

Adaptive Multimodal Signal Control Using Real-Time Cyclist Platoon Detection

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Abstract: This paper presents a real-time framework for cyclist platoon prioritization at signalized intersections, integrating fuzzy C-means (FCM)-based platoon detection with adaptive fuzzy signal control. Building on prior work that validated the detection approach, this study focuses on its closed-loop integration into signal control and its multimodal operational impacts. Detected platoon attributes: estimated time of arrival (ETA), size, and cohesion, are embedded directly into the controller to enable demand-responsive priority decisions. A demand sweep ranging from 120 to 1,200 cyclists per hour is evaluated in a two-intersection VISSIM test network using COM-based real-time data exchange. The results reveal three distinct operational regimes. Under low demand, the controller remains inactive and converges to fixed-time behavior, ensuring stability and avoiding unnecessary interventions. At medium demand, priority activation increases, producing substantial cyclist delay reductions while introducing moderate vehicle impacts, reflecting a transitional trade-off regime. At high demand, sustained priority operation leads to cyclist delay reductions of up to 40–45%, while vehicle delay impacts stabilize. A sensitivity analysis of the preference threshold highlights its role in governing multimodal trade-offs. Furthermore, incorporating a bounded cohesion term improves control stability and efficiency under higher demand conditions. The proposed approach demonstrates demand responsiveness and robustness, offering a scalable strategy for cyclist-aware adaptive signal control in urban networks.

1 INTRODUCTION

Cities are experiencing sustained growth in cycling due to improved infrastructure, evolving mobility patterns, and climate-oriented transport policies. In several European cities, peak-hour cyclist flows exceed 1,000 riders per direction at major signalised intersections (Senatsverwaltung für Umwelt, 2023; München, 2023). While this modal shift represents a positive development, most traffic control systems remain primarily vehicle-oriented and are not designed to recognize or respond to cyclist group behaviour. In practice, cyclists frequently form platoons due to upstream signals, bottlenecks, or coordinated riding patterns; however, conventional signal control strategies treat them as independent arrivals rather than structured groups.

In vehicular traffic research, platoon-based approaches have long been used to improve signal coordination, reduce lost time, and optimize progression along corridors (Dong et al., 2021; Li et al., 2023). Comparable concepts for cyclists remain limited. Ex-

isting cyclist detection strategies typically rely on aggregated counts or individual detections, overlooking the operational potential of identifying and prioritizing cohesive cyclist groups.

In previous work, we introduced and validated a real-time cyclist platoon detection framework based on fuzzy C-means (FCM) clustering applied to trajectory data (Salem and Leonhardt, 2026). That study demonstrated the ability to identify dynamically forming cyclist groups and to extract behaviourally meaningful descriptors, including platoon size, spatial cohesion, and estimated time of arrival (ETA). However, the integration of such detection into adaptive signal control and its impact on multimodal traffic performance were not investigated.

This paper addresses this gap by embedding real-time platoon detection into an adaptive fuzzy signal controller implemented via the VISSIM COM interface. The controller uses platoon attributes: ETA, size, and a bounded cohesion term, to evaluate a priority preference and dynamically switch between signal programs based on a threshold parameter P^* . In contrast to conventional priority schemes, the proposed approach explicitly incorporates group structure into

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the decision process and enables tunable trade-offs between cyclist efficiency and vehicle performance.

To assess system-level effects, a structured demand range (10–100 cyclists per 300 s) is evaluated in a two-intersection test network, complemented by a sensitivity analysis of the activation threshold P^* and the inclusion of controlled cohesion. The analysis focuses on activation dynamics, multimodal delay and stop impacts, and stability across stochastic replications.

The contributions of this paper are threefold:

1. Integration of real-time cyclist platoon detection with adaptive fuzzy signal control in a closed-loop simulation framework.
2. Systematic analysis of demand-dependent operational regimes and associated multimodal trade-offs.
3. Evaluation of controller tunability and stability through threshold sensitivity and controlled cohesion.

The results show that the proposed framework operates in distinct demand-dependent regimes: it remains inactive under low demand, exhibits transitional trade-offs at medium demand, and converges toward stable and efficient priority operation under high demand. These findings demonstrate the potential of platoon-informed adaptive control for scalable multimodal traffic management.

