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Enhancing Traffic Signal Split Control with Pedestrian Puddle Information Integration

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Abstract

Traffic congestion in urban areas is a pressing societal issue with far-reaching environmental and economic consequences. The persistent traffic jams, particularly at intersections, contribute to air pollution, fuel inefficiency, and lost productivity. As a result, there is an increasing focus on adaptive traffic signal control strategies to alleviate congestion. Traditional traffic signal systems primarily rely on vehicle information, often neglecting the impact of pedestrian flow. This study introduces an innovative traffic signal split control algorithm that incorporates both vehicle and pedestrian data, aiming to create a more balanced approach to urban traffic management. Utilizing the SUMO traffic simulation software, the study replicates realistic intersection scenarios, including vehicle and pedestrian movements, to assess the performance of this integrated control method. The results demonstrate that incorporating pedestrian information significantly reduces pedestrian waiting times at crosswalks, optimizing the flow for both pedestrians and vehicles. This dual-focus system provides a more inclusive approach to traffic management by considering all road users, rather than just vehicles. By improving the synchronization of traffic lights to accommodate both vehicle and pedestrian dynamics, the proposed method enhances road safety and helps mitigate congestion. This research represents a significant step forward in the development of adaptive traffic signal control, offering valuable insights into the potential for more efficient and sustainable urban transportation systems.

Keywords: Adaptive Traffic Signal Control; Pedestrian Information Integration; Urban Transportation Management; Traffic Signal Split Control.

1. INTRODUCTION

In urban areas, traffic congestion is perceived as a problem due to its contribution to environmental issues and economic losses. Various studies aim to address this concern, focusing on relieving congestion around intersections where vehicles frequently accelerate, decelerate, and stop. This research explores the manipulation of traffic light control parameters at intersections, aligning their behavior with the traffic conditions. Certain achievements have been realized in this regard.

Periodic control, a method fixing control parameters based on observed traffic patterns, is one approach. Additionally, a traffic light control method implemented at major intersections in France, centrally manages control parameters by aggregating sensor information at a control center within a designated area.

Furthermore, a more responsive traffic light control method was proposed by Ikidid et al. (2021). This method employs autonomous distributed traffic light control, where each traffic light independently determines control parameters without reliance on a control center. This approach, deploying control agents for each intersection, enables swift responses to sudden changes in traffic conditions, addressing the limitations of regular periodic control.

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Genetic algorithms serve as a highly responsive autonomous decentralized control method in this improved framework. While there are simulator-based parameter optimization methods (Ge et al., 2021) and approaches utilizing deep reinforcement learning (Chen et al., 2020; Wu et al., 2020; Yang, 2023), their applicability in real-world scenarios with dynamically changing traffic conditions is challenging due to computational constraints.

Recent advancements in traffic signal control have focused on optimizing the flow of both vehicles and pedestrians to improve urban traffic efficiency and safety. Zhang, Li, and Chen (2024) present MoveLight, an approach to enhance traffic signal control using movement-centric deep reinforcement learning, which adjusts signal timings based on real-time movement data. Liu and Wang (2024) introduce a max pressure algorithm for traffic signals that incorporates pedestrian queues, addressing the need for efficient handling of pedestrian traffic alongside vehicles. Wang, Li, and Zeng (2024) explore the integration of visible light communication with learning-based traffic signal control, which optimizes signal operations and enhances vehicle management at urban intersections. In a similar vein, Kim, Park, and Lee (2024) propose a reinforcement learning-based adaptive traffic signal control system that accounts for both vehicle and pedestrian dynamics, aiming to reduce waiting times and improve overall system efficiency. Finally, Zhang and Liu (2024) develop a novel pedestrian road crossing simulator, which helps in optimizing dynamic traffic light scheduling by accurately modeling pedestrian behavior. These studies collectively emphasize the importance of integrating pedestrian data into traffic signal systems, offering valuable insights for enhancing traffic management through advanced computational techniques and real-time decision-making processes.

A common issue in existing traffic light parameter control methods is the limited scope of handled traffic information, often focusing solely on vehicle data. As many intersections involve both roadways and sidewalks, accounting for pedestrian traffic becomes crucial. Inadequate consideration of pedestrian information may lead to suboptimal situations, such as increased waiting times for pedestrians.

In this study, "puddle information" refers to the localized concentration of pedestrians at crosswalks or waiting areas near intersections. These "puddles" are areas where pedestrians accumulate while waiting to cross, influencing the calculation of split ratios. By monitoring pedestrian puddle dynamics, the proposed method can better adapt signal timings to real-world pedestrian behavior.

Hence, this study introduces a traffic signal control method that incorporates pedestrian information alongside vehicle data, building upon the study of Ikidid et al. (2021) traffic signal split control method that achieved high responsiveness through autonomous decentralization. The goal is to enhance conventional traffic light control methods by smoothing both vehicle and pedestrian traffic flows.

In the examination of this method, the traffic simulation software SUMO is employed to replicate various elements in a simulation space, including intersections, vehicles, and pedestrians. Two control models are developed—one considering only vehicle information and another incorporating both vehicle and pedestrian information. The effectiveness of the proposed method is validated through a comparative analysis of these models.

