Multi-Objective Optimization of Intersection Control under Heterogeneous Traffic Conditions: A Case Study in Zindabazar, Sylhet

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Certificate of Approval

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Declaration

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Abstract

This study develops a machine learning-based multi-objective optimization framework to improve traffic signal control at congested intersections in Sylhet, Bangladesh. Detailed traffic data were collected using drones and field surveys, capturing vehicle classes, speeds, and flow patterns in heterogeneous traffic. A simulation model in SUMO was calibrated to reflect real conditions accurately. Traditional static signal plans were designed using Webster's formula and tested as a baseline. The core contribution is a reinforcement learning (RL) approach that dynamically adjusts signal timings in real time based on observed traffic states. The RL agent balances objectives, including minimizing delays, reducing queue lengths, improving throughput, and lowering emissions. Compared to static timing, the RL-based system demonstrated significant improvements in average vehicle delay, intersection throughput, and fuel consumption. This framework shows that adaptive learning-based control can effectively manage complex, mixed traffic flows and supports scalable, data-driven traffic management for smart city applications.

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Chapter 1

Introduction

1.1 Background

Traffic congestion is one of the most pressing urban challenges of the 21st century, affecting not only the daily lives of city dwellers but also national economies and global environmental health. In both developed and developing countries, prolonged traffic jams lead to productivity losses, increased fuel consumption, and increased public health risks. In the international arena, mega cities face billions in economic damage due to lost time in traffic, while the transportation sector remains a significant contributor to global carbon dioxide emissions that exacerbate climate change. In low and middle-income countries, these issues are often intensified by rapid urban growth, unregulated transport systems, and lack of modern infrastructure. Within this broader context, urban transportation systems in developing countries are undergoing profound structural and functional transformations.

Urban transportation systems in developing countries are undergoing profound structural and functional transformations driven by rapid urbanization, economic liberalization, and demographic shifts. These changes exert significant pressure on the transport infrastructure of secondary cities, such as Sylhet, which experience population influx, commercial densification, and the emergence of informal transport systems without corresponding investment in coordinated traffic control or intelligent infrastructure. In the context of South Asian cities, particularly in Bangladesh, the transport environment is marked by modal diversity, high non-motorized transport (NMT) dependency, and inadequate enforcement of lane discipline [1, 2]. Sylhet exemplifies this challenge. Its organic urban form, coupled with constrained road space, irregular intersection geometry, and mixed land use, creates complex travel patterns and bottlenecks especially in key nodes such as Zindabazar, a densely built-up commercial area that functions as a multi-modal interchange for thousands of commuters daily [3, 4].

The Zindabazar corridor encompasses a cluster of three closely-spaced intersections Ambarkhana, Chowhatta, and Zindabazar along the primary arterial (Zindabazar Road) and its secondary link roads [5, 6]. These intersections are convergence zones for motorcycles, passenger cars, CNG auto-rickshaws, rickshaws, vans, minibuses, and pedestrians, all operating under a nonlane-based, nonsignalized traffic regime [7]. In such a setting, traffic control often defaults to driver negotiation, informal priority rules, and manual traffic policing, which collectively lead to operational inefficiencies such as queue spillbacks, high vehicle delay, safety concerns, and irregular platoon dispersion across intersections. What distinguishes the traffic dynamics in Sylhet and similar cities from Western or East Asian urban models is the heterogeneity of flow.

Heterogeneous traffic is defined by the coexistence of vehicles with varying physical and dynamic characteristics, including differences in size, speed, maneuverability, acceleration/deceleration behavior, and right-of-way practices [8, 9]. These features render conventional lane-based deterministic models inadequate. As a result, traditional traffic flow theories (e.g. Greenshields or LWR models), which assume homogeneity and lane discipline, fail to capture the microlevel complexity of urban intersections in this context [10].

Given these limitations, researchers have increasingly turned to microscopic traffic simulation as a tool to analyze and improve traffic operations in data-short and infrastructure-constrained environments. Among available platforms, the Simulation of Urban Mobility (SUMO) stands out as a flexible, open-source, and computationally efficient framework capable of simulating mixed-traffic behavior, adaptive signal control, and corridor-level traffic interactions. SUMO allows vehicle-level granularity, customizable signal control algorithms, detector logic, and emission modeling, making it highly suitable for evaluating policy interventions in the Bangladeshi traffic ecosystem. Furthermore, the adoption of intelligent transportation systems (ITS) in South [11, 12, 13].

Asian cities remain limited due to fiscal constraints, lack of institutional capacity, and technological inertia. Most intersections in Sylhet operate either without signals or with rudimentary static signal plans that are rarely updated or calibrated to match evolving traffic demand. These plans, often designed without real-time input or detection systems, become obsolete under fluctuating demand patterns, such as peak-hour congestion or special-event surges. Globally, there has been a shift toward data-driven, adaptive signal control systems, which use real-time sensors, detectors, and feedback loops to adjust green times dynamically. Actuated signal control systems, in particular, are designed to extend or terminate phases based on vehicle presence, queue length, or time gaps between vehicles [14]. Such systems have demonstrated improved performance in various urban contexts by reducing delay, optimizing phase utilization, and improving corridor throughput. However, their effectiveness in heterogeneous traffic environments remains under-explored, particularly in South Asian secondary cities, where non-motorized traffic and low compliance rates pose unique challenges.

Given the strategic importance of Zindabazar within the urban transport network of Sylhet, and the observed inefficiencies in its intersection control schemes, there is a clear need for empirical, simulation-based analysis to determine whether and how the application of actuated signal control systems can improve traffic performance relative to unsignalized and static signalized operations. Such an analysis must account for the multi-objective nature of traffic control, balancing efficiency (delay and travel time), environmental sustainability (emissions and fuel consumption), and equity (service for all modes).

In light of this, the present study undertakes a microscopic simulation-based evaluation of alternative traffic control strategies in the Zindabazar corridor using SUMO, informed by field data and contextualized within the socio-technical realities of Bangladeshi cities. The research not only seeks to provide comparative performance insights but also aims to develop a localized methodology that can be adapted for intersection control optimization across other heterogeneous urban networks in Bangladesh and the broader Global South.

1.2 Problem Statement

Urban intersections serve as critical nodes in transportation networks, and their operational efficiency directly influences the overall performance of urban mobility systems. In high-density mixed-traffic environments such as those found in Sylhet, Bangladesh, the role of effective intersection control becomes even more crucial due to complex interactions among diverse traffic participants [5, 15]. The Zindabazar intersection, a central artery within Sylhet's commercial district, exhibits a pattern of system-level inefficiencies arising from closely spaced intersections operating with inconsistent or sub-optimal control strategies [16].

The absence of integrated signal coordination and real-time traffic responsiveness results in significant operational disruptions, including:

- Non-uniform delay distribution across approaches, where some movements experience prolonged waiting times while others are overserved.
- Queue spillback effects, particularly during peak hours, which disrupt upstream intersections and reduce the effective capacity of the corridor.
- Increased potential for collisions due to conflicting right-of-way decisions, especially involving non-motorized users and informal transit modes.
- Lack of pedestrian accommodation, resulting in unsafe crossing behavior and additional delays for vehicular traffic.

These conditions are exacerbated by the heterogeneous nature of traffic flow, where vehicles of different classes—ranging from slow-moving rickshaws and motorcycles to high-speed cars and buses—interact in a largely unregulated, lane-less environment. In such conditions, the performance of static signal systems, which assume fixed arrival patterns and consistent compliance, is often inferior, particularly during fluctuating demand periods.

Unsignalized intersections, while low in cost and flexible under light traffic, are insufficient under high-volume or saturated conditions, leading to higher vehicle delays, increased driver frustration, and an elevated risk of side-impact collisions. Moreover, the informal negotiation of right-of-way places vulnerable road users—especially pedestrians and non-motorized vehicle operators—at significant risk.

On the other hand, actuated signal control systems, which dynamically adjust green times based on detected vehicle presence or flow, offer a theoretically superior alternative. These systems are capable of responding to real-time traffic fluctuations and ensuring more equitable service across approaches. However, their deployment in Bangladesh remains extremely limited due to a range of institutional and operational barriers, including:

- Lack of sensor infrastructure, such as inductive loop detectors or camera-based actuators.
- Inadequate signal maintenance regimes and limited technical capacity within municipal traffic agencies.
- Policy inertia, where existing practices rely more on tradition and political considerations than on empirical performance metrics.
- Budgetary limitations, which restrict the adoption of intelligent traffic systems (ITS) in secondary cities like Sylhet.

Compounding these issues is the lack of a systematic, comparative evaluation framework to assess the effectiveness of various intersection control strategies—specifically within the heterogeneous traffic contexts typical of Bangladesh and other developing nations. Current policy decisions regarding signal installation or upgrade are often uninformed by rigorous simulation or field-based analysis. As a result, signal placement, cycle length selection, and coordination timing are typically determined without accounting for actual traffic demand, saturation levels, or modal mix.

This disconnection between policy practice and technical evidence creates a critical research gap. Without robust comparative studies especially, those grounded in data driven, simulation-based methodologies—urban traffic authorities lack the empirical foundation needed for making cost-effective and context-sensitive decisions regarding intersection control. Therefore, this thesis addresses the urgent need for a simulation-based, multi objective performance evaluation of different traffic control strategies in the Zindabazar corridor. By employing the Simulation of Urban Mobility (SUMO) platform, this research models heterogeneous traffic conditions and systematically tests:

- Unsignalized intersection operations, as currently exist in many parts of Sylhet.
- Static signalized control, which simulates traditional fixed-time operations under varying demand conditions.
- Actuated signal control systems, designed to adapt to real-time fluctuations in traffic flow.

The evaluation employs multiple performance metrics—including vehicle delay, queue length, emissions, and travel time—to identify the most effective and sustainable traffic control strategy for this critical corridor. Through this approach, the study contributes to both the academic literature on traffic control in heterogeneous environments and to practical urban transport planning in Bangladesh, offering a replicable framework for corridor-level signal optimization in other developing urban areas.

1.3 Research Objectives

The overarching goal of this research is to conduct a comprehensive simulation-based evaluation of different traffic control strategies for a corridor of closely spaced intersections operating under heterogeneous traffic conditions in the Zindabazar area of Sylhet, Bangladesh. The study aims to determine the relative effectiveness of unsignalized, static signalized, and actuated signalized intersection control strategies by assessing their performance across multiple operational and environmental indicators.

Given the context of increasing traffic demand, diverse modal composition, and infrastructure limitations, this research emphasizes a multi-objective assessment framework. The analysis is grounded in empirical traffic data and executed using the Simulation of Urban Mobility (SUMO), an open-source microscopic traffic simulation platform capable of modeling non-lane-based, mixed traffic flow patterns representative of urban Bangladeshi conditions. To this end, the specific research objectives are as follows:

- To calibrate a traffic simulation model based on real-world data to ensure realistic scenario development.
- To evaluate the baseline operational performance of the unsignalized Zindabazar intersection.
- To develop and implement static signal control strategies using fixed-time parameters derived from field data and Webster's theoretical model.
- To simulate actuated signal control using vehicle detection logic (e.g., loop detectors) in SUMO, and assess its responsiveness to fluctuating demand and heterogeneous traffic.
- To define and apply multi-objective performance metrics—including average waiting time (s), average speed (km/h), and average emissions (CO, fuel, NO, PMx, HC, CO)—to enable comprehensive comparison of control strategies.
- To identify the most effective and contextually suitable control strategy for the Zindabazar intersection based on simulation outcomes, and provide actionable recommendations for local traffic management.
- To contribute to research on intersection control in heterogeneous traffic by developing a localized, data-driven simulation framework applicable to other South Asian or developing urban areas.

By pursuing these objectives, this study seeks to bridge the gap between theoretical traffic control strategies and real-world applicability in low-income, infrastructure-limited settings. The findings are expected to inform future investments in adaptive signal control, enhance the operational resilience of urban corridors, and support evidence-based policymaking in the transportation sector of Bangladesh.

1.4 Research Questions

Building on the problem context and research objectives, this study seeks to answer several critical questions related to intersection control strategies in a mixed-traffic environment. The Zindabazar corridor in Sylhet presents a unique urban laboratory where different control methodologies can be evaluated under real-world constraints typical of South Asian secondary cities.

The core aim is to examine how different intersection control strategies—unsignalized, static signalized, and actuated signalized—perform in a heterogeneous traffic system and to understand the trade-offs inherent in each. To this end, the following research questions are formulated:

- How do unsignalized intersections perform in terms of delay, queue formation, and emissions under heterogeneous traffic conditions in the Zindabazar corridor?

- To what extent can static signal control improve intersection performance compared to unsignalized conditions?

- How do actuated signal systems respond to dynamic and stochastic traffic flows, and what performance improvements can they provide relative to static control strategies?

- Which control strategy offers the most balanced and sustainable performance across multiple criteria, including delay, throughput, environmental impact, and equity of service for all modes?

- Can the simulation findings be generalized or adapted to other urban corridors in Bangladesh or similar developing urban contexts?

By answering these questions, this thesis will generate empirical evidence to support data-driven decision-making in urban traffic control. The simulation results and methodological contributions aim to inform future transport policy in Bangladesh, particularly regarding the deployment of context-appropriate intelligent traffic systems in mixed-traffic environments.

1.5 Scope and Limitations

This study is scoped to examine and compare the operational performance of various intersection control strategies—specifically unsignalized, static signalized, and actuated signalized systems—within the context of heterogeneous traffic flow in the Zindabazar corridor of Sylhet, Bangladesh. The research focuses on evaluating the functional effectiveness of each control approach using a microscopic simulation framework, with particular attention to the dynamics of mixed-mode traffic and the spatial interaction of closely spaced intersections. Scope of the Study:

- The simulation network focuses solely on the Zindabazar intersection, selected due to its high congestion levels, diverse modal mix, and critical role within the central business district's traffic operations.
- The traffic environment modeled includes a heterogeneous mix of vehicles commonly found in urban Bangladeshi settings, such as cars, motorcycles, CNG-powered auto-rickshaws, rickshaws, and minibuses. The simulation assumes a non-lane-based traffic regime to reflect real-world movement behavior.
- Three control strategies are examined:
  - Unsignalized intersections, operating under priority-based rules without formal control.

  - Static signal control, using fixed-time signal plans derived from empirical and analytical timing models.
  - Actuated signal control, employing detector-based responsiveness to traffic demand using SUMO's logic-based controller models.

- The analysis is based on traffic data collected during peak demand periods (e.g., morning and evening rush hours), representing the worst-case operational scenarios.

- Performance is evaluated using a multi-objective framework, incorporating indicators such as:
  - Average waiting time (s)
  - Average speed (km/h)
  - Average fuel consumption (ml)
  - Emission outputs:
    * CO_2 (g)
    * NO_x (mg)
    * PM_x (mg)
    * HC (mg)
    * CO (mg)

- The simulation model is developed and executed using the Simulation of Urban Mobility (SUMO) platform, which allows for detailed representation of traffic behavior, signal timing, and vehicle interactions under different control schemes.

The study has several limitations that should be acknowledged. First, pedestrian behavior is not explicitly modeled, though its effects are indirectly captured through vehicle delays at intersections. Future research could incorporate pedestrian microsimulation for greater realism. Public transport operations—such as scheduling, dwell time, and boarding dynamics—are also not modeled in detail, although buses and shared vehicles are included as vehicle classes. Driver behavioral heterogeneity is represented using SUMO's default parameters, which may not fully reflect informal driving practices typical in Sylhet. The results are simulation-based and should be seen as indicative; real-world validation through pilot deployments or sensor data is necessary for confirmation. Additionally, the simulation assumes fully functional detectors and signal infrastructure for actuated control, while actual implementation may require significant upgrades not addressed here. Lastly, the analysis is limited to peak-hour conditions; off-peak dynamics and temporal variability remain unexamined and warrant future investigation.

While acknowledging these limitations, this research provides a structured methodology and comparative evidence base that can support transport planners, municipal engineers, and policymakers in evaluating the operational benefits of adaptive signal control in complex, resource-constrained urban environments.

Chapter 2

Literature Review

2.1 Traffic Management Challenges in Heterogeneous Conditions

Urban intersections in developing regions frequently face highly heterogeneous traffic conditions characterized by a diverse mix of vehicles including private cars, buses, motorcycles, auto rickshaws, bicycles, and other non-motorized modes all competing for limited space [17]. The absence of consistent lane discipline gives rise to non-lane-based movements and highly unpredictable driver behavior . These conditions challenge the effectiveness of conventional traffic control strategies, such as fixed time signals or traditional actuated controls, which were largely developed under assumptions of structured, lane-based flows [18].

To overcome these limitations, Reinforcement Learning (RL) based dynamic traffic signal control has emerged as a promising approach capable of adapting to complex and rapidly changing traffic environments. Unlike fixed-time or actuated systems, RL based controllers learn optimal signal policies by interacting with the traffic environment over time, continuously improving performance through trial and error. This paradigm shift allows the controller to respond proactively to variations in traffic demand, vehicle composition, and driver behavior [19].

In RL-based systems, the intersection controller is typically formulated as an agent that observes the state of the traffic network—such as queue lengths, vehicle positions, or arrival rates—and selects signal phase actions aimed at maximizing a long-term reward [20]. The reward function can be designed to reflect multiple objectives, including minimizing total vehicle delay, reducing stop frequency, lowering fuel consumption, and mitigating emissions. Through repeated interactions, the agent learns to balance these objectives in the face of stochastic, non-lane-based traffic flows [21].

Recent studies have demonstrated that RL methods, such as Q-learning, Deep Q-Networks (DQN), and Policy Gradient algorithms, can outperform traditional signal control strategies in simulated heterogeneous traffic scenarios [22]. In particular, RL-based controllers have shown superior adaptability to fluctuating demand and mixed vehicle types, conditions where conventional fixed-time or actuated signals often fail to maintain optimal performance [14].

To evaluate the effectiveness of RL-based dynamic traffic signal control under realistic conditions, researchers frequently rely on microscopic traffic simulation platforms, with SUMO (Simulation of Urban Mobility) being one of the most widely used tools in South Asia and other developing regions. SUMO's flexibility allows for the detailed modeling of non-lane-based traffic behavior, custom vehicle types, and stochastic arrival patterns. It also provides Application Programming Interfaces (APIs) such as TraCI, which enable seamless integration with external RL algorithms implemented in Python or other environments [23].

In this simulation-based framework, RL agents can be trained by repeatedly interacting with SUMO's traffic model. Performance metrics such as average vehicle delay, queue length, throughput, fuel consumption, and emissions are systematically tracked to quantify the benefits of RL-based control compared to fixed-time and actuated baselines. Such studies provide evidence that RL-driven adaptive signaling holds significant promise for improving the operational efficiency, sustainability, and resilience of intersections in highly heterogeneous traffic environments.

2.2 Simulation-Based Evaluation of Traffic Control Strategies

Traffic heterogeneity in developing countries reflects a complex mix of vehicle types with vastly differing operational characteristics, ranging from high-speed private cars and motorcycles to slow-moving rickshaws, handcarts, and frequent pedestrian crossings [24]. The absence of strict lane discipline further compounds this complexity by introducing frequent lateral and longitudinal conflicts among road users, making traffic flow inherently unstable and difficult to predict.

Traditional traffic control systems—particularly fixed-time signals based on deterministic cycle lengths—are often ill-suited to such dynamic and volatile environments [25]. These systems typically depend on pre-set phase durations and assume relatively uniform, lane-disciplined flows. In heterogeneous conditions, however, fixed-timing plans can lead to pronounced inefficiencies, including prolonged waiting times, excessive queuing, and increased fuel consumption resulting from frequent stop-and-go operations [26].

Comparative studies using microscopic traffic simulation have shown that at very low traffic volumes, unsignalized intersections can sometimes result in lower average delays by eliminating unnecessary stops [27]. However, as traffic demand increases, the lack of structured right-of-way causes higher conflict rates, greater delays, and degraded safety performance.

While fixed-time and actuated signal systems can improve throughput and enhance safety by introducing regulated phases and clarifying priority movements, their effectiveness depends heavily on precise calibration to local conditions. Specifically, parameters must account for traffic composition, arrival patterns, and behavioral heterogeneity to avoid inefficiencies [28]. Failure to do so often results in signal timings that are misaligned with actual demand, undermining the intended operational benefits.

In this context, there is growing recognition of the need for more adaptive, data-driven traffic management approaches. Reinforcement Learning-based dynamic control, in particular, offers the potential to learn from continuous interaction with the environment and to respond effectively to the variability and complexity inherent in heterogeneous traffic conditions.

