

Real-Time Cyclist Prioritization with Fuzzy Logic-Based Signal Control

Sarah Salem^a, Pascal Leone^b and Axel Leonhardt^c

Institute of Transport and Spatial Planning, University of the Bundeswehr Munich, Munich, Bavaria, Germany

Keywords: Cycling Priority, Fuzzy Logic, Traffic Signal Control.

Abstract: The integration of cycling into urban traffic systems has increased significantly. Which drives the expansion of dedicated bicycle lanes at intersections to accommodate the growing cyclist volumes while ensuring traffic efficiency and safety. Addressing cyclists' priority at signalized intersections presents a complex challenge, necessitating tailored traffic signals and control methods. This research proposes a cycling priority strategy for isolated intersections, using fuzzy logic to make high-quality decisions regarding cyclist priority while minimizing delays for all road users. The methodology involves developing a fuzzy logic-based cyclist priority strategy, using input variables such as vehicle queue and cyclist queue to determine cyclist priority. The evaluation, conducted using VISSIM microscopic traffic simulation, demonstrates that the proposed fuzzy logic-based control system effectively reduces delays and stops for cyclists, with an optimal preference threshold (P^*) value of 0.7 balancing the needs of both cyclists and motor vehicles. Sensitivity analysis against traditional control methods further emphasises the potential of the fuzzy logic approach to enhance overall traffic efficiency and promote sustainable urban mobility.

1 INTRODUCTION

Sustainable transportation is critical in metropolitan areas to address pollution and traffic congestion. Cycling has gained popularity due to its health benefits, low emissions, and efficient use of road space. However, integrating bicycles into traffic systems, especially at intersections prioritising motor vehicles, remains challenging. In Germany, cyclist demand is particularly high, exceeding 800 cyclists per hour per direction in Munich and 1,000 in Berlin during peak summer hours (München, 2023; Senatsverwaltung für Umwelt, 2023). These volumes emphasise the need for improved cyclist accommodation in traffic management systems and infrastructure.

Studies show that stops and delays significantly impact cycling experiences. Börjesson and Eliasson (2012) revealed that cyclists perceive a one-minute stop as equivalent to 3.1 minutes of cycling, reflecting the greater effort and hazards associated with interruptions (Börjesson and Eliasson, 2012). Fioreze

et al. (2019) found that cyclists often overestimate waiting times by up to five times the actual duration (Fioreze, 2019). Strategies like reducing signal cycle lengths or extending green phases for cyclists are cost-effective solutions to improve conditions, while extensive infrastructure changes, such as segregating bike and car flows, require higher investments (Gillis et al., 2020; Poliziani et al., 2022).

The first section of this paper will review the body of research on bike prioritising and traffic signal regulation. The fuzzy logic-based (FL-based) control system's design and approach, including the choice of input variables, membership functions, and rule base, will next be presented. Subsequently, the article will provide an overview of the simulation environment and showcase the findings of research that compares the suggested system with conventional traffic signal control techniques. The study will conclude with a discussion of the findings' implications and recommendations for further research directions.

This study proposes a FL-based cyclist priority strategy to address these issues. FL, a robust

^a <https://orcid.org/0009-0004-5581-9192>

^b <https://orcid.org/0009-0005-6265-1815>

^c <https://orcid.org/0009-0000-1382-3231>

artificial intelligence method for handling imprecise data (Zadeh, 1975), is ideal for managing the complexities of traffic flow. The system integrates cyclist-specific factors like speed, acceleration, and safety to improve travel experiences, reduce delays, and promote sustainable transportation.

2 LITERATURE REVIEW

In recent years, the integration of bicycles into traffic systems has gained attention, driven by the growth of dedicated bicycle lanes at intersections (Portilla et al., 2016; Wang et al., 2019). This reflects efforts to accommodate increasing number of cyclists while ensuring safe and efficient traffic flow. Specialised traffic signals and control strategies are essential for integrating bicycles smoothly into intersections (Portilla et al., 2016). For instance, Wang et al. (2019) proposed a group-based signal timing model focusing on safety in mixed traffic (Wang et al., 2019), while Portilla et al. (2016) developed a predictive control system to manage interactions between bicycles and vehicles (Portilla et al., 2016).

