To the Graduate Council:
I am submitting herewith a thesis written by Md Iftekharul Islam entitled "Beyond Traffic Signals: Coordinating Heterogeneous Mixed Traffic at Unsignalized Intersections." I have examined the final paper copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Computer Science.

Weizi Li, Major Professor

We have read this thesis
and recommend its acceptance:

Weizi Li

Fei Liu

Zhenbo Wang

Accepted for the Council:

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(Original signatures are on file with official student records.)

Beyond Traffic Signals: Coordinating Heterogeneous Mixed Traffic at Unsignalized Intersections

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Md Iftekharul Islam

May 2025

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To my wife, my partner in life and learning.

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Abstract

Urban intersections are inherently complex, hosting a diverse mix of vehicles ranging from small cars to large semi-trailers, each with distinct driving behaviors and space requirements. Managing such heterogeneous traffic becomes particularly challenging at **unsignalized intersections**, where the absence of traffic lights demands real-time coordination. This thesis explores how **robot vehicles (RVs)**, powered by **reinforcement learning (RL)**, can dynamically optimize mixed traffic flow under varying degrees of automation. By gradually increasing RV penetration from **10% to 90%**, our findings reveal a **substantial reduction in average waiting times**—up to **86% compared to signalized intersections**—demonstrating the efficiency of RL-based control. Notably, we observe a **rarity advantage**, where less frequent vehicle types, such as trucks, experience the most significant improvements, benefiting from RV-driven coordination by as much as **87%**. Additionally, space headways decrease consistently across all vehicle types, suggesting enhanced road space utilization. While RVs operate at higher speeds, leading to increased energy consumption, the overall efficiency gains surpass those of conventional traffic signals. These insights underscore the transformative potential of RL in **coordinating heterogeneous mixed traffic**, paving the way for more adaptive and scalable traffic management solutions in real-world urban mobility.

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Chapter 1

Introduction

1.1 Background and Motivation

Urban intersections are critical nodes in transportation networks, facilitating the movement of vehicles across different roadways. However, managing traffic at **unsignalized intersections** presents unique challenges due to the lack of explicit control mechanisms, leading to potential inefficiencies, increased congestion, and safety risks. The **heterogeneous nature of urban traffic**, consisting of vehicles like passenger cars, pickups, and trucks, further complicates traffic management at such intersections. Each vehicle type exhibits different kinematic and dynamic properties, affecting acceleration, deceleration, gap acceptance, and lane-changing behavior (Kong et al. (2021)).

The advent of **Robot Vehicles (RVs)**—autonomous or semi-autonomous vehicles capable of cooperative decision-making—offers a promising avenue to enhance traffic flow and efficiency in unsignalized environments. By leveraging **Reinforcement Learning (RL)**, RVs can learn to coordinate with other vehicles, optimize intersection throughput, and reduce congestion. Previous research has demonstrated the effectiveness of RL-based traffic control strategies, but **most studies assume homogeneous traffic**, where all vehicles share similar properties. This assumption

limits the applicability of findings to real-world scenarios, where vehicle diversity is a fundamental aspect of urban mobility.

1.2 Problem Statement

Despite advances in traffic management, current methods face several challenges in handling mixed traffic at unsignalized intersections:

- **Heterogeneous Vehicle Characteristics**: Different vehicle types require varying gaps, exhibit different reaction times, and contribute differently to congestion (Mohan and Chandra (2020, 2021)).
- **Lack of Coordination at Unsignalized Intersections**: Traditional rule-based approaches often fail during power failures, emergencies, or system malfunctions(Winck (2022); Ramirez (2022)), requiring alternative control strategies.
- **Limited Consideration of Mixed Traffic in RL-based Solutions**: Most RL-based traffic control frameworks primarily focus on homogeneous traffic (Wang et al. (2024a); Vinitsky et al. (2018)), ignoring the impact of vehicle diversity on decision-making and intersection throughput.

This study aims to **bridge this gap** by investigating the role of **heterogeneous mixed traffic** in RL-based intersection control, particularly examining how **varying RV penetration rates (10% to 90%) impact efficiency and safety** in real-world intersection settings.

1.3 Research Objectives

The primary objectives of this research are:

- To investigate RL-based **heterogeneous mixed traffic control strategy** for unsignalized intersections.

- To **evaluate traffic efficiency** by analyzing **waiting time and space headways** under different RV penetration rates.
- To assess **environmental impacts**, including **fuel consumption and CO_2 emissions**, under mixed traffic conditions.

1.4 Thesis Organization

This thesis is structured as follows:

- **Chapter 1** introduces the research motivation, problem statement, objectives, key research questions, and contributions.
- **Chapter 2** reviews related work in unsignalized intersection management, heterogeneous traffic dynamics, and RL-based traffic control.
- **Chapter 3** describes the methodology, including the RL framework, traffic simulation setup, vehicle behavior models, and evaluation metrics.
- **Chapter 4** presents the experimental results and a detailed analysis of traffic efficiency, emissions, and space headways.
- **Chapter 5** concludes the thesis with a summary of key insights and potential directions for future research.

Chapter 2

Literature Review

2.1 Heterogeneous Traffic Management

Heterogeneous traffic refers to road environments where vehicles of various types (cars, buses, trucks, motorcycles, etc.) mix, each with different sizes, speeds, and maneuverability. Managing such diversity is challenging because vehicle characteristics strongly influence traffic flow and safety. Larger and slower vehicles can create moving bottlenecks that amplify congestion and increase travel times (Kong et al. (2021); Mohan and Chandra (2020)). For instance, Kong et al. (2021) demonstrated that mixed traffic streams containing larger vehicles, such as trucks, can reduce overall traffic flow efficiency due to their larger spatial requirements, slower acceleration profiles, and blocking effects. Their study further highlights that truck-induced congestion is particularly pronounced at low velocities, while at higher speeds, physical performance differences play a greater role in shaping traffic dynamics. Similarly, field studies by Mohan and Chandra Mohan and Chandra (2020) on unsignalized intersections under heterogeneous conditions showed that large vehicles (like trucks and buses) require significantly longer gaps to cross or merge, which in turn reduces intersection capacity. Their follow-up work (Mohan and Chandra (2021)) further examined how the mix of conflicting vehicle types affects the critical gap–i.e.,

the threshold time gap a driver needs to safely enter an intersection–underscoring that a higher proportion of heavy vehicles leads to larger critical gaps and potentially increased delays.

Managing such traffic conditions requires models that explicitly incorporate the unique dynamics of each vehicle type, a complexity often overlooked in homogeneous traffic models. Studies like Sun et al. (2021) have underscored the importance of explicitly modeling heterogeneous vehicle interactions to accurately predict traffic performance and stability. Consequently, tailored control strategies have become increasingly essential.

2.2 Intersection Management Strategies

2.2.1 Traditional Intersection Control

Intersections are critical nodes in urban traffic networks where efficient control is paramount. Traditionally, management of intersection right-of-way has relied on fixed infrastructure and rules such as traffic signals, stop signs, and roundabouts (Rice (2010); Institute of Transportation Engineers (2015)). Traffic lights remain the most common form of control, operating on timed cycles or actuated sequences to allocate right-of-way. While effective under normal conditions, fixed-time lights can become inefficient when traffic demand fluctuates widely, leading to unnecessary waits or congestion (Tennessee Department of Transportation (2020)). Moreover, during unusual events like power outages or emergencies, signalized intersections can revert to uncontrolled states, causing significant delays and safety hazards (Ramirez (2022); Winck (2022)). Basic unsignalized control (stop or yield signs) works for lower-volume intersections, but as traffic volumes or complexity increase, these can lead to high driver uncertainty and conflict (Institute of Transportation Engineers (2015)).