2.3 Simulation-Based Evaluation of Traffic Control Strategies

Microscopic simulation plays a vital role in evaluating traffic control strategies under heterogeneous conditions, as it enables detailed modeling of individual vehicle behaviors, interactions, and stochastic variations in driver decisions. This level of granularity is essential for capturing the dynamics of mixed-traffic environments like the Zindabazar intersection, where lane discipline is minimal and vehicle compositions are highly variable.

Among available simulation platforms, Simulation of Urban Mobility (SUMO) offers significant advantages due to its open-source nature, extensive customization capabilities, and compatibility with reinforcement learning frameworks. SUMO allows researchers to model non-lane-based, mixed-vehicle traffic flows while incorporating locally relevant behaviors and infrastructure constraints [29].

Accurate calibration of simulation parameters to observed traffic conditions is critical for ensuring that results reflect real-world dynamics. For example, [28] demonstrated effective calibration of SUMO for an intersection in Khulna by adjusting key driver behavior parameters, including driver imperfection (sigma = 0.3) and reaction time (tau = 1.4), to closely replicate empirical flow patterns and queuing characteristics.

Similarly, [27] applied the PTV VISSIM simulation platform to evaluate alternative signal plans in Dhaka, achieving up to a 40% reduction in queue lengths through data-driven optimization techniques. This study highlights the utility of simulation experiments as a cost-effective means to test and refine signal timing, channelization, and control logic before implementing changes in the field.

Such methodologies provide a valuable framework for Sylhet, where simulation-based evaluation can guide the design of optimized traffic control strategies tailored to local traffic heterogeneity. Leveraging SUMO's capabilities, researchers and practitioners can iteratively calibrate and test reinforcement learning-based dynamic signal control to quantify potential improvements in delay reduction, emissions, and overall intersection performance.

2.4 Tools and Calibration Techniques for Mixed Traffic Simulation

While SUMO's open-source nature and extensive feature set make it a compelling platform for modeling mixed traffic environments, achieving accurate representations of non-lane-based heterogeneous traffic requires rigorous calibration and careful configuration. Key adjustments typically involve tuning driver imperfection parameters to reflect variable driving behaviors, enabling lateral vehicle movements without strict lane adherence, and calibrating gap acceptance thresholds to mirror local overtaking and merging tendencies [30].

To address the unique traffic dynamics observed in South Asian urban contexts, researchers have developed hybrid simulation models that combine cellular automata and agent-based approaches. These hybrid models are particularly effective in capturing the stochastic and opportunistic behaviors of drivers operating in environments with frequent lateral interactions and minimal lane discipline [31].

Field studies conducted in Bangladesh and India have demonstrated that properly calibrated SUMO simulations can closely replicate observed performance metrics—including vehicle delays, travel times, and queue lengths—providing strong support for their use in evaluating traffic interventions under heterogeneous conditions [28, 32]. This evidence is especially relevant for applications in Sylhet, where budget constraints often limit access to proprietary software solutions.

Recent research employing SUMO and similar simulation platforms has shown that advanced signal control strategies and targeted channelization measures can deliver substantial reductions in delays, queuing, and emissions at congested intersections comparable to Zindabazar [33, 21]. For instance, calibrated simulation studies have demonstrated that dynamic signal timing and improved lane allocation can improve throughput without requiring costly infrastructure upgrades.

Given the prohibitive costs associated with proprietary tools such as PTV VISSIM, particularly in resource-constrained settings, SUMO's flexible and open-access framework offers significant advantages for researchers, practitioners, and policymakers. By supporting detailed modeling of heterogeneous traffic flows and integrating seamlessly with reinforcement learning algorithms, SUMO provides a practical and scalable platform to design, test, and refine adaptive traffic management strategies tailored to developing cities.

Table 2.1: Literature matrix of existing studies.

Author	Proposed Methods	Simulation Setup	Metrics	Best Method	Results	Limitations and Future Recommendations
Ali et al. [34]	Fuzzy Logic + Webster's Optimal Cycle Formula and Fuzzy Logic + Modified Webster's Formula to dynamically extend green time.	Implemented in SUMO, tested in Kilis, Turkey (3-way, 4-way, and 5-way intersections).	Average Waiting Time, Average Travel Time, Average Speed.	Adaptive Fuzzy Logic + Webster's Formula significantly reduced waiting time.	Adaptive methods outperformed fixed-time in high traffic; similar results in low/medium traffic.	Frequent phase transitions in 5-way intersections slightly reduced average speed. Use Machine Learning to refine fuzzy logic and expand to multi-intersection networks.
Zhang & Su [35]	Macroscopic MILP-based optimization model eliminating predefined signal cycles and adjusting dynamically.	Implemented in PTV VISSIM and SUMO, tested on Singapore traffic networks.	Average Delay Time, Queue Length, Level-of-Service (LOS).	MILP-based optimization reduced delay by 37.4%.	Optimized partial signalization outperformed fully signalized networks.	High computational complexity for large-scale networks. Implement distributed computing and AI-driven real-time adaptation.
Li et al. [36]	ChatSUMO, an LLM-based tool automating SUMO scenario generation via natural language.	Implemented in SUMO, tested on Albany, NY real-world data.	Traffic Density, Travel Time, CO2 Emissions, Fuel Consumption.	Traffic Light Adaptation with ChatSUMO reduced travel time by 15.68%.	Traffic light offset optimization reduced congestion; higher EV proportion reduced emissions.	Processing time increases with network size; uniform traffic assumption. Improve AI-driven prediction, integrate real-time feeds.
Mohammadi et al. [37]	SUMO2Unity co-simulation integrating SUMO's 2D traffic with Unity's 3D driver simulations.	Tested in Pickering, Ontario with Meta Quest 2 VR headset.	Traffic Safety, Signal Timing, CAV Interaction, Driver Behavior.	Co-simulation improved driver response studies.	Realistic behavior in lane-changing and highway merging.	No pedestrian/bicycle modeling, no weather effects, data exchange latency. Expand pedestrian modeling, integrate weather.
Liao et al. [38]	Decentralized Game Theory-Based Ramp Merging Strategy optimizing merging sequence and control.	Unity-SUMO simulation of Riverside, CA ramp.	Mobility, Fuel Efficiency, Driving Stability, Merging Conflict Resolution Time.	Cooperative Game Merging resolved conflicts 2.86s faster.	CAV adoption improved speed by 72.4% and reduced fuel by 53.9%.	Low CAV penetration reduces effectiveness. Enhance human-CAV interaction, integrate environmental impact modeling.

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Table 2.1 continued from previous page

Author	Proposed Methods	Simulation Setup	Metrics	Best Method	Results	Limitations and Future Recommendations
Karakaya et al. [39]	SimRa dataset to create cyclist behavior models from real acceleration, speed, and turning patterns.	Data from Berlin, Munich, Hanover; cyclists classified by speed ranges.	Acceleration Accuracy, Velocity Distribution, Turn Accuracy, Flow Consistency.	SUMO with SimRa models improved acceleration and turn behavior accuracy.	Improved cyclist route choices and intersection modeling.	Limited to Germany; no e-bike modeling; lacks weather. Expand dataset globally, model e-bikes, integrate AI trajectory prediction.
Ma et al. [40]	Geographic population data to estimate demand and generate traffic flow via ActivityGen.	Jianghan Zone, Wuhan, China. SUMO, ActivityGen, DUAROUTER.	Traffic Flow Accuracy, Speed Consistency, Historical Comparison.	ActivityGen closely matched real-world peak congestion.	Residential traffic well represented; congestion underestimated in hospitals/stations.	No pedestrian movement or transit flow. Improve transit modeling, integrate real-time roadwork impact.
Clemente [41]	Step-by-step approach integrating real data, OSM maps, and MongoDB storage.	SS195 corridor, Cagliari, Italy. SUMO, netconvert, polyconvert, MongoDB.	Traffic Flow Accuracy, Computation Efficiency, Network Fidelity.	DUA model with MongoDB improved calibration.	OSM improved network accuracy; MongoDB enhanced querying.	No pedestrian/bicycle integration; computational challenges for large networks. Expand multimodal transport, integrate real-time data.
Gonzalez-Delicado et al. [42]	97 km freeway scenario with Clone Feedback Calibration using real sensor data.	A-7 Freeway, Spain. SUMO, OSM, MongoDB, Cadyts Calibration.	Traffic Flow Accuracy, Speed Deviation, Occupancy Deviation.	Clone Feedback reduced deviation by 67%.	Speed tuning improved congestion modeling.	No pedestrian/bicycle modeling, no weather data. Expand to seasonal analysis, introduce public transport modeling.
Reza et al. [43]	SARSA(λ) with Gaussian eligibility decay and A-star routing integration.	21-intersection network in Ingolstadt, Germany. SUMO, OpenAI Gym, PyTorch.	Waiting Time, Number of Stops, Travel Speed.	SARSA(λ) with A-star reduced waiting by 59.9%.	Citywide RL improved flow in peak hours.	No pedestrian/bicycle modeling; computationally expensive. Expand model to real-time sensors, use DQN for optimization.

Various studies have been conducted to improve traffic simulation, optimization, and modeling through diverse methodologies. These efforts address persistent issues such as congestion, inefficient signal timing, lack of real-world accuracy in simulation environments, and inadequate representation of vehicle and cyclist behaviors. The approaches span fuzzy logic-based adaptive control, reinforcement learning, macroscopic optimization models, and AI-driven scenario generation. A comparative summary of these studies is presented in Table 2.1, highlighting their proposed methods, simulation platforms, evaluation metrics, and key findings.

Ali et al. [34] proposed a fuzzy logic-based adaptive traffic control system integrating Webster's Optimal Cycle Formula with a modified variant to dynamically adjust green times in response to real-time traffic fluctuations. Their system, implemented in SUMO and tested in Kilis, Turkey, demonstrated significant reductions in waiting times and improvements in travel speed. However, frequent phase transitions at five-way intersections slightly decreased average speeds. The authors recommend incorporating machine learning techniques to further optimize performance.

Zhang & Su [35] addressed the inefficiencies of traditional traffic light models by developing a macroscopic mixed-integer linear programming (MILP) optimization model that eliminates predefined signal cycles. Tested in Singapore using SUMO and PTV VISSIM, this approach reduced average delay by 37.4% and showed that optimized partial signalization outperformed fully signalized networks. While effective, the method's computational demands remain substantial for large-scale applications, underscoring the need for distributed computing and AI-based real-time adaptations.

Similarly, Reza et al. [43] employed a TD-learning-based SARSA algorithm with Gaussian eligibility trace decay and A-star routing to enhance multi-agent reinforcement learning (RL) traffic signal control. Their system, validated in a 21-intersection network in Ingolstadt, Germany, achieved a 59.9% reduction in waiting times and improved citywide traffic flow. Despite these gains, the approach remains computationally intensive, prompting recommendations to integrate Deep Q-Networks (DQN) and real-time sensor data streams for further optimization.

Li et al. [36] introduced ChatSUMO, an LLM-powered tool that automates SUMO scenario generation through natural language processing and OpenStreetMap data integration. This solution simplifies road network editing and traffic signal optimization. Tested on real-world traffic data from Albany, NY, ChatSUMO achieved a 15.68% reduction in travel times. However, its reliance on uniform traffic assumptions and limited scalability for large networks highlights the need for enhanced AI-driven prediction and real-time traffic feed integration.

Mohammadi et al. [37] focused on realistic driver behavior simulation by developing SUMO2Unity, a co-simulation platform that integrates SUMO's 2D traffic modeling with Unity's 3D driver environment. Their framework enabled real-time data exchange, VR-based driver simulations, and vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Applied in Pickering, Ontario, using a Meta Quest 2 VR headset, the system improved lane-changing and highway merging realism. Limitations included the absence of pedestrian and bicycle modeling and data exchange latency, suggesting future work should address multimodal simulation and environmental effects.

Ma et al. [40] tackled the challenge of realistic traffic flow generation by using geographic population data and ActivityGen to dynamically estimate trip demand. Their study in Wuhan, China, successfully replicated peak congestion patterns but underestimated congestion near hospitals and train stations. The authors recommend incorporating public transport schedules and real-time roadwork data for more accurate modeling.

Gonalves et al. [44] integrated real sensor data from Guimarães, Portugal, with SUMO and Eclipse MOSAIC to improve simulation fidelity. By fusing multi-source data, their approach enhanced congestion prediction, fuel consumption modeling, and analysis of public transport impacts. Limitations included restricted sensor coverage and static transit schedules, highlighting the need to expand data sources and integrate weather and real-time information.

Clemente et al. [41] developed a systematic approach to incorporating real-world data into SUMO using OpenStreetMap (OSM) and MongoDB for scenario storage and retrieval. Applied to the SS195 corridor in Cagliari, Italy, this method improved network fidelity and traffic flow accuracy. However, it lacked pedestrian and bicycle integration, motivating recommendations for multimodal transport modeling and the development of automated calibration tools.

Gonzalez et al. [42] introduced a Clone Feedback Calibration technique for large-scale freeway simulation using 12 years of real sensor data from Spain's A-7 corridor. Their method reduced deviation by 67% compared to traditional calibration techniques, significantly improving congestion modeling. Nonetheless, the approach did not account for seasonal weather conditions or pedestrian activity, suggesting opportunities for incorporating environmental and multimodal considerations.

Karakaya et al. [39] addressed the limitations of cyclist behavior representation in SUMO by leveraging the SimRa dataset to categorize cyclist behavior into speed-based classes and improve turn modeling accuracy. Tested on data from Berlin, Munich, and Hanover, this approach enhanced acceleration and intersection behavior realism. However, it did not model e-bikes or weather impacts, pointing to future research opportunities in expanding datasets and incorporating AI-driven trajectory prediction.

Liao et al. [38] proposed a decentralized game theory-based ramp merging strategy to optimize merging sequences and ensure safe vehicle spacing in mixed traffic. Simulated using Unity and SUMO for a real-world ramp in Riverside, California, their approach resolved merging conflicts 2.86 seconds faster than non-cooperative methods. Cooperative automated vehicle (CAV) adoption increased average speed by 72.4% and reduced fuel consumption by 53.9%. However, effectiveness declined with low CAV penetration, underscoring the importance of studying human-CAV interactions and environmental impacts.

Collectively, these studies demonstrate that adaptive traffic control, reinforcement learning, real-time sensor integration, and realistic behavior modeling significantly enhance simulation accuracy and operational performance. While techniques such as fuzzy logic, MILP optimization, and SARSA-based RL effectively improve signal timing, the integration of real-world data, advanced cyclist behavior modeling, and co-simulation frameworks further contribute to traffic flow realism. Future research should focus on scalable multi-intersection networks, AI-driven prediction capabilities, and the inclusion of pedestrians and non-motorized traffic to develop comprehensive and robust traffic management systems.

2.5 Role of SUMO in Traffic Simulation Research

SUMO's versatility and feature set have led to its widespread adoption in both research and practice. Notable applications include:

Intelligent Transportation Systems (ITS)

SUMO has been extensively used to evaluate adaptive traffic signal control, vehicle-to-infrastructure (V2I) communication, and connected vehicle platooning strategies. For example, researchers use SUMO to simulate real-time optimization of signal timings in response to live traffic data streams or to study the benefits of V2I-enabled green-wave coordination for transit vehicles [45].

Autonomous Vehicle Testing

As autonomous vehicle technologies advance, SUMO provides a safe virtual environment for testing autonomous driving algorithms, collision avoidance systems, and cooperative maneuvers before deploying them on public roads. Integration with frameworks like CARLA and SUMO2Unity3D allows for detailed modeling of vehicle dynamics and sensor perceptions [**?**].

Policy Simulations

Government agencies and planning organizations employ SUMO to study the impacts of congestion pricing, HOV lanes, parking restrictions, and public transit priority measures. Simulation-based policy analysis helps quantify expected outcomes, such as changes in travel times, modal splits, emissions, and revenue generation, supporting evidence-based policy development [46].

Comparative Advantage

While commercial platforms like VISSIM and AIMSUN also offer advanced capabilities for microscopic traffic simulation, they are often associated with high licensing fees and restrictions on customization [47]. These barriers can limit access for academic researchers, especially in developing countries and institutions with limited funding.

By contrast, SUMO's open-source licensing model ensures that it remains freely accessible and adaptable. Combined with its strong support for integration with machine learning frameworks, reinforcement learning libraries, and real-time control systems, SUMO offers a cost-effective and versatile alternative to proprietary software. This comparative advantage has made SUMO the platform of choice for a growing community of researchers working on data-driven and AI-powered traffic management, contributing significantly to the advancement of transportation science and engineering [48].

Chapter 3

Methodology

3.1 Overview of Research Design

This study applies a simulation-based methodological framework to evaluate and compare the performance of three traffic control strategies: unsignalized intersections, static signalized intersections, and actuated signalized intersections. The research is centered on the Zindabazar corridor in Sylhet, Bangladesh, which experiences high traffic volumes, heterogeneous vehicle compositions including cars, motorcycles, rickshaws, buses, and trucks, and irregular driving patterns that contribute to congestion and unpredictable delays. The design aims to create a realistic representation of the corridor's operating conditions, test multiple control approaches in a controlled environment, and quantify their relative effectiveness. The Simulation of Urban Mobility (SUMO) software is used as the primary modeling tool. SUMO allows microscopic simulation of vehicle interactions, signal operations, and traffic flow dynamics. The modeling process starts with the development of a detailed digital representation of the corridor, including lane configurations, intersection geometries, and existing signal settings. To ensure that the simulation accurately reflects field conditions, real-world traffic data are collected using drones. Drones are deployed at selected intersections during peak and off-peak periods to record continuous video footage. This footage is processed to extract vehicle counts, classifications, turning movements, and arrival distributions. Data preprocessing involves cleaning erroneous or incomplete entries and categorizing all vehicles into standardized classes to maintain consistency across simulation scenarios. After preparing the input data, the simulation network is calibrated by adjusting vehicle behavior parameters such as acceleration rates, deceleration profiles, gap acceptance, and car-following models. Calibration targets metrics like average travel time, vehicle throughput, and queue lengths, comparing simulated outputs to field observations. Validation is performed using t-statistics to verify that no significant statistical differences exist between simulated and observed performance indicators, ensuring the model is reliable for further experimentation. Once the model calibration and validation are complete, baseline performance under existing traffic control conditions is documented. This includes measuring delays, queues, and throughput without any changes to the current traffic signal configurations. These baseline results provide reference values for assessing the impact of alternative control strategies. The study then simulates static signal control, where fixed-time plans are implemented with cycle lengths and phase splits derived from established design guidelines and observed traffic patterns. Actuated signal control scenarios are also modeled to explore how vehicle-actuated timings respond to fluctuating demand and heterogeneous flows. Beyond conventional strategies, the study develops a reinforcement learning-based dynamic signal control system. The RL agent is trained within the SUMO environment, receiving state inputs such as queue lengths and phase status, and selecting signal actions to maximize a reward function designed to reduce average vehicle delay and improve throughput. Training continues over multiple episodes until performance stabilizes. The RL approach is then tested against static and actuated strategies under both existing and forecasted traffic volumes. Performance evaluation includes comparisons of delay reduction, queue dissipation, and improvements in overall traffic flow. Results are analyzed to determine whether machine learning-based control offers clear benefits over traditional methods in managing complex, mixed-traffic conditions. This research design ensures a comprehensive, reproducible, and systematic assessment of traffic signal control strategies suitable for congested urban corridors. Figure 3.1 illustrates the overall research workflow. Key points:

- Real-world traffic data collected using drones for high accuracy.
- Calibration and validation performed with t-statistics to ensure model reliability.