FL has emerged as an effective tool for traffic signal optimisation (Koukol et al., 2015; Pandey et al., 2017). Introduced by Zadeh (1975), FL provides a framework to manage uncertainties and imprecise data in traffic systems (Zadeh, 1975). Studies have used FL to prioritise specific road users, such as emergency vehicles and public transit (Ikidid et al., 2021; Chuo et al., 2022). Chuo et al. (2022) demonstrated the use of FL for adaptive traffic control, showing reduced delays and congestion by dynamically adjusting signal timings based on queue lengths (Chuo et al., 2022). Similarly, Nae and Dumitrache (2019) applied FL to optimise signal timings in urban intersections, significantly reducing wait times and queues (Nae and Dumitrache, 2019). Bhatia and Aggarwal (2020) highlighted the environmental benefits of FL-based controllers and suggested IoT integration for enhanced traffic management (Bhatia and Aggarwal, 2020).

FL has also shown promise in transit and cyclist prioritisation. Stevanovic and Teodorović (2022) developed a Type-2 FL strategy to balance transit and traffic delays, improving public transportation operations while minimising disruptions to other road users (Stevanovic and Teodorović, 2022). Vial et al. (2023) explored cyclist prioritisation using connected autonomous vehicles (CAVs) and noted potential challenges, such as inconsistent prioritisation and increased delays for cars (Vial et

al., 2023). Other approaches include using sensors for cyclist priority during specific conditions, like rain, or providing “green waves” via radar or mobile apps (Fietsberaad, 2012; Verbeeke, 2020; Lai, 2021). However, cyclists’ low adoption of mobile apps creates communication gaps, reducing their effectiveness (Vial et al., 2023).

Integrating bicycles into urban traffic systems through advanced strategies like FL is critical for creating safer, more efficient traffic management. These systems must balance the needs of all road users, prioritising cyclists without significantly disrupting motorised traffic (Gillis et al., 2020; Poliziani et al., 2022).

3 METHODOLOGY

This research investigates a strategy to prioritise cyclists at isolated intersections, adapting the approach by Stevanovic and Teodorović (2022). The primary objective is to develop a system using approximate reasoning to make high-quality decisions about cyclists’ priorities while minimising delays for all road users.

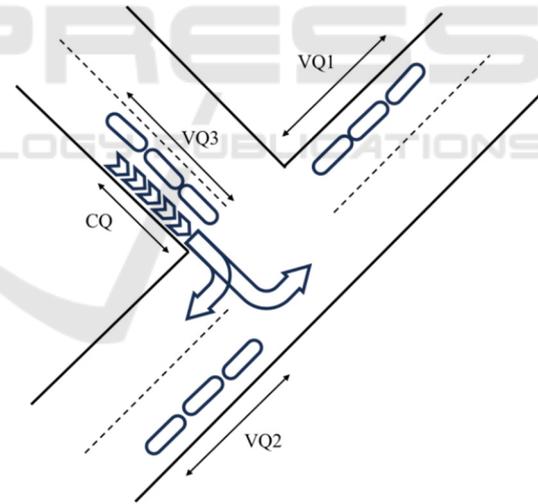


Figure 1: Intersection Layout.

3.1 Fuzzy Logic Control

The system’s core component is FL, introduced by Zadeh (1973). Fuzzy rules use descriptive expressions like small, medium, or large to categorise linguistic input and output variables, creating a fuzzy control algorithm that quantifies these expressions using fuzzy sets. This study employs the fuzzy Mamdani logic method, also known as the Max-Min method.

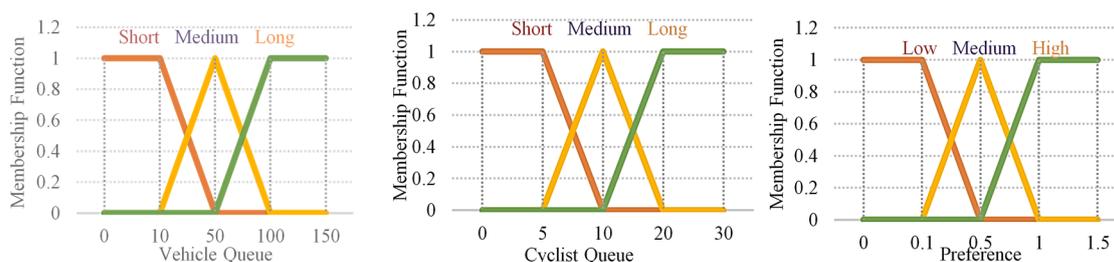


Figure 2: Membership Functions.

