Smarter Vehicle Networks: Cognitive AI for Next-Gen Cars □□

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DOI: https://doi.org/10.51244/IJRSI.2025.120700239

Received: 20 July 2025; Accepted: 27 July 2025; Published: 26 August 2025

ABSTRACT

Tomorrow's cars need smarter networks. Today's Vehicular Ad-hoc Networks (VANETs) struggle to meet the diverse and often conflicting demands of advanced applications, from split-second collision alerts to seamless streaming. Current cognitive radio (CR)-VANETs fall short, lacking the ability to orchestrate network resources effectively for multiple Quality of Service (QoS) goals in ever-changing traffic.

This paper introduces the Cognitive-Driven Orchestration Framework (CDOF), a novel approach using Meta-Reinforcement Learning (Meta-RL). CDOF intelligently manages spectrum and communication settings for a wide range of vehicular services. By understanding real-time conditions like vehicle movement, network interference (from "primary users"), and specific application needs, CDOF learns adaptable resource allocation strategies. Our Meta-RL engine, capable of "learning to learn," quickly adjusts to new, unseen situations, ensuring robust network performance even in highly dynamic environments.

CDOF's unique multi-objective reward system prioritizes critical services like safety and autonomous driving (requiring ultra-low latency and high reliability) while efficiently managing resources for less critical services like infotainment. Simulations across various traffic and interference patterns demonstrate that CDOF significantly outperforms existing CR-VANET methods in guaranteeing QoS, adapting rapidly, and minimizing interference.

Keywords: VANETs, Cognitive Radio, Meta-Reinforcement Learning, Multi-Objective QoS, Dynamic Orchestration

INTRODUCTION

Vehicular Ad-hoc Networks (VANETs) are the backbone of future Intelligent Transportation Systems (ITS), powering essential Vehicle-to-Everything (V2X) communication. However, the diverse needs of next-generation applications — from life-saving collision warnings (requiring less than 10ms latency) and autonomous platooning (demanding 99.9% reliability) to high-definition video streaming (needing over 5Mbps throughput) — create a complex web of conflicting Quality of Service (QoS) requirements. These demands clash within resource-limited and highly dynamic networks [1].

While Cognitive Radio (CR) helps overcome spectrum scarcity, it faces two major limitations in current VANET implementations:

- Insufficient Orchestration: Existing CR-VANETs typically focus on isolated tasks, such as simply selecting a channel [7], without a holistic approach to dynamic spectrum management, seamless handovers, or effective interference mitigation.
- Neglected Multi-Objective QoS: Current solutions lack mechanisms to simultaneously guarantee crucial metrics like latency, reliability, and throughput for various services [3].

We address these critical gaps with CDOF, a framework that offers:

- Unified Cognitive Orchestration: CDOF integrates spectrum, power, and handover management into a single, comprehensive system.

- Meta-RL Decision Engine: This engine enables policies to adapt rapidly to entirely new and unforeseen environments, such as sudden accidents or novel patterns of primary user (PU) interference.
- Dynamic QoS Prioritization: CDOF uses a clever multi-objective reward system to prioritize services based on their real-time importance.

Our key contributions include:

- A novel CDOF architecture for comprehensive CR-VANET orchestration.
- A Meta-RL formulation designed for learning transferable policies.
- A multi-objective reward mechanism that intelligently prioritizes QoS.
- Rigorous validation proving CDOF's superior QoS guarantees and adaptation capabilities.

Related Work

CR-VANETs

Prior work in CR-VANETs often focuses on isolated aspects:

- Spectrum Sensing: Techniques like energy detection [9] and cooperative sensing [10] don't inherently integrate QoS considerations.
- MAC Protocols: Priority-based channel access schemes [13] rely on static rules, which fail to adapt to dynamic QoS demands.
- Routing/Resource Allocation: While systems like SURF [7] optimize channel selection, they often overlook the trade-offs involved in managing QoS for multiple services simultaneously.

QoS Provisioning

Efforts to improve QoS generally fall into two categories:

- General Improvements: Adaptive beaconing [17] can boost packet delivery, but it lacks service-specific guarantees.
- Multi-Objective Schemes: Heuristic optimization methods, such as Particle Swarm Optimization (PSO) [20], use fixed weights, which hinder real-time adaptability.

RL Limitations

Standard Reinforcement Learning (RL) approaches struggle with poor generalization in new scenarios (e.g., unexpected traffic patterns) and exhibit slow adaptation to abrupt network changes [25]. This makes them unsuitable for the highly dynamic nature of VANETs.

