Optimizing Traffic Signal Control to Enhance Transportation Efficiency and Maximize Pedestrian Benefits in the Road Network

Vijayalakshmi K Kumarasamy[a], Abhilasha Jairam Saroj[b], Joseph Duhamel[a], Yu Liang[a], Dalei Wu[a]
Michael P. Hunter[c], Mina Sartipi[a]
[a] Department of Computer Science and Engineering, University of Tennessee at Chattanooga, USA
[b] Buildings and Transportation Sciences Division, Oak Ridge National Laboratory, USA
[c] School of Civil and Environmental Engineering, Georgia Institute of Technology, USA
Email: {lry466, duhamel}@mocs.utc.edu; sarojaj@ornl.gov; {yu-liang, dalei-wu}@utc.edu;
michael.hunter@ce.gatech.edu; mina-sartipi@utc.edu

***Abstract*— Increasing urban mobility requirements demand efficient transportation system strategies for both vehicular and pedestrian movement. This study enhances the Decentralized Graph-based Multi-Agent Reinforcement Learning (DGMARL) approach, originally tailored for vehicular traffic signal timing, to incorporate pedestrian traffic dynamics. The improved algorithm considers crucial metrics such as Eco_PI, assesses vehicle fuel consumption by factoring in stops and delays, and addresses pedestrian waiting time, crucial for system efficiency while acknowledging driver waiting time impact. Utilizing Digital Twin simulation along the MLK Smart Corridor in Chattanooga, Tennessee, the algorithm's performance is compared for various pedestrian control scenarios. The results compare two signal timing optimization strategy scenarios, 1) dynamic pedestrian signal management with automated pedestrian traffic detection developed using DGMARL algorithm, and 2) a real-world-based baseline actuated signal timing plan with pedestrian recall that enforces a pedestrian phase automatically every cycle. Findings indicate substantial improvements in scenario 1 with DGMARL: a 28.29% enhancement in vehicle Eco_PI, a 60.55% reduction in pedestrian waiting time, and a 55.74% decrease in driver stop delay, on average, compared to observations in scenario 2.**

***Index Terms*—** Intelligent Transportation Systems, Pedestrian Waiting Time, Traffic Signal Optimization, Fuel Consumption, Graph Neural Network, Multi-agent A2C Reinforcement Learning, Digital Twin.

I. Introduction and Background

Urban areas grapple with traffic congestion, leading to prolonged travel times, increased fuel consumption, and environmental pollution [1]. Although existing studies, such as [2], have explored traffic control, they predominantly focus on vehicular traffic dynamics. Adapting signal control strategies to evolving traffic patterns remains a persistent challenge, despite potential solutions proposed in studies like [3] and [4], which are often limited by computational efficiency.

This manuscript has been partly authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The publisher acknowledges the US government license to provide public access under the DOE Public Access Plan (https://energy.gov/downloads/doe-public-access-plan).

To overcome these challenges, this study introduces a novel approach that integrates dynamic pedestrian signal management with automated pedestrian traffic detection alongside vehicle traffic signal timing optimization. Leveraging a decentralized graph-based multi-agent reinforcement learning algorithm (DGMARL) [5], [6] which optimizes vehicle traffic signal timing and dynamic phase selection in real-time, aiming to reduce not only vehicles' Eco_PI which captures vehicle stops on fuel consumption and delay impact [7], [8], but also pedestrian waiting time and driver delays by considering both vehicular and pedestrian traffic. Key features include efficient pedestrian arrival distribution and observation, multi-agent reinforcement learning, and seamless interaction with the Digital Twin.

Despite efforts at vehicular traffic optimization, adapting signal control to dynamic traffic patterns remains challenging. Studies such as [9] and [10] often overlook environmental impacts in signal timing optimization. Advancements in Intelligent Transportation Systems (ITS) have been used to develop decentralized signal control algorithms [11], that integrate vehicle and pedestrian data, and there is progress in RL-based optimization [12]. However, reaching the global optimal solution considering multiple factors and constraints across the entire network remains challenging. This study bridges this gap by globally optimizing both vehicle and pedestrian traffic signal timing through the DGMARL algorithm by integrating automated pedestrian detection and a dynamic signal timing plan. Furthermore, a comprehensive analysis of pedestrian signal time allocation strategies, considering dynamic signal timing and fixed pedestrian recall, is conducted.

II. Overview of the Proposed System

This study presents a comprehensive approach to optimizing signal timing for both vehicles and pedestrians by integrating pedestrian and vehicular traffic demand. Building upon our previous work [5], [6], the Reinforcement Learning (RL) methodology is enhanced to incorporate pedestrian traffic state alongside vehicular traffic state, enabling global optimization of vehicle and pedestrian traffic signal timing in a decentralized distributed environment. This extended

DGMARL algorithm considers parameters such as vehicular and pedestrian traffic demand to reduce pedestrian and driver waiting times.