2.2.2 Modern and Autonomous Intersection Control

Modern intersection control strategies increasingly leverage connectivity and automation to overcome limitations of traditional methods. V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communications create a fundamental shift in traffic management. Instead of relying only on predetermined signal patterns, vehicles and roadside units can now share real-time data about their locations, speeds, and intended movements. This information sharing paves the way for adaptive, cooperative control. Pioneering work in this field was conducted by Dresner and Stone (2008), who introduced a multi-agent intersection control system. Their innovative approach allows CAVs to reserve specific space-time slots at intersections using a first-come, first-serve (FCFS) principle, effectively managing the flow of autonomous vehicles without traditional traffic signals. Building upon this concept, Jin et al. (2013) extended the FCFS scheduling method to accommodate platoons of CAVs, recognizing the potential efficiency gains of coordinated vehicle groups. In a different vein, Chen et al. (2022) proposed a dynamic approach with their controllable gap strategy. This method adaptively adjusts the time gap between vehicles based on their speeds and potential conflict scenarios, aiming to prevent collisions while optimizing traffic flow.

Decentralized control strategies have also gained traction in the research community. Mirheli et al. (2019) developed a consensus-based control method for managing CAV trajectories, leveraging the distributed decision-making capabilities of autonomous vehicles. Similarly, Malikopoulos et al. (2018) focused on optimizing energy consumption in CAV systems through decentralized control, highlighting the potential environmental benefits of autonomous traffic management. While these approaches demonstrate significant promise in managing unsignalized intersections, it's important to note that they typically operate under the assumption of a fully autonomous environment. This assumption, while simplifying the problem space,

may limit their immediate applicability in mixed traffic scenarios where human-driven vehicles coexist with CAVs.

Game-theoretic models have been explored to optimize intersection flow (Elhenawy et al. (2015); Bui and Jung (2018); Tian et al. (2020); Zohdy and Rakha (2012)). For example, Suriyarachchi et al. (2024) propose a cooperative game-theoretic framework (GameOpt+) for multi-lane unsignalized intersections with heterogeneous traffic. Their approach treats the intersection entry order as an optimization problem, aiming to minimize fuel consumption and delay by scheduling vehicles' crossing times. While such models show benefits in simulation (like reduced fuel use through intelligent vehicle ordering), they often face scalability challenges when traffic becomes more unpredictable or when the number of participating vehicles grows large.

2.3 Mixed Traffic Control via Robot Vehicles

In the foreseeable future, urban traffic will be mixed-autonomy: a combination of human-driven vehicles (HVs) and autonomous or robot vehicles (RVs). The presence of RVs opens up opportunities for new control strategies, as these intelligent agents can actively influence the behavior of surrounding traffic. Instead of treating each vehicle as an independent driver, mixed traffic control envisions some vehicles as mobile controllers or coordinators (Rios-Torres and Malikopoulos (2016); Li et al. (2017)). In mixed traffic, RVs can take on a supervisory role. One strategy is for RVs to serve as "leader" vehicles that human drivers implicitly follow. By strategically adjusting speed or lane position, an RV can dampen stop-and-go waves and organize the flow at merges or intersections. Vinitsky et al. (2018) famously demonstrated in a ring-road experiment that a single autonomous vehicle in a flow of 20 human-driven cars could eliminate phantom traffic jams by modulating its speed intelligently. Yue et al. (2023) review the benefits and drawbacks associated with connected and automated vehicles operating within mixed traffic environments,

noting that while CAVs can improve throughput and reduce collisions by reacting faster than humans, they may also introduce new issues like sensor interference or unpredictable interactions with non-automated drivers. Nonetheless, the consensus is that a modest proportion of autonomous vehicles, if properly used, can improve traffic performance disproportionately. Villarreal et al. (2023) explored a novel approach where an autonomous vehicle control policy was derived with the help of a large language model (ChatGPT) to manage mixed traffic. These efforts illustrate how RVs can be interwoven into traffic not just as participants, but as active traffic managers that enhance flow efficiency and safety in real time.

2.4 Reinforcement Learning in Traffic and Intersection Management

Reinforcement Learning (RL), a subset of artificial intelligence in which agents refine their decision-making through trial-and-error interactions with their environment, has become a powerful approach for optimizing traffic management. In the context of intersections, RL offers a way to handle complex, stochastic situations by learning policies that map observed traffic states to optimal control actions. An advantage of RL is its ability to optimize performance criteria (like vehicle delay or queue length) in complex scenarios that are hard to explicitly program. For example, Yan and Wu (2021) developed a multi-agent RL approach for unsignalized intersections in mixed autonomy traffic. In their framework, each intelligent vehicle or an intersection agent learns a policy to cooperate on the right-of-way assignment. By decomposing the joint policy into individual decisions and using local observations, their approach achieved better throughput and safety than traditional uncontrolled intersection behavior. Similarly, Peng et al. (2021) applied deep reinforcement learning for connected autonomous vehicles navigating an unsignalized intersection, showing that

an RL-trained policy could improve traffic efficiency (e.g., higher average speeds and lower waiting times) compared to heuristic right-of-way rules.

More recent works have scaled up the complexity of traffic scenarios where RL is employed. Wang et al. (2024b) introduced decentralized multi-agent RL methods to coordinate mixed traffic through robot vehicles at complex intersections. Their 2024 study in particular tackled real-world intersection layouts (with multiple lanes and approaches) and showed that as the penetration of autonomous RVs increases, the learned policy dramatically reduces average vehicle waiting time and queue lengths compared to traditional control. Poudel et al. (2024a) introduced an RL framework called EndURL that incorporates real human driving behaviors and randomness during training to make the learned policy more robust to unexpected events in mixed traffic. By training with a variety of perturbations (e.g., sudden braking or aggressive lane changes by human drivers), their RL agents achieved safer and more stable traffic flow in test scenarios. Villarreal et al. (2024) showed that RVs can effectively control intersection traffic using only raw visual inputs (camera images) rather than precise sensor data. In their system, cameras (or an RV's vision) observe the intersection, and an AI agent (running on the RV or infrastructure) decides when the RV should proceed or pause, implicitly choreographing the human vehicles.

2.5 Current Research Gaps

While significant progress has been made in heterogeneous traffic management and autonomous vehicle control, several research gaps and limitations remain evident in the literature.

- **Limitations in Vehicle Type Consideration:** Most existing studies in mixed traffic control still operate under the assumption of homogeneous traffic or otherwise simplify the vehicle population. While some research has addressed specific vehicle types, few studies have comprehensively examined the full range

of vehicle types commonly found in urban environments. The interaction effects between different vehicle classes, particularly in the context of automated vehicle integration, remain poorly understood.

- **Scalability and Real-World Implementation:** Current research often relies on simplified intersection geometries and idealized traffic conditions. The scalability of proposed solutions to complex, real-world intersections with varying layouts and demand patterns requires further investigation. Additionally, the impact of practical constraints such as communication limitations and sensor uncertainties on system performance needs more thorough examination.

