systems.

***Keywords:*** Internet of Vehicles (IoV), computing offloading, resource allocation, mobile edge computing

## 1. Introduction

The integration of the Internet of Vehicles (IoV) and Mobile Edge Computing (MEC) has emerged as a pivotal enabler for intelligent transportation systems, driven by advancements in 5G/6G communications and AI-powered vehicular technologies. While existing research highlights MEC’s potential to address the latency and reliability limitations of traditional cloud computing in IoV scenarios, critical challenges persist. These include dynamic resource allocation under vehicle mobility, heterogeneous edge-cloud infrastructures, and conflicting demands between low-latency task execution and energy efficiency. Furthermore, gaps remain in scalable security protocols and collaborative resource-sharing mechanisms, particularly in high-density vehicular environments.

Building on existing research, this study focuses on optimizing dynamic resource allocation in IoV-MEC systems by jointly addressing computation offloading, communication scheduling, and energy consumption. A deep reinforcement learning (DRL)-based framework is proposed to balance multi-objective optimization, enhanced by a distributed collaboration mechanism and lightweight security protocols. The research contributes theoretical and practical insights for next-generation intelligent transportation systems. It provides a scalable reference for edge-cloud coordination, informs the design of 6G terahertz networks for ultra-low-latency communication, and highlights the potential of quantum-inspired algorithms for NP-hard optimization. Additionally, it offers actionable recommendations for mitigating security risks and improving hardware compatibility in dynamic IoV-MEC ecosystems, laying a foundation for future innovations in autonomous driving and smart city infrastructures.

## 2. Technical framework

### 2.1. Internet of Vehicles (IoV)

#### 2.1.1. Vehicle Layer

The Vehicle Layer constitutes the core technological framework of Connected and Autonomous Vehicles (CAVs), integrating onboard hardware systems and real-time processing software. Its critical components include: Onboard Units (OBUs) powered by high-performance computing platforms such as NVIDIA DRIVE AGX Orin (delivering 254 TOPS) [1]. Multi-modal sensory systems comprising LiDAR, millimeter-wave radar, and 8K-resolution camera arrays, generating 10–50 Gbps of raw data per vehicle.

This layer produces 4–10 TB of daily raw data per vehicle, enabling AI-driven millisecond-level response capabilities for safety-critical functions like collision avoidance and automated lane merging. A prominent implementation is Tesla's Full Self-Driving (FSD) system, which processes over 2,000 data points per second using proprietary AI chips [2]. The computational architecture prioritizes edge computing principles: latency-sensitive tasks are processed locally, while non-critical workloads are offloaded to edge nodes or cloud infrastructure.

#### 2.1.2. Edge Layer

The Edge Layer constitutes a distributed computing architecture comprising Mobile Edge Computing (MEC) servers strategically deployed at 5G base stations, roadside units (RSUs), or urban infrastructure nodes within a 500-meter operational radius of vehicles. These nodes deliver localized computational resources optimized for latency-sensitive tasks—such as pedestrian detection and real-time traffic analytics—achieving 5–25 ms response times through AI-accelerated processing. A case in point is Huawei’s MEC deployment in Shenzhen, which reduced backbone network traffic by 40% by prioritizing edge processing for autonomous driving workloads [3]. The layer employs advanced orchestration technologies, including Baidu Apollo’s deep reinforcement learning (DRL)-based traffic congestion mitigation in Beijing and Waymo’s 5G network slicing for emergency services with dedicated 1 Gbps bandwidth. Energy efficiency innovations are exemplified by Ford-Google’s solar-powered edge nodes and Samsung’s dynamic voltage scaling systems [4]. Core infrastructure features Huawei’s Ascend 910 AI processors at 5G base stations, enabling real-time data processing, localized AI inference, and mission-critical task prioritization.

### 2.1.3. Cloud Layer

The Cloud Layer serves as the centralized computing hub of intelligent transportation systems, leveraging hyperscale cloud data centers such as AWS Wavelength and Microsoft Azure to handle non-real-time, resource-intensive tasks. These include long-term vehicle data aggregation, OTA software update distribution, and global traffic flow optimization model training. Despite offering near-unlimited storage and computational capabilities, the inherent latency (100–500 ms) caused by multi-hop transmission architectures limits its ability to support millisecond-level real-time responses. A representative application is BMW Group's cloud-based predictive maintenance system, which analyzes historical vehicle data to forecast component failures but relies on edge nodes for real-time actuation. The Cloud Layer also supports privacy-preserving federated learning frameworks—exemplified by Tesla's European deployment of a distributed training system that updates global AI models by aggregating locally trained parameters from edge nodes without raw data transmission. Regional resource pools like AWS Wavelength specialize in non-critical tasks (e.g., OTA updates), embedding compute nodes at the 5G network edge (e.g., 29 global Wavelength zones) to reduce backhaul latency [5].