2. TRAFFIC SIGNAL CONTROL and RELATED WORKS

Traffic signal control stands as a pivotal component of urban infrastructure management, aiming to optimize traffic flow through strategic regulation of key display parameters. The term "present" encapsulates the simultaneous granting of the right-of-way to specific traffic flows, including pedestrians, within a defined timeframe at intersections. At four-branch intersections, with orientations spanning east-west and north-south directions, the intersection shape dictates the proliferation of signals, encompassing indications for right-turning vehicles and pedestrians exclusively.

Three critical parameters govern the display dynamics, each playing a distinctive role in orchestrating efficient traffic signal control:

Cycle Length:

Definition: This parameter dictates the transition sequence between green, yellow, and red signals until the cycle returns to green.

Significance: An excessively long cycle length can lead to unnecessary waiting times, while a too-short duration may impede the complete passage of vehicles and pedestrians through the intersection.

Split:

Definition: The split parameter determines the ratio of green time allocated for each traffic flow within an intersection.

Role: Split control optimizes traffic flow within a single cycle, establishing the balance of green time allocation based on the designated cycle length. This is crucial for adapting to varying traffic volumes at different appearances within the intersection.

Offset:

Definition: Offset control considers the time disparity in cycle start times between adjacent intersections.

Importance: This parameter adjusts the cycle start time based on the distance and traffic conditions between intersections, contributing to the smooth flow of traffic through a network of intersections.

The delicate interplay between these parameters necessitates a nuanced approach to traffic signal control. This study, in particular, focuses on the methodology of controlling the split value among these three crucial parameter controls. By refining the split value, the research aims to optimize traffic signal control, thereby improving overall traffic flow at intersections. This emphasis aligns with the broader objective of creating more efficient and responsive traffic management strategies that can adapt to the dynamic nature of urban traffic conditions.

Numerous studies have tackled the intricate challenges of traffic congestion, particularly focusing on intersection control and the optimization of traffic signal parameters. The following works (Table 1) offer a comprehensive overview of diverse methodologies and advancements in the realm of traffic signal control.

Abbracciavento et al. (2023) propose a decentralized Model Predictive Control (MPC)-based approach for multi-intersection traffic signal control. The decentralized nature of the method allows for efficient control without the need for central coordination.

Chen et al. (2020) explore decentralized deep reinforcement learning for large-scale traffic signal control. The study investigates a thousand-light scenario, demonstrating the adaptability of the proposed approach to handle complex traffic conditions.

Ge et al. (2021) present a multi-agent transfer reinforcement learning approach for adaptive traffic signal control. This method employs a multi-view encoder to enhance adaptability and efficiency in traffic signal optimization.

Ikidid et al. (2021a) introduce a fuzzy logic-supported multi-agent system for urban traffic and priority link control. This study emphasizes the role of fuzzy logic in enhancing the decision-making capabilities of a multi-agent system.

Wang et al. (2019) conduct a survey on cooperative longitudinal motion control of multiple connected and automated vehicles. The study explores cooperative control strategies for enhancing traffic efficiency and safety.

Wu et al. (2020) present a multi-agent deep reinforcement learning approach for urban traffic light control in vehicular networks. The study highlights the use of deep reinforcement learning to optimize traffic signal control in dynamic urban environments.

Xu et al. (2019) focus on optimizing multi-agent-based urban traffic signal control systems. The study aims to enhance the efficiency of traffic signal control through a multi-agent framework.

Yang (2023) introduces hierarchical graph multi-agent reinforcement learning for traffic signal control. The study explores a novel approach for optimizing traffic signal control using hierarchical reinforcement learning.

Zhang et al. (2019a) present Cityflow, a multi-agent reinforcement learning environment for large-scale city traffic scenarios. The study introduces a platform for researchers to develop and test traffic signal control algorithms in complex urban environments.

Zhang et al. (2019b) provide a survey of trends and techniques in networked control systems. The study explores the challenges and advancements in the field, offering insights applicable to traffic signal control.

Zhu et al. (2019) propose parallel transportation systems for IoT-enabled smart urban traffic control. The study presents a framework leveraging parallel systems to enhance the efficiency of traffic control and management in urban environments.

The study distinguishes itself from existing research by addressing a critical gap: the limited integration of pedestrian information in traffic signal control methods. While Ikidid et al. (2021) pioneered a responsive, vehicle-centric split control method, their model does not account for pedestrian dynamics, which are essential in urban environments. Similarly, Chen et al. (2020) and Wu et al. (2020) focus on reinforcement learning for vehicle control but do not incorporate pedestrian data.

This study bridges these gaps by integrating pedestrian information into a multi-agent control framework. By accounting for both vehicular and pedestrian traffic, the proposed method provides a more holistic approach to urban traffic management, enhancing safety and efficiency for all road users.