- **Penetration Rate Analysis:** While several studies have explored the impact of automated vehicle penetration rates, most focus on homogeneous vehicle scenarios. The relationship between penetration rates and system performance in heterogeneous traffic environments, particularly considering different vehicle types, remains an open research question.

To address these shortcomings and advance the state of the art, our research aims to bridge this divide by demonstrating the efficacy of reinforcement learning (RL) approaches in managing heterogeneous mixed traffic within complex, realistic environments. By incorporating a diverse range of vehicle types, real-world intersection layouts, and varying penetration rates of autonomous vehicles, we seek to provide a more comprehensive and applicable framework for traffic management. This approach not only addresses the current limitations in the literature but also paves the way for more robust and adaptable traffic control systems that can effectively handle the complexities of real-world urban traffic scenarios.

Chapter 3

Methodology

3.1 Problem Formulation

The control and coordination of heterogeneous mixed traffic at unsignalized intersections presents unique challenges that require a systematic approach to modeling and problem formulation. While recent work (Wang et al. (2024b)) established an effective reinforcement learning framework for mixed traffic control, the introduction of multiple vehicle types with varying physical characteristics presents new opportunities to investigate the framework's performance under more realistic traffic conditions. This chapter presents our methodology for studying heterogeneous mixed traffic control, detailing the problem formulation, vehicle modeling, traffic composition, and control framework.

3.1.1 POMDP Framework

Given the stochastic nature of traffic interactions and the inherent uncertainty in real-world traffic environments, we formulate the heterogeneous mixed traffic control problem as a Partially Observable Markov Decision Process (POMDP). This framework captures both the dynamic nature of traffic evolution and the partial observability that RVs experience at complex intersections.

We define our POMDP as a tuple $(X, U, P, R, Y, V, \gamma)$. The state space X represents all possible traffic states, while U denotes the set of available actions for each RV. The transition dynamics are captured by $P(x'|x, u)$, which describes how the traffic state evolves in response to RV actions. The reward function $R(x, u)$ provides feedback on action effectiveness, guiding the learning process toward desired behaviors. The observation space Y and observation probability function $V(y|x)$ model the partial information available to RVs about the true state of the environment. Finally, the discount factor $\gamma \in [0, 1)$ balances the importance of immediate and future rewards.

This formulation enables the systematic development of control policies that can handle the complexities of heterogeneous mixed traffic while accounting for partial information and environmental uncertainties.

3.1.2 State, Action, and Observation Spaces

The state space X provides a comprehensive representation of the traffic environment, encompassing both microscopic vehicle states and macroscopic traffic conditions. For an intersection with K approaching directions, each state incorporates the spatial distribution of vehicles across intersection and approach lanes, along with individual vehicle velocities and accelerations. The state representation also includes vehicle type classifications, directional queue lengths, and accumulated waiting times, providing a complete picture of the current traffic situation.

The action space U implements a hybrid control approach that combines high-level decision-making with detailed vehicle dynamics. Within the control zone (30 meters from the intersection), RVs select from $U = \{\text{Stop}, \text{Go}\}$, with each action triggering specific acceleration behaviors:

$$a_t = \begin{cases} a_{\max} & \text{if } u_t = \text{Go}, \\ -u^2/(2d_{\text{int}}) & \text{if } u_t = \text{Stop}. \end{cases} \tag{3.1}$$

Here, a_t represents the resulting acceleration, u denotes the current velocity, and d_{int} is the distance to the intersection. This formulation allows for precise control while maintaining compatibility with the underlying vehicle dynamics.

The observation space Y defines the partial information available to each RV for decision-making. At time t, an RV constructs its observation y_t as:

$$y_t = \oplus_{k \in K} \langle l_k, w_k \rangle \oplus_{k \in K} \langle o_k \rangle \oplus \langle d_{\text{int}} \rangle \tag{3.2}$$

This observation vector integrates queue lengths l_k and average waiting times w_k for each direction $k \in K$, along with occupancy status o_k indicating vehicle presence in different intersection zones. The RV's distance to the intersection d_{int} is also included, providing crucial spatial information for decision-making.

3.1.3 Reward Function Design

The reward function orchestrates multiple objectives: improving traffic efficiency, maintaining safety, and managing potential conflicts. For each time step t, the reward r_t is computed as:

$$r_t = \alpha h_t + c_t \tag{3.3}$$

The local reward component h_t evaluates traffic efficiency using directional waiting times. The weighting parameter α is used to maintain an appropriate balance between efficiency and safety considerations. When an RV decides to stop, it receives a negative reward proportional to the current waiting time in its direction. Conversely, proceeding through the intersection yields a positive reward, encouraging efficient traffic flow when safe:

$$h_t = \begin{cases} -w_k & \text{if } u_t = \text{Stop} \\ w_k & \text{if } u_t = \text{Go} \end{cases} \tag{3.4}$$

where w_k represents the average waiting time in the RV's direction k.

The conflict penalty c_t implements crucial safety constraints by penalizing potentially dangerous interactions:

$$c_t = \begin{cases} -1 & \text{if conflict detected} \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

When multiple RVs from conflicting streams simultaneously decide to proceed through the intersection, a sophisticated priority mechanism resolves these conflicts.

3.2 Vehicle Modeling

3.2.1 Vehicle Characteristics

The heterogeneous nature of urban traffic necessitates detailed modeling of multiple vehicle categories, each with distinct characteristics that significantly influence traffic dynamics. Our framework incorporates five primary vehicle types, each type characterized by specific physical and dynamic parameters that determine its behavior and interactions within the traffic stream. These parameters, detailed in Table 3.1, include vehicle dimensions, mass, and performance capabilities.

The substantial differences in these parameters, particularly between passenger cars and larger vehicles like semi-trailers, create complex interaction patterns that must be carefully managed. For instance, the greater mass and length of semi-trailers not only affect their acceleration and braking capabilities but also influence their space requirements and turning radiuses at intersections.

Table 3.1: The kinematic and dynamic parameters of each vehicle type.

Parameter	**Passenger Car**	**Pickup**	**Van**	**Semi-trailer**	**Truck**
Length (m)	5	5.8	5.5	16.5	7.1
Width (m)	1.8	2	2	2.55	2.4
Height (m)	1.5	1.9	2.1	4	2.4
Mass (kg)	1500	2500	3000	15000	12000
Min Gap (m)	2.5	2.5	2.5	2.5	2.5
Accel. (m/s^2)	2.6	2.6	2.6	1.0	1.3
Decel. (m/s^2)	4.5	4.5	4.5	4	4
Max Speed (m/s)	55.56	33.33	27.78	36.11	36.11

3.2.2 Vehicle Motion

Our framework implements two distinct behavioral models to govern vehicle motion:

For human-driven vehicles, we employ the Intelligent Driver Model (IDM) (Treiber and Kesting (2013)), which determines acceleration based on current traffic conditions:

$$a_{\text{IDM}} = a_{\max}\left[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right] \tag{3.6}$$

The desired gap between vehicles is computed as:

$$s^*(v,\Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{a_{\max}b}} \tag{3.7}$$

These equations capture the essential car-following behavior, where v represents current velocity, v_0 the desired velocity, s the current gap to the leading vehicle, and $s^*(v,\Delta v)$ the desired gap. Parameters s_0, T, and b represent the minimum gap at standstill, desired time headway, and comfortable deceleration, respectively.

