**Problem Statement**  
Current autonomous vehicle systems face major challenges in achieving real-time adaptability, safety, communication reliability, and energy-efficient decision-making under dynamic traffic and environmental conditions. While path planning approaches based on traditional algorithms or Deep Reinforcement Learning (DRL) offer partial solutions, they struggle with generalization, interpretability, and real-world deployment. Similarly, 5G/6G-enabled V2X communication and Wireless Sensor Networks (WSNs) improve simulation metrics but lack integrated, resilient, and intelligent frameworks in real-world mixed traffic environments. A unified system that combines adaptive learning-based motion planning, formal safety guarantees, reliable communication, and energy-aware routing is crucial to bridge this gap and enable robust, scalable, and sustainable autonomous vehicle operation.

**✅ What Exactly You Need to Do**

**1. Develop a Hybrid Path Planning and Communication Framework**

**Objective**: Design a system that integrates DRL-based motion planning with V2X communication and WSNs to address safety, reliability, comfort, and efficiency.

**Actions**:

* Combine **DRL/LfD** with **Signal Temporal Logic (STL)** for safe and adaptive path planning.
* Use *traditional algorithms (A, RRT\*)*\* for initial path estimation.
* Apply **edge computing or federated learning** to enable decentralized decision-making.
* Integrate **5G/6G-based V2X communication** with priority-based groupcasting and IR-HARQ.
* Link vehicle decisions to **WSN feedback** for environment-aware motion updates.

**2. Implement Real-Time Adaptive Behavior**

**Objective**: Ensure dynamic response to real-world changes such as moving obstacles, traffic flow, and network fluctuations.

**Actions**:

* Use **POMDP or actor-critic architectures** for policy decision-making under uncertainty.
* Develop a **replanning module** with **Model Predictive Control (MPC)** for local adjustments.
* Simulate **mixed traffic environments** (CAVs + human drivers) using CARLA/SUMO.

**3. Design Comfort-Aware and Energy-Efficient Modules**

**Objective**: Enhance passenger experience and network sustainability.

**Actions**:

* Use a **Full Velocity Difference Model** and **multi-predecessor feedback control** for comfort-aware control.
* Apply **Reinforcement Learning (RL)** and **Residual Energy-based clustering** for WSN optimization.
* Optimize routing with **Multi-Objective Improved Seagull Algorithm (MOISA)** in NS-2/NS-3.

**4. Ensure Formal Safety Verification**

**Objective**: Guarantee safe decision-making during vehicle operation.

**Actions**:

* Define traffic rules, obstacle zones, and constraints using **STL** or **LTL**.
* Quantify path safety using **robustness metrics**.
* Validate DRL decisions using **runtime STL constraints**.

**5. Integrate All Modules into One Scalable System**

**Objective**: Achieve seamless coordination among all subcomponents.

**Actions**:

* Use a **modular architecture** for motion planning, V2X, WSN, and feedback modules.
* Enable **data exchange** (e.g., sensor network data → V2X planner).
* Simulate at different scales: from single-lane to multi-lane urban traffic.

**6. Evaluate the System Using Standard Metrics**

**Objective**: Benchmark the integrated framework for reliability and performance.

**Tools**:

* **CARLA, SUMO** for mobility simulation
* **NS-2/NS-3** for communication simulation
* **MATLAB/Python** for algorithms

**Metrics**:

* V2X: Packet delivery ratio, delay, throughput, resilience
* Comfort: Acceleration variance, stability index
* Path Planning: Collision rate, STL score, path length, computation time
* WSN: Energy usage, network lifetime

**7. Final Deliverables**

1. **System Architecture Diagram** (modular)
2. **Simulation Code** (motion, communication, routing)
3. **Evaluation Report** (comparative graphs, case studies)
4. **XAI Layer** (explainability for decisions)
5. **Final Project Report** (literature review, methods, results, conclusion)