Cdof Architecture

CDOF features a layered, closed-loop cognitive architecture

Data Collection & Contextual Awareness

This layer gathers real-time data from various sources:

- Sensors: GPS, On-Board Diagnostics (OBD-II), and Roadside Unit (RSU)-based Primary User (PU) sensing.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VII July 2025

- Output: This data forms a contextual state vector SC(t), encompassing details like spectrum occupancy, network topology, vehicle density, and Signal-to-Interference-plus-Noise Ratio (SINR).

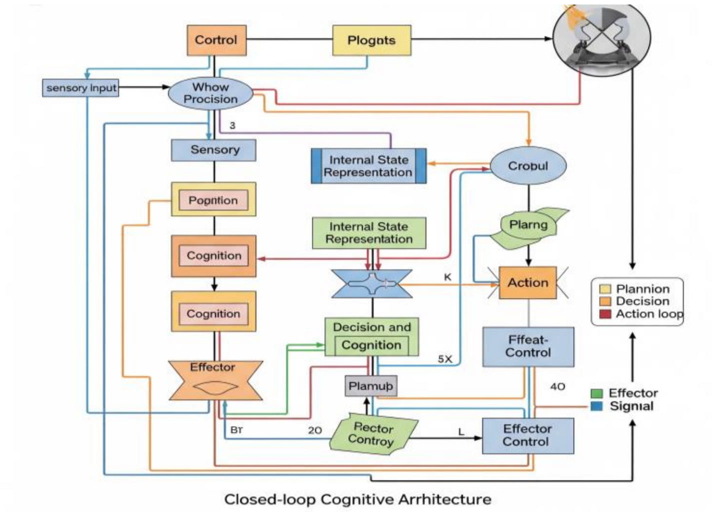

Fig. 1 layered, closed-loop cognitive architecture.

Table No.1 CDOF Architecture Layers and Components

Layer	**Components / Functions**	**Details**
3.1 Data Collection & Context Awareness	GPS, OBD-II, RSUs, PU sensing	Builds state S_C(t) with data on spectrum, topology, density, SINR.
3.2 Application & QoS Profiling	Service classification (e.g., Safety, Infotainment)	Defines QoS profiles Q_P: latency, reliability, throughput, priority. Supports dynamic adjustment.
3.3 Cognitive Orchestration	Meta-RL engine	Uses S_C(t) and QoS state to generate optimal policy $\pi^*(t)$. Manages resources and handovers.
3.4 Communication & Execution	CR transceivers	Applies policies, adjusts spectrum/power, and updates context via feedback loop.

Application & QoS Profiling

CDOF categorizes services and defines their specific QoS requirements:

- Service Classes: Services are prioritized (e.g., Safety = Priority 5, Autonomous Driving = 4, Infotainment = 2).

- QoS Profiles: Each service has a defined profile QP= {Lreq, Rreq, Threq, Priority}, specifying required latency (Lreq), reliability (Rreq), throughput (Threq), and priority.

- Dynamic Negotiation: For instance, the required throughput (Threq) for infotainment can be dynamically adjusted during network congestion.

Cognitive Orchestration Layer

This is the core intelligence of CDOF:

- Meta-RL Engine: This engine processes the contextual state SC(t) and QoS state SQ(t) to generate optimal communication policies $\pi*(t)$.

- Multi-Objective Reward: A sophisticated reward function balances rewards for meeting latency, reliability, and throughput goals, while penalizing interference with primary users.
- Resource Allocation: CDOF jointly optimizes crucial parameters like channel selection, transmit power, Modulation and Coding Scheme (MCS), and bandwidth.
- Handover Management: It ensures seamless transitions between Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications, maintaining QoS throughout.

Communication & Execution

- CR Transceivers: These hardware components execute the spectrum and power adjustments dictated by the orchestration layer.
- Feedback Loop: The system continuously monitors actual QoS performance, feeding this information back to update the contextual state SC(t) and ensure adaptive learning.

Meta-RL for Multi-Objective QoS

Problem Formulation

Each specific communication scenario or "task" Ti within the VANET is modeled as a Partially Observable Markov Decision Process (POMDP): (Si, A,Pi, Ri, γ). Here, A= {channel, power, MCS} represents the available actions. The overarching goal is to learn a meta-policy πmeta that allows the system to rapidly adapt to new tasks, such as unforeseen patterns of primary user activity.