The cyclist priority strategy based on FL includes two input variables—vehicle queue (VQ) and cyclist queue (CQ)—and one output variable, preference (P), which represents the percentage preference to prioritise cyclists. VQ is the sum of vehicle queue lengths in competing stages ($VQ = VQ1 + VQ2 + VQ3$), as shown in Figure 1. At a signalised intersection, vehicle/cyclist queue length is defined as the distance from the stop line to the rear of the last vehicle/cyclist waiting in any lane during a red signal phase. Intelligent transportation system technologies, such as smart roadside sensors and advanced surveillance cameras, are being widely adopted globally. These traffic cameras can function independently or enhance the capabilities of other smart roadside sensors, enabling the measurement and detection of queue lengths in designated traffic lanes with greater accuracy (Makino et al., 2018; Umair et al., 2021).

The fuzzy sets for this system use triangle-shaped membership functions, as shown in Figure 2, to describe different categories. For vehicle queues (VQ), there are three categories: Short, Medium, and Long. These categories correspond to queue lengths of 0 to 10 meters for Short, 10 to 50 meters for Medium, and 50 to 100 meters for Long. Similarly, for cyclist queues (CQ), the membership functions define Short (0 to 5 meters), Medium (5 to 10 meters), and Long (10 to 20 meters). The output variable, called “Preference,” is also divided into three categories: Low, Medium, and High. This variable determines how much priority cyclists should get. The system uses an inference engine with a set of rules to decide the level of preference based on the input values for VQ and CQ. For instance, if the vehicle queue is short but the cyclist queue is long, the system gives high priority to cyclists. On the other hand, if both queues are medium, the system assigns a medium level of priority to cyclists. The centroid method is used for defuzzification, determining the crisp output value by finding the “centre” of the area under the curve formed by the membership functions.

Table 1: Fuzzy Rules.

Bike Q	Vehicle Q		
	Short	Medium	Long
Short	Medium	Low	Low
Medium	High	Medium	Low
Long	High	High	Medium

3.2 Cyclist Prioritization Strategy

Figure 3 shows a Pseudo code for the proposed control strategy’s formulation through descriptive rules. The decision on whether a cyclist approaching the intersection should pass without stopping is based on the detectors’ VQ and CQ values. A higher CQ value increases the cyclist’s preference to pass without stopping, while a higher VQ value decreases this preference. The preference P (%) to prioritize the cyclist can be low, medium, or high. If the FL-calculated preference P exceeds a predetermined threshold value P^* , the cyclist should take priority. The parameter P^* value significantly impacts cyclist and car delays. When cyclists are given priority, actions are taken to allow them to pass through the intersection without stopping. The cyclist signal group extends its green light until the cyclist queue clears or the maximum green time for that stage is reached. If the cyclist signal group is showing a red light, it transitions to a green light. This thorough approach ensures a robust analysis and evaluation of the proposed cyclist priority strategy, aiming to improve the integration of cyclists into urban traffic systems while maintaining overall traffic efficiency.

4 EXPERIMENTAL SETUP

We selected the three-legged intersection at the entrance of the University of the Bundeswehr Test track as the model area to assess the effectiveness and robustness of our proposed methodology. For simplicity we assumed that the cyclists are coming from one direction. This setup allows us to

IF Sensor detected a Bike
Received: numbers of vehicles in queue at each phase
Calculate: queue ratio
IF $P > P^*$
IF bike signal is green
Extend green time until bike queue is cleared, or max green time is reached
IF NOT activate bike signal stage until bike queue is cleared or max green time is reached
IF NOT continue with normal signal timing plan

Figure 3: Pseudocode of FL-based Signal Control Strategy.

eventually test our algorithm on a real intersection. We used the VISSIM microscopic traffic simulation software by PTV AG, a tool commonly employed by researchers in road traffic developments. VISSIM features an intuitive graphical user interface (GUI) for designing road network geometries and running simulations. Additionally, the VISSIM-COM interface creates a hierarchical model enabling programmers to control simulator functions and parameters initially set by the GUI. Programmers can use any language that supports COM objects, such as C++, Visual Basic, Java, or Python.