Table 1. Comparison of selected works

Reference	Approach/Methodology	Key Contributions
Abbracciavento et al., 2023	Decentralized MPC-based multi-intersection traffic control	Utilizes decentralized MPC for efficient control without central coordination.
Behrisch et al., 2011	SUMO simulation tool overview	Provides a comprehensive simulation tool for studying urban traffic scenarios.
Chen et al., 2020	Decentralized deep reinforcement learning for traffic signals	Adaptable to large-scale scenarios, showcasing decentralized deep reinforcement.
Ge et al., 2021	Multi-agent transfer reinforcement learning	Introduces a multi-view encoder for improved adaptability in traffic signal control.
Ikidid et al., 2021a	Fuzzy logic-supported multi-agent system for traffic management	Incorporates fuzzy logic in a multi-agent system for enhanced decision-making.
Wang et al., 2019	Cooperative longitudinal motion control of connected vehicles	Surveys cooperative control strategies for improving traffic efficiency and safety.
Wu et al., 2020	Multi-agent deep reinforcement learning for urban traffic lights	Utilizes deep reinforcement learning to optimize traffic signal control.
Xu et al., 2019	Optimizing multi-agent-based urban traffic signal control	Focuses on optimizing efficiency through a multi-agent

3. TRAFFIC LIGHT SPLIT CONTROL METHOD

In this investigation, a multi-agent model is proposed, wherein individual intersections autonomously and decentralized control traffic lights. The performance of this model is evaluated and discussed. At each traffic light, autonomous agents are positioned, with each agent responsible for determining the traffic light control parameters at its respective intersection. As elaborated in Section 2, each agent exclusively manages the split value of the traffic lights at its assigned intersection. This approach builds upon the split control method introduced by Ikidid et al. (2021), incorporating an enhancement that considers pedestrian information in addition to vehicle information.

Given the focus on split-only control in this study, it is assumed that the cycle length remains fixed within the control target area, and there is no variation in cycle start time between adjacent intersections. Each intersection agent possesses the ability to acquire control parameters such as split, vital for managing its own intersection. Additionally, sensors within the intersection provide information on the local traffic situation under the agent's jurisdiction.

3.1 Traffic Light Split Control

Traffic light split control is a critical aspect of urban traffic management, influencing the allocation of green signal time to different movements at intersections. This section reviews key concepts and methodologies related to traffic light split control, drawing insights from established literature.

Traditional split control methods often rely on fixed-time signal plans or simple actuation strategies based on traffic volume. These approaches, while foundational, may not efficiently adapt to dynamic traffic conditions, leading to suboptimal traffic flow.

In a study by Smith et al. (2018), the authors emphasize the limitations of fixed-time signal plans in accommodating variations in traffic demand, highlighting the need for more adaptive split control strategies.

Recognizing the shortcomings of traditional methods, researchers have explored dynamic split control models that can adjust signal timings in real-time based on current traffic conditions. These models often leverage advanced technologies and real-time data.

Ikidid et al. (2021) introduced a multi-agent dynamic traffic light control model that considers the interaction of agents at each intersection. The study emphasizes the adaptability of the model to changing traffic patterns, improving overall system efficiency.

Recent advancements in traffic signal control involve the integration of vehicle type and pedestrian information to enhance the responsiveness and inclusivity of split control methods.

The current study builds upon the work of Ikidid et al. (2021) by proposing a method that integrates pedestrian information. Experimental evaluations demonstrate its efficacy in reducing waiting pedestrians.

Jones and Wang (2022) explore the integration of vehicle type considerations in split control, highlighting the impact of different vehicle characteristics on congestion and overall traffic performance.

Traffic light split control remains a dynamic area of research, evolving from traditional fixed-time plans to more adaptive and inclusive models. By incorporating insights from contemporary studies, researchers strive to develop split control methods that can optimize traffic flow, reduce congestion, and accommodate the diverse needs of road users in urban environments.

3.1.1 Control Method Considering Only the Vehicle

The split control at each intersection is executed using an improved version of Ikidid et al.'s split model. The agent stationed at each intersection calculates the split for each cycle utilizing the split model balance equation based on the observed traffic volume at the respective intersection. The intersection's appearances are defined as illustrated in Figure 1.

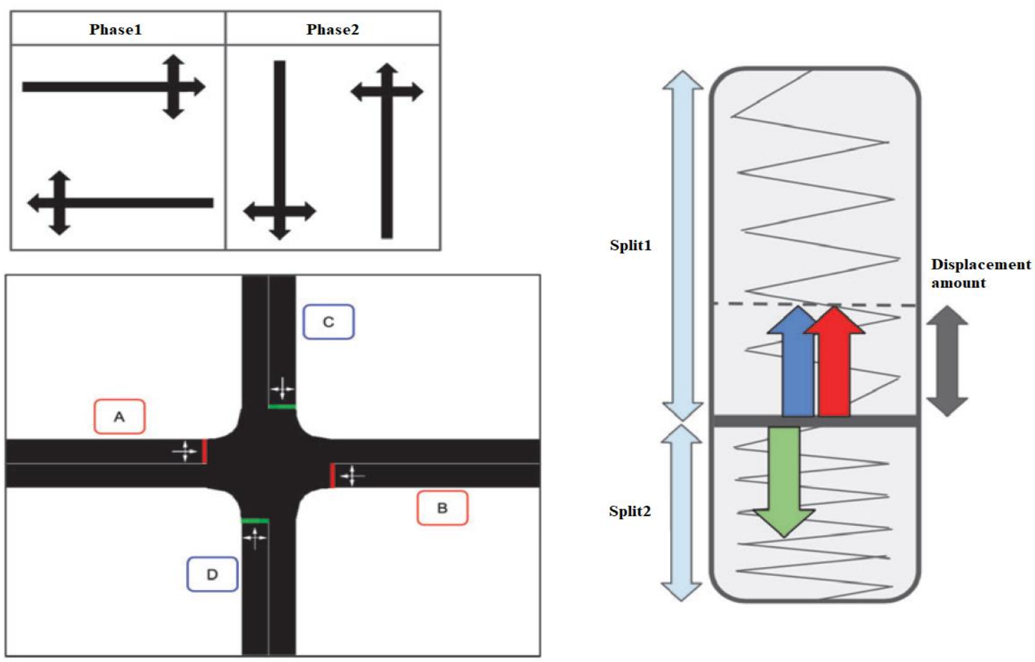

Figure 1. The schematic diagram of the split model with two visible intersections