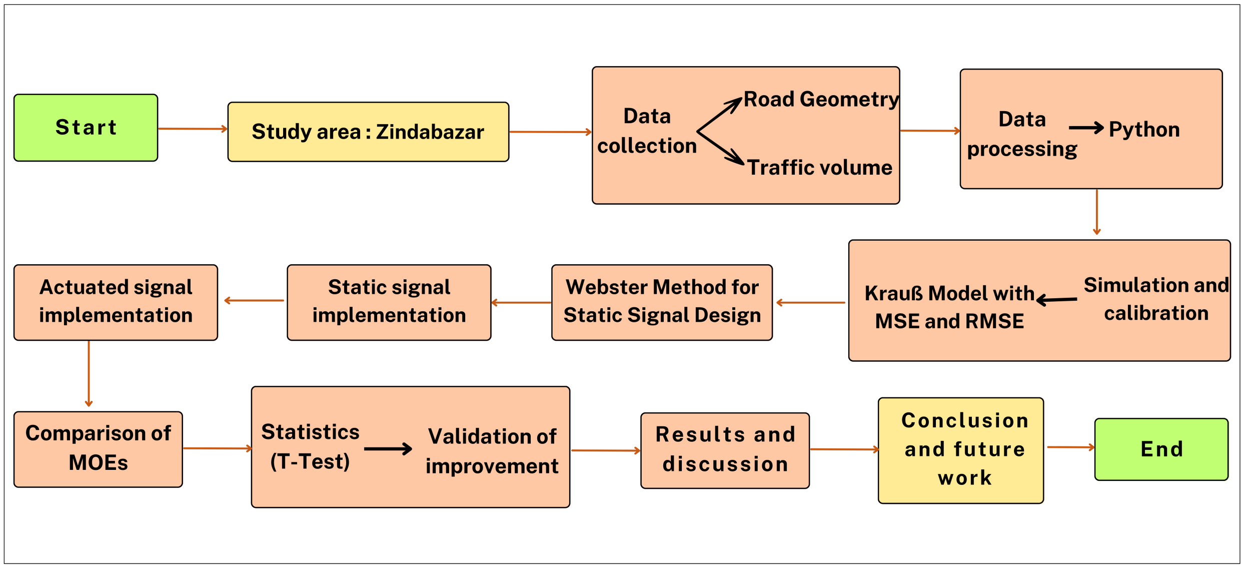

Figure 3.1: Methodology.

- SUMO simulation used as a testbed to compare static, actuated, and RL-based control.
- Reinforcement learning model trained to dynamically optimize signal timings.

3.2 Study Area and Data Collection

This section presents a comprehensive description of the study area and the complete process of data collection and preparation, ensuring the accuracy, reliability, and reproducibility of the simulation and optimization framework.

3.2.1 Study Area Description

The selected study area is the Zindabazar corridor, located within the central business district of Sylhet, Bangladesh. This corridor represents one of the most critical urban links in the city's transport network, facilitating the movement of people and goods across a wide range of socio-economic activities. The corridor extends over approximately 1.2 kilometers and comprises three to four major intersections exhibiting different control types, geometric layouts, and operational characteristics. These intersections include:

- A signalized intersection with fixed-time operation where congestion during peak hours is chronic.
- An unsignalized intersection managed informally by traffic police or yielding behavior.
- An intersection with partial signal control where certain approaches are signalized and others remain uncontrolled.
- A minor intersection predominantly controlled through driver negotiation.

Land use along the corridor is primarily commercial, with dense clusters of retail shops, wholesale markets, small offices, banks, and informal street vendors. This pattern contributes to high pedestrian activity, frequent roadside parking maneuvers, and loading/unloading operations that interfere with traffic flow. Traffic within the corridor is highly heterogeneous and non-lane-based. Vehicles do not adhere strictly to lane discipline, and diverse vehicle types—including passenger cars, motorcycles, CNG auto-rickshaws, cycle rickshaws, minibuses, trucks, and pedestrians—share the roadway. **Justification for Selection:**

- The Zindabazar corridor is of strategic economic and mobility importance, serving as a key connector between residential neighborhoods and commercial districts [45].
- The corridor suffers from persistent congestion and inefficient traffic operations due to the lack of coordinated signal control and enforcement [49].
- The area provides a representative case of mixed-traffic conditions and informal driving behavior common in many urban centers in Bangladesh [50].
- The diversity in intersection types, control strategies, and traffic patterns enables a robust comparative assessment of different traffic management approaches [51].

Figure 3.2: (a) Aerial drone view of Zindabazar intersection capturing real-time heterogeneous traffic. (b) Mobile application for traffic counting.

3.2.2 Data Collection Approach

A rigorous, multi-layered data collection process was developed to ensure comprehensive coverage of all factors influencing traffic performance. Data collection combined aerial drone surveillance, manual observation, geometric measurements, and digital mapping resources. Figure 2 illustrates a top-down aerial view of the study intersection captured using drone surveillance, showcasing real-time traffic movement, vehicle composition, and spatial interactions across multiple approaches.

Equipment and Setup: Drones were selected as the primary data collection tool due to their ability to capture wide-area video footage without obstructing traffic or requiring in-road equipment installation [52].

- Drones Used: A DJI Mini 2 SE drone was employed for aerial data collection. This high-resolution drone is equipped with a 4K camera, integrated GPS modules for precise georeferencing, and advanced image stabilization technology to ensure clear and stable video footage during operation.

- Positioning Strategy: Drones were deployed at heights ranging from 50 to 100 meters, depending on local obstructions and the size of the intersection footprint. The elevation was optimized to minimize occlusions from buildings, trees, billboards, and utility infrastructure.
- Flight Patterns: Drones operated in stationary hover mode directly above intersections to maintain consistent camera angles. Additional slow orbital passes were conducted to document approach geometry and adjacent land uses.
- Recording Duration: Each intersection was recorded for a minimum of one hour per session to capture traffic variability and queuing patterns. Sessions were repeated across different times of the day to reflect temporal fluctuations.
- Time Period: Evening peak: 5:00–6:00 PM The combination of multiple recording periods allowed the study to establish a reliable baseline for daily demand cycles.

Data Types Collected The drone video recordings and field surveys produced a rich set of data elements necessary for accurate simulation and calibration:

- Traffic Volume: Vehicle counts per minute per approach were extracted to determine demand profiles.Vehicle Types: Vehicles were classified into the following categories:
  - Passenger cars
  - Motorcycles and scooters
  - CNG auto-rickshaws
  - Cycle rickshaws
  - Minibuses and buses
  - Medium and heavy trucks
  - Bicycles and pedestrian crossings
- Speeds and Acceleration: Individual vehicle speeds and acceleration patterns were measured to model realistic driving behavior and stop-and-go dynamics.

– Queue Lengths: Maximum and average queue lengths during red signal phases and periods of congestion were measured.

– Turning Movements: Origin-destination movements through each intersection were documented to support turning probability calibration.

– Pedestrian Activity: Pedestrian crossings during green phases and mid-block crossings were noted to account for conflicts.

3.2.3 Geometric and Vehicle Data

Accurate modeling and performance evaluation of intersection operations require detailed documentation of geometric design and prevailing traffic conditions. Field investigations were therefore conducted to capture critical geometric attributes and directional traffic flows for the study intersection. These datasets served as fundamental inputs for subsequent signal optimization and simulation modeling. The geometric layout and directional traffic volumes observed at the Zindabazar intersection are illustrated in Figure X.

Geometric features: Field teams conducted thorough on-site surveys to document the physical layout of the intersection. Measured parameters included lane widths, approach lengths, number of lanes per leg, and corner turning radii. Key infrastructural elements—such as medians, channelization islands, pedestrian crossings, and refuge zones—were also recorded due to their influence on vehicle maneuverability, pedestrian safety, and lane utilization. To enhance spatial accuracy and supplement the field measurements, satellite imagery from Google Earth and geospatial data from OpenStreetMap were used. These resources helped verify road alignments, intersection footprints, and land use contexts, providing a reliable spatial foundation for network modeling and analysis.

Traffic Volume Data: Directional traffic flow data were collected and categorized based on movement types: Straight, Left Turn, and Right Turn. Each approach was identified according to its geographical orientation—East side, South side, West side, and North side. Traffic volumes were recorded in Passenger Car Units (PCU) during the evening peak period (5:00–6:00 PM) on both Sunday and Thursday, representing variability at the beginning and end of the typical workweek in the local context.As shown in Table X, the straight movement from the North side recorded the highest traffic volume at 699 PCU, while the right turn from the East side recorded the lowest volume at 198 PCU. This disaggregated movement data is essential for identifying dominant flow directions, allocating green time efficiently, and designing effective signal timing strategies.

Table 3.1: Directional Movement-wise Traffic Volumes at the Study Intersection (in PCU)

Direction Side	**Directional Movement**	**Total PCU**
3*East side	Straight	480
	Left	333
	Right	198
3*South side	Straight	591
	Left	336
	Right	216
3*West side	Straight	489
	Left	435
	Right	240
3*North side	Straight	699
	Left	273
	Right	234

Characteristics of vehicle attributes: As shown in Table X, the length and width of each vehicle classification were manually recorded during field observations. Standard values for acceleration and deceleration were applied to all vehicle categories, except for three-wheelers, which exhibit distinct operational behavior. The maximum speed of each vehicle class was estimated through field-based travel time measurements. A stopwatch was used to record the time required for vehicles to traverse known roadway segments, enabling an estimation of their speed. Although simple, this method proved effective for comparing the mobility characteristics of different vehicle types under real-world conditions. This section also discusses the proposed transportation mode classification framework, along with the algorithm used to extract feature values and the underlying rationale for each feature selected.

Table 3.2: Attributes of the Different Vehicular Modes

Transport Mode	Passenger Capacity	Length (m)	Width (m)	Max Speed (m/s)
CNG	5	2.9	1.8	10.71
Bus	24	9.5	2.0	9.80
Motorcycle	2	1.9	0.6	11.85
Rickshaw	2	2.3	1.5	6.90
Cycle	1	1.8	0.5	7.50
Car	4	4.6	1.7	13.45
Truck	2	12.0	2.5	11.45

3.2.4 Directional Volumes

Finally, directional volumes were calculated to quantify traffic movement patterns in each direction through the corridor and across intersections. These directional splits were derived from observed turning movement counts and supplemented with synthetic data where gaps existed. Directional volumes informed routing definitions, lane utilization models, and signal timing configurations in the simulation environment, ensuring that modeled flows closely matched real-world directional distributions.

3.2.5 Data Extraction and Processing Tools

The drone video recordings and field surveys yielded a comprehensive dataset essential for accurate simulation modeling and calibration. Traffic volume data were extracted by continuously observing the drone footage, focusing on one approach of the intersection at a time. While watching the recorded video, observers manually counted the vehicles passing through the selected leg and entered the data into a digital counter application. The recorded counts were then systematically compiled and organized in a Microsoft Excel file for further analysis and integration into the traffic simulation model. This method ensured accurate documentation of vehicle movements by direction (e.g., straight, left turn, right turn) for each leg of the intersection.

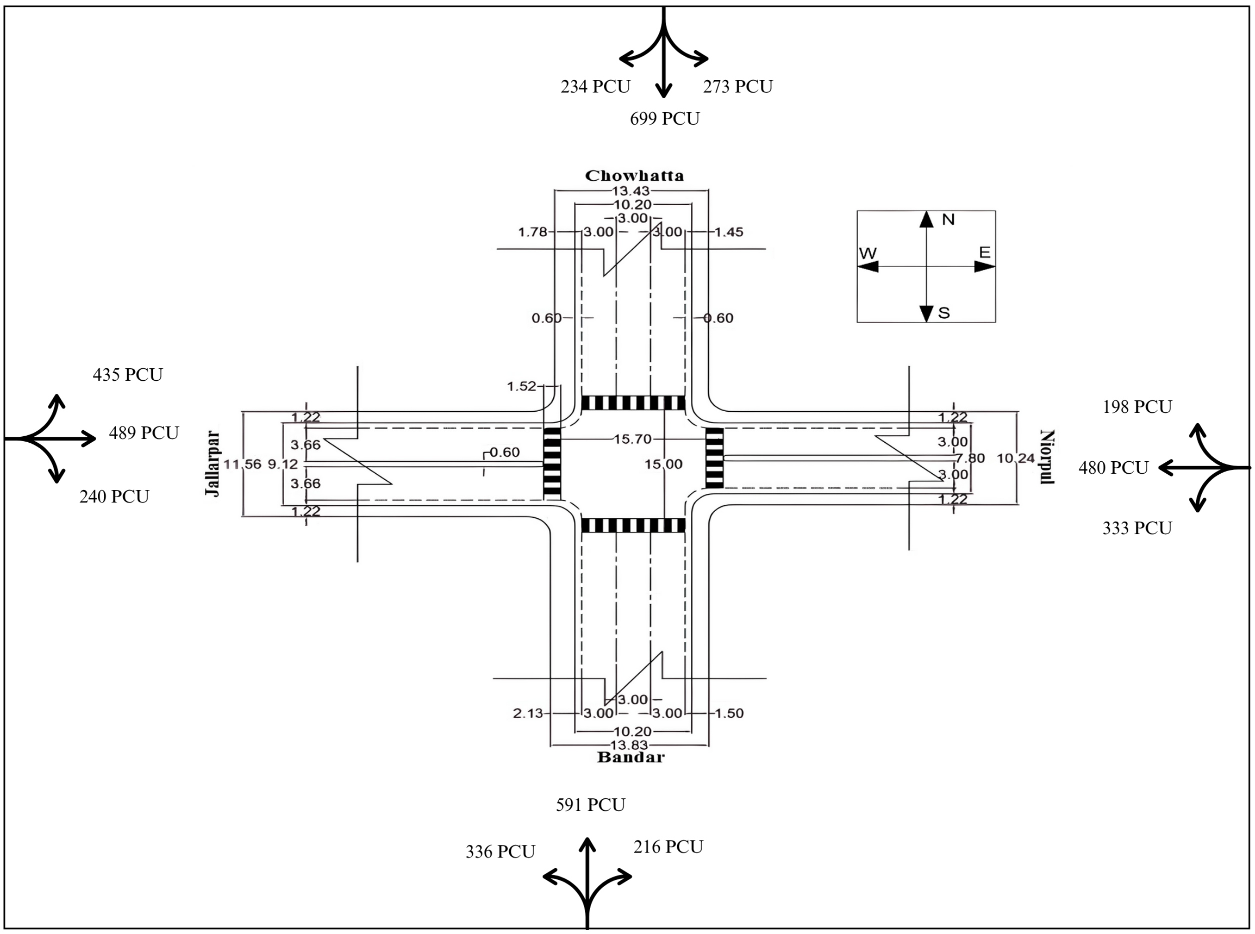

Figure 3.3: Zindabazar Intersection

Field teams conducted detailed surveys to document intersection geometry and signal operations:

- Travel Times: Average and range of travel times across segments were measured using visual time-stamping in video recordings.
- Queue Lengths: Peak queue lengths per approach were extracted to validate simulation congestion levels.
- Saturation Flow Rates: Saturation flow was estimated during periods of continuous movement to calibrate discharge rates in the simulation.
- Arrival Profiles: Arrival headways were analyzed to understand variability and randomness of vehicle arrivals.

These datasets were used to iteratively adjust simulation parameters until modeled outputs closely matched field observations.

3.3 Traffic Modelling and Simulation

3.3.1 Network Modeling

The network modeling process aimed to replicate the physical and operational characteristics of the Zindabazar corridor as accurately as possible. A multi-step workflow was implemented to ensure both geometric fidelity and consistency with observed field conditions. The foundational road network was generated using OpenStreetMap (OSM) data. The OSM extracts provided essential information on:

- Road alignments
- Intersection locations

- Lane counts
- Basic priority rules

The OSM data were converted into SUMO-compatible network files (.net.xml) using the netconvert tool, which translates geographic data into a routable simulation network. Automated imports often contain simplifications or inaccuracies unsuitable for high-precision simulation. Therefore, substantial manual edits were performed in netedit:

- Alignment Correction: Intersections and approaches were adjusted to match actual surveyed geometries observed in drone footage and field measurements.
- Turning Radii: Curb radii and corner shapes were edited to capture realistic vehicle turning behavior, particularly important for modeling slow-speed maneuvers by larger vehicles and rickshaws.
- Lane Attributes: Lane widths and number of lanes per approach were modified to reflect field conditions, including informal shoulder use.
- Connections: Turn connections between lanes were manually specified to ensure vehicles could execute observed movements without routing conflicts.
- Priority Rules: Give-way, yield, and right-of-way priorities were explicitly set for unsignalized intersections to represent local driving norms accurately.
- Pedestrian Crossings: Crosswalk locations were added where frequent pedestrian movement was observed, even if not formally marked on maps.
- Signal Configurations: For signalized intersections, existing phase sequences, cycle lengths, and offsets were programmed to reproduce current operation as the baseline scenario.

The network model underwent several iterations of visual checks, test simulations, and cross-verification against field imagery to ensure spatial alignment and logical connectivity. This process ensured that all vehicle types could navigate the network without routing errors or unrealistic maneuvers.

3.3.2 Traffic Demand Modeling

Accurate traffic demand modeling was essential to replicate the observed flow patterns and temporal variability characteristic of the corridor. Origin-Destination (OD) matrices were developed based on:

- Manual counts of turning movements at each intersection
- Video-derived vehicle trajectories
- Estimated trip generation and attraction zones within the corridor

These OD patterns defined how many vehicles of each type entered the network, their entry times, and their intended destinations.Using SUMO's duarouter tool, route files were created for each simulation scenario. duarouter computes the shortest or user-defined routes between OD pairs while distributing vehicle flows across multiple paths to avoid overloading specific links unrealistically.

- Vehicle Type Specifications: For each vehicle type, the following parameters were defined to represent distinct behavior:
  - Maximum acceleration and deceleration
  - Length and width
  - Desired speed distributions
  - Gap acceptance
  - Car-following and lane-changing aggressiveness

  This level of detail allowed simulation of heterogeneous interactions, such as rickshaws slowing general traffic and motorcycles filtering between lanes.

- Demand Temporal Distribution: Vehicle arrivals were scheduled using realistic arrival profiles reflecting field-observed peak and off-peak patterns. Randomization was applied to introduce variability in headways and platoons.

- Validation of Demand Realism: Preliminary simulation runs were performed to compare resulting flow rates, queue lengths, and intersection occupancy against recorded field data. Adjustments were iteratively applied to OD matrices and route choice probabilities until simulated traffic closely matched observed volumes and congestion levels.

3.3.3 Scenario Development

To enable a robust and transparent comparative analysis of different intersection control strategies, four distinct simulation scenarios were designed and implemented in the SUMO environment. These scenarios were structured to reflect a progression from unmanaged, rule-based operations to advanced, intelligent control systems capable of dynamic adaptation. Each scenario incorporates specific assumptions, configurations, and objectives to comprehensively evaluate their performance under heterogeneous traffic conditions in the Zindabazar corridor. Figure 3.4 shows the SUMO interface displaying the microscopic road network of the Zindabazar intersection.

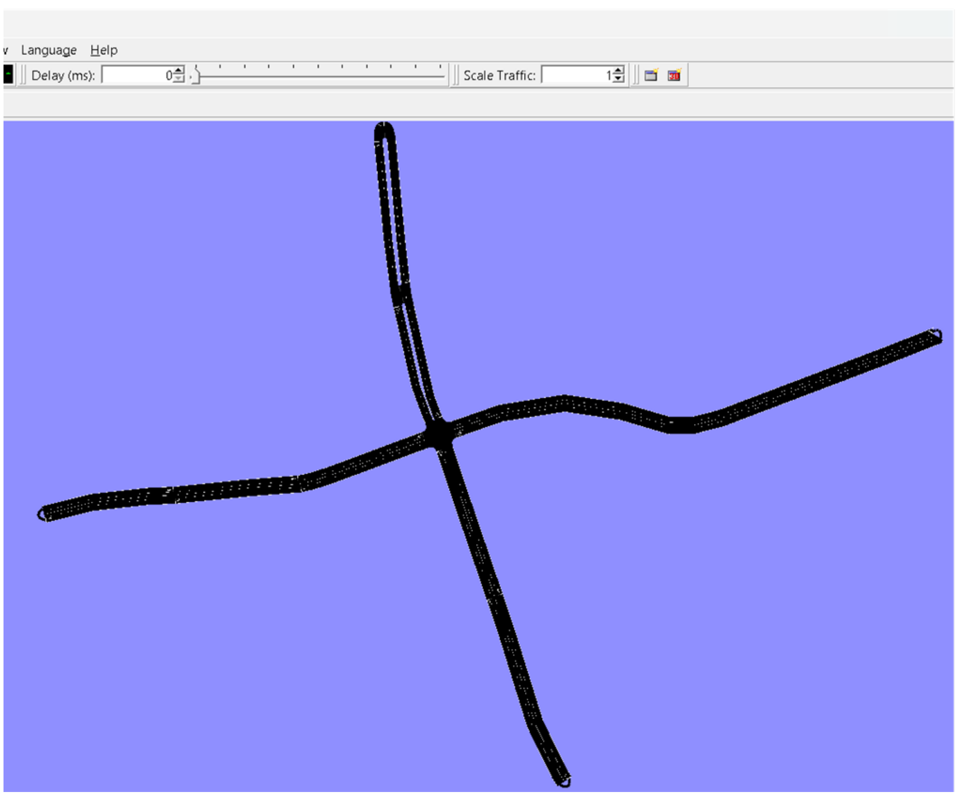

Figure 3.4: SUMO simulation interface displaying the microscopic road network

The first scenario models unsignalized intersections operating purely under priority-based control logic. In this setup, vehicles navigate intersections without the aid of traffic signals, relying instead on SUMO's default give-way and right-of-way rules. Drivers are assumed to make decisions based on available gaps and accepted thresholds for safe crossing, with behavior further influenced by vehicle-specific parameters such as aggressiveness and reaction times. This baseline scenario represents the current or historical practice in many parts of the study area, where intersections lack formal signal infrastructure and rely on informal yielding behaviors or occasional manual intervention. Simulating this scenario establishes reference conditions for queue formation, delays, and throughput in an unmanaged environment.