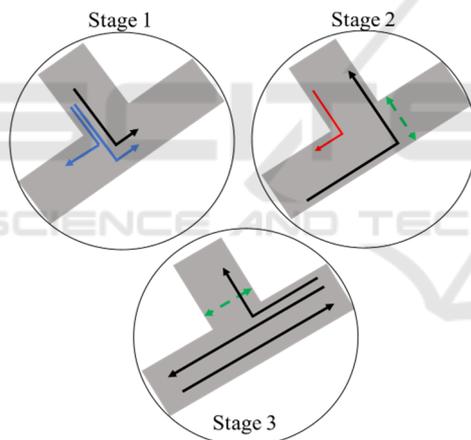


Figure 4: Traffic Stages.

Signal data is managed by the VISSIG module, with VAP defining control logic and VisVAP offering a graphical interface. Static signal data is stored in PUA files, while control logic is in VAP files. By modifying VAP files, researchers can evaluate and optimize signal control strategies, adjusting parameterized stage lengths to improve traffic flow and efficiency. This methodology allows for a thorough evaluation of cyclist priority strategies within urban traffic systems while maintaining overall traffic efficiency. The control logic encompasses three stages (Figure 4), with lane widths between 2.75 and 3.50 meters and a vehicle composition of 5% heavy goods vehicles (HGV) and

95% passenger cars, traveling at an average speed of 50 km/hr. Maximum green times are set at 30, 30, and 40 seconds for stages 1, 2, and 3 respectively, with minimum green times of 7, 4, and 10 seconds. We utilize VISSIM to extract data on vehicle and cyclist queues, as well as performance measures for all road users.

The developed code implements a traffic signal control algorithm that uses FL to prioritize traffic flow based on real-time vehicle and cyclist queue lengths. This program is designed to run every second, ensuring timely traffic signal adjustments at the intersection. It begins by defining several constants necessary for its operation, including the minimum and maximum green times for the three traffic signal stages. These constants are parameters for the FL subroutine and the main traffic control logic, ensuring the program operates within set limits. Figure 5 shows part of the signal control logic implemented in the Vis-VAP module, with the FL calculations executed using a Python script.

5 RESULTS AND ANALYSIS

This section evaluates the performance of the proposed FL-based cyclist prioritization system across various traffic scenarios. The results focus on understanding the impact of the preference threshold on key traffic metrics, such as delays and stops for both cyclists and vehicles. The analysis also compares the FL-based system's performance against traditional traffic control strategies to highlight its relative advantages.

5.1 Validation Analysis

This section presents the results of our evaluation of the proposed FL for a traffic signal control program with varying preference threshold P^* values. The objective of this evaluation is to understand how different P^* settings impact the average delays and stops experienced by vehicles and bicycles. By analysing these results, we aim to identify optimal

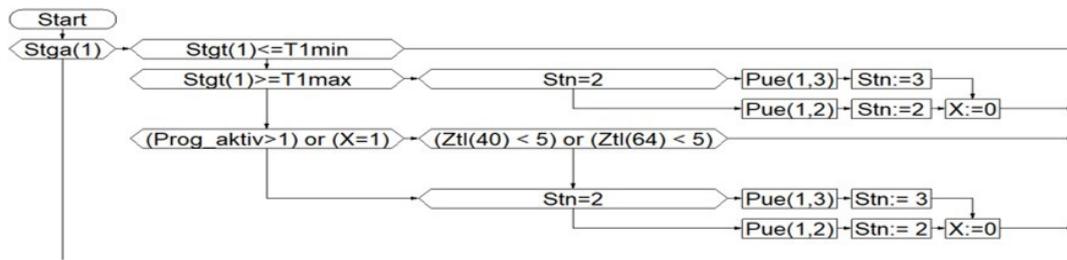


Figure 5: Example of the Logic implemented in VisVap.

configurations that balance the needs of different road users and improve overall traffic efficiency. Figures 6(a) and 6(b) illustrate the average delays and average number of stops experienced by personal cars (PKW) and bicycles under various P* values, respectively.