2 LITERATURE REVIEW

2.1 Cyclists at Signalised Intersections

The integration of bicycles into urban traffic systems has received increasing attention, driven by the expansion of cycling infrastructure and rising cyclist volumes at intersections (Portilla et al., 2016; Wang et al., 2019). As cyclist flows intensify, signalised intersections become critical interaction points between motorised and non-motorised users, requiring control strategies that ensure both safety and operational efficiency.

Several studies have explored cyclist-oriented signal control approaches. Portilla et al. (Portilla et al., 2016) proposed predictive control methods to manage bicycle–vehicle interactions, while Wang et al. (Wang et al., 2019) introduced group-based signal timing concepts to improve safety in mixed traffic conditions. Although these approaches acknowledge the importance of cyclist demand, most implementations rely on aggregated flow or queue-based logic, without

explicitly capturing the dynamic formation of cyclist groups.

2.2 Fuzzy Logic in Traffic Signal Control

Fuzzy Logic (FL), introduced by Zadeh (Zadeh, 1975), has been widely applied in traffic signal control due to its ability to handle uncertainty and nonlinear system behaviour. Numerous studies have demonstrated that FL-based controllers can reduce delays and improve intersection performance under variable traffic conditions (Koukol et al., 2015; Pandey et al., 2017; Nae and Dumitrache, 2019).

FL has also been applied to priority strategies for specific user groups, including emergency vehicles and public transport (Ikidid et al., 2021; Chuo and Wu, 2022). These systems typically use inputs such as queue length, arrival rate, or delay to dynamically adjust signal timing. However, most existing approaches rely on instantaneous or threshold-based measurements and do not explicitly incorporate structured group characteristics such as platoon cohesion or estimated arrival time.

2.3 Multimodal Priority and Trade-Offs

Adaptive priority control inherently introduces trade-offs between competing traffic streams. Studies on Transit Signal Priority (TSP) have shown that improving performance for one mode often increases delay for others, requiring tunable mechanisms to balance modal objectives (Stevanovic and Teodorović, 2022). Similar challenges arise in cyclist prioritisation, where extending green time for cyclists may disrupt vehicle progression and signal coordination.

Recent research on cyclist priority in connected environments highlights both benefits and unintended consequences, including inconsistent activation and increased motor vehicle delay (Vial and Fioreze, 2023). These findings emphasize the need for adaptive control strategies that are both demand-responsive and capable of balancing multimodal performance.

2.4 From Platoon Detection to Control Integration

Cyclist platoons frequently emerge due to upstream signals, intersection geometry, and social riding behaviour (Dillen et al., 2020). Previous work has demonstrated that fuzzy clustering can reliably detect such groups and derive behaviourally meaningful de-

scriptors, including platoon size, spatial cohesion, and estimated time of arrival (ETA).

While platoon detection provides a richer representation of cyclist flow, its integration into real-time signal control remains limited. In particular, existing studies have not systematically examined how platoon-based information can be used to guide adaptive control decisions, nor how such strategies affect multimodal system performance.

2.5 Research Gap

The literature reveals three key limitations:

- cyclist priority strategies rarely incorporate real-time platoon structure into signal control decisions;
- fuzzy signal control applications for cyclists have not systematically evaluated multimodal trade-offs across varying demand levels;
- tunable parameters governing priority activation and the stabilising role of cohesion remain insufficiently explored.

This paper addresses these gaps by integrating real-time cyclist platoon detection into a fuzzy signal controller and evaluating its system-level effects. The proposed framework enables demand-dependent priority activation, supports tunable trade-offs through a preference threshold, and introduces a controlled cohesion formulation to improve stability and multimodal efficiency.

3 METHODOLOGY

3.1 System Overview

This study proposes a closed-loop framework that integrates real-time cyclist platoon detection with adaptive fuzzy signal control as shown in Figure 1. Unlike previous work focused on detection alone (Salem and Leonhardt, 2026), the present approach embeds platoon information directly into the signal control process and evaluates its operational impact.

The system operates within the VISSIM simulation environment using the COM interface. At each simulation step, cyclist trajectories are processed, platoon attributes are extracted, and signal control decisions are updated dynamically. The overall workflow can be summarized as:

Trajectory data → Platoon detection → Attribute extraction → Fuzzy control → Signal switching

This closed-loop structure enables continuous adaptation of signal timing based on evolving cyclist flow conditions.

3.2 Platoon Representation

Cyclist platoons are identified using a previously validated fuzzy clustering framework (Salem and Leonhardt, 2026). For each detected platoon, three key attributes are extracted:

- **Estimated Time of Arrival (ETA):** time to reach the stop line based on centroid distance and average speed,
- **Platoon size:** number of cyclists in the group,
- **Cohesion:** inverse measure of spatial dispersion within the group.