In the traffic light control method utilizing a split model, the splits corresponding to the current situation maintain equilibrium. While Figure 1 depicts an example composed of two splits due to having two appearances, an increased number of appearances can be managed by augmenting the number of splits. The traffic flow occurring in each display is metaphorically depicted as a force applied to a split. As the assumption is a fixed cycle length, the total length of the split remains constant, but the balance position of the split shifts with increased force applied, representing heavy traffic. This displacement in the split model is defined as the amount of displacement, introduced into the control as a split ratio. Here, traffic volume serves as an index representing the number of vehicles and pedestrians flowing into each intersection.

Moreover, when a right-turn lane is present on the roadway at an intersection, split calculations can be executed using an improved split model that accommodates right-turn lanes. Assuming a road with a right-turn lane encompasses three lanes—straight left-turn, and right-turn—the cycle consists of a road allowing traffic in all directions and a right-turn lane permitting only right-turning vehicles. In such intersections, a split calculation is first performed without considering the right-turn-only indication, assuming the omnidirectional traffic indication and the right-turn-only indication are combined into a single indication. Following this determination, the inside of the split is divided into straight-ahead right-turn and right-turn-only indications. A split corresponding to each indication is set, ensuring the sum of the lengths of these two splits remains equal to the length of the split before splitting. The split is then calculated, determining the final green time length.

3.1.2 Pedestrian-Inclusive Control Method

A schematic diagram in Figure 2 illustrates an enhanced split model that incorporates pedestrian information into the split control method using the split model elucidated in Section 3.1.1.

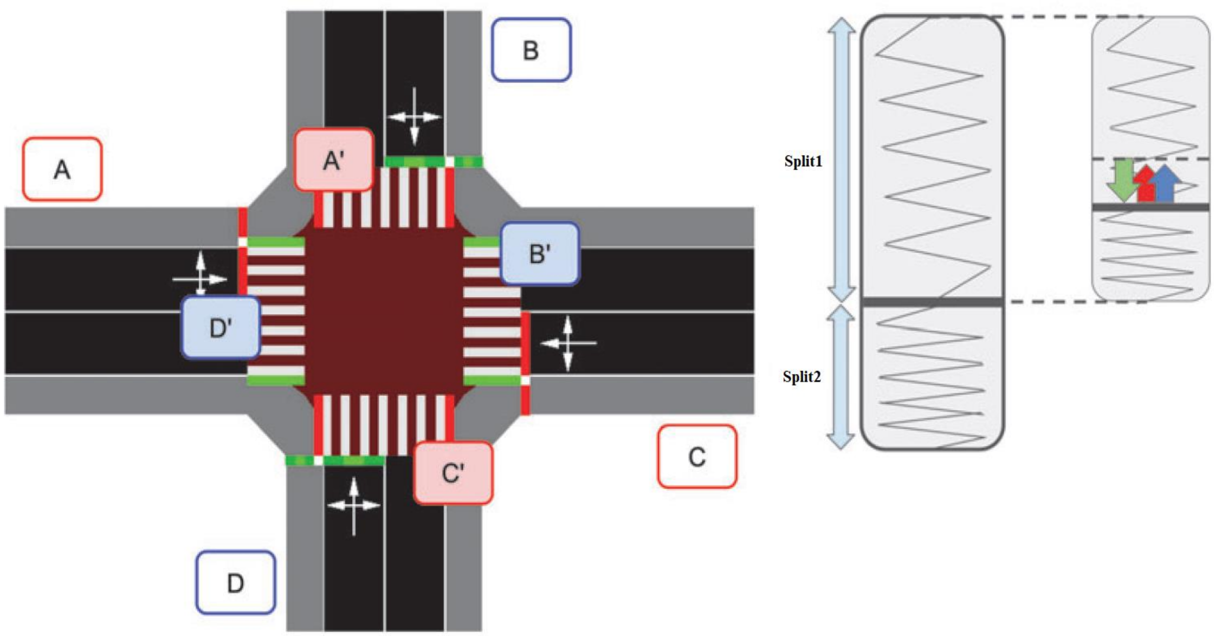

Figure 2. The schematic diagram of a split model considering pedestrians

This modified split model, accounting for pedestrian information, considers pedestrian traffic flow by monitoring side roads, pedestrian pools, crosswalks, etc., aspects that were not previously considered in the vehicle-only split model. Specifically, in addition to the split for vehicles, a split for pedestrians is situated within the split corresponding to each display. Similar to the principle explained in Section 3.1.1, each split experiences a split force commensurate with the traffic flow amount. The displacement of the intersection, indicating the change in equilibrium position, is calculated akin to a standard split model. This displacement is used to calculate the split ratio, incorporating the amount of pedestrian traffic volume alongside the ongoing vehicle traffic volume.