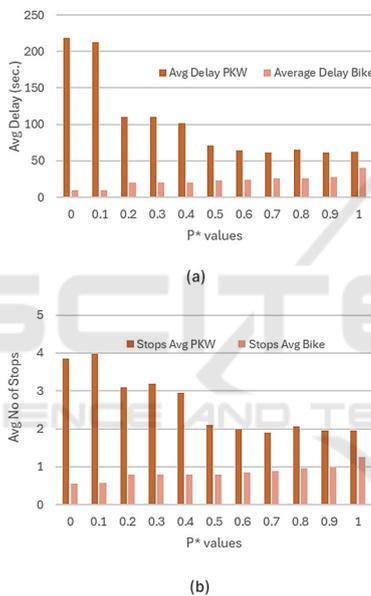


Figure 6: Impact of Different P* Values on (a) Average Delay and (b) Average Number of stops for Personal cars, and Cyclists.

In Figure 6(a), the average delay for personal cars shows a sharp decline as the P* value increases, with the highest delay observed at P* = 0. This delay decreases significantly up to P* = 0.3, after which the reduction becomes more gradual, indicating a balancing trend. For bicycles, the delay exhibits the opposite behaviour: it is lowest at P* = 0 and steadily increases with higher P* values, peaking at P* = 1. This trend highlights how prioritising bicycles (lower P* values) effectively minimises their delays while increasing delays for personal cars.

Figure 6(b) shows the average number of stops for personal cars and bicycles. Similar to the delay trends, the number of stops for personal cars

decreases as P* values increase. The highest number of stops is observed at P* = 0, while fewer stops occur as P* approaches 1. Conversely, cyclists experience the fewest stops at P* = 0, with the number of stops gradually increasing as P* values rise, reaching a maximum at P* = 1. These patterns emphasize the trade-off in optimizing delays and stops for either personal cars or bicycles, depending on the prioritization set by the P* value.

Based on the results, a preference threshold of P* = 0.7 was selected as the optimal setting. This value balances minimizing delays and stops for both personal cars and cyclists. While lower P* values (closer to 0) strongly prioritize bicycles, they result in significantly higher delays and stops for personal cars. Conversely, higher P* values (closer to 1) disproportionately favor personal cars at the expense of bicycle delays. The intermediate value of P* = 0.7 offers a compromise, reducing the gap between the two road user groups and achieving a more equitable and efficient traffic management solution.

Table 2: Traffic Scenarios Data.

	Base	1	2	3	4
North-East	500	1000	500	500	500
West-East	600	600	600	600	1200
North-West	300	300	600	300	300
East	400	400	400	800	400
Cyclists	500	500	500	500	500

To validate the effectiveness of our proposed logic and optimize its parameters, we compared the average delay and stops produced by the fuzzy logic (FL) controller (with P* = 0.7) to a fixed control plan and a strategy from the German traffic light guidelines (RiLSA). RiLSA is a technical standard in Germany that includes specifications and recommendations for planning and operating traffic signals. The specific strategy used for comparison is RiLSA Freigabezeit Anpassung (FZA), which adjusts the green time for each signal group based on inbound gap time data. This strategy extends the green time for a signal group with detected demand

Table 3: Comparison of Average Delay and Person Delay.

	Avg Delay Vehicles		Avg Delay Cyclists		Person Delay	
	Fixed	RiLSA FZA	Fixed	RiLSA FZA	Fixed	RiLSA FZA
Base	0.40	0.05	-0.63	-0.49	-0.13	-0.15
1	0.78	-0.21	-0.60	-0.34	0.07	-0.24
2	0.89	0.10	-0.63	-0.58	0.14	-0.13
3	1.46	0.07	-0.62	-0.46	0.43	-0.05
4	0.62	0.55	-0.66	-0.53	0.04	0.15