For robot vehicles, we implement a hybrid control scheme that seamlessly transitions between IDM behavior and learned policies:

$$a_{\text{RV}} = \begin{cases} a_{\text{IDM}} & \text{if } d > d_{\text{control}} \\ a_{\text{policy}} & \text{if } d \leq d_{\text{control}} \end{cases} \tag{3.8}$$

This approach ensures smooth transitions between normal driving conditions and intersection navigation while maintaining compatibility with surrounding traffic.

3.3 Traffic Composition and Intersections

The composition of heterogeneous traffic and intersection structures significantly influence performance and control strategies. Our framework incorporates real-world

traffic patterns and intersections to ensure realistic simulation scenarios that capture the complexities of urban traffic flow.

3.3.1 Real-world Traffic Analysis and Distribution

The vehicle type ratio in our framework reflects the actual composition of urban traffic, derived from the I-24 MOTION dataset Gloudemans et al. (2023), analyzing traffic data along a 6.75 km stretch of the highway over a period of 4 hours (Poudel et al. (2024b)). Representing five primary vehicle types that commonly traverse urban intersections, the distribution includes passenger cars (70%), vans (15%), semi-trailers (11%), pickups (3%), and trucks (1%). This distribution serves as the foundation for our traffic generation process, ensuring that simulated scenarios accurately reflect real-world traffic conditions.

A critical aspect of our study is the systematic introduction of RVs into the traffic stream. We implement RVs exclusively as passenger cars, considering their prevalence in urban traffic and their suitability for automation. The RV penetration rate η modifies the baseline distribution according to two distinct regimes:

For penetration rates up to 70% ($\eta \leq 70\%$), the adjustment affects only the passenger car population:

$$\begin{aligned} P_{\text{cars}}^{\text{RV}} &= \eta \\ P_{\text{cars}}^{\text{HV}} &= 70\% - \eta \\ P_{\text{other}} &= \text{unchanged} \end{aligned} \tag{3.9}$$

For higher penetration rates ($\eta > 70\%$), having exhausted the passenger car population, the remaining vehicle types are proportionally reduced:

$$
\begin{aligned}
P_{\text{cars}}^{\text{RV}} &= \eta \\
P_{\text{cars}}^{\text{HV}} &= 0 \\
P_{\text{other}}^{\text{new}} &= P_{\text{other}}^{\text{original}} \cdot \frac{100\% - \eta}{30\%}
\end{aligned}
\tag{3.10}
$$

Table 3.2 summarizes the type distributions for different RV penetration rates.

3.3.2 Traffic Demand Patterns and Intersections

The traffic demand at each intersection is derived from real-world data collected at Colorado Springs, CO (Fig. 3.1). Each intersection is characterized by distinct incoming lane configurations and varying traffic demands. Intersection I has the highest complexity with 21 incoming lanes, accommodating a peak traffic demand of 1,157 vehicles per hour. Following this, Intersection II consists of 19 lanes with a traffic demand of 1,089 vehicles per hour, reflecting a slightly lower but still substantial volume. Intersection III features 18 lanes and serves 928 vehicles per hour, demonstrating moderate traffic intensity. Finally, Intersection IV, the least complex of the four, comprises 16 lanes and experiences a comparatively lower demand of 789 vehicles per hour.

These demand levels are distributed across incoming lanes according to turning count data (Wang et al. (2024b)). The vehicle type ratios are maintained across all turning movements, ensuring consistent representation of heterogeneous traffic throughout the network.

3.4 Control Framework

We adopt the reinforcement learning framework developed by Wang et al. (2024b) to investigate its performance and implications in heterogeneous traffic scenarios. Our investigation applies this framework to a fundamentally different traffic composition

Table 3.2: Vehicle Type Ratios for Different RV Penetration Rates.

RV (%)	**Passenger Car (non-RV)** (%)	**Pickup** (%)	**Van** (%)	**Semi-trailer** (%)	**Truck** (%)
10	60	3	15	11	1
20	50	3	15	11	1
30	40	3	15	11	1
40	30	3	15	11	1
50	20	3	15	11	1
60	10	3	15	11	1
70	0	3	15	11	1
80	0	2	10	7.3	0.7
90	0	1	5	3.7	0.3

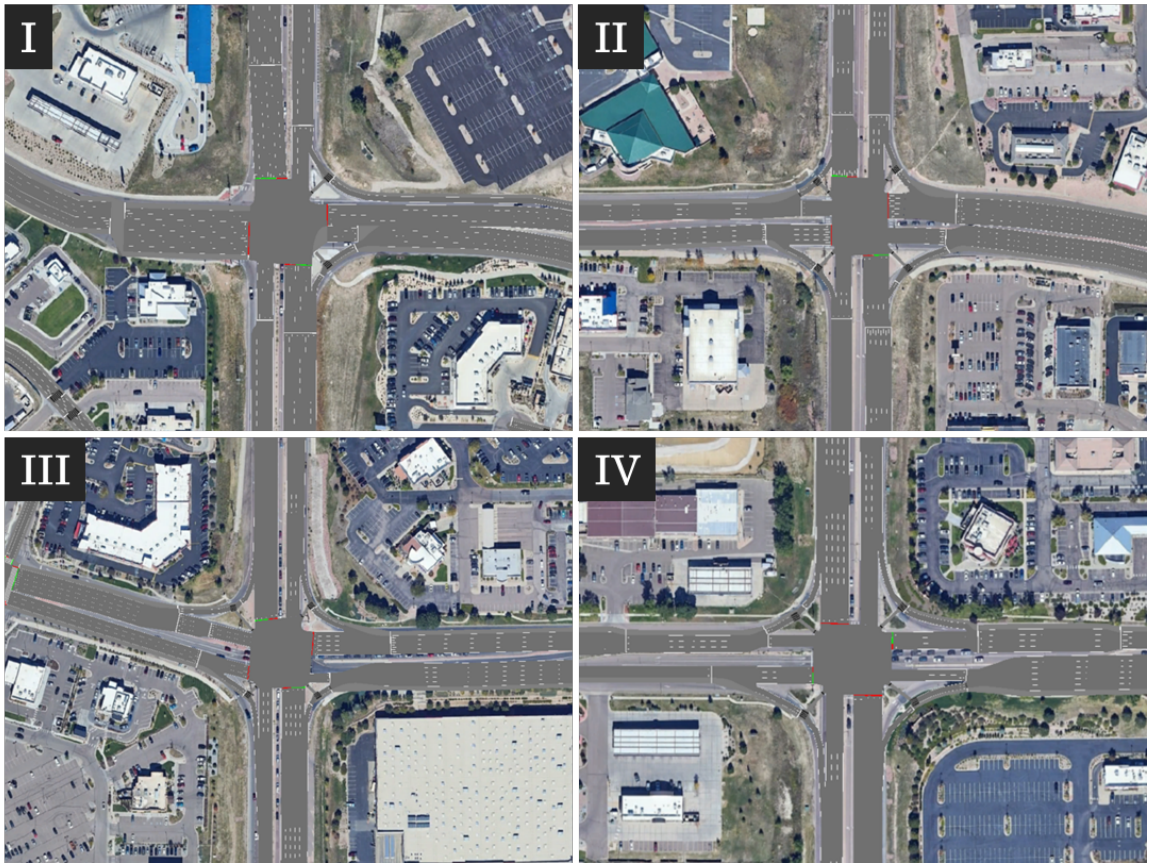


Figure 3.1: Real-world and complex intersections used in our study.

that incorporates multiple vehicle types, each with distinct physical characteristics and behavioral patterns. The framework's application to such diverse traffic conditions provides insights into its effectiveness in real-world scenarios where vehicle heterogeneity is inherent. This section details the control architecture, training process, and implementation specifics of the framework as applied to heterogeneous mixed traffic.