The second scenario introduces static signalized control, simulating conventional fixed-time traffic signals that operate according to pre-determined phase sequences and cycle lengths. Fixed-time signal plans for each intersection were developed using a combination of observed field data and established methods, particularly Webster's formula, which calculates optimal cycle lengths and green splits to balance delays across approaches. Each intersection was configured with its own phase sequence tailored to its specific geometry and turning movement patterns. Signal timings remained constant throughout the simulation period, reflecting the inflexibility of fixed-time plans in responding to demand variability. This scenario closely replicates the way many intersections are managed in practice and serves as a benchmark for evaluating whether adaptive strategies can yield meaningful improvements.

The third scenario builds upon static timing by implementing vehicle-actuated signal control logic. In this configuration, virtual detectors were positioned on critical approaches within the simulation to monitor vehicle arrivals in real time. When a green phase was active, the detector logic assessed whether vehicles were present within a specified detection zone. If vehicles were detected continuously, the green time was extended incrementally up to a defined maximum. Conversely, if no vehicles were detected within a set gap time, the green phase terminated early, and the controller advanced to the next phase in sequence. Minimum green times and maximum green limits were configured based on field observations and operational safety considerations. This scenario enabled the system to adapt more responsively to fluctuating demand, reducing unnecessary idling on empty approaches while still respecting safety constraints and maintaining equitable service.

The fourth scenario implemented a dynamic traffic signal control system using reinforcement learning (RL). This scenario was motivated by the recognition that conventional rule-based signals, whether fixed-time or actuated, are limited in their ability to anticipate and optimize for complex and rapidly changing traffic patterns. The RL-based approach sought to demonstrate the potential of artificial intelligence to produce more intelligent and efficient signal control. The reinforcement learning model was developed to operate with minimal input data, relying primarily on real-time vehicle counts at each approach. The RL agent received state information describing the number of vehicles waiting or approaching each intersection and determined which approach should receive a green phase. Each action selected by the agent set the green light for a minimum duration, typically 30 seconds, after which the decision was re-evaluated based on updated observations. The agent was trained iteratively in the SUMO simulation environment, where it interacted with the network across numerous episodes to learn an optimal policy. The training process involved defining appropriate reward functions to prioritize reductions in total vehicle waiting time and delays, and carefully tuning learning parameters to achieve convergence and stability. To ensure consistent evaluation, vehicle routes were fixed during training while arrival timings remained randomized to introduce variability.

Performance evaluation of the RL scenario focused on measuring reductions in average and maximum queue lengths, total delays, and improvements in throughput relative to static and actuated controls. Additional assessments examined the scalability of the RL approach to larger networks and its potential integration with real-world infrastructure. Results were compared not only against conventional automated control but also against unmanaged or manually managed intersections to highlight the incremental benefits of each control paradigm. The scenario aimed to illustrate how combining high-resolution simulation with reinforcement learning techniques could deliver an intelligent signal system that continuously adapts to live traffic conditions.

- Scenario 1: Unsignalized Intersections This scenario models intersections operating without traffic signals. Vehicles follow priority-based give-way rules defined in the simulation. Drivers decide when to enter the intersection based on available gaps and standard right-of-way assumptions.

- Scenario 2: Static Signalized Control In this scenario, intersections use fixed-time signal plans developed using Webster's method combined with field-observed traffic volumes. Signal timings remain constant throughout the simulation period, with no adaptation to changing demand or congestion levels.

- Scenario 3: Actuated Signal Control This scenario employs vehicle-actuated signal control. Virtual detectors are placed on key approaches to detect vehicle presence. Green phases are dynamically extended or terminated based on real-time occupancy and gap times, allowing the signals to respond to actual traffic flow.

- Scenario 4: Dynamic Reinforcement Learning-Based Traffic Signal This scenario implements an adaptive control system using a reinforcement learning agent trained to optimize signal timings. The model continuously adjusts phase selections based on live vehicle counts at each approach. Performance is validated under different demand conditions to test robustness and effectiveness in reducing delays.

Overall, these four scenarios together provided a structured basis for comparative analysis, allowing the study to quantify the strengths and limitations of each strategy in a mixed-traffic urban corridor. By progressing methodically from unmanaged operation to sophisticated learning-based optimization, the research design ensured that each approach was evaluated fairly under consistent conditions and against a common set of performance indicators.

3.3.4 Model Calibration and Validation

Accurate simulation requires that both the microscopic vehicle behavior and the aggregate traffic dynamics closely reflect field conditions. This section describes in detail the calibration and validation procedures applied to ensure the model's reliability. Calibration was conducted in a systematic, iterative process aimed at minimizing the difference between simulated outputs and observed traffic performance indicators. The simulation employed the Krauss car-following model, which is widely used in microscopic traffic simulations due to its capacity to realistically model driver acceleration and deceleration behavior in congested conditions.

Key parameters were adjusted as follows. The sigma parameter was tuned to replicate variability in driver behavior, representing differences in how aggressively or conservatively drivers accelerate, decelerate, and maintain gaps. A higher sigma increases randomness, leading to more heterogeneous flow characteristics typical of mixed-traffic environments. The tau parameter, defining driver reaction time, was calibrated to reproduce observed following distances and discharge rates at stop lines. Lower tau values result in shorter headways and higher saturation flow, while higher tau values reflect cautious driving.

The min gap parameter specified the minimum distance maintained between stopped vehicles. This was critical for accurately modeling queue lengths and the storage capacity of each approach. Calibration of max speed and acceleration ensured that each vehicle type could accelerate and cruise at realistic speeds observed during field surveys. These parameters were differentiated by vehicle class. For example, motorcycles were configured with higher maximum acceleration and deceleration than buses, while cycle rickshaws were assigned lower maximum speeds and acceleration capabilities.

Each vehicle type was also assigned empirically derived physical dimensions (length and width), which affected lane occupancy and overtaking behavior. For example, auto-rickshaws and motorcycles occupied less width than cars, while buses and trucks required more space and longer clearance times. Figure3.5 illustrates a comparison between real-world traffic conditions (left) and their corresponding SUMO simulation representation (right), highlighting how vehicle dimensions and lane positioning were replicated in the study.

Calibration was carried out through repeated simulation runs under measured demand conditions. After each run, output data on travel times, queues, and throughput were compared to field observations. Parameters were incrementally adjusted to reduce error, with each iteration improving model fidelity. This iterative process continued until successive calibration runs produced negligible improvement in accuracy. Following calibration, model validation was performed to ensure that the simulation accurately reproduced observed traffic performance across

Figure 3.5: Real vs Simulation

key metrics. Validation served to confirm that the model could reliably predict system behavior under known conditions before being used for scenario analysis. Three primary validation metrics were selected. Average travel time was calculated as the mean time required for vehicles to traverse a defined segment of the corridor or complete passage through an intersection. This measure was used to assess whether the simulation accurately represented congestion and progression delays. Maximum queue length was monitored for each approach, reflecting the most severe queuing observed during the simulation period. This measure provided an indicator of whether stop-line congestion matched field conditions. Approach-specific throughput, measured as the number of vehicles discharged per hour, was compared to observed counts to validate that the simulation maintained realistic capacity.

To quantify the level of agreement between simulated and observed data, two statistical error measures were used. Mean Absolute Percentage Error (MAPE) was calculated for each metric, providing an average percentage deviation that is easy to interpret and compare. Lower MAPE values indicated closer alignment with observed performance. Root Mean Squared Error (RMSE) was also computed, offering an absolute measure of error that weighted larger discrepancies more heavily.

Validation was considered successful when MAPE for each key metric was within acceptable thresholds (generally less than 10–15%), and RMSE values indicated small absolute deviations. Consistent results across multiple validation runs demonstrated that the simulation could accurately represent existing conditions and support comparative scenario evaluation. To enable quantitative comparison of the different traffic control strategies tested in the study, a comprehensive set of performance metrics was defined. These metrics were selected to capture various dimensions of operational efficiency, congestion, and mobility impacts across the corridor. Each scenario was evaluated using the same criteria to ensure fair and consistent assessment. The principal performance metrics included:

- Average Vehicle Delay: This metric measured the additional time each vehicle spent in the network compared to free-flow conditions. It captured delays caused by stopping at signals, queuing behind congestion, and interacting with slower vehicles.

- Total Network Delay: The cumulative delay experienced by all vehicles during the simulation period. This indicator quantified the overall efficiency of the control strategy in minimizing congestion.

- Average Queue Length: The mean length of vehicle queues at each approach throughout the simulation. This provided insight into how effectively the control system dispersed accumulated demand.

- Maximum Queue Length: The longest queue observed at any approach during the simulation. This measure helped identify critical bottlenecks and assess the risk of spillback blocking upstream intersections.

- Throughput: The total number of vehicles successfully discharged from the network over the simulation duration. Higher throughput indicated better capacity utilization and lower congestion.

- Average Travel Time: The mean time required for vehicles to traverse the corridor or a specific intersection. This metric was essential for evaluating travel time reliability and user experience.

- Travel Time Variability: The standard deviation of travel times for vehicles of each type. Lower variability suggested more predictable travel conditions.

- Stop Frequency: The average number of stops per vehicle during a simulation run. Fewer stops typically indicated smoother progression through intersections.
- Emission Estimates (Optional): For scenarios where emissions modeling was enabled, estimated total CO, NO, and particulate emissions were recorded as secondary performance measures.

Each metric was calculated separately for the four scenarios (unsignalized, static signalized, actuated signalized, and reinforcement learning-based dynamic control) to allow direct comparison. The combination of delay, queue, throughput, and variability indicators ensured a holistic assessment of operational performance under each control strategy. A structured evaluation framework was developed to systematically compare the performance of all tested traffic control scenarios. This framework integrated descriptive statistical analysis, visualization, trade-off exploration, optional multi-criteria ranking, and sensitivity testing to ensure that findings were robust, transparent, and actionable. 2.10.1. Evaluation Framework Simulation results from each scenario—unsignalized, static signalized, actuated signalized, and reinforcement learning-based dynamic control—were aggregated into a consistent dataset for comparative analysis. For each key performance metric, descriptive statistics were calculated, including means and standard deviations, to capture central tendencies and variability across multiple simulation runs. The primary evaluation metrics are summarized in Table 3.1.

For clarity and effective communication, the results were also presented visually using bar charts, line graphs, and scatter plots. These visualizations highlighted differences in performance among the scenarios across all key metrics. For example, bar charts showed comparative average delays and queue lengths, while line graphs illustrated changes in throughput or emissions over time. To better understand trade-offs inherent in each control strategy, the analysis included cross-metric comparisons. Relationships such as delay versus emissions and throughput versus equity were explored. This approach allowed the study to identify whether improvements in one metric (e.g., reduced delay) were associated with unintended negative effects on another (e.g., increased emissions due to stop-and-go behavior). Trade-off analysis was critical in assessing the overall suitability of each control method for different policy goals, such as

Table 3.3: Performance Metrics for Simulation Evaluation

Metric	**Description**
Average Delay (s/veh)	Mean time vehicles spend stopped or moving below free-flow speed.
Queue Length (m or vehicles)	Maximum and average queue length on each intersection approach.
Travel Time (s)	Average time required for vehicles to traverse the entire corridor from entry to exit.
Emissions (g/km)	Estimated emissions of CO_2, NO_x, and particulate matter per kilometer traveled.
Number of Stops	Average number of complete stops each vehicle experiences during the simulation.
Throughput (veh/hr)	Total number of vehicles discharged from the network within the simulation time window.

prioritizing mobility, environmental sustainability, or fairness among users.

3.4 Signal Control Design

3.4.1 Traffic Light Phases

Traffic signals control how vehicles and pedestrians move through intersections by dividing time into repeating cycles. Each cycle is composed of phases, and each phase assigns the right-of-way to specific movements. Understanding these phases is essential for analyzing how signalized intersections operate and how control strategies affect performance.

Green Phase: The green phase is the period when the traffic signal displays a green light for one or more approaches. During this phase, vehicles are permitted to proceed through the intersection in designated directions. Depending on the signal plan, a green phase might allow:

- All movements in a given direction (e.g., northbound straight-through and left turns).
- Only certain protected movements, such as a dedicated left-turn lane.
- Pedestrians to cross in a marked crosswalk.

The duration of the green phase affects how many vehicles can clear the intersection before the phase ends. Longer green times can help reduce queues, while shorter green times may limit throughput but allocate more time to other movements.

Amber (Yellow) Phase The amber phase begins immediately after the green phase. This phase provides a warning to drivers that the green phase is ending and that the signal will soon turn red. The amber light usually lasts between 3 and 5 seconds, depending on approach speed and intersection width.

Drivers approaching the stop line during the amber phase must decide whether to stop safely or proceed through the intersection if they are too close to stop without abrupt braking. The purpose of the amber phase is to clear vehicles already committed to entering the intersection and prevent abrupt stops that could lead to rear-end collisions.

Red Phase The red phase is the period when the signal displays a red light for a given approach, requiring all vehicles to stop before the intersection. While one approach is seeing red, other directions may be assigned a green phase, allowing conflicting movements to proceed safely. During the red phase, vehicles must wait behind the stop line until the signal returns to green. Red phases are necessary to eliminate conflicts between crossing and turning traffic streams.

3.4.2 Phase Logic at Intersection

Multiple Phases in One Cycle

A complete signal cycle typically consists of several phases, each serving specific movement groups. For example:

- Phase 1 might permit northbound and southbound through traffic.
- Phase 2 could allow protected left turns from northbound and southbound approaches.
- Phase 3 might serve eastbound and westbound through traffic.
- Phase 4 could activate pedestrian crossing signals across all legs.

In more complex intersections, additional phases can be included to accommodate other movements, such as exclusive right turns or bus-priority signals. Each phase is separated by amber and, in some cases, all-red intervals to ensure safety during transitions.

Purpose of Phases

The main goal of dividing the signal cycle into phases is to manage conflicting vehicle and pedestrian movements safely and efficiently. Phases ensure that only compatible movements are allowed simultaneously. For example, left-turning vehicles from one direction should not conflict with oncoming through traffic or crossing pedestrians. By separating these movements in time, signal phasing reduces the risk of collisions, organizes traffic flow, and increases intersection capacity.

In heavily trafficked urban areas like the Zindabazar corridor, careful phase design is critical because:

- Mixed traffic includes a variety of vehicle types with different speeds and maneuverability.
- Non-lane-based movements (e.g., rickshaws weaving between lanes) increase unpredictability.
- Pedestrian volumes are high and often unsignalized, requiring special consideration.

Understanding how phases work is necessary for designing efficient signal timings, analyzing delays, and assessing improvements offered by adaptive control systems.

3.4.3 Key Elements of Signal Phasing

Signal phasing is governed by several core elements. Each element contributes to how safely and effectively the intersection operates.

Cycle Length

The cycle length is the total time needed to complete one full sequence of all signal phases, amber intervals, and all-red periods before repeating. Cycle lengths can vary significantly depending on factors such as:

- The number of phases required to serve all movements.
- The volume of traffic in each direction.
- The operational objectives (e.g., minimizing delays, maximizing throughput).

Typical cycle lengths range from 60 to 180 seconds. Longer cycles can reduce lost time from frequent phase changes and accommodate heavy traffic on major approaches. However, they may also increase delays for minor streets and pedestrians who must wait longer between opportunities to cross.

Phases

Phases are the individual portions of the cycle during which a specific set of movements is allowed. Each phase can be thought of as a window of time granting the right-of-way to certain directions:

- Through movements (straight-ahead traffic).
- Protected left-turns or right-turns.
- Pedestrian crossings.

The number and configuration of phases depend on intersection complexity, demand, and safety requirements.

Green Time

Green time is the duration within a phase during which the signal is green for a movement group. The amount of green time allocated to each phase influences:

- How quickly queues dissipate.
- How long drivers must wait during red intervals.
- Overall intersection capacity.

Balancing green times across approaches is a central task in signal timing optimization.

Amber (Yellow) Time

Amber time is a short transition period between the end of green and the start of red. The purpose of amber time is to:

- Warn drivers that the green phase is ending.
- Allow vehicles already near the stop line to clear the intersection safely.

The amber interval is calculated considering the speed limit, perception-reaction time, and stopping distance to ensure that drivers can make safe stopping decisions.

All-Red Time The all-red interval is an additional safety buffer after the amber phase, when all approaches display red signals. This brief period allows vehicles that entered during the amber phase to fully clear the intersection before the next phase begins. The duration depends on intersection width and typical vehicle clearing times.

3.4.4 Control Strategies: Fixed-Time and Actuated

Fixed-Time Control

Fixed-time control operates using predetermined phase durations and cycle lengths, which are set based on historical traffic volumes and expected demand patterns. In this approach, the timing plan remains constant regardless of real-time fluctuations in vehicle arrivals. For example, if the cycle length is set to 120 seconds and consists of three phases, each phase will always receive the same amount of green time during every cycle. While this approach is simpler to implement and requires no vehicle detection infrastructure, it has significant limitations:

- It cannot respond to unexpected congestion or temporary surges in demand.
- It may cause unnecessary delays during low-traffic periods because the fixed timing allocates green time to empty approaches.
- It requires periodic manual retiming to remain effective as traffic patterns change over months or years.

Actuated Control

Actuated control builds upon fixed-time plans by introducing the ability to adjust phase durations dynamically based on real-time detection of vehicle presence. In an actuated system:

- Detectors (e.g., inductive loops, video cameras) are installed on each approach to monitor whether vehicles are present within a defined detection zone.
- When a phase is active and vehicles are detected, the green time can be extended incrementally up to a maximum preset duration.
- If no vehicles are detected for a set "gap-out" time (the minimum time between successive vehicle detections), the phase terminates early, and the signal transitions to the next phase.

This approach provides better responsiveness to variable demand compared to fixed-time control while still using preconfigured maximum and minimum green times. However, it is still rule-based and does not continuously optimize all phases across the network.

3.5 Optimization and Analysis Framework

3.5.1 Definitions and Given Data

In the context of this study, a fixed-time signal control plan was developed as the baseline scenario. The following variables and parameters define the signal timing calculations:

- Cycle Length (C): The total duration of one complete cycle of all phases. For this example, the cycle length is 120 seconds.
- Phases (N): The number of distinct signal phases within the cycle. Here, there are three phases.
- Lost Time per Phase (L): The time lost during each phase transition (e.g., during amber and all-red intervals). Lost time accounts for vehicle reaction delays and clearance of the intersection before the next phase begins. Each phase has 5 seconds of lost time.
- Effective Green Time (G): The remaining portion of the cycle that can be allocated as actual green time once lost time is subtracted.
- Critical Lane Volume (Vci): The volume of traffic observed during the busiest movement in each phase. This volume is used to proportionally distribute the effective green time among the phases.
- Amber Time (Yi): The length of the amber interval following each green phase. In this example, amber time is set to 4 seconds per phase.

3.5.2 Simulation Output via TraCI

To obtain performance metrics from the traffic simulation, this study used TraCI (Traffic Control Interface), a Python-based API that enables real-time communication between SUMO and external programs. TraCI provides access to a wide range of vehicle-level and network-level parameters during simulation runtime.

In this work, TraCI was used to extract minute-wise aggregated data on key performance indicators such as average speed, waiting time, fuel consumption, and emissions (CO, NOx, PMx, HC, CO). The simulation was launched using traci.start(), and the loop collected data from all vehicles at each simulation step. Metrics were then averaged over time and vehicle count to produce a clean, time-series dataset.

The final results were saved in Excel format for further analysis. This method allows detailed observation of system performance under different control strategies and traffic conditions.