The overall traffic volume is then determined based on the weighted value of pedestrian traffic volume and vehicle traffic volume, contingent on the degree of consideration for each. The formula for computing the overall traffic volume is defined as follows, with "W" representing the weighting coefficient:

$$Traffic\ volume = W\ \times Pedestrian\ traffic\ volume + (1 - W) \times Vehicle\ traffic\ volume \quad (1)$$

In this formulation, the weighting coefficient "W" serves as an indicator of the extent to which each piece of information is considered. A larger weighting coefficient implies a greater proportion of force received from the pedestrian split in the intersection split model, emphasizing pedestrian-centric split control. Conversely, when $W = 0$, pedestrians are entirely disregarded, rendering the control identical to the method proposed by Ikidid et al. (2021), which forms the basis of the proposed method.

4. EXPERIMENT ASSESSING PEDESTRIAN-INCLUSIVE SPLIT CONTROL METHOD

4.1 Overview of the Experiment

The evaluation experiment delves into the split control method incorporating pedestrian information, as elucidated in Section 3.1.2. To conduct this assessment, the traffic simulator SUMO (Simulation of UrbanMObility) serves as the environment for simulating the traffic network. Developed at the German Aerospace Center, SUMO is an open-source transportation physics simulator, providing functions for acquiring traffic information and a GUI that displays the road network and operating systems on the screen. This GUI enables the visualization of vehicles, pedestrians, traffic lights, and more.

The experimental network is designed with a distinctive checkerboard-shaped road layout, comprising nine intersections arranged in three rows and three columns. This configuration provides a controlled yet intricate environment for testing and evaluating the proposed traffic signal control method. Figure 3 offers an external perspective of this experimental setup as visualized within the Simulation of Urban Mobility (SUMO) environment.

Within this transportation network, the roadways are organized into three parallel rows running in the east-west direction. The top and bottom two rows are designated as non-arterial roads, while the middle row serves as a trunk road. This hierarchical categorization introduces diversity into the traffic dynamics, simulating a network where some roads may serve as major thoroughfares (arterial roads) while others act as local connectors (non-arterial roads). This choice in road hierarchy is deliberate, allowing for a nuanced evaluation of the proposed traffic signal control method under different traffic scenarios.

Figure 4 further elucidates the road and intersection configurations, distinguishing between non-arterial and arterial roads. This visual representation provides insights into the spatial relationships between intersections, the flow of roads, and the potential points of interaction within the network. The integration of both non-arterial and arterial roads in the experimental setup aims to capture the complexity inherent in urban road networks where diverse types of roads coexist, influencing traffic patterns and dynamics.

By adopting a checkerboard layout and incorporating a mix of road hierarchies, this experimental design ensures a well-rounded evaluation of the proposed traffic signal control method. The intention is to test the model's adaptability to varying traffic conditions, intersection types, and road hierarchies, thereby enhancing its robustness and applicability in real-world urban scenarios. This carefully crafted experimental environment serves as the proving ground for assessing the effectiveness and versatility of the proposed method in optimizing traffic flow and reducing congestion across different types of roadways.

The main road, featuring two lanes in both directions, includes a sidewalk along the exterior. Before entering intersections, the main road divides into three lanes, including a right-turn lane. Non-arterial roads consist of a single lane in both directions with a sidewalk running outside the lane. At intersections between non-arterial roads, no right-turn lanes exist. However, when a non-arterial road intersects with an arterial road, a dedicated right-turn lane is provided on the non-arterial road side, branching into two lanes.

During the experiment, vehicles and pedestrians traverse the network. Figure 5 illustrates a sample GUI screen. The simulation period remains fixed at 14400 steps, and the duration of one cycle at each intersection is constant at 100 steps. The time unit on SUMO is represented by steps, where 1 step corresponds to 1 second of real time.