3.4.1 RL Algorithm Architecture

Our framework employs Rainbow DQN (Hessel et al. (2018)), a state-of-the-art reinforcement learning algorithm that enhances the original DQN architecture with several crucial improvements. At the core of this system is a neural network that approximates the Q-function, estimating expected future rewards for each possible action in any given state.

The neural network architecture consists of three fully connected layers, each containing 512 hidden units with ReLU activation functions. The network's forward pass can be expressed as:

$$\begin{aligned} h_1 &= \text{ReLU}(W_1 y_t + b_1) \\ h_2 &= \text{ReLU}(W_2 h_1 + b_2) \\ h_3 &= \text{ReLU}(W_3 h_2 + b_3) \\ Q(y_t, u) &= W_4 h_3 + b_4 \end{aligned} \tag{3.11}$$

where y_t represents the current observation, W_i and b_i denote the weights and biases of layer i, and $Q(y_t, u)$ provides Q-values for each possible action.

3.4.2 Training Process

The training process incorporates multiple mechanisms to ensure stable and efficient learning. A key component is the experience replay buffer, which stores 50,000 recent transitions in the form (y_t, u_t, r_t, y_{t+1}). Training batches of 32 samples are drawn

from this buffer using prioritized experience replay, where sampling probabilities are weighted by temporal difference errors: $P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$. Here, p_i represents the priority of transition i, and α determines the degree of prioritization in the sampling process.

To enhance training stability, we employ a target network with parameters θ^-, separate from the online network θ. This target network computes Q-values for training updates: $y_i = r_i + \gamma \max_{u'} Q(y_{i+1}, u'; \theta^-)$. The parameters of the target network are periodically updated with those of the online network, reducing the correlation between target and predicted Q-values (Hessel et al. (2018)).

3.4.3 Policy Implementation

During operation, each RV independently executes the learned policy to determine its actions. The policy produces high-level Stop/Go decisions that translate into specific vehicle control commands through the following algorithm:

Algorithm 1 RV Policy Execution

Input: Current observation y_t
Output: Vehicle acceleration command a_t
if $d_{int} \leq 30m$ **then** ▷ Within control zone
    $u_t \leftarrow \underset{u}{\text{argmax}} Q(y_t, u; \theta)$
    if $u_t = \text{Go}$ **then**
        $a_t \leftarrow a_{max}$
    else
        $a_t \leftarrow -v^2/(2d_{int})$
    end if
else
    $a_t \leftarrow a_{IDM}$ ▷ Use IDM outside control zone
end if
return a_t

3.4.4 Coordination Mechanism

While RVs make individual decisions, a coordination mechanism prevents conflicts when multiple RVs from different directions simultaneously decide to proceed. The mechanism assigns priorities based on a composite score:

$$S_i = \omega_1 w_i + \omega_2 l_i \tag{3.12}$$

The score combines waiting time w_i and queue length l_i in the RV's direction, weighted by factors ω_1 and ω_2. The RV with the highest score receives priority, while others must wait for the next decision cycle, ensuring safe and efficient intersection management.

3.5 Experimental Setup

3.5.1 Simulation Environment

Our evaluation utilizes SUMO (Simulation of Urban MObility) (Lopez et al. (2018)), a high-fidelity microscopic traffic simulator. The simulation environment reconstructs four complex intersections from Colorado Springs, CO, incorporating their unique geometries and traffic patterns. Each simulation episode runs for 1000 seconds, providing sufficient duration to observe stable traffic patterns and evaluate control performance.

3.5.2 Baseline Comparisons

To evaluate the effectiveness of our approach, we implement two baseline scenarios:

1. **HV-Signalized**: All vehicles are human-driven, with traffic controlled by traffic signals. The signal timing follows the existing programs deployed at the Colorado Springs intersections.

2. **HV-Unsignalized**: All vehicles are human-driven with no traffic signals, representing the scenario where traditional control methods are absent.

These baselines provide reference points for assessing the performance improvements achieved through RV-based traffic control.

3.5.3 Evaluation Metrics

We employ multiple metrics to comprehensively evaluate system performance:

Traffic Efficiency Metrics

The average waiting time W_{avg} for vehicles of type v is calculated as (Wang et al. (2024b)):

$$W_{\text{avg}}^{v} = \frac{1}{N_v} \sum_{i=1}^{N_v} W_i^v \tag{3.13}$$

where N_v is the total number of type v vehicles and W_i^v is the waiting time of vehicle i.

Space headway H_{space} measures the average distance between consecutive vehicles (Treiber and Kesting (2013)):

$$H_{\text{space}} = \frac{1}{M} \sum_{j=1}^{M} (X_{j+1} - X_j) \tag{3.14}$$

where M is the number of vehicle pairs and X_j represents vehicle positions.

Environmental Impact Metrics

CO_2 emissions are calculated using SUMO's HBEFA3-based emissions model (SUMO (2024a,b)) for each vehicle type:

$$E_{\text{CO2}}^{v} = \frac{1}{N_v} \sum_{i=1}^{N_v} E_i \tag{3.15}$$

Similarly, fuel consumption is measured as:

$$F_{\text{avg}}^{v} = \frac{1}{N_v} \sum_{i=1}^{N_v} F_i \tag{3.16}$$

where E_i and F_i represent the CO_2 emissions and fuel consumption of vehicle i, respectively.

3.5.4 Experimental Protocol

The evaluation process follows a systematic protocol:

1. RV penetration rates are varied from 10% to 90% in 10% increments
2. For each penetration rate, 10 independent experiments are conducted
3. Each experiment runs for 1000 simulation steps
4. Results are averaged across experiments to ensure statistical significance
5. Performance metrics are computed separately for each vehicle type

This comprehensive evaluation framework enables detailed analysis of how heterogeneous mixed traffic control performs under various conditions and provides insights into the impact of RV penetration on different vehicle types.

Chapter 4

Results and Analysis

4.1 Introduction

This chapter presents a comprehensive analysis of heterogeneous mixed traffic control at unsignalized intersections. The analysis encompasses multiple dimensions of traffic management, including intersection-specific performance metrics, vehicle type-dependent behaviors, and environmental impacts across varying robot vehicle (RV) penetration rates. Through systematic evaluation of four complex intersections under different traffic scenarios, we examine both system-wide performance improvements and granular impacts on individual vehicle classes.

4.2 System-wide Performance Analysis

4.2.1 Intersection-specific Performance

The evaluation of the framework across four distinct intersections reveals significant variations in performance improvements. Each intersection, characterized by unique geometric configurations and traffic demands, demonstrates different patterns of efficiency gains as RV penetration increases. We observe these improvements clearly

when comparing performance across the intersections, as detailed in Table 4.1. A sample scenario is at intersection I is also shown in Fig. 4.1.

For **Intersection I**, a significant reduction in waiting time is observed as RV penetration increases. Starting from **122.35 seconds** at **10% RV**, the waiting time drops to a minimum of **12.90 seconds** at **90% RV**. The most notable improvement occurs at **40% RV** where waiting time decreases from **90.85** to **47.78 seconds**, highlighting the effectiveness of coordinated RV decision-making. However, beyond **40% RV**, diminishing returns are observed, with marginal gains at higher penetration rates.