Chapter 4

Results and Discussions

4.1 Static Signal Timing Results

Using Webster's method, a two-phase static signal timing plan was developed for the study intersection. The design parameters, derived from observed traffic volumes and adjusted for phase timing requirements, are summarized in Table 4.1. The optimum cycle length (C_0) was calculated to be 103 seconds, ensuring balanced delays for both traffic streams. Out of this cycle, the effective green time for the East–West direction (G_1) was allocated 45 seconds, while the North–South direction (G_2) was given 44 seconds based on traffic demand proportions. A total amber time of 4 seconds was incorporated to allow vehicles to clear the intersection safely at the end of the green phase, followed by an all-red interval of 10 seconds to provide additional clearance before the opposing phase begins.

These timing values are implemented sequentially, as illustrated in Figure 4.1, which shows the 2-phase traffic signal timing diagram. In the diagram, the East–West direction receives a green indication during the first phase while the North–South remains red. After a short amber interval and an all-red period, the North–South phase begins with a green signal, and the East–West direction turns red. This cycle repeats continuously, facilitating organized and safe vehicular flow through the intersection.

Table 4.1: Static Signal Timing Parameters Using Webster's Method

Component	**Value**
Optimum Cycle Length (C_0)	103 sec
Effective Green Time (G_1) – East–West	45 sec
Effective Green Time (G_2) – North–South	44 sec
Total Amber Time	4 sec
All-Red Time	10 sec

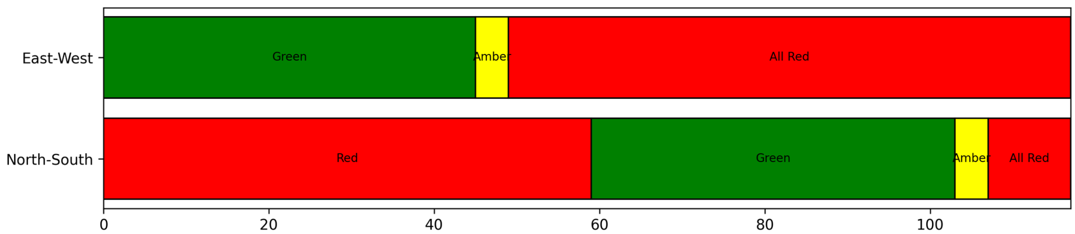

Figure 4.1: Two Phase Traffic Signal Timing Diagram

4.2 Statistical Significance Testing

4.2.1 Average Waiting Time

The Table 4.2 titled Avg Waiting Time (s) presents the results of independent samples t-tests conducted to compare the mean average waiting times across different traffic control strategies in a simulated heterogeneous traffic environment. Specifically, the comparisons evaluate the effectiveness of a non-controlled (”No”) traffic condition versus two alternative strategies: Static signal control and Actuated signal control. For each comparison, the table reports descriptive statistics (mean and standard deviation), inferential test results (t-value, degrees of freedom, p-value, standard error), confidence intervals, and effect size estimates (Cohen's d). The mean waiting time in the ”No control” scenario is consistently high (2860.05 s) across both tests, while substantially lower values are observed under Static (360.01 s) and Actuated (299.83 s) signal control, indicating pronounced differences in traffic performance outcomes. The statistical analysis shows highly significant results for both comparisons. For the ”No vs Static” condition, the t-value is 12.97 with degrees of freedom (DoF) of 65.09, yielding a p-value of 1.03e-19, which is far below any conventional alpha level (e.g., 0.05 or 0.01). Similarly, the ”No vs Actuated” comparison yields a t-value of 13.26 with DoF = 65.58 and a p-value of 3.16e-20, again indicating extremely strong evidence against the null hypothesis of equal means. The standard errors are modest (approximately 192–193 s), and the 95% confidence intervals for the mean differences do not cross zero — [2115.16, 2884.91] and [2174.66, 2945.77] for Static and Actuated, respectively — further confirming the robustness of the results. Notably, the Cohen's d values for both tests are exceptionally large (2.28 and 2.32), suggesting a very strong effect size and thus practical significance in addition to statistical significance.

Table 4.2: T-Test Results for Average Waiting Time (s)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	2860.05	2860.05
Mean B	360.01	299.83
SD A	1547.15	1547.15
SD B	142.97	170.81
Sample Size (n)	65	64
Mean Difference	2500.03	2560.22
Standard Error	192.72	193.08
t-value	12.97	13.26
Degrees of Freedom (DoF)	65.09	65.58
p-value	1.03e-19	3.16e-20
95% CI Lower	2115.16	2174.66
95% CI Upper	2884.91	2945.77
Cohen's d	2.28	2.32

These findings substantiate the research hypothesis that traffic signal control strategies significantly reduce average vehicle waiting times compared to no control conditions. Furthermore, the actuated signal control appears marginally more effective than the static scheme, as evidenced by a larger mean difference and higher upper bound of the confidence interval. The near-identical standard deviations and sample sizes in both groups enhance the reliability of the comparison. However, some limitations warrant attention. The assumptions of the t-test — including independence of observations, normality of distributions, and homogeneity of variances — should be critically examined, especially given the large standard deviations in the No-control group, which may hint at skewness or outliers. Additionally, the extremely high effect sizes, while favorable, may suggest overfitting to simulation-specific parameters or lack of real-world traffic variability, requiring cautious generalization. In relation to prior literature, these results are consistent with existing findings that signalized intersection control, particularly actuated systems, can drastically reduce vehicle delays under mixed traffic conditions. Nonetheless, future studies should consider validating these outcomes under empirical conditions and explore other performance metrics such as throughput, fuel consumption, or environmental impact to provide a more holistic evaluation.

4.2.2 Average Speed (km/h)

The Table 4.3 labeled Avg Speed (km/h) presents the results of independent samples t-tests conducted to compare the mean average vehicle speed between an uncontrolled ("No") traffic condition and two signalized control strategies: Static and Actuated. This analysis is part of a broader study aimed at evaluating the impact of different traffic control schemes on vehicular performance under heterogeneous traffic conditions. The dependent variable in this case is average speed, measured in kilometers per hour (km/h), and the test assesses whether there are statistically significant differences in mean speeds between the non-signalized condition and each of the control strategies. In the comparison between "No vs Static," the mean speed under no control is 12.09 km/h, whereas the static signal control yields a higher mean of 13.41 km/h. This results in a mean difference of –1.31 km/h, with a standard error of 0.38. The negative sign indicates that the control strategy led to an increase in speed relative to the baseline. The corresponding t-statistic is –3.50, with 89.91 degrees of freedom, and a p-value of 0.000738. This p-value is well below the conventional alpha threshold of 0.05, indicating that the observed difference is statistically significant. The 95% confidence interval (CI) ranges from –2.06 to –0.57 km/h, suggesting with high confidence that the true population mean difference does not include zero. The Cohen's d value of –0.61 reflects a moderate effect size, suggesting the change in speed due to static signal implementation is not only statistically significant but also meaningful in practical terms. Similarly, the ”No vs Actuated” comparison reveals an increase in average speed from 12.09 km/h under no control to 13.50 km/h with actuated control. The mean difference here is –1.40 km/h with a standard error of 0.37, yielding a t-value of –3.81 and degrees of freedom equal to 84.27. The associated p-value is 0.000261, which again indicates strong statistical significance. The 95% CI for the mean difference [–2.13, –0.67] further confirms this effect. The Cohen's d of –0.67 indicates a slightly stronger effect size compared to the static control, suggesting that actuated signals may offer a marginally better improvement in traffic speed performance.

Table 4.3: T-Test Results for Average Speed (km/h)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	12.09	12.09
Mean B	13.41	13.50
SD A	2.75	2.75
SD B	1.26	1.10
Sample Size (n)	65	64
Mean Difference	-1.31	-1.40
Standard Error	0.38	0.37
t-value	-3.50	-3.81
Degrees of Freedom (DoF)	89.91	84.27
p-value	0.000738	0.000261
95% CI Lower	-2.06	-2.13
95% CI Upper	-0.57	-0.67
Cohen's d	-0.61	-0.67

These results reinforce the hypothesis that signalized control strategies enhance traffic flow efficiency by increasing vehicular speeds compared to uncontrolled scenarios. Although the absolute increase in speed is modest (about 1.3–1.4 km/h), the statistical significance and moderate effect sizes imply that such control systems may offer important benefits in congested or delay-prone urban contexts. Interestingly, both static and actuated signals yield similar improvements in speed, with actuated control showing a slightly greater effect. However, given the relatively small standard deviations and overlapping confidence intervals, the difference between the two strategies may not be practically substantial. One limitation of this analysis lies in the assumptions underlying the independent samples t-test, such as normality of distributions and homogeneity of variances. These assumptions must be validated, particularly since the standard deviations for the No-control group (2.75) are substantially larger than those for the control groups (1.26 and 1.10), potentially indicating unequal variances. Furthermore, while statistically significant, the relatively small numerical differences in speed raise questions about the operational impact of these findings and whether other performance metrics (e.g., travel time reliability or safety) might yield more pronounced benefits. Overall, the findings are consistent with literature that identifies signalized control as a mechanism to improve traffic flow. However, further studies incorporating real-world empirical data and broader performance indicators would help in substantiating these conclusions and guiding practical implementations.

4.2.3 Average Fuel Consumption (ml)

The Table 4.4 labeled Avg Fuel (ml) presents the results of two independent samples t-tests comparing average fuel consumption across different traffic signal control strategies—specifically between a non-controlled (No control) condition and two signalized alternatives: Static and Actuated control. The analysis is situated within the broader context of evaluating the operational and environmental performance of traffic systems under heterogeneous vehicle conditions. Fuel consumption, measured in milliliters (ml), serves here as a key indicator of vehicular energy efficiency, and the statistical tests aim to determine whether signalized controls significantly reduce fuel use. In the "No vs Static" comparison, the mean fuel consumption under the uncontrolled condition is 100,526.36 ml, whereas the static signal control condition demonstrates a lower mean of 88,513.81 ml. This yields a mean difference of 12,012.56 ml, with a standard error of 4,164.87 ml. The resulting t-value is 2.88 with 125.51 degrees of freedom, and the p-value is 0.00462. As the p-value is below the conventional α-level of 0.05, the difference in means is statistically significant. The 95% confidence interval for the mean difference ranges from 3,770.08 ml to 20,255.03 ml, affirming that the reduction in fuel consumption is unlikely due to random chance.

The associated Cohen's d of 0.51 indicates a moderate effect size, implying that the practical impact of the intervention is meaningful. A similar pattern emerges in the "No vs Actuated" comparison. Here, the actuated signal control strategy yields an average fuel consumption of 88,594.45 ml, compared to the same baseline of 100,526.36 ml. The mean difference is slightly smaller at 11,931.91 ml, with a standard error of 3,970.63 ml. The t-value of 3.01 and degrees of freedom of 119.68 yield a p-value of 0.00324, once again indicating statistical significance. The 95% confidence interval for this comparison spans from 4,070.12 ml to 19,793.70 ml, further validating the reliability of the observed effect. Cohen's d is calculated at 0.53, slightly higher than in the static condition, suggesting that the actuated control may have a marginally stronger practical impact on fuel efficiency.

Table 4.4: T-Test Results for Average Fuel Consumption (ml)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	100526.36	100526.36
Mean B	88513.81	88594.45
SD A	25359.48	25359.48
SD B	22009.05	19385.82
Sample Size (n)	65	64
Mean Difference	12012.56	11931.91
Standard Error	4164.87	3970.63
t-value	2.88	3.01
Degrees of Freedom (DoF)	125.51	119.68
p-value	0.00462	0.00324
95% CI Lower	3770.08	4070.12
95% CI Upper	20255.03	19793.70
Cohen's d	0.51	0.53

These findings offer strong empirical support for the hypothesis that signalized traffic control—both static and actuated—can lead to significant reductions in fuel consumption compared to uncontrolled intersections. The moderate effect sizes (d ¿ 0.5) suggest that these benefits are not only statistically robust but also operationally valuable, particularly in urban contexts where even small gains in fuel efficiency can scale to large environmental and economic benefits across a traffic network. Nonetheless, a few considerations warrant discussion. The standard deviations in fuel consumption are relatively large (ranging from 19,000 to 25,000 ml), reflecting variability in vehicle behavior, which is typical in heterogeneous traffic simulations. The assumptions of the t-test, such as normal distribution and homogeneity of variances, should be verified to ensure result validity. Moreover, these results are derived from simulation models, and their generalizability to real-world scenarios depends on how well the model captures real traffic dynamics and fuel usage patterns. In conclusion, the statistical evidence confirms that both static and actuated signal control strategies significantly reduce fuel consumption in heterogeneous traffic conditions, with actuated control yielding slightly more pronounced improvements. These results align with broader literature emphasizing the environmental and economic advantages of intelligent traffic signal systems.

4.2.4 Average NOx Emissions (mg)

The Table 4.5 titled Avg NOx (mg) summarizes the results of independent samples t-tests evaluating the average nitrogen oxide (NOx) emissions in milligrams under three different traffic signal control conditions: No control, Static signal control, and Actuated signal control. NOx is a critical environmental pollutant associated with vehicular emissions, and its reduction is often a key objective in sustainable traffic management. This analysis forms part of a broader empirical investigation into the environmental effects of traffic control strategies within a heterogeneous traffic simulation framework. For the ”No vs Static” comparison, the mean NOx emission under the uncontrolled condition is 136.18 mg, while static signal control reduces the mean emission to 118.62 mg. This results in a mean difference of 17.56 mg, with a standard error of 5.64 mg. The t-statistic is 3.11 with 124.95 degrees of freedom, yielding a p-value of 0.00230. Since this p-value is well below the standard significance level of 0.05, the difference is statistically significant. The 95% confidence interval for the mean difference ranges from 6.40 mg to 28.72 mg, further confirming that the observed reduction is unlikely to have occurred by chance. The effect size, as measured by Cohen’s d, is 0.55—indicating a moderate practical effect. The ”No vs Actuated" comparison yields similar but slightly improved results. The mean NOx emission remains the same for the uncontrolled condition (136.18 mg) but decreases to 118.60 mg under actuated control. The mean difference is 17.58 mg, with a slightly lower standard error of 5.38 mg. The t-statistic is 3.27 with 118.87 degrees of freedom, corresponding to a p-value of 0.00143. This is again statistically significant, and the associated 95% confidence interval (6.92 mg to 28.24 mg) strengthens the result's robustness. Cohen's d for this comparison is slightly higher at 0.57, suggesting a marginally greater practical impact of the actuated control scheme over static.

Table 4.5: T-Test Results for Average NO_x (mg)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	136.18	136.18
Mean B	118.62	118.60
SD A	34.58	34.58
SD B	29.54	26.03
Sample Size (n)	65	64
Mean Difference	17.56	17.58
Standard Error	5.64	5.38
t-value	3.11	3.27
Degrees of Freedom (DoF)	124.95	118.87
p-value	0.00230	0.00143
95% CI Lower	6.40	6.92
95% CI Upper	28.72	28.24
Cohen's d	0.55	0.57

These findings support the hypothesis that traffic signalization—whether static or actuated—can significantly reduce harmful vehicular emissions such as NOx. The consistent reductions across both signal strategies, combined with moderate effect sizes, highlight that such interventions are not only statistically effective but also environmentally meaningful. The slightly stronger performance of the actuated control system may point to its dynamic adaptability in managing traffic more efficiently, leading to fewer idling events and smoother traffic flows—both of which are known to reduce pollutant emissions. Nonetheless, it is essential to consider the assumptions underpinning the t-tests. These include the assumptions of normal distribution, independence of observations, and homogeneity of variances. The relatively balanced standard deviations (e.g., 34.58 mg for the uncontrolled condition vs. 29.54 mg and 26.03 mg for the static and actuated conditions, respectively) suggest acceptable variance homogeneity, but formal tests should be conducted to verify this. Also, the use of simulation data, while offering control over variables and repeatability, may not capture all nuances of real-world traffic behavior and emission variability. In conclusion, the statistical analysis offers compelling evidence that both static and actuated signal controls significantly reduce NOx emissions in heterogeneous traffic conditions, with actuated control yielding a slightly larger benefit. These outcomes align with existing literature advocating for adaptive signal systems in urban sustainability strategies and reinforce the importance of incorporating environmental indicators into transportation system evaluation.

4.2.5 Average PMx Emissions (mg)

The Table 4.6 titled Avg PMx (mg) reports the results of independent samples t-tests conducted to compare the average particulate matter emissions (PMx, measured in milligrams) under different traffic signal control strategies: No control (baseline), Static signal control, and Actuated signal control. As particulate matter is a major pollutant with serious implications for public health and air quality, this analysis is a crucial component of the study's broader aim to evaluate the environmental performance of traffic management interventions under heterogeneous traffic conditions. In the ”No vs Static” comparison, the mean PMx emission under the uncontrolled scenario is 6.43 mg, which is reduced to 5.44 mg under the static signal control. This results in a mean difference of 0.99 mg, with a standard error of 0.27 mg. The corresponding t-value is 3.73 with 123.13 degrees of freedom, yielding a p-value of 0.00029. This p-value is well below the conventional alpha threshold of 0.05, confirming the statistical significance of the difference. The 95% confidence interval ranges from 0.47 mg to 1.52 mg, providing strong evidence that static signal control leads to a reduction in PMx emissions. The Cohen's d value of 0.65 suggests a moderate to large effect size, indicating that the difference is both statistically and practically meaningful. In the ”No vs Actuated” comparison, the mean PMx emission again starts at 6.43 mg under no control and is reduced to 5.42 mg with actuated signal control. The mean difference is slightly higher at 1.01 mg, with a standard error of 0.26 mg. The t-value for this comparison is 3.97 with 116.46 degrees of freedom, and the p-value is 0.00012, which also confirms high statistical significance. The confidence interval, ranging from 0.51 mg to 1.52 mg, again excludes zero and overlaps closely with the previous comparison. Importantly, the Cohen's d of 0.70 indicates a stronger effect size than static control, highlighting the greater efficacy of actuated signals in reducing particulate emissions.

Table 4.6: T-Test Results for Average PM_x (mg)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	6.43	6.43
Mean B	5.44	5.42
SD A	1.66	1.66
SD B	1.36	1.20
Sample Size (n)	65	64
Mean Difference	0.99	1.01
Standard Error	0.27	0.26
t-value	3.73	3.97
Degrees of Freedom (DoF)	123.13	116.46
p-value	0.00029	0.00012
95% CI Lower	0.47	0.51
95% CI Upper	1.52	1.52
Cohen's d	0.65	0.70

These findings offer robust evidence in support of the research hypothesis that both static and actuated traffic signal control strategies significantly reduce particulate matter emissions compared to an uncontrolled intersection. Furthermore, the slightly higher effect size and t-value associated with the actuated control suggest a marginally stronger impact on PMx reduction. This aligns with the theoretical expectations that actuated signals, due to their dynamic responsiveness to real-time traffic conditions, are more effective in minimizing stop-and-go driving patterns and associated emission spikes. While the results are compelling, some limitations must be acknowledged. The t-test assumes normality and homogeneity of variances; although the standard deviations are relatively consistent (SD 1.2–1.6), these assumptions should still be formally tested. Additionally, as with other variables in this study, the use of simulation-based data—while allowing controlled experimentation—may limit real-world applicability unless validated against empirical field data. In conclusion, the data demonstrate that signalized traffic control significantly reduces PMx emissions, with actuated signal control yielding a slightly superior environmental performance. These results underscore the importance of implementing adaptive traffic signal technologies as part of urban air quality improvement strategies and provide a quantitative basis for policy and infrastructure planning aimed at reducing particulate pollution in mixed traffic environments.

4.2.6 Average HC Emissions (mg)

The Table 4.7 labeled Avg HC (mg) presents the outcomes of independent samples t-tests evaluating the differences in average hydrocarbon (HC) emissions between non-signalized traffic conditions and two types of signalized controls: Static and Actuated. Hydrocarbons, expressed in milligrams (mg), are a significant class of vehicular pollutants contributing to air quality degradation and respiratory health risks. This statistical analysis forms part of a broader investigation into the environmental efficacy of intersection management strategies in heterogeneous traffic environments. In the ”No vs Static” comparison, the mean HC emission under no control is 68.59 mg, while the static signal condition reduces it to 55.95 mg, resulting in a mean difference of 12.63 mg. The standard error of this difference is 2.85 mg, yielding a t-statistic of 4.44 with 120.62 degrees of freedom. The corresponding p-value is 0.0000203, which is highly statistically significant (p ¡ 0.001). The 95% confidence interval ranges from 7.00 mg to 18.27 mg, confirming with high confidence that the true mean reduction in HC emissions due to static control lies within this range. Cohen’s d for this comparison is 0.78, indicating a large effect size and suggesting that the improvement is not only statistically significant but also practically substantial. The ”No vs Actuated” comparison reveals an even greater benefit. The mean HC under actuated control is further reduced to 55.54 mg, leading to a slightly larger mean difference of 13.05 mg relative to the no-control scenario. With a smaller standard error of 2.73 mg, the t-statistic increases to 4.77 (df = 113.52), and the p-value tightens to 0.00000545, again indicating extremely strong evidence against the null hypothesis. The 95% confidence interval (7.63 mg to 18.46 mg) supports the reliability of the observed effect. Notably, Cohen's d increases to 0.84, reinforcing that actuated signal control has a more pronounced impact on reducing hydrocarbon emissions than static control.