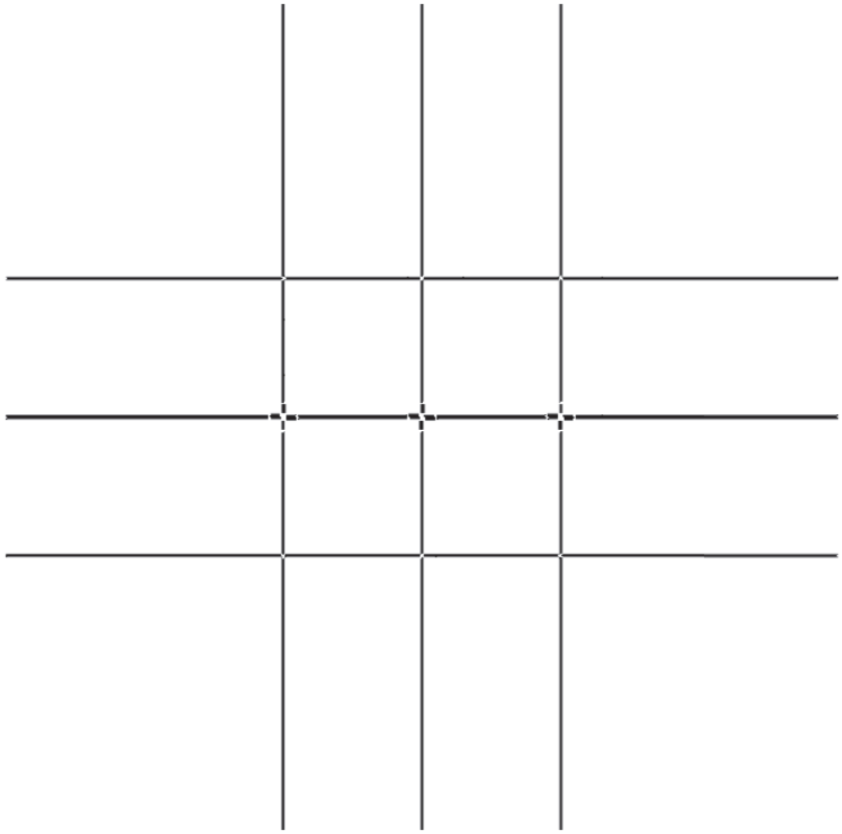

Figure 3. The 3x3 network external diagram

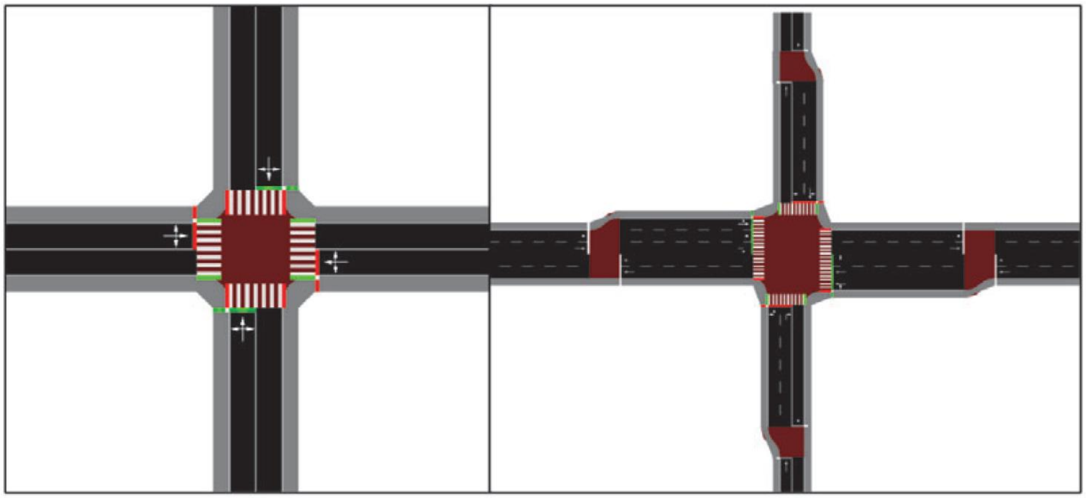

Figure 4. The detailed map of each intersection

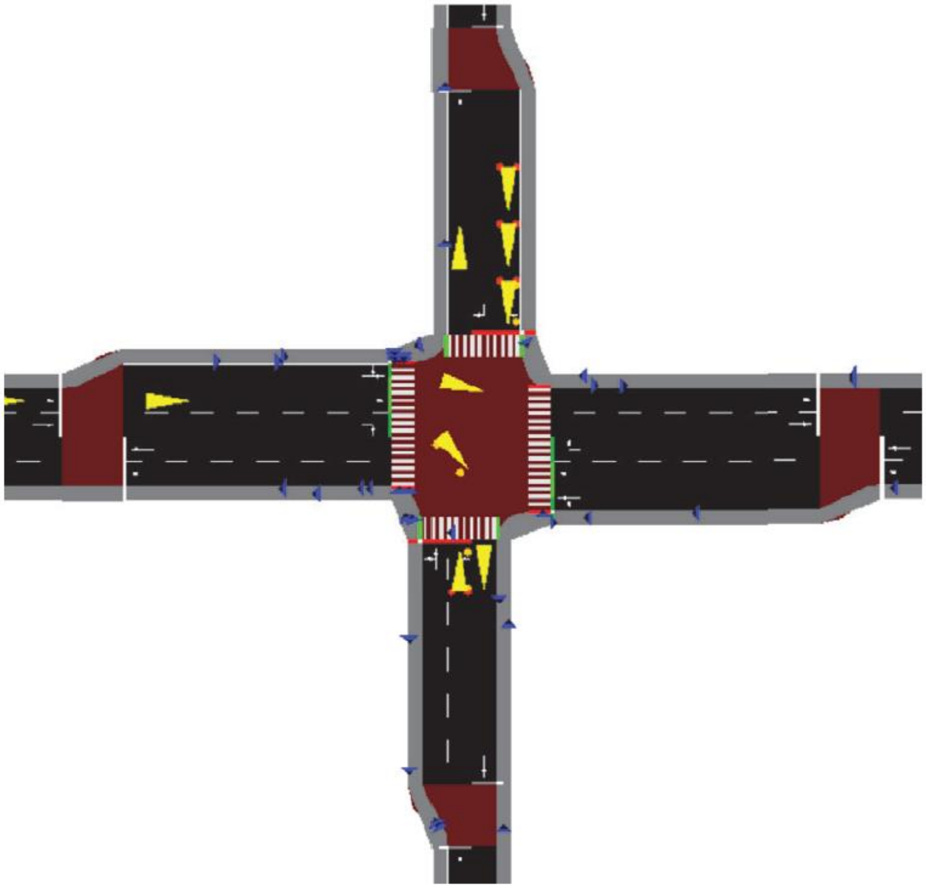

Figure 5. The experiment screen example

Table 1 outlines various settings for vehicles and pedestrians, including the "Size," indicating the length of vehicles and pedestrians in the simulation, and "Traffic priority," determining the order of passage at intersections. Pedestrians are granted priority in this experiment.