These attributes provide a compact and behaviorally meaningful representation of cyclist flow suitable for real-time control decisions.

3.3 Adaptive Fuzzy Signal Control

The signal controller evaluates platoon characteristics using a fuzzy inference system. The primary decision variables are ETA and platoon size, representing arrival urgency and flow magnitude. A preference value $P \in [0, 1]$ is computed to quantify the need for priority. Signal control decisions follow a threshold-based rule:

If $P > P^* \rightarrow$ activate priority signal program

Else $\rightarrow$ maintain baseline signal timing

where P^* is a tunable parameter controlling the aggressiveness of priority activation.

To prevent unnecessary switching, priority is only evaluated when ETA falls below a predefined temporal window. This ensures that the controller responds to imminent arrivals rather than distant or uncertain platoons. In addition, once activated, priority is maintained until a termination condition is met (e.g., platoon served or ETA no longer critical), reducing short-term switching instability. The decision-making process of the proposed controller is illustrated in Figure 1.

3.4 Controlled Cohesion Extension

In addition to the baseline ETA–size formulation, a controlled cohesion term is introduced as a bounded modulation factor. Cohesion does not independently trigger priority; instead, it scales the strength of the

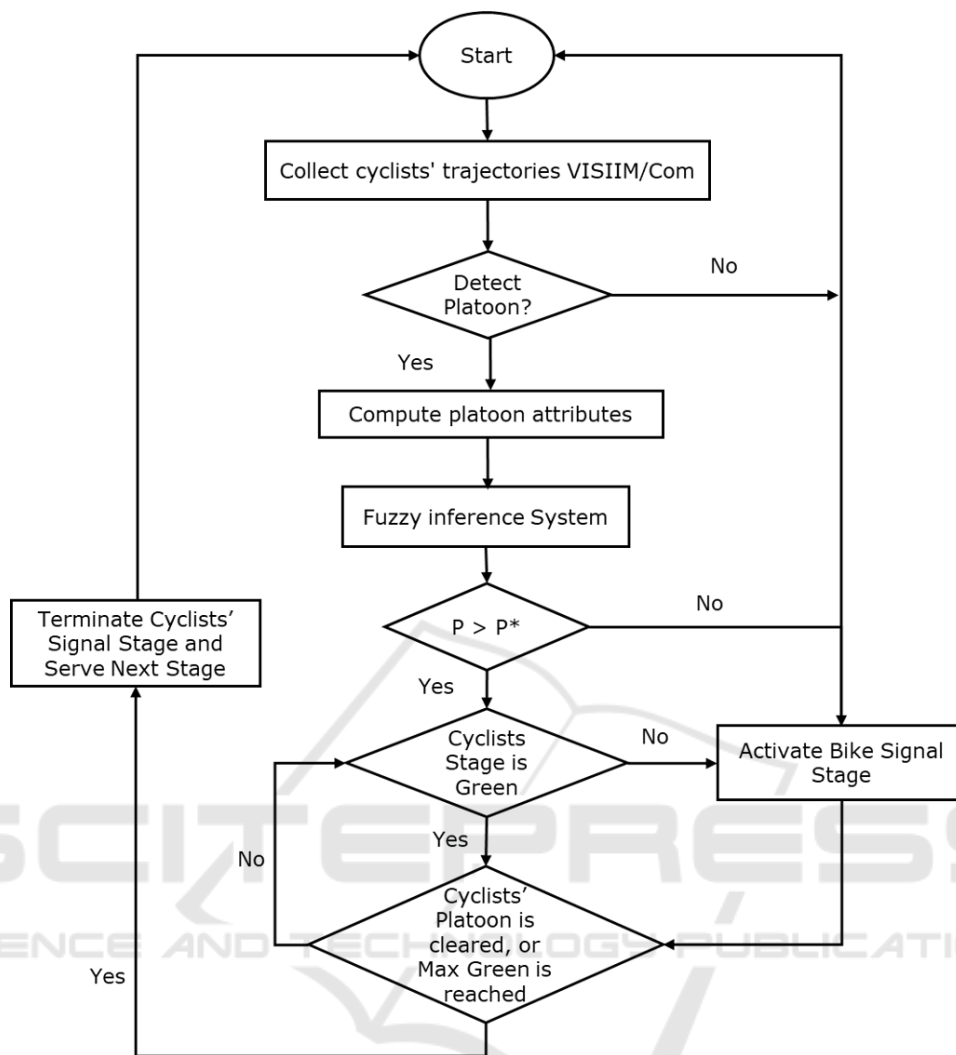


Figure 1: Closed-loop framework integrating platoon detection, fuzzy evaluation, and adaptive signal switching.

high-priority rule. This design favors tightly grouped cyclists while preventing dispersed or unstable formations from dominating control decisions. The inclusion of cohesion is intended to improve stability, particularly in transitional demand regimes.