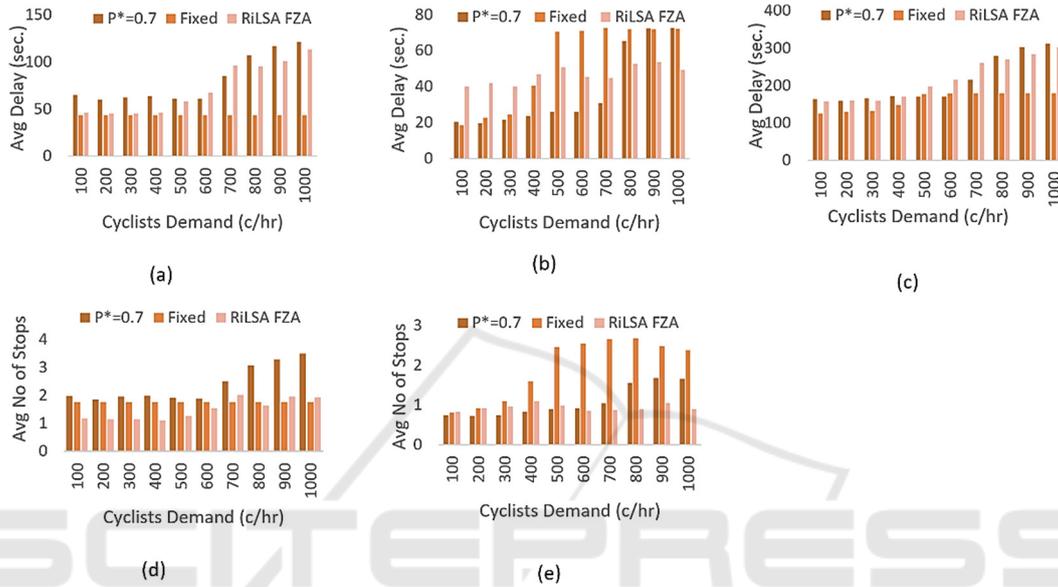


Figure 7: The Effect of Cyclist Demand on Various Traffic Performance Metrics. (a) Avg Delay for Vehicles, (b) Avg Delay for Cyclists, (c) Avg person Delay including Pedesterians, (d) Avg no of Stops for Vehicles, (e) Avg no of Stops for Cyclists.

(in this case, cyclists) within pre-defined minimum and maximum limits, without altering the stage sequence. To comprehensively evaluate performance, we employed metrics such as average vehicle delay, total cyclist delay, and overall person delay, assuming an average vehicle occupancy rate of 1.5 passengers per vehicle. Table 2 outlines the different demand scenarios used in this evaluation.

In this analysis, negative values indicate that the FL controller produces less delay compared to the baseline strategies, while positive values indicate an increase in delay. Our results demonstrate that the proposed logic significantly outperforms both the RiLSA and fixed-time controllers in reducing the average delay for cyclists across all demand scenarios. However, this improvement for cyclists comes at the cost of a slight increase in the average delay for personal cars. These results suggest that the FL controller effectively prioritizes cyclists, reducing their delays even under varying traffic volumes. As shown in Table 3, the proposed logic not only significantly reduces delays for cyclists but

also improves overall person delay. While delays for personal cars increase slightly, the pronounced benefits for cyclists result in a more favorable overall performance. This highlights the ability of the proposed traffic signal control program to balance the trade-offs between different road users, optimizing delays for cyclists without neglecting the needs of vehicles and pedestrians.

5.2 Sensitivity Analysis Under Different Cyclists Demand

The analysis conducted here aims to evaluate the effect of cyclist demand on various traffic performance metrics while maintaining vehicle demand fixed. The comparison is made across three strategies: FL with P* = 0.7, Fixed signal control, and RiLSA FZA.

Figure 7 illustrates the performance of the FL system across various traffic metrics under different cyclist demand levels and in comparison with

traditional traffic control systems. For average delay of vehicles (Figure 7a), the FL system shows a moderate increase in delays as cyclist demand rises but consistently maintains lower delays compared to the fixed signal control. However, RiLSA FZA performs better at higher cyclist demands, likely due to its longer green times allocated to clear queues efficiently.

In terms of average delay for cyclists (Figure 7b), the FL system results in slightly higher delays compared to RiLSA FZA, especially under higher cyclist demand scenarios. This can be attributed to the shorter green times allocated under FL, which aim to balance traffic flow for both vehicles and cyclists. The average person delay (Figure 7c), which includes pedestrians, reflects a key trade-off between the three strategies. While RiLSA FZA generally achieves the lowest person delays, the FL system strikes a balance, avoiding excessively high delays for vehicles. The fixed signal control, in contrast, shows the highest overall person delay, highlighting its limitations in handling mixed traffic efficiently.