Table 1. Various settings for vehicles and pedestrians

Setting items	Vehicle	Pedestrian
Size	4.3 m	0.215 m
Maximum speed	180 km/h	5.4 km/h
Traffic priority	Low	High

Table 2. Vehicle inflow number settings

[step]	North-south direction [vehicles/h・lane]	East-west direction [vehicles/h・lane]
0 ~ 3600	180	540
~ 7200	540	180
~ 10800	180	540
~ 14400	540	180

Table 3. Pedestrian inflow number setting

[step]	North-south direction [person/h・lane]	East-west direction [person/h・lane]
0 ~ 3600	180	540
~ 7200	540	180
~ 10800	180	540
~ 14400	540	180

Tables 2 and 3 detail the settings for each step zone concerning the number of vehicles and pedestrians used in the experiment. The east-west and north-south ratios for both vehicles and pedestrians are altered every 3600 steps, simulating a more complex road environment. The weighting coefficient "W," signifying the degree of consideration for pedestrian information, is varied between 0.1, 0.3, and 0.5, with experiments conducted for each value. Finally, to assess the effectiveness of the proposed method, which does not account for pedestrians, serves as the comparative method in this experiment.

4.2 Analysis of Experimental Outcomes

Pedestrians and vehicles underwent testing using each control method. Table 4 provides insights into the cumulative counts of both waiting people and cars. The data reveal a consistent reduction in the cumulative count of waiting individuals when pedestrian information is considered at varying rates denoted by the constant "W," compared to control methods that overlook pedestrian information. Specifically, the control with W = 0.5, emphasizing pedestrian consideration the most, achieves a noteworthy 2.9% decrease in the count of waiting people compared to control without pedestrian consideration.

Table 4. Experimental results

Control method	Number of people waiting [people]	Number of waiting vehicles[vehicles]
Fixed period control	1387223	2940408
Ikidid et al. (2021) Control	1334365	1962861
W=0.1	1304768	2054131
W=0.3	1306859	2102415
W=0.5	1295494	2117677

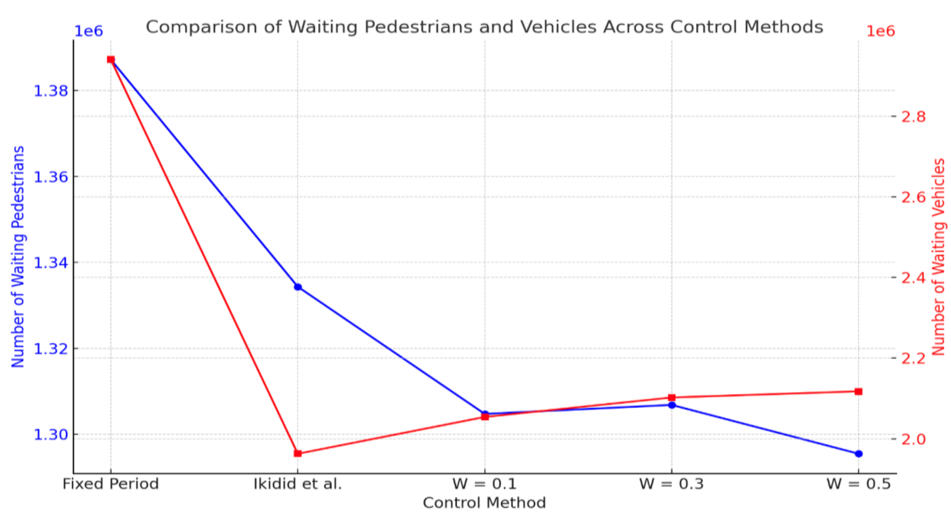

Figure 6. The Comparison of Waiting Pedestrians and Vehicles Across Control Methods

Conversely, in the control method incorporating pedestrian information, the cumulative count of waiting cars is smaller than that in periodic control but registers an increase compared to Ikidid et al. (2021)'s method which can be seen from Figure 6. Particularly, when the weighting coefficient, indicating the extent of pedestrian information consideration, is at its highest with W = 0.5, the count of waiting cars escalates by approximately 7.9% compared to the control without pedestrian consideration.

4.3 Deliberation on Results

The empirical evidence derived from the experimental investigations highlights a noteworthy outcome: the integration of pedestrian information into a split control method, utilizing a split model, effectively achieves a reduction in the overall count of waiting pedestrians across the network. This positive impact stems from the acknowledgment of pedestrian traffic flow and its influence on the calculated split ratios, thereby enhancing the efficiency of pedestrian passage at intersections.

However, in this pursuit of optimizing pedestrian movements, an unintended consequence emerges as a trade-off. The simultaneous reduction in waiting pedestrians is accompanied by an amplification in the cumulative count of waiting vehicles. This counterbalancing effect is rooted in the intricate interplay between pedestrian and vehicular dynamics within the traffic system.