3.5 Experimental Design

The framework is evaluated in a two-intersection VISIM network consisting of an upstream three-leg intersection (A) and a downstream four-leg intersection (B), separated by approximately 250 m. The upstream intersection is based on the entrance layout of the University of the Bundeswehr test track (Figure 2).

To focus on platoon movement and simplify the control setup, cyclist demand is modeled as coming mainly from one direction. This controlled setup allows a clear evaluation of the proposed algorithm and

provides a foundation for future testing at real intersections. Cyclist demand is varied across five levels:

10, 25, 50, 75, and 100 cyclists per 300 s

, corresponding to approximately 120–1200 cyclists per hour. For each demand level, three independent stochastic replications are conducted. Three control configurations are tested:

1. Fixed-time baseline,
2. Fuzzy control (ETA + size),
3. Fuzzy control with controlled cohesion.

Additionally, a threshold sensitivity analysis is performed by varying P^* between 0.3 and 0.8 to evaluate tunability and multimodal trade-offs. Performance is assessed using network-level KPIs extracted from VISSIM, including average delay and number of stops for both cyclists and motorized vehicles. Relative changes with respect to the fixed-time baseline

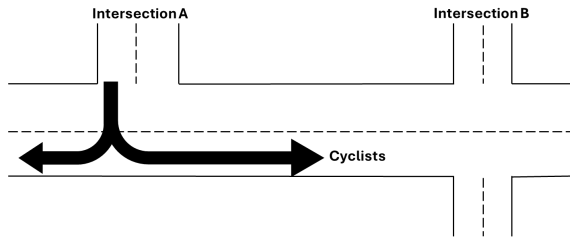


Figure 2: Schematic layout of the two-intersection test network.

are computed, and activation ratios are recorded at both intersections to analyze demand-dependent control behavior and spatial asymmetry.

4 RESULTS

4.1 Demand-Dependent Performance Regimes

The proposed platoon-based fuzzy signal controller was evaluated under five cyclist demand levels (10, 25, 50, 75, and 100 cyclists per 300 s), corresponding to 120–1200 cyclists per hour. Each configuration was simulated using three independent stochastic replications. The demand-dependent scenarios can be summarized in Table 1.

The results reveal three distinct demand-dependent operational regimes. Under low demand (10 and 25 cyclists per 300 s), activation ratios at both intersections remained negligible ($\text{Activation}_A \leq 0.03$, $\text{Activation}_B = 0$). Under these conditions, the controller converges to fixed-time behavior, with no measurable changes in cyclist or vehicle delay. This confirms that the system remains inactive under sparse flow and does not introduce unnecessary priority interventions.

At medium demand (50 cyclists per 300 s, 600 cyclists/h), a transition regime emerges. Activation at Intersection A increases sharply to approximately 0.73, while Intersection B remains inactive due to reduced downstream flow. Cyclist delay decreases by approximately 33%, while vehicle delay increases by approximately 43%, indicating the onset of a trade-off regime where priority activation begins to dominate system behavior.

At higher demand levels (75 and 100 cyclists per 300 s), the system enters a stable priority regime. Activation at Intersection A exceeds 0.85, and downstream activation at Intersection B becomes significant ($\text{Activation}_B \approx 0.28$ and 0.49). Cyclist delay reductions increase to 36–42%, while vehicle delay penalties decrease relative to the transition regime

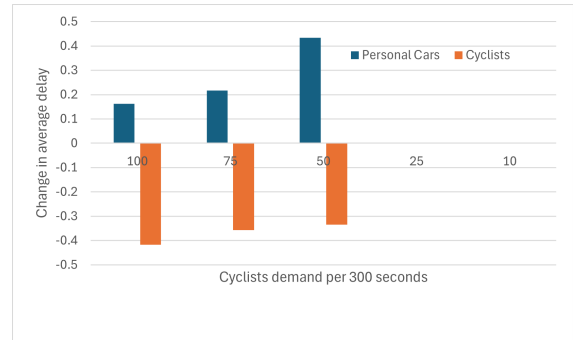


Figure 3: Change in average delay versus cyclist demand (Fuzzy – Fixed) for cyclists and personal cars.