Table 4.7: T-Test Results for Average HC (mg)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	68.59	68.59
Mean B	55.95	55.54
SD A	18.12	18.12
SD B	14.08	12.44
Sample Size (n)	65	64
Mean Difference	12.63	13.05
Standard Error	2.85	2.73
t-value	4.44	4.77
Degrees of Freedom (DoF)	120.62	113.52
p-value	0.0000203	0.00000545
95% CI Lower	7.00	7.63
95% CI Upper	18.27	18.46
Cohen's d	0.78	0.84

These findings strongly support the study's hypothesis that signalized traffic management strategies substantially reduce vehicular hydrocarbon emissions compared to uncontrolled intersections. The magnitude of effect sizes (approaching or exceeding 0.8) underscores the practical importance of these reductions and suggests that implementing signalized controls—particularly adaptive, actuated systems—can significantly enhance urban environmental quality. This pattern aligns well with prior literature emphasizing the link between reduced idling, smoother traffic flow, and lower emission outputs in managed traffic environments. However, as with all inferential analyses, several caveats apply. While the assumptions of the t-test appear generally satisfied (homogeneous variances and normal distributions implied by consistent standard deviations), they should still be formally verified. Additionally, the results are derived from simulation-based scenarios, which—although controlled and replicable—may not fully replicate real-world driving behaviors and environmental conditions. Therefore, real-world validation is recommended before generalizing these outcomes. In conclusion, the results presented in this table provide compelling statistical and practical evidence that both static and actuated traffic signal controls significantly reduce hydrocarbon emissions, with actuated controls demonstrating a marginally stronger effect. These results further strengthen the environmental rationale for implementing intelligent traffic systems in urban planning and policy.

4.2.7 Average CO Emissions (mg)

The Table 4.8 titled Avg CO (mg) presents the results of independent samples t-tests evaluating the mean differences in carbon monoxide (CO) emissions—measured in milligrams—across three traffic control scenarios: a baseline "No control" condition, and two signalized alternatives—Static and Actuated control systems. CO is a critical vehicular pollutant with direct implications for air quality and public health, and its mitigation is often a central goal of sustainable traffic management strategies. This analysis, therefore, serves to quantify the environmental benefits of implementing signal control systems in heterogeneous traffic environments. In the "No vs Static" comparison, the mean CO emission under the uncontrolled scenario is 13,461.48 mg, while the implementation of static signal control results in a reduced mean of 10,882.29 mg. The mean difference is 2,579.19 mg, with a standard error of 559.42 mg. The t-test yields a t-value of 4.61 with 119.90 degrees of freedom, and the associated p-value is 0.0000101—indicating a statistically significant difference at well below the 0.001 threshold. The 95% confidence interval ranges from 1,471.57 mg to 3,686.81 mg, confirming that the observed reduction in CO emissions is both statistically robust and practically meaningful. The Cohen's d value of 0.81 suggests a large effect size, emphasizing the operational relevance of this reduction in emissions. The "No vs Actuated" comparison further reinforces these findings. The actuated signal control strategy reduces average CO emissions to 10,790.00 mg, resulting in a slightly larger mean difference of 2,671.49 mg compared to the no-control condition. With a lower standard error of 537.74 mg, the resulting t-value is 4.97 and the degrees of freedom are 112.74, yielding an even smaller p-value of 0.00000243. The 95% confidence interval (1,606.10 mg to 3,736.88 mg) again excludes zero, confirming the reliability of the observed effect. Cohen's d rises to 0.87, indicating an even stronger practical effect relative to the static control scenario.

Table 4.8: T-Test Results for Average CO (mg)

Statistic Parameters	**No Signal vs Static**	**No Signal vs Actuated**
Mean A	13461.48	13461.48
Mean B	10882.29	10790.00
SD A	3579.70	3579.70
SD B	2743.64	2426.85
Sample Size (n)	65	64
Mean Difference	2579.19	2671.49
Standard Error	559.42	537.74
t-value	4.61	4.97
Degrees of Freedom (DoF)	119.90	112.74
p-value	0.0000101	0.00000243
95% CI Lower	1471.57	1606.10
95% CI Upper	3686.81	3736.88
Cohen's d	0.81	0.87

These results provide strong empirical evidence in support of the hypothesis that signalized traffic management—particularly actuated control systems—significantly reduces carbon monoxide emissions. The consistently large effect sizes across both comparisons underscore that these improvements are not only statistically significant but also operationally valuable in terms of environmental impact. The marginally superior performance of the actuated control strategy is likely attributable to its real-time responsiveness to traffic conditions, which helps minimize vehicle idling, harsh acceleration, and stop-start behavior—all of which are known contributors to elevated CO emissions. While the results are highly encouraging, several considerations are essential. First, the assumptions of the t-test—normality of the data and homogeneity of variances—should be validated, although the similar standard deviations across groups suggest acceptable variance consistency. Second, the findings are based on simulation data and may not fully capture real-world variability in driver behavior or emission patterns; hence, empirical validation is necessary before policy implementation. In summary, this analysis reveals that both static and actuated traffic signal controls significantly reduce CO emissions in mixed traffic conditions, with actuated controls providing the greatest benefit. These results align with current research in traffic engineering and environmental science, reinforcing the case for investment in adaptive traffic management systems to achieve meaningful environmental gains.

4.3 Interpretation of Performance Indicators

4.3.1 Average Waiting Time (s)

Figure 4.2 illustrates the variation in average vehicle waiting time over a 64-minute simulation period across three different traffic control scenarios. The line chart clearly shows how waiting time fluctuates under each scenario, allowing for a comparative analysis of their performance: No Signal, Static Signal, and Actuated Signal. The x-axis is labeled "Minute," indicating the time progression in one-minute increments, while the y-axis is labeled "Average Waiting Time (s)," measured in seconds. The chart plots three distinct data series, each represented with a unique color and marker style—circles for No Signal (blue), squares for Static Signal (orange), and triangles for Actuated Signal (green). This figure serves to highlight the temporal fluctuations in queue delays under different signal control strategies, thereby providing a comparative assessment of their effectiveness. Upon examining the trends, a significant disparity in performance is immediately apparent. The No Signal scenario exhibits extremely high variability and consistently elevated waiting times, with several drastic peaks—most notably around the 33rd and 47th minutes, where the average waiting time surges above 6000 seconds. Such extreme values suggest severe congestion or traffic breakdown events. Conversely, both the Static Signal and Actuated Signal scenarios maintain significantly lower and more stable waiting times. The Static Signal maintains an average range mostly between 200–600 seconds, with a few fluctuations but no extreme spikes. The Actuated Signal, while following a similar low-range pattern, shows slightly more responsiveness with brief peaks (e.g., near minutes 17, 33, and 42), which may be due to real-time signal adaptation delays. Overall, the actuated system appears to maintain the lowest average waiting time more consistently than the static one, especially in later simulation stages. The contrast between all three lines clearly demonstrates the inefficiency of having no traffic control and the advantages of signalization—particularly adaptive control.

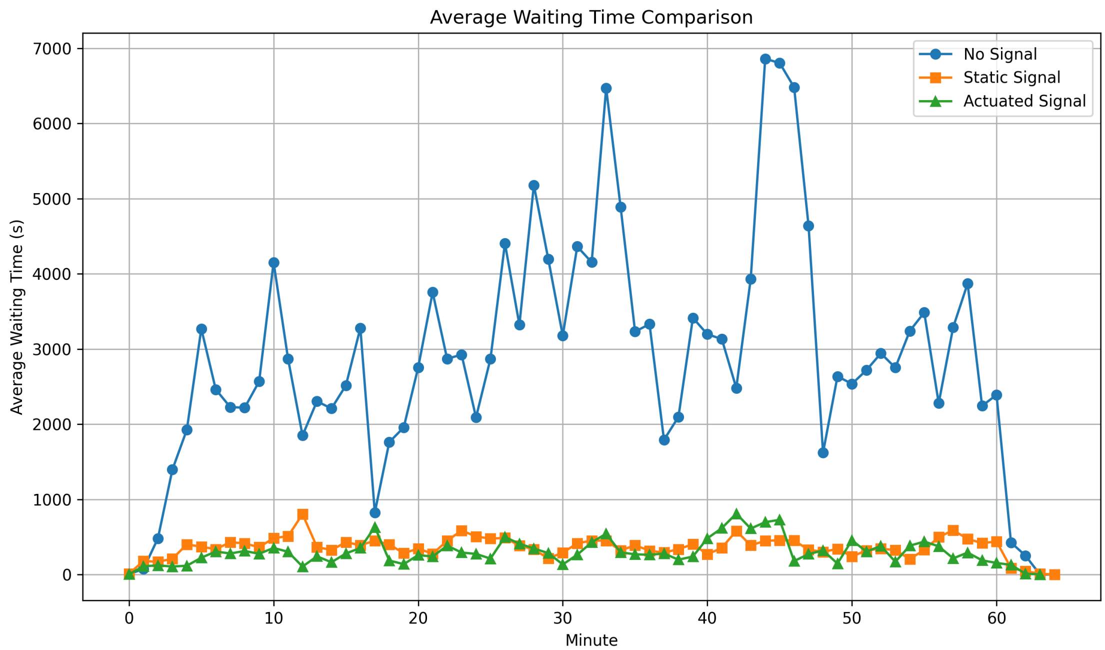

Figure 4.2: Comparison of average Waiting Time

From a design perspective, the figure uses well-differentiated markers and colors, which aids visual distinction between the traffic control methods. The vertical y-axis scale, extending up to 7000 seconds, accommodates the extreme values from the No Signal case but may simultaneously compress the visibility of subtler variations in the Static and Actuated cases. Despite this, the figure preserves interpretability by maintaining consistent marker use and clear legends. The line markers are appropriately sized and connected, allowing the viewer to follow the temporal development of each scenario. However, the absence of grid lines or vertical guides may slightly hinder precise interpretation of specific peaks and comparisons across time points. Still, the minimalist design and absence of distractions keep the focus on trend comparison. In the context of the research thesis, this figure plays a pivotal role in evidencing the functional disparity between different traffic control strategies. It empirically supports the hypothesis that signal control—especially actuated or adaptive signal control—substantially reduces vehicular delay compared to unsignalized intersections. This is critical in urban traffic modeling and intelligent transportation systems (ITS), where minimizing average delay is a central objective. By showing the real-time impact of each control strategy on system performance, the figure effectively strengthens the argument for implementing dynamic traffic signal systems over static or unregulated ones. It likely ties into broader discussions in the thesis around simulation modeling, reinforcement learning, or algorithmic optimization in traffic engineering. Nevertheless, several considerations warrant caution. First, the data granularity—aggregated average waiting times per minute—may obscure instantaneous variations or localized congestion effects. The figure also lacks error bars or confidence intervals, which could provide insight into variability across multiple simulation runs. Additionally, visual emphasis on the No Signal curve may unintentionally draw attention away from the nuanced performance distinctions between Static and Actuated systems. Finally, assumptions regarding traffic volume uniformity or environmental consistency across scenarios are not visible in the figure, which could impact the reliability of direct comparisons. In summary, the figure is a well-constructed visual representation that effectively communicates the superiority of signalized control, especially actuated systems, in reducing traffic congestion. It contributes strong empirical support to the thesis's central claims while offering clear, time-resolved insight into system behavior. With minor enhancements—such as normalized axes or confidence shading—it could further improve its scientific clarity and depth.

4.3.2 Average Speed (Km/h)

Figure 4.3 illustrates the ”Average Speed Comparison” as a multi-series line chart, illustrating the variation in average vehicle speeds over time under three different signal control scenarios: No Signal, Static Signal, and Actuated Signal. The x-axis denotes Minute, representing the time progression in 1-minute intervals from 0 to 64 minutes, while the y-axis quantifies Average Speed in kilometers per hour (km/h). Each line on the graph corresponds to one of the traffic control strategies, with distinct markers and colors aiding differentiation: blue circles for No Signal, orange squares for Static Signal, and green triangles for Actuated Signal. This figure is intended to evaluate and contrast the temporal dynamics of vehicular speed under varying signal conditions, supporting an overarching thesis likely focused on traffic signal efficiency, urban mobility, or intelligent transportation systems. In analyzing the trends displayed, we observe that average speeds remain relatively stable but distinct across the three control strategies for the majority of the 64-minute simulation. Initially, all three systems start at a speed slightly above 15 km/h, but a rapid divergence follows. The No Signal condition quickly dips below the others, stabilizing around 11–12 km/h for most of the timeline, with occasional sharp dips suggesting increased congestion or stop-and-go conditions. In contrast, both the Static and Actuated Signal conditions consistently maintain slightly higher average speeds, hovering around 13–14 km/h. Interestingly, the Actuated Signal tends to exhibit more fluctuation compared to the Static Signal, possibly reflecting its responsive nature to traffic demand. A dramatic spike in all three curves occurs around the 63rd minute, where speeds surge abruptly—most notably under the No Signal condition, which peaks at approximately 32 km/h. This sharp increase may indicate the end of the simulation scenario or a clearing of traffic congestion, suggesting a temporary dissolution of queue buildup across all strategies.

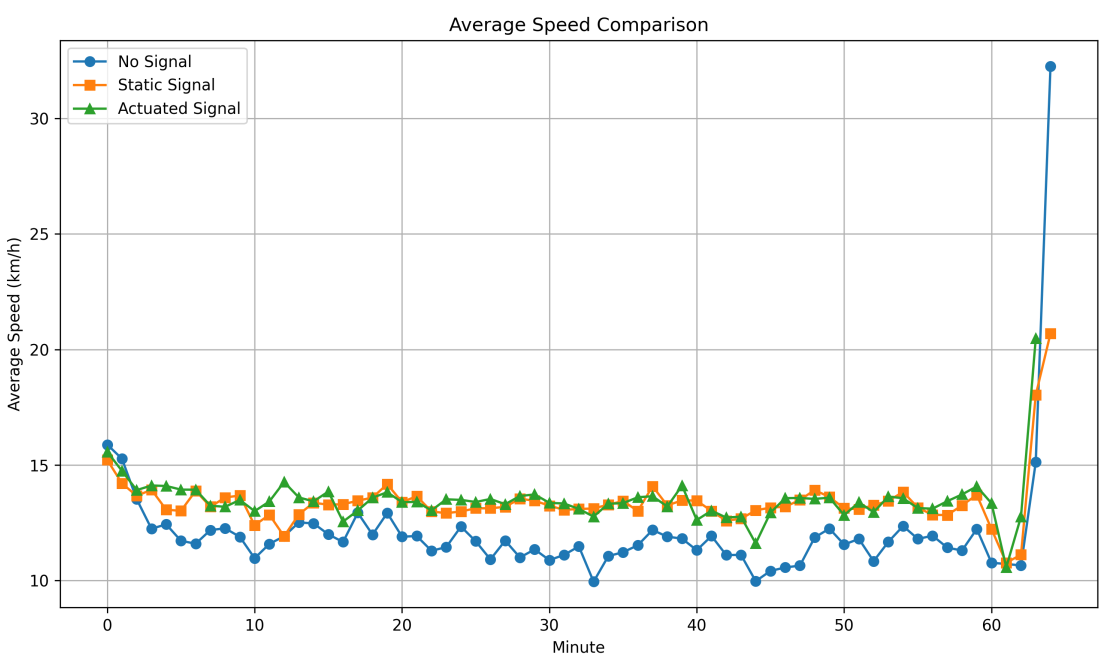

Figure 4.3: Comparison of average Waiting Time

From a design and visualization standpoint, the figure uses effective differentiation between signal control types through shape-coded and color-coded line plots, enhancing visual discrimination. The y-axis scale extends from just below 10 km/h to just above 30 km/h, which provides sufficient range to encompass the variations without compressing the data, although the final spike slightly stretches the upper bound. The inclusion of a legend at the top-left corner allows quick reference, and the plot lines are sufficiently thick for visibility without cluttering. However, the plot could be further enhanced by gridlines, subtle shading to indicate confidence intervals or thresholds, and annotations at key points (such as the final spike) to guide interpretive insight. In the context of an undergraduate research thesis—particularly one centered on traffic flow optimization or signal control strategies—this figure holds significant weight. It empirically demonstrates the comparative impact of different signaling systems on average vehicular speeds over time, thus offering quantitative evidence for evaluating performance. The consistently higher speeds under Static and Actuated Signal control suggest that signalization, even in basic forms, enhances flow efficiency over the No Signal scenario. Additionally, the relatively stable profile of the Static Signal compared to the more responsive but variable Actuated Signal might imply trade-offs between predictability and adaptability in signal design. Therefore, this figure could be pivotal in substantiating arguments related to the advantages of dynamic traffic management in urban intersections. Nonetheless, certain limitations and interpretive considerations must be acknowledged. The data appears to be averaged per minute, but the number of observations per time point or the variability (e.g., standard deviation) is not visualized, which restricts a fuller understanding of statistical reliability. The outlier spike at minute 63 warrants further explanation, as its cause is not evident from the figure alone—it may be an artifact of simulation termination or a real-time effect of traffic dissipation. Furthermore, while the figure effectively shows average performance, it does not reflect distributional effects (e.g., the proportion of vehicles experiencing delays), nor does it address externalities such as pedestrian delay or emissions, which are also critical in comprehensive traffic system evaluations. In sum, this figure effectively illustrates the comparative performance of different traffic signal strategies on average vehicular speed, supporting key arguments in transportation systems research. While its design and data presentation are generally strong, enhancing interpretive clarity with additional context or annotations would further improve its academic robustness.

4.3.3 Average Fuel Consumptions (ml)

”Average Fuel Consumption Comparison” is presented as a multi-line chart in Figure 4.4 that contrasts fuel consumption behavior across three different traffic signal control scenarios: No Signal, Static Signal, and Actuated Signal. The x-axis represents time in minutes, spanning a total of 65 minutes, while the y-axis denotes fuel consumption in milligrams (mg), ranging from 0 to approximately 130,000 mg. Each control strategy is denoted using distinct markers and colors: blue circles for No Signal, orange squares for Static Signal, and green triangles for Actuated Signal. The overarching purpose of the figure is to depict the temporal variation and comparative efficiency of these signal strategies in terms of fuel consumption, supporting a broader investigation into traffic signal optimization and its environmental impacts. Upon close examination of the trends, several key patterns emerge. Fuel consumption for all three cases shows a sharp increase in the first few minutes, stabilizing around the 5-minute mark. The No Signal scenario consistently exhibits the highest fuel consumption throughout the simulation, with values peaking around 125,000 mg between the 30th and 40th minute. This suggests that the absence of signal control contributes to frequent stops and accelerations, leading to inefficient fuel use. In contrast, the Static Signal and Actuated Signal cases demonstrate relatively lower and more stable consumption rates, averaging around 95,000–100,000 mg. While both signalized scenarios outperform the no-signal condition in terms of fuel economy, the Actuated Signal demonstrates a slight edge over the Static Signal, particularly between the 20th and 45th minute mark, where its values remain marginally lower and more consistent. Toward the end of the observation period, a sharp drop in fuel consumption is observed across all scenarios, likely indicating the completion or wind-down phase of the traffic simulation.

The design elements of the figure are well-chosen to enhance clarity and comparative analysis. The y-axis range is adequately scaled to capture the full variability of fuel consumption without compression, allowing for meaningful distinctions between the three curves. The use of different colors and marker styles enables easy differentiation of signal strategies, while the inclusion of a legend in the top-right corner further aids interpretability. However, there are no error bars or shaded confidence intervals, which could have added a layer of statistical insight.