Intersection II shows a consistent decrease in waiting time with increasing RV penetration, reaching its lowest point of **8.32 seconds** at **80% RV**. However, a non-linear trend is noticed with an initial increase at **20% RV**, likely due to partial coordination disruptions where RVs are not dominant enough to control the flow. Optimal performance is achieved between **30% and 50% RV**, indicating a tipping point in traffic dynamics where RV coordination significantly enhances efficiency.

At **Intersection III**, waiting times gradually decrease from **105.07 seconds** at **10% RV** to **31.05 seconds** at **90% RV**. The most significant drop is noted at **60% RV** with **25.24 seconds**, reflecting effective RV coordination. However, a plateau effect is observed beyond **60% RV**, suggesting that additional RVs yield minimal efficiency gains.

Intersection IV experiences substantial improvements in waiting times, particularly between **30% and 50% RV** penetration, reaching **8.92 seconds** at **50% RV**. Interestingly, a slight increase in waiting time is noted beyond **50% RV**, potentially due to synchronized RV behaviors affecting traffic flow variability. Nevertheless, efficiency remains consistent at **90% RV** with **10.39 seconds**, demonstrating robust performance even at high RV penetration rates.

Table 4.1: Average Waiting Time (s) at Intersections for Different RV Penetration Rates.

Intersection	**HV-**	**HV-**	**RV Penetration Rate**								
	Signalized	**Unsignalized**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
I	37.37	127.97	122.35	97.16	90.85	47.78	38.52	21.70	23.31	17.31	**12.90**
II	61.13	25.54	31.88	38.13	11.72	16.77	9.54	8.34	9.63	**8.32**	8.81
III	50.61	112.94	105.07	81.71	62.95	46.51	50.15	**25.24**	39.94	44.46	31.05
IV	39.71	101.32	54.08	56.33	50.12	14.59	**8.92**	22.11	17.87	11.83	10.39

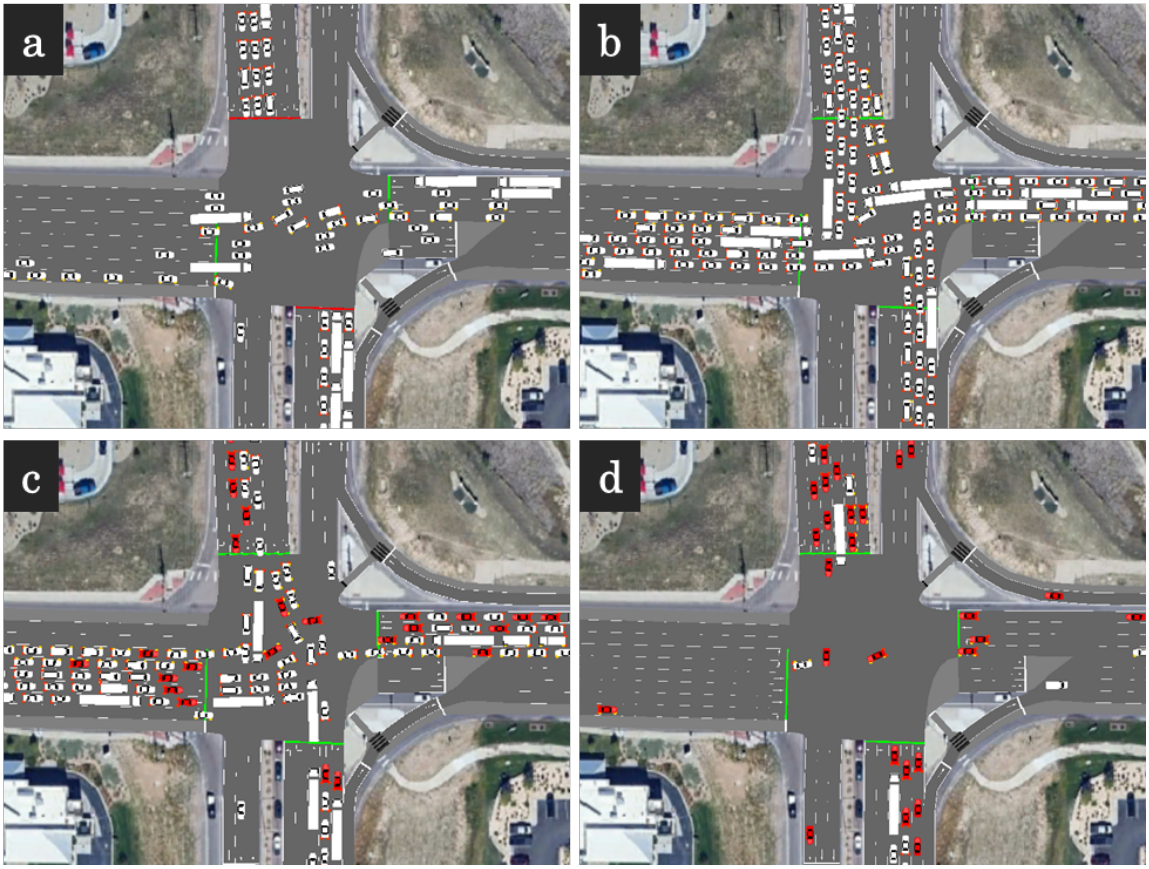


Figure 4.1: Traffic conditions at intersection I at 10-minute mark, RVs in red and HVs in white. (a) HV-Signalized: Flow regulated by traffic lights. (b) HV-Unsignalized: Severe gridlock in all directions. (c) 10% RV: RVs have limited influence due to HV dominance in the flow. (d) 60% RV: RVs effectively reduce congestion under unsignalized conditions.

Overall, the results highlight that complex intersections benefit the most from RV coordination, while less complex intersections stabilize at lower RV rates. A diminishing return effect is consistently observed beyond **50% RV** penetration, indicating that maximum efficiency can be achieved without fully automating all vehicles. This finding suggests that phased RV deployment can be an effective strategy for enhancing intersection performance. Additionally, the intersection geometry and traffic demand play crucial roles in determining the optimal RV penetration rates, emphasizing the need for customized traffic control strategies tailored to specific intersection characteristics.

4.3 Vehicle Type-Specific Analysis

4.3.1 Performance Variations Across Vehicle Classes

The heterogeneous nature of urban traffic necessitates a detailed examination of how each vehicle type responds to RV-based traffic control. Our analysis reveals distinct patterns of improvement across all vehicle categories, demonstrating both the framework's versatility and its varying impact on different vehicle classes, as depicted in Fig. 4.2.

Waiting Time Analysis by Vehicle Type

Each vehicle category exhibits unique patterns of improvement in waiting times as RV penetration increases:

Passenger cars, constituting 70% of traffic volume, demonstrate consistent improvement despite their high frequency. Their average waiting time decreases from the baseline to 23.99 seconds at 90% RV penetration, achieving a 52.46% improvement over signalized control. This substantial improvement, even for the most common vehicle type, underscores the framework's effectiveness in managing high-volume traffic components.