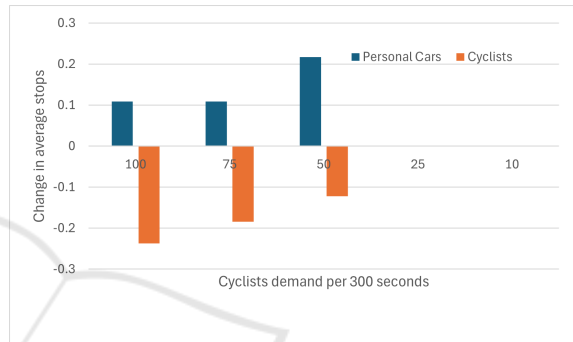


Figure 4: Change in average stops versus cyclist demand (Fuzzy – Fixed) for personal cars and cyclists.

(approximately 16–22%). This indicates convergence toward sustained priority operation, where green time allocation becomes more stable and predictable.

4.2 Stop-Based Performance Effects

In addition to delay, stopping behavior provides further insight into control stability. Figure 4 shows the change in average stops relative to fixed-time control. At low demand, no measurable differences are observed, confirming inactive behavior. In the transition regime (600 cyclists/h), cyclist stops decrease while vehicle stops increase, reflecting frequent switching and short-term instability in signal allocation.

At higher demand levels, cyclist stop reductions become more pronounced, while increases in vehicle stops stabilize. This indicates that sustained priority reduces stop–go oscillations for cyclists while preventing excessive additional interruptions for motorized traffic. Stop-based results reinforce delay findings: instability peaks in the transition regime and diminishes under high demand.

Table 1: Summary of demand operational regimes.

Regime	Demand (cyclists/h)	Activation	System Behavior
Low-demand	120–300	Near zero	Fixed-time equivalent
Transition	600	Rapid increase	High trade-off, instability
High-demand	900–1200	Sustained high	Stable priority operation

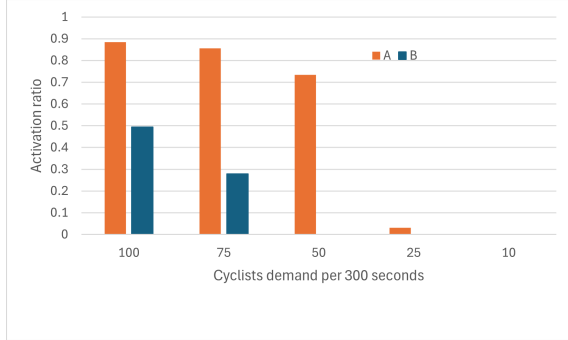


Figure 5: Activation ratio (ProgNo=2) versus demand for Intersections A and B.

4.3 Activation Dynamics

Activation ratios vary systematically with demand and intersection location. Intersection A exhibits near-monotonic growth from negligible activation to approximately 0.88 at the highest demand level. Intersection B, which receives only a portion of cyclists due to turning splits at A, activates only at higher demand levels.

This asymmetric activation confirms that the controller responds locally to platoon formation rather than enforcing uniform corridor-wide priority.

4.4 Threshold Sensitivity Analysis (P^* Without Cohesion)

A sensitivity analysis was conducted for the preference threshold parameter P^* . Lower values result in more aggressive priority activation, yielding higher cyclist delay reductions but increased vehicle delay penalties. As P^* increases, activation frequency declines and vehicle impacts are moderated.

At medium demand (600 cyclists/h), $P^* = 0.5$ produces the highest vehicle delay penalty, indicating switching instability in the transition regime. Moderate values of $P^* \in [0.4, 0.6]$ provide a more balanced trade-off between cyclist benefit and vehicle impact.

4.5 Impact of Controlled Cohesion

Introducing cohesion as a bounded modulation factor improves control stability and efficiency. Cohesion

enhances priority strength for compact platoons while suppressing activation for dispersed arrivals.

At 600 cyclists/h, vehicle delay increase is reduced from approximately +43% to +12%, while cyclist delay reduction improves slightly. At higher demand levels (900–1200 cyclists/h), cyclist delay reduction increases further (up to approximately 49%), while vehicle penalties remain moderate.