**Communication Analysis Table**

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| **Aspect** | **Communication 1** | **Communication 3** |
| **Title** | Managing Connected Automated Vehicles in Mixed Traffic Considering Communication Reliability: a Platooning Strategy | Impact of Connected and Automated Vehicles on Passenger Comfort of Traffic Flow with Vehicle-to-vehicle Communications |
| **Main Idea** | Proposes a decentralized platooning strategy where CAVs follow a human-led vehicle to reduce complexity in mixed traffic. | Studies the effect of CAV feedback gains on passenger comfort in mixed traffic by optimizing stability using V2V. |
| **Key Findings** | Human-led (HL) platooning improves integration in mixed traffic.Communication reliability greatly affects platoon performance.Rule-based strategies significantly influence travel time and driving mode duration. | Optimal traffic flow stability via controlled feedback enhances passenger comfort.Stability improves with V2V-based feedback tuning in local platoons. |
| **Survey/Method Used** | Microsimulation of one-lane road with RSUs and CAVs.Evaluated under varying packet loss ratios (PLR).Rule-based decision models implemented for leader-follower roles. | Numerical simulations using car-following models (Full Velocity Difference model).Applied transfer function theory to evaluate traffic stability and comfort impact. |
| **Most Important/Common Point** | Communication reliability is crucial in real-world CAV deployment and directly impacts traffic efficiency and automation time. | Passenger comfort depends on minimizing acceleration/deceleration fluctuations, tied to optimized stability in traffic flow. |
| **Current Progress According to Paper** | Initial decentralized platooning concept tested in controlled simulation.Functional under reliable V2X conditions.Social acceptance model considered. | Proven that optimal feedback tuning can improve comfort metrics significantly.Model accommodates randomness and MDV-CAV mix. |
| **Literature Gaps Identified** | Lack of real-world testing on HL-based platooning.Insufficient consideration of non-CAV behavior impact on platoons.No scalability tested beyond one-lane roads. | Sparse literature on direct CAV impact on passenger comfort in mixed flow.Lack of unified comfort metrics.Limited application of feedback-based control in practical tests. |
| **Unresolved Problems / Future Work** | Need to extend to multilane or urban scenarios.Test with diverse traffic patterns and human driver behavior variability.More adaptive role-switching algorithms. | Apply model in dynamic real-world traffic with non-uniform platoon sizes.Study lateral vehicle behavior effects.Further explore impact under varying road and weather conditions. |

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| **Aspect** | **Communication 1** | **Communication 3** | **Communication 4** | **Communication 5** |
| **Title** | Managing Connected Automated Vehicles in Mixed Traffic Considering Communication Reliability: a Platooning Strategy | Impact of Connected and Automated Vehicles on Passenger Comfort of Traffic Flow with Vehicle-to-Vehicle Communications | Enhancing Reliability in 5G NR V2V Communications Through Priority-Based Groupcasting and IR-HARQ | Collaborative Energy-Efficient Routing Protocol for Sustainable Communication in 5G/6G Wireless Sensor Networks |
| **Main Idea** | Decentralized platooning where CAVs follow a human-led vehicle to simplify integration. | Optimizing passenger comfort by minimizing traffic instability via feedback gains in CAVs. | Enhancing 5G NR V2V communication reliability using groupcasting and IR-HARQ under delay/outage constraints. | Proposes collaborative routing protocol (CEEPR) using RL and MOISA to improve WSN energy efficiency. |
| **Key Findings** | HL platooning improves integration and mode duration; PLR impacts performance. | Controlled feedback improves stability and comfort in mixed traffic. | Throughput improved by 98% with IR-HARQ; groupcasting outperforms traditional broadcast. | Energy consumption reduced by 50%; extended network lifespan with better throughput. |
| **Survey/Method Used** | Microsimulation (1-lane road), RSUs, PLR scenarios, rule-based role switching. | Car-following simulations with FVD model; uses transfer function theory. | WiLabV2Xsim simulations, system-level analysis, 3GPP-compliant abstraction. | RL-based clustering, RE-based head selection, MOISA optimization, NS-2 simulation. |
| **Most Common/Important Point** | Communication reliability is key for effective platooning. | Comfort relies on stability optimization using feedback. | Reliable transmission in V2V depends on proper HARQ and casting strategies. | Adaptive routing and clustering is vital for sustainable WSNs in 5G/6G. |
| **Current Progress** | Simulation-based validation of platooning roles and effects under varying V2X. | Proven improvements in comfort and stability with V2V-tuned feedback gains. | Validated enhanced reliability and throughput in system-level tests. | Verified in NS-2 with strong performance over standard WSN routing. |
| **Literature Gaps** | No real-world trials; limited to one-lane, no multi-agent testing. | Sparse studies linking CAV control with passenger comfort in real-world setups. | Limited adaptability in changing traffic; no AI-integrated scheduling. | Lack of edge-AI and real-time sensing integration; resilience not well addressed. |
| **Unresolved Problems** | Expand to multilane/urban, include diverse driver behaviors, enhance role flexibility. | Apply to realistic mixed traffic, lateral motion effects, and adverse weather. | Evaluate in dense urban networks; develop AI-based adaptive retransmission. | Add federated learning, enhance security layers, validate with real WSN devices. |