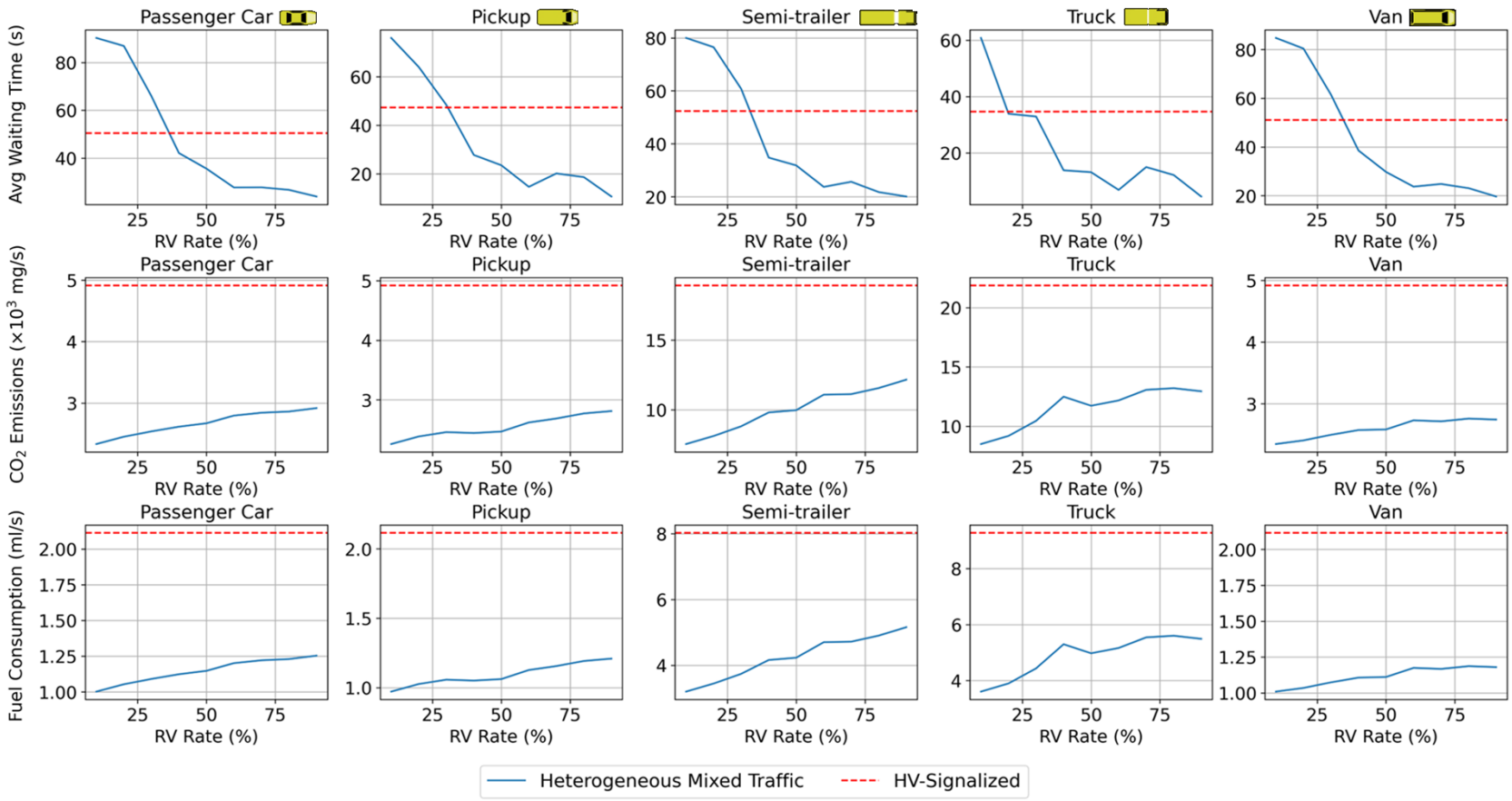


Figure 4.2: Average Waiting Time (top row), CO_2 Emissions (middle row), and Fuel Consumption (bottom row) for different vehicle types across RV rates (10% to 90%) compared to HV-Signalized.

Vans, representing 15% of traffic volume, show similar improvement patterns to passenger cars but with slightly better gains. Their waiting times reduce to 19.68 seconds, marking a 61.51% improvement over the signalized baseline. This enhanced performance compared to passenger cars might be attributed to their larger size creating more predictable gap patterns in traffic flow.

Semi-trailers, comprising 11% of traffic, present an interesting case with waiting times reducing from 79.97 seconds to 20.12 seconds—a 61.57% improvement over signalized control. Despite their size and maneuverability challenges, semi-trailers achieve substantial improvements, suggesting the framework's robustness in handling larger vehicles.

Trucks, despite representing only 1% of traffic volume, show the most dramatic improvement. Their waiting time decreases from 60.80 seconds to 4.50 seconds, achieving an 87.03% reduction compared to signalized control. This exemplifies what we term the "rarity advantage," where less frequent vehicle types benefit disproportionately from RV coordination.

Pickups (3% of traffic) demonstrate the second-highest improvement rate, with waiting time reductions of up to 77.52% compared to signalized intersections, further supporting the rarity advantage phenomenon.

4.3.2 Environmental Impact Assessment

CO_2 Emissions and Fuel Consumption Patterns

The environmental impact analysis reveals varying patterns across vehicle types, with each category showing distinct responses to increased RV penetration:

Passenger cars exhibit moderate increases in both emissions and fuel consumption. Their CO_2 emissions rise by 25% (from 2,333 mg/s to 2,917 mg/s) as RV penetration increases from 10% to 90%. This is accompanied by a proportional increase in fuel consumption from 1.0 ml/s to 1.25 ml/s, suggesting a consistent relationship between emissions and fuel usage for smaller vehicles.

Vans show slightly higher increases than passenger cars but maintain relatively moderate environmental impacts. Their emission patterns closely follow their fuel consumption trends, indicating efficient energy utilization despite increased continuous motion.

Semi-trailers demonstrate the most significant environmental impact changes. Their CO_2 emissions increase by 61% (from 7,554 mg/s to 12,165 mg/s), while fuel consumption rises from 3.2 ml/s to 5.2 ml/s—a 62.5% increase. This substantial rise reflects the greater energy demands of maintaining continuous motion for larger vehicles.

Trucks follow a similar pattern to semi-trailers but with slightly lower increases. Their emissions rise by 52% (from 8,497 mg/s to 12,946 mg/s), with fuel consumption increasing from 3.6 ml/s to 5.6 ml/s (55.5% increase).

Pickups maintain relatively modest increases in both metrics, showing patterns more similar to passenger cars than larger vehicles.

4.3.3 Space Utilization Analysis

The examination of space headway patterns (Fig. 4.3.3) reveals systematic improvements across all vehicle categories, though with varying magnitudes.

Passenger cars achieve the most significant space utilization improvement, with headways reducing from 57.49 m to 35.78 m—a 38% reduction. This substantial improvement for the most common vehicle type suggests effective optimization of available road space.

Semi-trailers, despite their larger size, show notable improvements with headways decreasing from 70.55 m to 53.21 m—a 25% reduction. This improvement is particularly significant given the additional space requirements and safety considerations for larger vehicles.