These results indicate that cohesion stabilizes the transition regime and improves prioritization of dense cyclist groups.

4.6 Controller Behavior Analysis

To better understand the observed performance trends, the controller behavior can be interpreted in terms of activation dynamics and signal switching patterns. In the transition regime (600 cyclists/h), frequent activation and deactivation cycles lead to short priority intervals, resulting in increased switching frequency. This behavior explains the observed peak in vehicle delay and stops, as green time is repeatedly reallocated without reaching stable phase durations.

In contrast, under high demand conditions (900–1200 cyclists/h), platoon arrivals become more continuous and predictable. As a result, the controller maintains longer priority phases, reducing switching frequency and enabling more efficient green time allocation. This leads to improved cyclist performance while limiting additional disruption to motorized traffic.

These observations indicate that the system behavior is governed not only by activation frequency but also by the temporal stability of priority phases. The transition from short, fragmented activations to sustained priority intervals is a key mechanism underlying the observed regime shift.

4.7 Practical Implications

The proposed framework provides several practical insights for urban traffic management. First, the demand-dependent behavior suggests that cyclist priority should not be universally applied, but instead activated selectively based on real-time flow conditions.

Second, the preference threshold P^* can be in-

terpreted as a policy parameter, allowing practitioners to balance cyclist benefits against vehicle performance depending on local priorities. Lower thresholds favor cyclist-oriented strategies, while higher thresholds maintain more balanced multimodal performance.

Third, the introduction of cohesion highlights the importance of distinguishing between structured platoons and dispersed arrivals. By prioritizing compact groups, the controller improves efficiency without introducing excessive instability.

These findings suggest that platoon-informed adaptive control can serve as a flexible and scalable approach for integrating cycling into existing traffic management systems.

5 LIMITATIONS AND FUTURE WORK

The present study is based on a microscopic VIS-SIM simulation environment with predefined cyclist arrival patterns and idealised trajectory extraction through the COM interface. While this setup enables controlled evaluation of the integrated detection–control framework, it does not fully capture the variability and uncertainty inherent in real-world traffic systems. In particular, simulated trajectories are noise-free and do not reflect sensing limitations such as occlusion, tracking errors, misclassification, or latency that may arise in camera- or radar-based detection systems.

The current platoon detection model relies on spatial position and speed information. Although sufficient for identifying dynamic group formations in simulation, higher-level behavioural attributes—such as route choice, turn intention, compliance behaviour, and interactions with motorised traffic—are not explicitly considered. In addition, clustering parameters (e.g., membership thresholds and temporal windows) were selected based on empirical stability rather than systematic optimisation across diverse network conditions.

The experimental setup is limited to a two-intersection corridor. While this configuration enables analysis of asymmetric activation and demand propagation, it does not capture corridor-wide coordination, offset optimisation, or network-level interactions such as spillback effects under high demand.

Future work will focus on validating the proposed framework using real-world cyclist trajectory data obtained from video-based or sensor-based detection systems. Such data will allow assessment of robustness under measurement noise and heterogeneous riding

behaviour.

Further research will explore adaptive parameter tuning, including dynamic adjustment of the preference threshold P^* and data-driven calibration of clustering parameters. Incorporating control enhancements such as hysteresis or minimum-hold constraints may improve stability in transitional regimes. Finally, extending the framework to corridor- and network-scale applications, including coordinated multi-intersection control, represents a key step toward practical deployment in urban traffic management systems.

An additional limitation concerns the directional structure of cyclist demand. In the current setup, cyclists approach the intersections predominantly from a single direction, resulting in unidirectional platoon formation. While this configuration allows controlled analysis of platoon propagation and priority activation, it does not capture more complex scenarios where cyclists arrive from multiple approaches simultaneously. In real-world networks, bidirectional or multi-leg cyclist flows may introduce competing priority requests, increased interaction between platoons, and more complex signal phase conflicts. These conditions could affect both the stability of the control logic and the resulting multimodal trade-offs. Future work should therefore extend the framework to multi-directional cyclist demand scenarios to evaluate its robustness under more complex intersection dynamics.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: S. Salem, A. Leonhardt; data collection: S. Salem; analysis and interpretation of results: S. Salem; draft manuscript preparation: S. Salem. All authors reviewed the results and approved the final version of the manuscript. Portions of this manuscript were developed with assistance from OpenAI's ChatGPT to improve clarity, structure, and formatting.

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