**Movement Analysis Table**

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| **aspect** | **Movement 1.pdf<br>(Two-Layered Planning Model)** | **Movement 2.pdf<br>(Optimized A\* Algorithm)** | **Movement 3.pdf<br>(DRL Survey for Motion Planning)** | **Movement 4.pdf<br>(Temporal Logic for Safe Planning)** | **Common/Key Points Across All Papers** |
| **Actual Idea** | Proposes a two-layered model using Bi-RRT + VFH polynomial in Frenet coordinates to achieve real-time, smooth, safe path planning in dynamic environments. | Enhances A\* with turn penalty, obstacle raster coefficients, and smoothing to improve safety, reduce path length, and handle sparse/dynamic obstacles. | Surveys use of Deep Reinforcement Learning (DRL) for hierarchical motion planning, covering end-to-end and layered strategies with vehicle dynamics. | Uses Learning from Demonstrations (LfD) with temporal logic (STL) to ensure path planning adheres to safety rules, static/dynamic obstacle avoidance, and runtime constraints. | All aim to improve autonomous vehicle path planning with respect to safety, adaptiveness, and real-world constraints using either search, learning, or logic. |
| **Findings** | Bi-RRT improved with steering constraints, VFH enables adaptive goal shifting; outperforms traditional methods in cluttered environments. | 84% reduction in traversed nodes, 39% less turning angle, smoother paths; ensures fewer redundant nodes and better computational efficiency. | DRL can model strategic, motion, and control layers; DQN, DDPG, actor-critic methods applied to car-following, merging, lane-keeping. | Proposed method yields safe trajectories validated against STL rules (e.g., traffic lights, safety zones); works in continuous real-time cycles with partial environment perception. | Advanced methods improve motion planning by ensuring safety, path feasibility, and efficiency. |
| **Survey Conducted / Evaluation Method** | Simulation + real vehicle in complex scenarios using real sensors (GPS, LiDAR); evaluation on various obstacle setups. | Simulation-based comparison with baseline A\*; tested on rasterized real maps; trajectory metrics used for benchmarking. | Literature survey with algorithm taxonomy, simulators, vehicle models, and reward structures; categorized by behavior, motion, and control level. | Evaluated in IR-SIM simulator on valet parking tasks with dynamic/static obstacles and traffic lights; used STL to verify real-time performance over multiple path cycles. | All methods are either simulation-tested or benchmarked against standard environments; validation includes static and dynamic obstacle cases. |
| **Current Progress** | Real-time two-layer path planning combining geometry and dynamic adjustments is viable. | Optimized A\* adapts well to irregular and sparse environments but still lacks real-world deployment. | DRL shows promise but struggles with generalization, real-time inference, and safety guarantees. | Demonstrated real-time STL-based optimization of learned trajectories with robust handling of evolving constraints. | Hybrid approaches combining planning, ML, and verification are trending; however, deployment and standardization are still evolving. |
| **Literature Gaps** | Lacks adaptability in highly dynamic/multi-agent environments; sensitive to map noise and VFH reliability. | Fails to fully adapt to moving obstacle changes in real-time; struggles with large-scale deployment. | Sparse reward signal, model interpretability, and training time are major issues; limited real-world deployments. | Needs real-world testing and expansion to more complex STL constraints; optimization speed still limits scalability. | Need for real-world validation, standard benchmarks, model explainability, and scalability across varying scenarios. |
| **Problems Yet to be Addressed** | Needs better robustness to environment changes; Bi-RRT still suffers in very narrow spaces. | Difficulties in ensuring consistent safety margins across varying environments; lacks dynamic trajectory adaptation. | Safety verification, real-time computation, and policy generalization under uncertainty remain open problems. | Bridging simulation-to-reality gap, dynamic updates to STL rules, and reducing optimization latency. | Real-time adaptability, multi-agent coordination, and safety assurance under uncertain inputs are common unsolved issues. |