The average number of stops for vehicles (Figure 7d) shows that the FL system performs better than the fixed signal control but is slightly less efficient than RiLSA FZA at reducing stops as cyclist demand increases, which indicates that FL provides smoother vehicle flow. Finally, for the average number of stops for cyclists (Figure 7e), the FL system shows moderate performance, with fewer stops than the fixed signal control but slightly more than RiLSA FZA at higher cyclist demands. This is consistent with the FL system's balanced approach, which prioritizes equitable green time distribution across all road users.

In summary, the fuzzy logic system demonstrates a well-balanced approach to managing traffic at intersections, effectively distributing green time between vehicles, cyclists, and pedestrians. While it may not outperform RiLSA FZA in cyclist-centric scenarios, it provides a more equitable solution, maintaining lower vehicle delays and fewer stops for all road users compared to the fixed signal control.

As shown in Figure 8, the FL system activated the bicycle signal less often than the RiLSA FZA strategy, and the green time per actuation was noticeably shorter. As cyclist demand increased, the green time allocated per cyclist under FL stayed fairly limited, ensuring that many cyclists could cross during the green phase without excessively prolonging the signal. This highlights how FL prioritizes the efficient use of green time, enabling cyclists to clear the intersection quickly, though this comes at the cost of longer delays for larger cyclist queues. In contrast, RiLSA FZA, which triggered the bicycle signal more frequently, provided

significantly longer green times as demand grew. This allowed it to clear larger queues in one cycle, but it also sometimes resulted in unused green time once all cyclists had passed. As a result, the green time per cyclist under RiLSA FZA was higher compared to FL. The shorter green times under FL reflect its focus on balancing the needs of vehicles and cyclists. By avoiding overly long green phases for cyclists, FL minimizes excessive delays for vehicles while maintaining fairness for all road users. Although this approach might result in slightly higher cyclist delays during periods of heavy demand, it supports a more balanced distribution of green time across the entire traffic system.

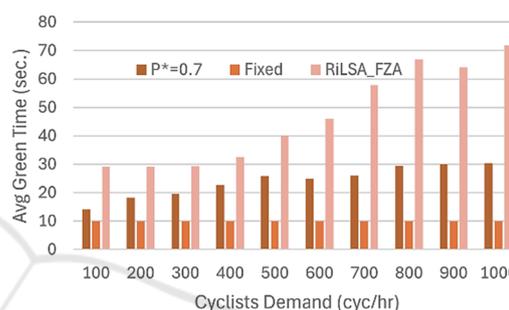


Figure 8: Effect of Cyclists Demand on Average Green Time.

6 CONCLUSIONS

This study explored and tested a new way to prioritize cyclists at traffic signals using fuzzy logic, a method designed to handle the complexities of real-world traffic. The system adjusts the signal timings dynamically, taking into account the number of cyclists and vehicles waiting at an intersection. The results indicate that this approach significantly reduces delays and stops for cyclists, providing them with a smoother and more efficient experience, while ensuring that vehicle delays remain at acceptable levels. By maintaining this balance, the system promotes a more equitable traffic flow for all road users.

A key finding of the study was that a preference threshold (P^*) value of 0.7 worked best, ensuring that cyclists and vehicles shared green time equitably. While this approach slightly increased delays for vehicles, it delivered noticeable improvements for cyclists and reduced overall delays for all road users. Compared to traditional traffic control methods, this system stands out as a practical solution to prioritize cyclists without causing major disruptions to vehicle traffic.

The study also highlights the potential of fuzzy

logic to manage the unpredictable and ever-changing nature of traffic. Its ability to adapt in real-time makes it a significant improvement over fixed or rigid systems. Beyond just benefiting cyclists, this strategy supports larger sustainability goals, encouraging more people to cycle by making it a more attractive alternative to driving. This, in turn, could help reduce emissions and contribute to healthier urban environments.

Looking ahead, there's room to refine this system further. Future work could expand its design to better include pedestrians and adapt to intersections of different layouts. While this study found that a P* value of 0.7 worked well, future research could explore ways to make this value adjustable in real time, optimizing performance based on changing traffic conditions. The next step will involve testing the system in a real-world setting at the entrance of the University of the Bundeswehr Test Track. These real-life trials will help determine how effective and practical the system is outside of simulation, paving the way for broader adoption in urban traffic systems.