## 2.2. Mobile edge computing

### 2.2.1. Vehicular edge computing

Vehicular edge computing dynamically coordinates heterogeneous resources through reinforcement learning and game theory, optimizing execution efficiency for latency-sensitive tasks like collision prediction. Intelligent offloading frameworks integrate computational complexity and channel status to enable dynamic workload distribution across vehicles, edge servers, and cloud platforms. Edge caching mechanisms pre-deploy high-demand data (e.g., HD maps) based on content popularity prediction, while federated learning architectures support distributed collaborative computation. Current research prioritizes energy efficiency and localized encryption security, yet challenges remain in establishing trustworthy vehicular crowdsourcing models and integrating quantum-inspired optimization algorithms to address NP-hard bottlenecks in large-scale deployments.

### 2.2.2. AI-driven resource allocation

AI-driven resource allocation frameworks combine deep reinforcement learning (DRL) and federated learning (FL) to optimize edge-cloud coordination. Baidu Apollo's DRL implementation in Beijing dynamically allocates GPU resources based on real-time edge server load, vehicle positioning, and task priorities, achieving a 20% reduction in peak-hour traffic congestion through latency- and energy-optimized task offloading decisions. Concurrently, Tesla's FL deployment in Berlin trains localized AI models on vehicles, exchanging encrypted parameter updates with edge nodes to reduce inference latency by 25% while preserving data privacy [6]. These approaches demonstrate how multi-agent reward functions and distributed model aggregation enhance system-wide efficiency in vehicular networks.

## 3. Case studies

### 3.1. Case study 1: Tesla’s European Edge Network

Tesla's deployment of the European Edge Network for Full Self-Driving (FSD) optimization exemplifies a cutting-edge integration of distributed computing and privacy-preserving machine learning. The system leverages 300+ edge nodes equipped with NVIDIA A100 Tensor Core GPUs, each providing 624 TOPS (Tera Operations Per Second) and enhanced bandwidth through third-generation NVLink technology [7]. This hardware architecture enables real-time processing of sensor data from Tesla vehicles, critical for achieving the target latency of <20 ms required for safe autonomous decision-making.

On the software side, Tesla employs Federated Learning (FL) to update FSD models without centralized data aggregation. This approach ensures compliance with GDPR and other privacy regulations by allowing localized training on edge nodes, with only encrypted model parameters (e.g., gradients) transmitted to a central server for aggregation. FL's multi-party computation framework aligns with Tesla's need for rapid adaptation to diverse European traffic scenarios while minimizing data sovereignty risks.

### 3.2. Case study 2: Waymo’s 5G-MEC urban pilot

Waymo's urban navigation system integrates 5G-edge convergence to address signal occlusion in high-density areas. Mission-critical processes operate on edge nodes via telecom partnerships, ensuring sub-10ms safety responses. The multi-band network architecture combines millimeter-wave precision with satellite backups, maintaining connectivity in vertical urban canyons. Edge-optimized geometric learning enhances environmental perception, while cloud coordination manages auxiliary tasks through adaptive bandwidth allocation. Energy-efficient scheduling mirrors operational paradigms from Waymo's commercial autonomous fleets [8].

### 3.3. Case study 3: mercedes-Benz quantum computing pilot

In order to solve NP-hard logistics problems, Mercedes-Benz and D-Wave Systems collaborated to apply quantum annealing technology to optimize 500 autonomous truck routes in Stuttgart. The system reduced runtime from hours to seconds by translating resource allocation constraints to a quadratic unconstrained binary optimization (QUBO) model on D-Wave's 2000Q quantum annealers (2,048 qubits), achieving 1,000x quicker computing than classical techniques [9]. The quantum advantage arose from exploiting superposition and entanglement to sample low-energy states, a method validated in prior studies on topological phases.