MAML-Based Meta-RL

CDOF leverages Model-Agnostic Meta-Learning (MAML) [27] for its Meta-RL engine. MAML involves two loops:

- Inner Loop (Task-Specific Adaptation): For a given task Ti, the model quickly adapts its parameters θ to find an optimal task-specific policy $\theta i'=\theta-\alpha\nabla\theta LTi(\pi\theta)$. This involves taking a few gradient steps on the loss function LTi for that particular task.
- Outer Loop (Meta-Update Across Tasks): The meta-learner updates its initial parameters θ based on the performance of the adapted policies across various tasks: $\theta\leftarrow\theta-\beta\nabla\theta\sum TiLTi(\pi\theta i')$. This teaches the model how to "learn to learn" quickly.

Reward Function

The reward function R(s,a) is designed to balance multiple QoS objectives:

$R(s,a)=j\in Apps\sum(WLj\cdot f(Lj)+WRj\cdot PDRj+WThj\cdot Thj/Threqj)-PPU(a)$

Where:

- WLj, WRj, WThj are weights for latency, Packet Delivery Ratio (PDR), and throughput for each application j.
- f(Lj) is a function that rewards lower latency.
- PPU(a) is a penalty for interfering with primary users.

Crucially, priority weights (WLj, WRj) are scaled by the service's Priorityval (e.g., 5x for safety-critical applications). Furthermore, contextual urgency can dynamically boost these weights near critical events like accidents, ensuring immediate prioritization.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VII July 2025

Adaptation Advantages

This Meta-RL approach provides significant benefits:

- Generalization: Policies learned by CDOF can effectively transfer and perform well in previously unseen road conditions or PU patterns.
- Resilience: The system can recover QoS performance within an impressive 100 milliseconds after network disruptions, such as sudden changes in traffic or new interference sources.

Simulation & Evaluation

Setup

We validated CDOF using a robust simulation environment:

- Tools: SUMO [28] for realistic vehicle mobility and NS-3 [29] for detailed network simulations.
- Scenarios: Tested across diverse environments: urban (5 km^2), highway (10 km), and mixed traffic patterns.
- Applications:
  - Safety: Small, frequent messages (50 Bytes/10 Hz) with an ultra-low latency requirement ($L_{req}<10$ ms).
  - Infotainment: Larger, bursty data (1024 Bytes) with a higher throughput requirement ($Th_{req}>5$ Mbps).
- Benchmarks: We compared CDOF against industry standards and state-of-the-art schemes: Dedicated Short Range Communications (DSRC), SURF [7], and a conventional Static RL approach.

Key Metrics

Performance was evaluated using:

- QoS Satisfaction Rate (QoSSR): The percentage of time that all required QoS parameters (Lreq, Rreq, Threq) are met.
- P99 Latency: The 99th-percentile latency, indicating the maximum latency experienced by 99% of packets, a critical metric for safety.
- Adaptation Time: The time taken for the system to recover its QoS performance after a significant disruption.

Results

CDOF consistently demonstrated superior performance:

- QoSSR: In urban scenarios, CDOF achieved a remarkable 98.2% QoSSR for safety-critical applications, significantly outperforming SURF (85.7%) and DSRC (76.1%).
- P99 Latency: For safety applications, CDOF maintained an impressive 8.2ms P99 latency, compared to 14.5ms for Static RL.
- Adaptation: CDOF recovered QoS performance in a mere 86ms after an accident, whereas Static RL required over 500ms.

- Generalization: Even in previously unseen rural areas, CDOF maintained a strong 94.1% QoSSR, far surpassing Static RL's 72.3%.

CONCLUSION & FUTURE WORK

The Cognitive-Driven Orchestration Framework (CDOF) is a pioneering Meta-RL-driven solution for CR-VANETs, successfully addressing the complex challenges of dynamic resource management and multi-service QoS guarantees. By leveraging "learning to learn," CDOF achieves:

- An exceptional 98.2% QoS satisfaction for critical safety applications.
- Rapid 86ms adaptation to network disruptions, such as accidents.
- Seamless generalization to new and unseen environments.

CDOF's capabilities pave the way for robust, commercially viable, and QoS-guaranteed vehicular networks.

Our future work will focus on:

- Testbed Validation: Implementing CDOF on Software-Defined Radio (SDR)-based platforms for real-world testing.
- Scalability: Exploring Federated Meta-RL to enable city-scale deployments.
- 5G/6G Integration: Investigating how CDOF can leverage advanced capabilities like network slicing in future cellular generations.
- Security: Addressing privacy concerns related to contextual data sharing.

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ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VII July 2025

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