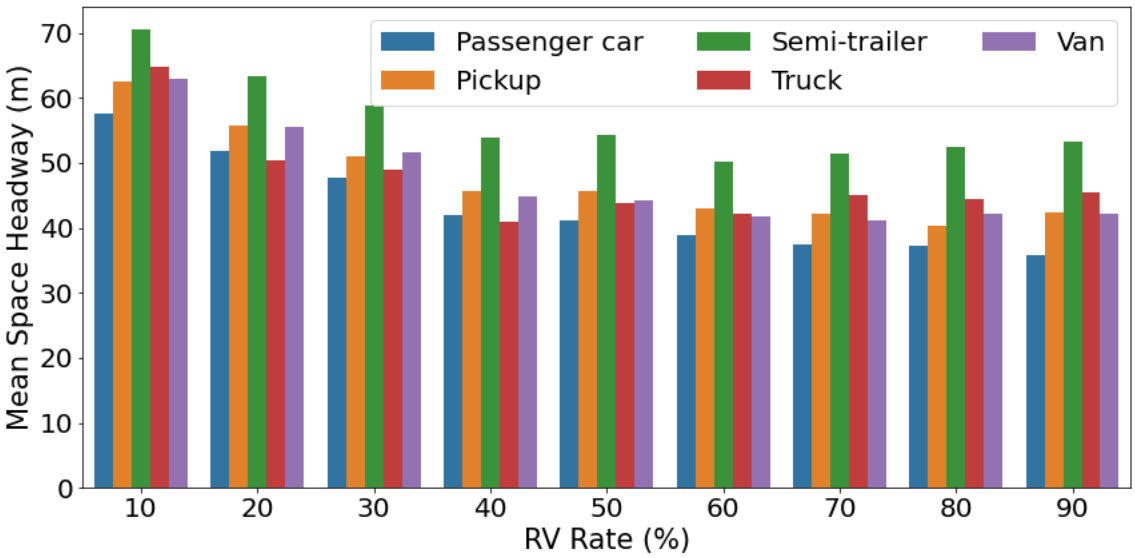


Figure 4.3: Space headways for different vehicle types at varying RV penetration rates.

Vans demonstrate space headway reductions comparable to passenger cars, reflecting their similar maneuverability characteristics despite larger dimensions. Their headway patterns show consistent improvement with increasing RV penetration, suggesting effective integration into the optimized traffic flow.

Trucks and pickups exhibit unique space headway patterns, particularly at higher RV penetration rates. Unlike other vehicle types, they show a plateau effect where headways stabilize or slightly increase beyond certain RV penetration thresholds. This phenomenon can be attributed to several factors:

- Lower frequency of occurrence reducing the pressure for space optimization
- Reduced interaction with other similar vehicles at intersections
- Natural spacing created by their distribution within the traffic stream

4.4 Synthesis of Vehicle Type-Specific Impacts

The comprehensive analysis of vehicle-specific responses to RV-based traffic control reveals several significant patterns and relationships that merit further discussion.

4.4.1 The Rarity Advantage Phenomenon

One of the most striking findings is the consistent inverse relationship between vehicle frequency and performance improvement. This "rarity advantage" is pronounced in waiting time reductions. Table 4.2 illustrates this relationship, showing percentage improvements in waiting times for vehicle types at different RV rates.

Table 4.2: Percentage improvements in waiting times for vehicle types at different RV rates compared to HV-Signalized.

Vehicle Type	**RV Penetration Rate**					
	40%	**50%**	**60%**	**70%**	**80%**	**90%**
Passenger Car	16.49	29.40	45.00	44.89	46.98	**52.46**
Pickup	41.40	50.36	69.09	57.46	60.67	**77.52**
Semi-trailer	33.55	39.16	54.63	50.95	58.41	**61.57**
Truck	60.22	62.14	80.30	56.88	65.02	**87.03**
Van	24.58	41.78	53.58	51.43	54.82	**61.51**

The mechanism behind this advantage appears to be two-fold:

1. **Temporal Distribution**: Less frequent vehicles naturally experience greater temporal separation, allowing the control system to optimize their passage through intersections more effectively.

2. **Resource Availability**: When rare vehicle types approach the intersection, the system typically has more flexibility in accommodating their passage due to fewer competing demands from similar vehicles.

4.4.2 Environmental Impact Trade-offs

The analysis reveals a complex relationship between traffic efficiency and environmental impact. While all vehicle types experience reduced waiting times, the corresponding changes in emissions and fuel consumption present varying trade-offs:

- **Smaller Vehicles** (passenger cars and pickups) demonstrate modest increases in emissions despite significant efficiency gains, suggesting a favorable balance between performance improvement and environmental impact.

- **Larger Vehicles** (trucks and semi-trailers) show more substantial increases in emissions and fuel consumption, though these increases are offset by dramatic reductions in waiting times and improved flow efficiency.

4.4.3 Space Utilization Dynamics

The patterns of space headway reduction reveal important insights about the system's ability to optimize traffic density. The varying responses across vehicle types suggest that:

1. The framework effectively manages the trade-off between safety and efficiency, maintaining appropriate spacing while reducing unnecessary gaps.

2. Vehicle size and frequency interact to determine optimal spacing patterns, with larger vehicles maintaining more conservative headways despite overall reductions.

3. The plateau effect observed in less frequent vehicles indicates a natural limit to space optimization based on vehicle type characteristics and traffic composition.

Chapter 5

Conclusions

This study investigates the impact of heterogeneous mixed traffic control using RL-controlled robot vehicles (RVs) in complex environments. Our results demonstrate that higher RV penetration rates significantly reduce average waiting times for all vehicle types, with reductions of up to 86% and 91% compared to HVs at signalized and unsignalized intersections, respectively. The findings further highlight a *rarity advantage*, indicating that certain vehicle types, particularly less frequent ones like trucks and pickups, benefit more from RV-based control strategies. This suggests that adaptive traffic control approaches incorporating vehicle-type recognition could further enhance efficiency. Additionally, while RV-based control increases emissions and fuel consumption due to higher speeds, the overall efficiency gains surpass those of signalized intersections. Moreover, consistent reductions in space headways are observed across all vehicle types, with passenger cars experiencing the largest decrease.

Several future research directions can build upon this work. First, expanding RV operation to more diverse test environments, such as roundabouts, three-way intersections, and larger-scale urban networks, would assess the system's adaptability and scalability. Leveraging existing traffic simulation, reconstruction, and prediction

techniques could further enhance these evaluations. Second, investigating communication strategies among RVs under varying communication constraints—both short- and long-range—through network optimization could improve coordination efficiency. Finally, considering RVs of different vehicle types with tailored reward functions, such as prioritizing fuel efficiency for trucks, could refine traffic management strategies to better align with the operational needs of each vehicle category.

In conclusion, this research highlights the potential of reinforcement learning in coordinating mixed traffic environments by dynamically adapting to real-time traffic conditions. By addressing current limitations and extending the proposed methods, future work can advance RL-based traffic control systems, making them more efficient, scalable, and applicable to real-world urban mobility challenges.

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Vita

Md Iftekharul Islam was born in Dhaka, Bangladesh. He received his Bachelor of Science in Computer Science and Engineering from Rajshahi University of Engineering & Technology in December 2018.

After completing his undergraduate studies, Iftekharul worked as a Lecturer in the Department of Computer Science & Engineering at Bangladesh University from 2019 to 2023. He taught courses in Algorithm Design, Data Structures, Database Systems, and Computer Architecture, while also helping develop the curriculum for the Computer Science program.

Iftekharul's research interests focus on machine learning, particularly reinforcement learning, transportation autonomy, and remote sensing image analysis. In 2024, he began pursuing his Ph.D. in Computer Science at the University of Tennessee, Knoxville, under the guidance of Dr. Weizi Li.

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Iftekharul is passionate about both teaching and research. His long-term goal is to blend these interests by sharing knowledge with students while contributing meaningful research to the field of computer science.