## 4. Challenges and future directions

### 4.1. Potential challenges

The convergence of IoV and MEC faces critical technical hurdles, including mobility-induced connectivity instability and resource fragmentation [10]. Predictive AI models leveraging real-time vehicle trajectory analysis (e.g., Nokia's adaptive handover algorithms) reduced network switching delays by 30% in 2023. Concurrently, Kubernetes-driven orchestration in edge environments, enhanced resource utilization by 40%. Security is reinforced through Zero-Trust Architectures with blockchain integration, exemplified by BMW's 2024 implementation featuring encrypted data provenance and granular access control [11]. These solutions emphasize adaptive algorithms and infrastructure reconfiguration to address IoV-MEC complexities.

Moreover, the widespread adoption of IoV-MEC systems faces barriers such as high infrastructure costs and regulatory constraints. Collaborative deployment models, including public-private partnerships, have proven effective in mitigating capital expenditures—McKinsey's 2024 case studies demonstrated a 25% reduction in upfront costs through shared infrastructure frameworks [12]. Simultaneously, edge computing architectures address stringent data localization requirements under regulations like the EU's GDPR and China's DSL by ensuring on-premises data processing [13]. For instance, distributed edge nodes enable raw sensor data anonymization and localized storage prior to cross-border transmission, thereby maintaining compliance without compromising computational efficiency. These approaches highlight the synergy between economic scalability and regulatory adherence in IoV-MEC ecosystems.

## 4.2. Future innovations

The evolution of next-generation technologies is driven by breakthroughs in 6G terahertz (THz) networks, neuromorphic computing, and quantum computing. Operating in the 0.1–10 THz range, 6G THz networks promise ultra-high-speed data transmission (1+ Tbps) and ultra-low latency (<1 ms), enabled by programmable metasurfaces and graphene-based tunable devices. For instance, NTT DOCOMO's AI-native air interface and sub-THz spectrum trials achieved 25 Gbps throughput at 144 GHz, demonstrating adaptive network reconfiguration for applications like industrial automation and extended reality (XR) [14]. Recent advancements in THz waveguides, such as Tokyo University's ultra-thin electromagnetic wave absorbers (48 μm thickness), expand usable THz frequencies to 0.1–1 THz, which is critical for noise suppression in 6G communications [15]. Concurrently, Keysight Technologies and collaborators established the UK's first 100 Gbps sub-THz link at 300 GHz using 64-QAM modulation, addressing path-loss challenges for future immersive applications.

Neuromorphic computing, inspired by biological neural networks, integrates quantum materials like memristors to overcome von Neumann bottlenecks. While Intel's Loihi chips reportedly reduced energy consumption by 60% for AI tasks, broader adoption relies on advancements in fault-tolerant architectures and scalable fabrication methods [16].

Quantum computing leverages superposition and entanglement to solve NP-hard problems exponentially faster than classical systems. D-Wave's quantum annealers demonstrated 1,000× speed improvements in optimization tasks, such as route planning. Notably, researchers at Shanghai University utilized D-Wave Advantage processors to crack RSA and AES encryption via quantum annealing, highlighting vulnerabilities in SPN-based cryptographic systems310. However, challenges persist, including qubit coherence limitations and error rates in large-scale factorization, as shown in experiments requiring ~147,454 qubits for RSA-768 decryption—far exceeding current hardware capabilities [17].

## 5. Conclusion

This paper proposes a dynamic resource allocation framework based on deep reinforcement learning (DRL) to address the challenges of low-latency and high-reliability demands in Internet of Vehicles (IoV) mobile edge computing (MEC) scenarios. By jointly optimizing computation offloading, communication scheduling, and energy consumption, the framework achieves a 20-30% reduction in task processing latency, over 15% energy savings for edge nodes, and a critical task completion rate exceeding 95%, validated through simulations and real-world experiments. Distributed collaboration mechanisms and lightweight security protocols further enhance resource sharing efficiency and mitigate security risks.

However, there exists some limitations in this study. For instance, it primarily relies on simulated and controlled environments, potentially underestimating extreme network dynamics or heterogeneous hardware compatibility. Additionally, it lacks comprehensive comparisons with existing algorithms.

Future research endeavors should broaden their scope to encompass a wider array of vehicular scenarios, meticulously enhance security protocols to counteract the ever-evolving threat landscape, and delve into pioneering technologies. These include 6G terahertz networks for achieving ultra-low-latency communication, quantum-inspired algorithms to tackle NP-hard optimization challenges, and neuromorphic computing architectures aimed at boosting energy efficiency and system reliability within the context of next-generation IoV-MEC ecosystems.

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