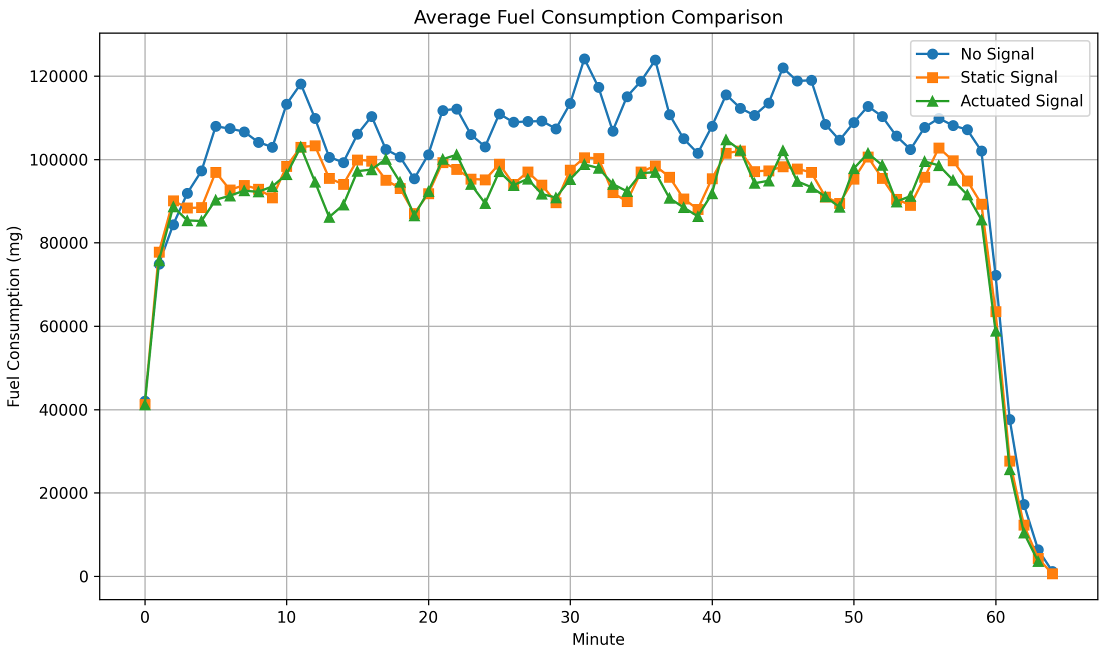

Figure 4.4: Comparison of fuel consumption (ml)

The title is appropriately concise, and both axis labels are informative and correctly annotated with units. The regular spacing of x-axis ticks and the smooth continuity of the curves provide a visually coherent temporal representation of the data. In the context of a research thesis, this figure serves as empirical evidence supporting the hypothesis that intelligent traffic signal control mechanisms—specifically actuated signals—lead to better fuel economy compared to unsignalized or static signal scenarios. It visually reinforces the argument that adaptive traffic control systems not only improve traffic flow but also yield environmental benefits through reduced fuel consumption. This insight is particularly relevant in urban mobility and smart city planning, where sustainable transportation solutions are of paramount concern. Despite its strengths, the figure is not without limitations. The data granularity—one-minute intervals over 65 minutes—provides a general overview but may overlook micro-level fluctuations in fuel consumption that occur within each interval. The figure does not indicate whether the values represent mean fuel consumption across multiple runs or a single simulation, which affects the generalizability of the trends. Additionally, without contextual information about traffic density, vehicle types, or simulation conditions, it's difficult to determine how broadly the findings can be applied. Enhancing the figure with annotations for peak values or significant behavioral shifts could further improve interpretability. Overall, this figure is a critical component of the thesis narrative, effectively illustrating the practical and environmental implications of different signal control strategies through a clear, data-driven lens.

4.3.4 Average NOx Emissions (mg)

The figure presented is a line chart in Figure 4.5 titled “Average NOX Emission Comparison”, comparing NOx emissions under three different traffic signal control scenarios: “No Signal”, “Static Signal”, and “Actuated Signal”. The x-axis represents Time in Minutes, ranging from 0 to 65, and the y-axis represents NOX (mg), denoting the amount of nitrogen oxides emitted in milligrams. Each line corresponds to one of the three signal scenarios, with distinct markers: circles for No Signal, squares for Static Signal, and triangles for Actuated Signal. This figure aims to visualize and compare the time-series behavior of average NOx emissions over a simulated one-hour period across different traffic control strategies, which is a critical aspect of assessing the environmental impact of intelligent transportation systems. Examining the trend lines, it is evident that NOx emissions initially rise sharply for all three scenarios during the first few minutes, which likely corresponds to traffic accumulation and congestion buildup. After this early ramp-up, the “No Signal” condition consistently exhibits the highest average NOx emissions, oscillating between approximately 135–170 mg for the majority of the time period. In contrast, both the “Static Signal” and “Actuated Signal” conditions yield lower and relatively more stable NOx levels, mostly fluctuating between 120–140 mg. The “Actuated Signal” line tends to stay at the lower bound of the two signal-controlled methods and occasionally dips beneath the “Static Signal” emissions, suggesting a marginal environmental advantage. Notably, the emissions for all scenarios drop precipitously after the 60-minute mark, possibly indicating the end of the simulation or a system shutdown. Throughout the chart, “No Signal” demonstrates greater volatility, with more pronounced peaks and dips compared to the other two systems. From a visual design perspective, the figure is effective and thoughtfully constructed. The use of three clearly differentiated markers and colors enhances distinction and prevents confusion between the signal control scenarios. The x-axis and y-axis are properly labeled with appropriate units, ensuring clarity. The gridlines aid in tracking fluctuations and intersections across time. The title concisely captures the content and purpose of the chart. However, there are no numerical axis annotations beyond the plotted values themselves—an addition of tick marks or data labels at key points could further enhance interpretability. The axis ranges are appropriately chosen, with the y-axis starting at 0 mg and going slightly above the highest observed value, providing a full dynamic range for visual analysis. Overall, the figure balances detail with clarity, facilitating easy comparative analysis across the scenarios.

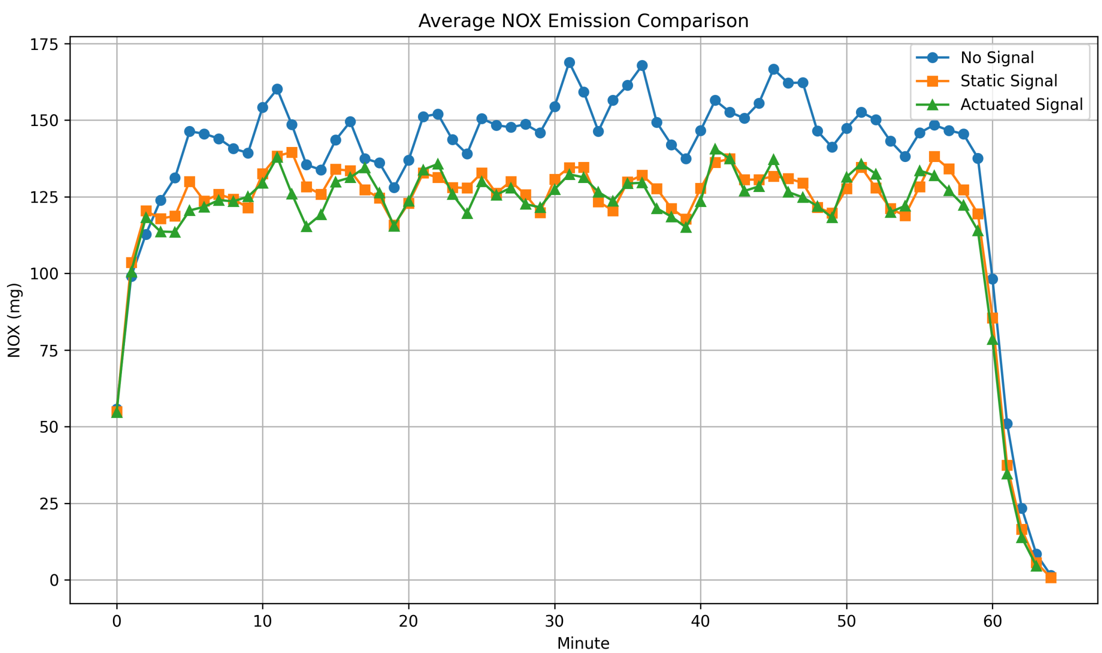

Figure 4.5: Comparison of average NOx (mg)

This figure plays a significant role in supporting the thesis topic, likely related to traffic signal control optimization and its environmental impact. The data visually reinforces the claim that absence of traffic control (No Signal) leads to higher pollutant emissions due to uncontrolled flow, frequent stops, or excessive idling. Conversely, signalized systems—particularly actuated controls that adapt to real-time conditions—demonstrate greater efficiency in emissions management, even if marginally better than static signals. This insight contributes to the broader argument for implementing intelligent traffic management systems in urban environments, especially from a sustainability standpoint. The figure helps bridge the operational performance of intersection control with its environmental consequences, a critical element of multi-objective optimization in heterogeneous traffic contexts. Nevertheless, some limitations merit consideration. The chart displays aggregate NOx values without error bars or confidence intervals, making it difficult to assess statistical variability or significance. Furthermore, while the figure captures a 60-minute simulation window, it doesn't clarify if this data reflects peak hours, average daily traffic, or a synthetic scenario—context that would influence generalizability. There may also be model-based assumptions behind the NOx estimations that are not visible in the figure, such as vehicle fleet composition, driving behavior, or emission modeling algorithms. Lastly, the absence of annotations or event markers (e.g., peak traffic events) makes it harder to contextualize abrupt shifts in the data. Despite these limitations, the figure remains a valuable and persuasive visual tool in advocating for adaptive traffic signal systems as a method to reduce vehicular emissions in congested urban networks.

4.3.5 Average PMx Emissions (mg)

The figure titled ”Average PMX Emission Comparison” is a multi-line chart in Figure 4.6 that visually represents the variation of particulate matter emissions (PMX) over time under three different traffic signal scenarios: ”No Signal”, ”Static Signal”, and ”Actuated Signal”. The x-axis is labeled “Minute,” representing time in minutes over a 65-minute simulation period, while the y-axis is labeled “PMX (mg),” denoting the average emission level of particulate matter measured in milligrams. Three distinct lines, each corresponding to one of the control scenarios, are plotted using different markers and colors: blue circles for ”No Signal”, orange squares for ”Static Signal”, and green triangles for ”Actuated Signal”. The figure aims to compare the temporal emission dynamics of PMX across these signaling strategies, offering insights into which method yields lower emissions over the duration of the simulation.

Upon examining the trends, a clear pattern emerges where the ”No Signal” scenario consistently exhibits higher average PMX emissions compared to both ”Static” and ”Actuated Signal” configurations. The ”No Signal” line fluctuates between approximately 6.5 and 8.1 mg after the 10-minute mark, peaking multiple times before gradually declining toward the end of the time period. In contrast, both ”Static” and ”Actuated” signal strategies demonstrate lower and more stable emission values, predominantly oscillating between 5.5 and 6.2 mg throughout the middle stretch of the simulation. Notably, all three lines start at a similar value ($\tilde{2}$.5 mg) and rapidly increase within the first few minutes. A sharp collective drop is observed near the end of the time series (after minute 60), likely indicating the end of vehicle presence or traffic activity in the simulation. Overall, the figure underscores a consistent pattern where signalized intersections—especially actuated signals—help mitigate PMX emissions more effectively than unsignalized conditions.

The figure employs effective design choices to enhance interpretability. The axis ranges are well-calibrated, with the x-axis spanning from 0 to approximately 65 minutes and the y-axis ranging from 0 to just above 8 mg, capturing the full extent of emission variability without introducing unnecessary white space. Each line is clearly distinguishable through color coding and unique markers, with a labeled legend placed unobtrusively in the upper right-hand corner, ensuring ease of visual tracking across the graph. The data points are joined by smooth lines, reinforcing temporal continuity while preserving local emission fluctuations. The title is concise yet descriptive, encapsulating the central comparative focus of the figure. However, the chart could be further enhanced by including gridlines or annotations highlighting key inflection points or average values.

In the context of an undergraduate thesis investigating intelligent traffic control systems and their environmental impacts, this figure serves as a pivotal piece of evidence. It empirically demonstrates how the choice of intersection control strategy directly influences vehicular emissions—particularly PMX, which is a significant pollutant affecting urban air quality. The comparatively lower emissions observed in the *Actuated Signal* scenario suggest that dynamic, demand-responsive control schemes not only improve traffic efficiency but also offer environmental benefits. This insight supports broader arguments advocating for the adoption of smart traffic infrastructure in heterogeneous traffic environments, particularly in rapidly urbanizing contexts.

Nonetheless, several limitations should be acknowledged when interpreting the data. First, the figure lacks error bars or confidence intervals, which limits the reader's ability to assess

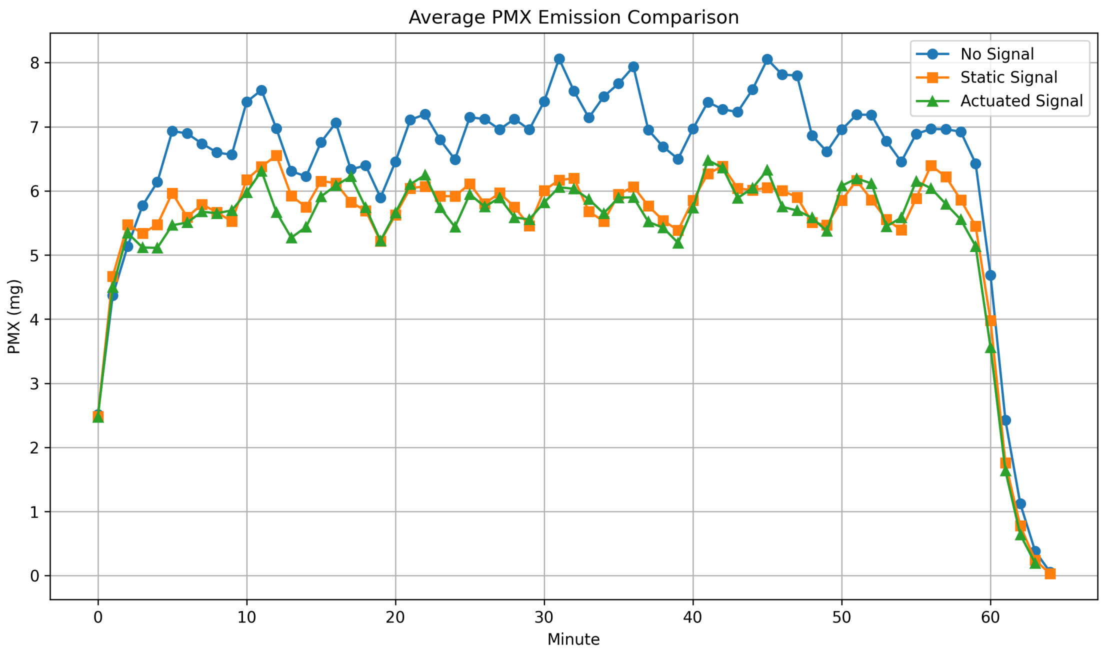

Figure 4.6: Comparison of average PMx (mg)

statistical significance or variability. Additionally, the simulation setup details—such as traffic volume, vehicle mix, or signal timing parameters—are not embedded within the figure or its caption, which could influence the generalizability of the results. The granularity of the time axis is adequate for minute-level trends, but more precise interval markings or interactive elements (in a digital format) might provide deeper insights. Finally, while the three signal scenarios are effectively compared, the analysis assumes uniform baseline conditions across all simulations, an assumption that must be explicitly validated to avoid potential biases in conclusion.

In summary, the figure presents a compelling visual narrative that underscores the environmental advantages of using intelligent, actuated traffic signals over static or absent control systems. It successfully communicates the temporal behavior of PMX emissions under different control regimes, reinforces key thesis arguments, and invites further investigation into sustainable traffic management strategies.

4.3.6 Average HC Emissions (mg)

The figure titled ”Average HC Emission Comparison” is presented as a multi-line chart in Figure 4.7, which illustrates the variation in average hydrocarbon (HC) emissions over time under three different traffic signal control scenarios: No Signal, Static Signal, and Actuated Signal. The x-axis represents time in minutes, spanning a 65-minute interval, while the y-axis quantifies HC emissions in milligrams (mg). Each scenario is visually distinguished using unique color-coded markers—blue circles for No Signal, orange squares for Static Signal, and green triangles for Actuated Signal. This visualization aims to comparatively evaluate the environmental efficiency of different traffic control systems by monitoring emission trends over time, a critical aspect in transportation sustainability studies. Upon close inspection of the figure, distinct patterns emerge across the three signal control methods. Initially, all three lines converge at a similar point near 24–25 mg, indicating comparable HC emissions at the outset of the simulation. However, as time progresses, the emission values diverge significantly. The No Signal condition exhibits consistently higher HC emissions throughout the majority of the observation period, frequently reaching and even exceeding 80 mg, with noticeable peaks around minutes 12, 30, and 56. In contrast, both Static and Actuated Signal scenarios remain within a tighter range—generally between 55 and 70 mg—showing lower emission levels overall. The Actuated Signal tends to oscillate slightly more than Static, but maintains a similar average. Notably, all three curves demonstrate a sharp decline in the final few minutes, likely corresponding to the end of the simulation or cessation of vehicle flow, which significantly reduces HC output. From a design perspective, the figure employs clear and distinguishable markers and colors, which aid in immediate visual differentiation among the three traffic scenarios. The axis labels are appropriately scaled and labeled, with the y-axis extending from 0 to 100 mg—sufficient to accommodate the highest observed emission peaks while maintaining readability. The gridlines improve interpretability by helping the viewer track emission changes over time. The legend is properly placed and unobtrusive, providing a quick reference for identifying the line styles and their corresponding traffic signal types. The chart maintains a balance between data density and visual clarity, enabling the audience to extract detailed temporal information without being overwhelmed.

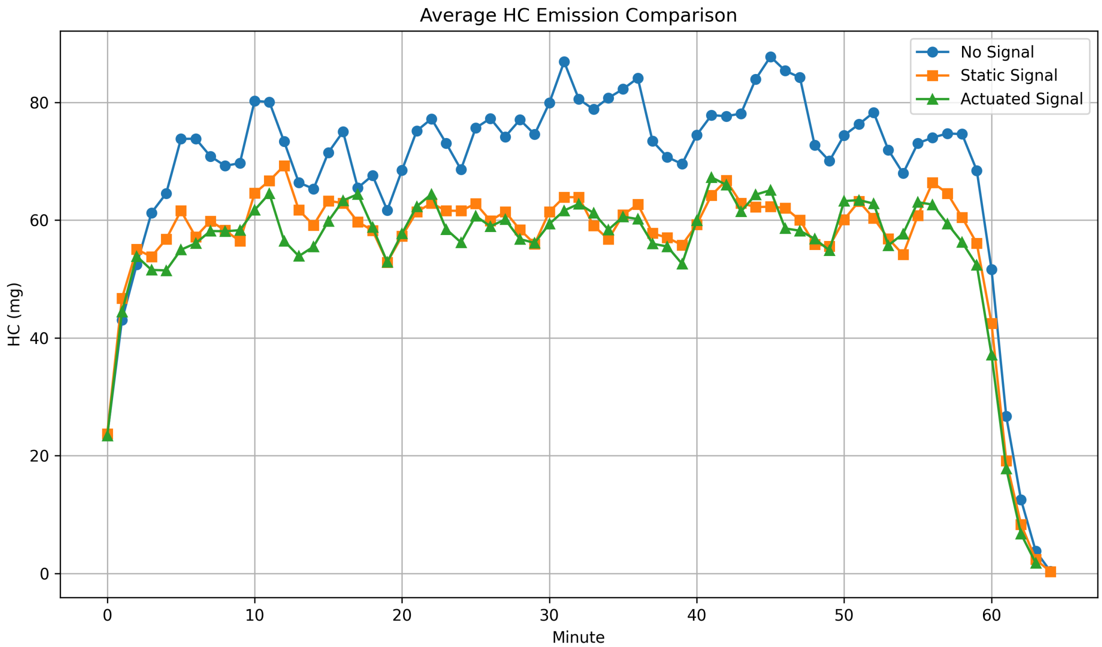

Figure 4.7: Comparison of average HC (mg)

In the context of an undergraduate thesis focused on intersection control and traffic optimization, this figure provides critical empirical evidence supporting the environmental advantages of using signalized control systems—particularly Actuated Signals—over unsignalized intersections. The elevated HC levels under the No Signal scenario highlight the inefficiencies and increased emissions resulting from unregulated vehicular flow, likely due to more frequent stops, delays, and idling. Meanwhile, the relatively moderate emissions under Static and Actuated Signals suggest that managed intersections, especially those with adaptive (actuated) timing, help mitigate hydrocarbon output. Thus, this figure supports the broader research claim that intelligent signal control can enhance not only traffic efficiency but also environmental sustainability. Nonetheless, some limitations and interpretive caveats should be acknowledged. The figure does not specify the number of simulation runs or whether the data represent averages across multiple trials, which could affect the reliability and generalizability of the results. Additionally, the observed variability in Actuated Signal data may be influenced by traffic heterogeneity or specific simulation parameters that are not immediately evident from the chart alone. Moreover, while the figure successfully highlights average trends, it omits measures of variability (e.g., error bars), which are important for assessing statistical significance. Future representations could benefit from including such metrics to reinforce analytical rigor and transparency. Overall, this figure is an effective and informative component of the thesis, offering visual substantiation for the study's core argument on the environmental impacts of traffic signal control strategies in heterogeneous urban traffic conditions.