ACKNOWLEDGEMENTS

This research is part of the project MORE – Munich Mobility Research Campus (MORE, 2023). The project is funded by dtec.bw – Digitalization and Technology Research Center of the Bundeswehr. dtec.bw is funded by the European Union – NextGenerationEU.

REFERENCES

- Bhatia, M. S. and Aggarwal, A. (2020). Congestion control by reducing wait time at the traffic junction using fuzzy logic controller. *International Journal of Sensors, Wireless Communications and Control*, 10(6):989–1000.
- Börjesson, M. and Eliasson, J. (2012). The value of time and external benefits in bicycle appraisal. *Transportation Research Part A: Policy and Practice*, 46(4):673–683.
- Chuo, H. S. E., Seah, Y. E., Tan, M. K., Lim, K. G., Liao, C. F., and Teo, K. T. K. (2022). On-demand priority traffic optimizer with fuzzy logic microcontroller. In *2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAET)*.
- Fietsberaad (2012). *Groningen gives cyclist the green light more often*. CROW.
- Fioreze, T. (2019). Perceived waiting time versus actual waiting time: a case study among cyclists in Enschede, The Netherlands.
- Gillis, D., Gautama, S., Van Gheluwe, C., Semanjski, I., Lopez, A. J., and Lauwers, D. (2020). Measuring delays for bicycles at signalized intersections using smartphone GPS tracking data. *ISPRS International Journal of Geo-Information*, 9(3):174.
- Ikidid, A., Fazziki, A. E., and Sadgal, M. (2021). A fuzzy logic supported multi-agent system for urban traffic and priority link control. *Journal of Universal Computer Science*, 27(10):1026–1045.
- Koukol, M., Zajilková, L., Marek, L., and Tuček, P. (2015). Fuzzy logic in traffic engineering: A review on signal control. *Mathematical Problems in Engineering*, 2015:1–14.
- Lai, M. (2021). Intersection control for cyclists with isignum.
- Makino, H., Tamada, K., Sakai, K., and Kamijo, S. (2018). Solutions for urban traffic issues by its technologies. *IATSS Research*, 42(2):49–60.
- München, L. (2023). Daten zum radverkehr.
- Nae, A. C. and Dumitrache, I. (2019). Fuzzy-logic adaptive control of traffic in an urban junction. *U.P.B. Sci. Bull.*, 81(2).
- Pandey, S., Mathur, P., and Patil, T. (2017). Real time traffic signal control using fuzzy logic controller: Review. In *Proceedings of the International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*.
- Poliziani, C., Rupi, F., Schweizer, J., Saracco, M., and Capuano, D. (2022). Cyclist's waiting time estimation at intersections, a case study with GPS traces from bologna. In *Transportation Research Procedia*, volume 62, pages 325–332.
- Portilla, C., Valencia, F., Espinosa, J., Núñez, A., and De Schutter, B. (2016). Model-based predictive control for bicycling in urban intersections. *Transportation Research Part C: Emerging Technologies*, 70:27–41.
- Senatsverwaltung für Umwelt, Mobilität, V.-u. K. (2023). *Fahrradverkehr in zahlen*.
- Stevanovic, A. and Teodorović, D. (2022). Type-2 fuzzy logic based transit priority strategy. *Expert Systems With Applications*, 187:115875.
- Umair, M., Farooq, M. U., Raza, R. H., Chen, Q., and Abdulhai, B. (2021). Efficient video-based vehicle queue length estimation using computer vision and deep learning for an urban traffic scenario. *Processes*, 9(10):1786.
- Verbeeke, R. (2020). Green wave-apps for cyclists.
- Vial, A., Salomons, M., Daamen, W., Van Arem, B., Hoogendoorn-Lanser, S., and Hoogendoorn, S. (2023). Prioritizing cyclists at signalized intersections using observations from connected autonomous vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2677(12):29–43.
- Wang, F., Tang, K., Li, K., Liu, Z., and Zhu, L. (2019). A group-based signal timing optimization model considering safety for signalized intersections with mixed traffic flows. *Journal of Advanced Transportation*, pages 1–13.
- Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—i. *Information Sciences*, 8(3):199–249.