The observed reduction in waiting pedestrians is, in part, attributed to the recalibration of split ratios influenced by pedestrian flow. The model dynamically adjusts the signal timings to accommodate the ebb and flow of pedestrians, creating a more pedestrian-friendly environment. This adaptability, however, introduces a disruptive force on the established balance of split ratios conducive to vehicular flow, leading to an increase in the count of waiting vehicles.

Essentially, the integration of pedestrian information introduces a dynamic element into the split control model, creating a tension between optimizing pedestrian and vehicular movements. While the model succeeds in streamlining pedestrian passage, the unintended consequence is a compromise on the efficiency of vehicular flow.

This dual impact underscores the complexity of balancing the needs of diverse road users within a unified traffic management strategy. As cities increasingly prioritize pedestrian-friendly urban spaces, understanding and mitigating the trade-offs between different modes of transportation become imperative. Future research and refinement of the proposed method should thus focus on finding an equilibrium that optimally caters to both pedestrians and vehicles, seeking a harmonious coexistence within the urban mobility landscape. This nuanced understanding will be pivotal in shaping more comprehensive and inclusive traffic signal control strategies for the cities of tomorrow.

4.3.1. In-depth Analysis of Increased Vehicle Waiting Times Trade-offs and Proposed Solutions

One of the key findings of this study is the reduction in pedestrian waiting times achieved by incorporating pedestrian information into the traffic signal split control method. However, this comes at the cost of increased vehicle waiting times, particularly when the weighting coefficient emphasizes pedestrian considerations (e.g., led to a 7.9% increase in vehicle waiting times compared to methods excluding pedestrians). To address this trade-off, future work can explore dynamic weighting strategies that adjust in real-time based on traffic density and priority requirements. For instance, during peak hours, could prioritize vehicles to alleviate congestion, while during off-peak times, a higher could prioritize pedestrians to improve safety and accessibility.

Additionally, adaptive signal timing algorithms could be introduced to dynamically allocate green times based on real-time vehicle and pedestrian counts. For example, using reinforcement learning or optimization-based approaches, intersections could balance waiting times dynamically rather than relying on static weight settings. Incorporating such solutions can minimize trade-offs and improve overall system efficiency.

5. CONCLUSIVE REMARKS

This study represents a significant leap forward in the evolution of the multi-agent dynamic traffic light control model initially introduced by Ikidid et al. (2021). Building upon this foundation, the research introduces a novel traffic light control method that seamlessly integrates pedestrian information into the decision-making process. The incorporation of pedestrian data in the control model is a crucial enhancement, as it expands the scope of the traffic signal system beyond the optimization of vehicular traffic flow, making it more holistic and applicable to real-world urban environments.

Experimental evaluations conducted as part of this study provide compelling evidence for the effectiveness of the proposed method, particularly in mitigating the number of waiting pedestrians. This outcome underscores the practicality and relevance of the traffic signal control model in addressing the needs of diverse road users, including pedestrians. By considering both vehicular and pedestrian dynamics, the model demonstrates its potential to enhance overall traffic efficiency and safety, fostering a more inclusive and adaptable urban transportation infrastructure.

Looking ahead, the research acknowledges the challenges inherent in simulating real-world spaces, such as the constraints imposed by limited sensor installations and fixed time intervals for information acquisition. These challenges present opportunities for future research endeavors, with a particular focus on refining the model's applicability in complex, dynamic urban environments. The research team anticipates delving into these issues as part of a planned demonstration experiment, which will serve as a crucial testing ground for further improvements and refinements to the proposed method.

As a part of future work, the research aims to address the intricacies of simulating real-world conditions more accurately. This includes exploring advanced sensor technologies, adaptive data acquisition strategies, and dynamic modeling techniques that can better capture the nuances of urban spaces. The planned demonstration experiment will play a pivotal role in validating the practicality and robustness of the proposed method, serving as a stepping stone towards its potential implementation in real-world traffic management systems.

The practical implementation of the proposed method involves several challenges. Effective sensor placement is crucial for accurately detecting vehicle and pedestrian flows. Overhead sensors, such as cameras or LiDAR systems, can provide comprehensive coverage of intersections, capturing both vehicular and pedestrian movements. Embedded sensors, like inductive loops and pressure plates, can complement these by offering reliable data on vehicle presence.

Another challenge is ensuring that the system dynamically updates traffic signal parameters in response to real-time data. IoT-enabled devices can play a pivotal role by continuously transmitting data to a centralized control system or local intersection agents. However, issues like data latency, environmental interference, and sensor maintenance must be addressed to ensure robust operation. Strategies like redundant sensor deployments and real-time calibration algorithms can mitigate these challenges.

Lastly, implementation in urban environments requires attention to energy efficiency and cost. Solar-powered sensors and energy-efficient data transmission protocols can be explored to make the system more sustainable and economically viable.

In summary, this study not only enhances the existing multi-agent dynamic traffic light control model but also pioneers a more inclusive approach by integrating pedestrian information. The research sets the stage for future advancements, recognizing the imperatives of addressing real-world challenges and refining the proposed method for practical implementation in the ever-evolving landscape of urban mobility.

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