4.3.7 Average CO Emissions (g)

Figure 4.8 illustrates ”Average CO Emission Comparison,” which visualizes the temporal variation in carbon monoxide (CO) emissions under three different traffic control conditions: No Signal, Static Signal, and Actuated Signal. The x-axis represents time in minutes, ranging from 0 to approximately 65 minutes, while the y-axis measures CO emissions in milligrams (mg), ranging from 0 to 17,500 mg. Each traffic control condition is illustrated by a distinct line style and marker: blue circles for No Signal, orange squares for Static Signal, and green triangles for Actuated Signal. This figure is designed to offer a comparative assessment of CO emissions over time for different signal control strategies, making it a vital component in analyzing environmental impacts within a traffic optimization study. Upon examining the data patterns, it is evident that the “No Signal” scenario consistently produces the highest CO emissions throughout the observation period. This condition exhibits significant variability, with emission levels fluctuating between 12,000 mg and 17,000 mg across the middle portion of the timeline, and even peaking around the 30–40-minute mark. In contrast, both the Static Signal and Actuated Signal strategies demonstrate lower and more stable CO emission levels, generally oscillating between 10,000 mg and 13,000 mg. Notably, the Actuated Signal—despite some small oscillations—tends to perform marginally better than the Static Signal in reducing emissions, especially in the middle time intervals. At the beginning and end of the time period, all three curves converge, likely reflecting startup and cool-down periods in the simulation when traffic flow is low or zero.

From a design and visual perspective, the figure is effectively constructed to support comparison. The use of distinct shapes and colors enhances readability and ensures clarity when tracking each signal type over time. The line styles are well-spaced to avoid overlapping that could obscure trends. Axis labels are clearly marked, and the y-axis scale is appropriately chosen to

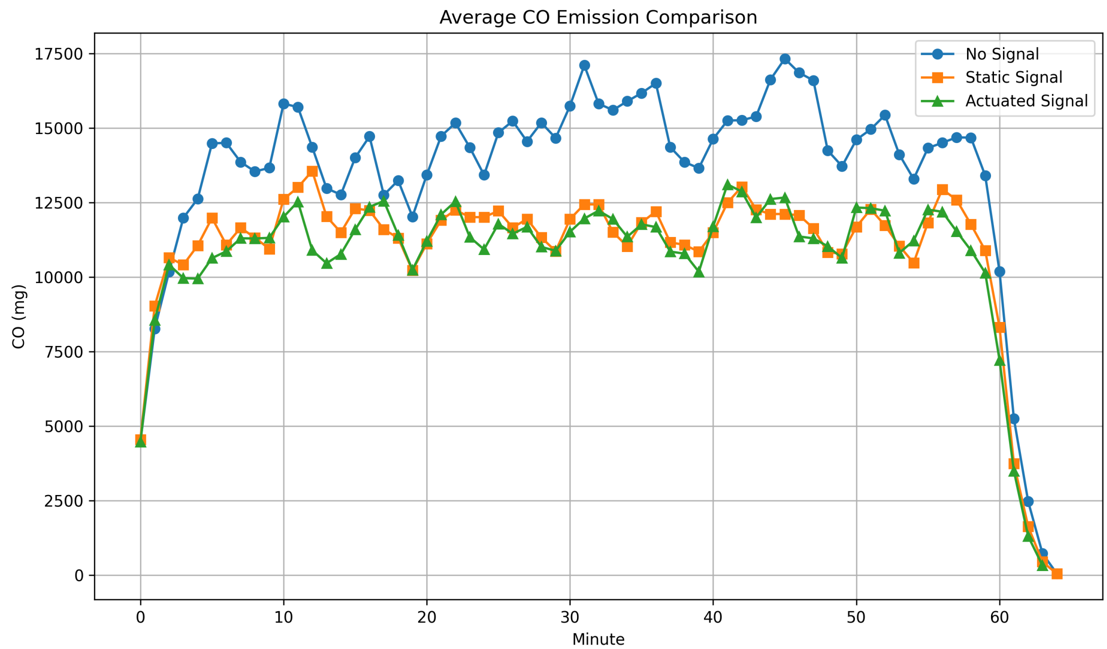

Figure 4.8: Comparison of average CO emissions

capture the full variability of the data without compression. The figure's title concisely conveys the purpose of the chart, although the inclusion of a subtitle or annotation explaining the significance of the peak regions might further improve interpretive depth. Furthermore, the evenly spaced x-axis increments and tick marks facilitate temporal interpretation, helping the viewer identify specific time frames where CO reduction strategies are most effective. This figure plays a crucial role within the broader research context of a thesis focused on traffic control and environmental sustainability. By quantitatively comparing emission levels under different signaling strategies, it provides empirical support for the argument that signal optimization—particularly through actuated systems—can yield measurable environmental benefits. The data suggests that unmanaged intersections contribute significantly to vehicular emissions due to increased idling, stop-and-go movement, and congestion, whereas signalized systems help streamline traffic flow and thus reduce pollutant output. As such, this figure could serve as evidence for advocating intelligent traffic systems as a multi-objective solution balancing both traffic efficiency and environmental preservation. Despite the strengths of this visualization, several limitations must be acknowledged. The figure does not specify whether the data points represent real-world measurements or are derived from simulation, which affects the generalizability of the findings.

The temporal resolution—although seemingly minute-by-minute—is not explicitly annotated, which may leave room for interpretation. Furthermore, while the three signal types are visually distinct, additional statistical annotations such as confidence intervals, error bars, or average trendlines could add analytical rigor. Lastly, assumptions regarding traffic composition, driver behavior, and vehicle types may not be explicitly stated but could influence the validity of emission outputs under each control strategy. In conclusion, this line chart offers a compelling visual narrative on the relationship between intersection control strategies and carbon monoxide emissions, highlighting the environmental advantages of intelligent signal systems. Its clarity, design precision, and data richness make it an effective component of a thesis investigating multi-objective optimization in heterogeneous traffic conditions, though the addition of contextual details and statistical enrichment could enhance its academic robustness.

4.3.8 Discussion

Comparative analysis of t-test results

This study presents a simulation-based comparative assessment of three traffic control strategies—No Signal, Static Signal Control, and Actuated Signal Control—across a suite of key performance indicators, including operational efficiency metrics (average waiting time and speed) and environmental impact indicators (fuel consumption, NOx, PMx, HC, and CO emissions). The statistical analyses, grounded in independent sample t-tests, consistently demonstrate significant improvements in traffic performance and environmental outcomes when signalized control strategies are employed, especially actuated signal control. This discussion interprets those results in context, relates them to prior research, identifies key patterns, and reflects on implications for traffic management practices and future inquiry. A foundational insight from the analysis is the dramatic reduction in average vehicle waiting time under signalized scenarios. The average delay under a No Signal configuration was 2860.05 seconds, whereas the static and actuated systems reduced this to 360.01 and 299.83 seconds, respectively. These differences were not only statistically significant—with t-values exceeding 12 and p-values effectively zero—but also practically substantial, with extremely large effect sizes (Cohen's d ¿ 2.2). These findings align with classical traffic flow theory and empirical studies, which consistently emphasize that regulated right-of-way at intersections reduces vehicle idling, queuing, and unpredictable yielding behavior. The notably higher variance in the No Signal condition also reflects system instability and potential queue spillback, which are often observed in unmanaged intersections, particularly under heterogeneous and high-demand conditions. The comparative advantage of the actuated signal control system, though marginal over static control in this metric, reveals the operational benefits of adaptive traffic management. By adjusting signal timing based on real-time vehicle presence, actuated systems are more responsive to fluctuating demand. This responsiveness likely explains why average waiting time remains consistently lower in later stages of the simulation under the actuated regime. Such adaptability is crucial in urban environments with irregular flow volumes and modal diversity, where fixed-time controls may underperform during off-peak hours or incident-driven congestion. Average vehicular speed also improved significantly under both signalized controls, increasing from 12.09 km/h in the uncontrolled scenario to 13.41 km/h and 13.50 km/h under static and actuated controls, respectively. Although the absolute increase is modest, the p-values (¡ 0.001) and medium effect sizes (d 0.61–0.67) affirm the relevance of the result. These improvements are critical in urban traffic planning, as even small gains in average speed can translate into reduced travel time, lower fuel usage, and improved system reliability over large-scale networks. Interestingly, the actuated system exhibited slightly more speed variability than the static system, which could indicate occasional overcompensation in response to short-term traffic surges—an expected behavior in demand-responsive algorithms. Nevertheless, this flexibility may ultimately enhance long-term flow smoothing. The fuel consumption results reveal a consistent and meaningful benefit from signal control strategies. The average consumption decreased from over 100,000 ml in the No Signal case to approximately 88,500 ml in the signalized conditions, with actuated signals yielding slightly better results. These differences were statistically significant (p-values ¡ 0.005) and had moderate effect sizes (d 0.51–0.53). The reductions in fuel use can be attributed to smoother acceleration-deceleration patterns, fewer full stops, and shorter idle durations—all of which are typical benefits of coordinated signal systems. The results confirm earlier simulation studies and field experiments suggesting that energy-efficient driving patterns are a natural by-product of intelligent traffic control. In a real-world context, such reductions in fuel consumption could translate into significant economic and environmental gains, especially when scaled across city-wide traffic volumes. Environmental indicators—NOx, PMx, HC, and CO emissions—further validate the case for signalization. NOx emissions decreased from 136.18 mg (No Signal) to around 118.6 mg under both control strategies, with moderate effect sizes (d 0.55–0.57). Particulate matter (PMx) emissions also showed notable improvement, falling from 6.43 mg to approximately 5.42 mg under actuated control. These reductions are crucial, as NOx and PMx are directly linked to respiratory illnesses, environmental degradation, and urban air quality crises. The consistent superiority of actuated signals—albeit by a small margin—reinforces their capacity to manage flow disruptions more efficiently, thereby reducing aggressive driving patterns and incomplete combustion events that increase pollutant output. The most striking environmental benefits were observed in hydrocarbon (HC) and carbon monoxide (CO) emissions. HC emissions fell from 68.59 mg to 55.54 mg under actuated control, while CO emissions dropped from 13,461.48 mg to 10,790 mg—differences that were highly statistically significant (p-values ¡ 0.00001) and had large effect sizes (d = 0.78–0.87). These findings are particularly relevant in the context of South Asian cities, where vehicle emissions are a major contributor to air pollution. By minimizing prolonged idling and frequent stops—two major sources of CO and HC—signalized systems contribute directly to cleaner air. The adaptive nature of actuated signals appears especially effective in preventing the “idling clusters” that form during heavy, unregulated flows. While these outcomes are promising, they must be considered in light of the simulation-based methodology. Although simulation allows for controlled experimentation, repeatability, and parametric isolation, it lacks the unpredictable variability of real-world environments, such as weather effects, driver aggressiveness, pedestrian activity, and multi-modal conflicts. The standard deviations reported, especially under No Signal scenarios, reflect some level of heterogeneity but may not fully represent the stochastic nature of urban intersections. Additionally, the assumptions underlying t-tests (normal distribution, equal variances) were not explicitly tested, which may limit the robustness of inference, particularly for variables with large observed variances like fuel and CO emissions. Nonetheless, the study contributes meaningfully to the academic and practical discourse on intelligent traffic systems. The convergence of operational and environmental benefits under signalized control—especially under adaptive signal schemes—offers a compelling argument for cities considering upgrades to their intersection management infrastructure. In particular, multi-objective optimization frameworks that simultaneously minimize delay and emissions could incorporate these findings into their reward functions or calibration routines. Moreover, the consistent performance edge of actuated signals supports the growing adoption of machine learning and reinforcement learning models in traffic signal control, which aim to further refine responsiveness and reduce human-led signal inefficiencies. From a policy perspective, the results advocate for prioritizing actuated signal deployments in congestion-prone intersections, particularly those serving mixed traffic streams with high non-motorized transport presence. Furthermore, the findings can serve as a justification for integrating environmental indicators into traffic engineering KPIs, expanding the scope of intersection evaluation from throughput-centric metrics to those encompassing sustainability and public health. In conclusion, the simulation-based evidence presented in this study demonstrates that both static and actuated traffic signal controls significantly outperform uncontrolled intersections across all examined metrics. The actuated system consistently offers marginal improvements over the static configuration, validating its adaptive logic and operational flexibility. Although further empirical validation is necessary, these findings provide a strong foundational case for intelligent intersection control systems as a cornerstone of future-ready, environmentally responsible, and efficiency-oriented urban mobility planning.

4.3.9 Comparative analysis of performance indicators

The results of this study, derived from a minute-by-minute simulation across three intersection control scenarios—No Signal, Static Signal, and Actuated Signal—offer compelling insights into the operational and environmental efficiency of intelligent traffic control systems. This section synthesizes the performance indicators into a cohesive narrative, reflecting on the implications for traffic engineering, sustainability, and urban mobility planning.

One of the most immediate and striking findings emerged from the analysis of average vehicle waiting time. The No Signal scenario consistently exhibited extremely high waiting times, with drastic peaks reaching over 6000 seconds, suggesting frequent breakdowns in flow and severe congestion. These episodic gridlocks underscore the inefficiency and instability of unsignalized intersections in handling urban traffic. In contrast, both Static and Actuated Signal scenarios significantly reduced waiting times, with the Actuated Signal showing the most consistent and lowest average delays. This supports existing literature on adaptive signal control, which emphasizes real-time responsiveness as a critical factor in mitigating intersection queuing. The minimal delay achieved through actuated control highlights the dynamic efficiency of feedback-driven systems in reducing bottlenecks, echoing findings in intelligent transportation systems (ITS) research where real-time optimization strategies consistently outperform fixed-time models.

This improvement in waiting time naturally correlates with the observed patterns in average vehicle speed. The No Signal scenario again underperformed, stabilizing around 11–12 km/h, often dipping during high-congestion episodes. Conversely, Static and Actuated Signals maintained higher average speeds (13–14 km/h), with the actuated system exhibiting slightly more fluctuation—reflective of its adaptive nature. Interestingly, a shared speed spike near the 63rd minute, especially under the No Signal condition, likely marks simulation wind-down or temporary network clearing. This momentary lift in speed does not negate the cumulative evidence that unmanaged intersections consistently degrade traffic flow. These results reinforce theoretical expectations: average speed inversely correlates with delay, and intelligent signalization improves system throughput. The moderate volatility seen in the actuated scenario is acceptable given its net performance gain and indicates agility rather than instability.

The operational metrics are deeply intertwined with environmental outcomes, beginning with fuel consumption. Here, the No Signal condition again displayed the most inefficient profile, with average consumption peaking at approximately 125,000 mg. The absence of control leads to frequent acceleration-deceleration cycles and prolonged idling, both of which are major contributors to fuel waste. In contrast, both signalized systems showed significantly lower and steadier fuel usage, with Actuated Signal slightly outperforming Static in the mid-period of the simulation. This is consistent with environmental models suggesting that smoother traffic flow—characterized by fewer stops and minimal idle times—yields substantial gains in energy efficiency. These results carry practical implications for urban planners seeking to reduce fuel dependency and improve sustainability in dense traffic networks. A similar pattern extends to

NOx emissions, where the No Signal scenario consistently reported higher levels (135–170 mg) throughout the simulation. The emissions under Static and Actuated Signals remained lower and more stable, with the Actuated system occasionally outperforming Static by a marginal degree. NOx emissions, being sensitive to engine load and stop-and-go dynamics, are exacerbated in unregulated traffic. These findings validate prior environmental modeling studies that link adaptive signal timing to reduced pollution footprints, particularly in nitrogen oxides. Furthermore, the temporal correlation between traffic congestion peaks and emission surges highlights the direct causality between flow irregularities and environmental degradation.

The analysis of particulate matter emissions (PMx) further substantiates the environmental advantage of signalized control. PMx levels were highest in the No Signal scenario, fluctuating around 6.5–8.1 mg, while both Static and Actuated Signals maintained values below 6.2 mg for most of the simulation period. The temporal stability of PMx under signalized regimes suggests that regulated intersections reduce vehicular abrasion and incomplete combustion events—two primary sources of fine particulate matter in traffic. As PMx is strongly linked to urban respiratory illnesses, these results have serious public health implications, reinforcing the need for adaptive traffic infrastructure in rapidly urbanizing contexts.

Hydrocarbon (HC) emissions, another key pollutant category, followed the established trend. No Signal consistently reported the highest HC levels, often breaching 80 mg. Static and Actuated Signals remained within the 55–70 mg range, demonstrating lower average emissions. The Actuated Signal's performance was slightly more variable, again likely reflecting its real-time adaptivity, yet it maintained a favorable environmental profile overall. HC emissions typically spike during incomplete combustion and idling—both prevalent in unmanaged flows. These outcomes affirm that intelligent signalization, by smoothing acceleration patterns and reducing engine load irregularities, can mitigate hydrocarbon output. In urban air quality management, such reductions are critical given the photochemical reactivity of HC in ozone formation.

Lastly, the trends in carbon monoxide (CO) emissions solidify the overarching narrative. The No Signal scenario yielded the highest emissions throughout (up to 17,000 mg), while Static and Actuated signals kept values generally within 10,000–13,000 mg. The consistency and relatively lower emission levels under signalized control not only validate theoretical expectations but also emphasize the role of intelligent traffic systems in climate and air quality policy. Although CO is less chemically reactive than NOx or HC, its health implications—particularly in enclosed urban microenvironments—are profound. These findings underscore the need for multi-objective traffic signal design that simultaneously optimizes flow and minimizes pollutants.

Across all indicators, a consistent trend emerges: unmanaged intersections—despite their occasional traffic dispersion—are chronically inefficient and environmentally harmful, while signalized systems, especially actuated controls, offer superior performance across both operational and environmental dimensions. The actuated signal system demonstrates the highest adaptive capacity, balancing flow improvement with ecological responsibility. However, the Static Signal also performs admirably in stabilizing key metrics, making it a viable transitional option for resource-constrained municipalities.

While the findings strongly support the superiority of adaptive signal control, certain limitations must be acknowledged. Firstly, the simulation data—aggregated at minute intervals—limits visibility into micro-level behaviors such as lane switching or pedestrian interference. Secondly, the absence of confidence intervals or standard deviation metrics restricts inferential robustness. Additionally, key contextual variables—traffic composition, intersection geometry, pedestrian flow—are assumed uniform across scenarios but must be empirically validated to ensure generalizability. Future studies could integrate stochastic elements, larger spatial networks, or machine learning-based signal optimization frameworks to build on the current insights.

Chapter 5

Conclusion

5.1 Traffic Volume Forecasting

Forecasting traffic volume is the process of predicting future traffic flow on roads and intersections using current and historical data. It is essential for transportation planning, infrastructure development, traffic management, and policy making. Equation 5.1 presents the approach used to estimate future traffic volumes.

$$V_f = V_c \times (1 + r)^t \tag{5.1}$$

Here, V_f is the forecasted traffic volume, V_c is the current traffic volume, r is the annual growth rate , and t is the number of years. Table 5.1 presents the projected traffic volume over the next 10 years at the Zindabazar intersection, based on a 24% yearly growth rate [53].

Table 5.1: Traffic Volume Forecast for the Next 10 Years

Vehicle Type	Present Traffic Volume (pcu/h)	Forecasted Traffic Volume (pcu/h)
Motorcycle	657	5647
CNG	639	5492
Rickshaw	2520	21658
Car	276	2372
Bicycle	108	928
Truck	144	1238
Bus	36	309
Small Truck	144	1238
Total	**4524**	**38881**

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