The DGMARL model from previous work optimizes signal timing by considering vehicular traffic and enforcing mandatory constraints such as minimum green serving time with walk plus flashing "don't walk" time regardless of pedestrian traffic demand, and yellow and red clearance time. This study extends the DGMARL model to incorporate automated pedestrian traffic detection and a dynamic pedestrian signal phase. The proposed DGMARL-based signal timing plan optimizes both pedestrian and vehicular traffic signal timing according to their respective demands. To assess the benefits of the extended DGMARL algorithm, a comprehensive comparison is conducted between DGMARL-based signal timing and traditional actuated signal timing with pedestrian recall. Performance evaluation includes vehicles' Eco_PI, pedestrian waiting time, and drivers' waiting time across the scenarios: 1) Baseline model using real-time signal timing configuration, including pedestrian recall. 2) Automated pedestrian traffic detection and activating pedestrian and vehicle signal phases based on the traffic demand. 3) Dynamically adjust the pedestrian signal phase timing based on pedestrian traffic demand. 4) The effectiveness of automated pedestrian traffic detection and dynamic pedestrian signal timing, along with push buttons is evaluated. To analyze the system, theoretical modeling

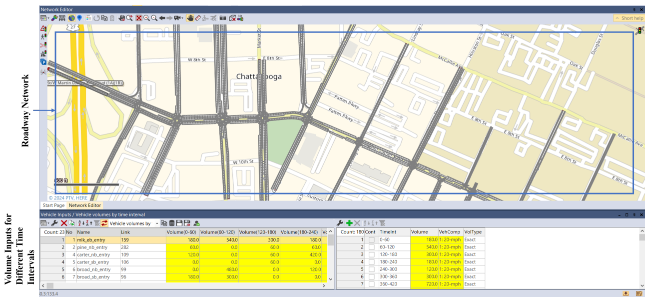

Fig. 1. MLK Smart Corridor network layout in PTV-Vissim [5], [6]

is combined with empirical data using an offline Digital Twin (DT) simulation model developed with PTV Vissim [13]. This model represents the 2-mile MLK Smart Corridor in Chattanooga, Tennessee, with 11 signalized intersections and bidirectional traffic flows. The developed DT model is driven using real-time traffic volume, turn count, and Signal Phasing and Timing (SPaT) data. While an online version of the DT emulates field signal indications using SPaT data, the offline version (utilized in this study) employs traffic signal timing plans provided by the City of Chattanooga. Data from cameras and zone-detection devices deployed along the corridor informs the model. The DT facilitates the simulation and analysis of various scenarios, offering insight into the optimization process and its impacts on vehicular and pedestrian traffic. Figure 1 illustrates the developed DT model, depicting the MLK Corridor traffic network's realistic intersection geometry.

III. Architecture of the Proposed System

In the original DGMARL framework [5], [6], Advantage Actor-Critic (A2C) reinforcement learning agents are deployed at individual intersections. The framework has been extended to incorporate pedestrian traffic state, pedestrian and driver waiting time, along with other crucial traffic state features, such as vehicle presence time in the detector. Agents exchange this information with neighboring agents to collaboratively gather data and determine optimal policies for controlling traffic signals. DGMARL can handle heterogeneous data from various sources, ensuring comprehensive awareness of traffic dynamics. This study utilizes DGMARL to optimize both vehicular and pedestrian signal timing, improving the performance and sustainability of the traffic system. Figure 2 shows the architecture of the proposed

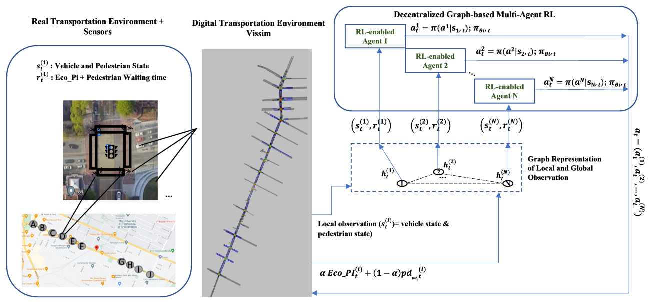

Fig. 2. Architecture of the proposed model

model. The traffic environment is represented as a bi-directional graph $G(\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ consists of intersections modeled as A2C RL agents, and $\mathcal{E}$ comprises roads or links connecting these intersections. Each link $e_{i,j} \in \mathcal{E}$ connects the intersections i and j. The intersections have various static features, including approach links, signal controllers, signal phases, detectors, lane numbers, uncontrolled approaching links, and neighboring intersections $\mathcal{N}_i \subset \mathcal{V}$. Signal controllers at each intersection are linked to a set of signal phases ϕ_i, each associated with specific static features, such as signal lists, minimum mandatory green serving time, yellow time, red clearance time, pedestrian walk, and flashing "don't walk" time [5], [6].

The methodology in this study leverages real-time data on vehicle traffic state, along with a random distribution of pedestrian volume, to calculate pedestrian waiting times at signalized intersections. These data are utilized to construct a bi-directional graph environment for the RL agent's interactions [5], [6]. Within this environment, the RL agent explores diverse signal timing and pedestrian recall configurations, closely observing their effects on both vehicle flow and pedestrian movement. Through continuous learning from these interactions, the RL agent enhances its decision-making abilities, progressively converging towards an optimized signal timing for both vehicular and pedestrian traffic that minimizes vehicles' Eco_PI performance and reduces pedestrian and driver waiting times. Eco_PI is the fuel consumption impact related to vehicle stops and stop delays. The reward function is designed to incentivize the RL agent to prioritize efficient vehicle flow, reducing Eco_PI and driver waiting time while minimizing pedestrian waiting time. The agent aims to maximize cumulative rewards by identifying signal timing configurations that balance vehicle and pedestrian needs. Multiple simulations, covering various traffic scenarios, are conducted in offline DT using real-world data. RL agents are trained on these models to optimize signal timings compared to fixed signal timing strategies.

IV. The Proposed RL-based Method

The traffic signal control problem is formulated as a Markov Decision Process (MDP), denoted as $(\mathcal{S}, \mathcal{A}, p, r)$, where $\mathcal{S}$ represents the state space, $\mathcal{A}$ denotes the action space, and r signifies the reward associated with an action. The goal is to find the optimal policy p, maximizing cumulative discounted rewards. To enhance learning efficiency and informed decision-making, neighboring agents exchange observations through message passing, allowing for broader insights into traffic conditions and more effective action selections, thereby improving signal timing optimization.

A. State Space

As an extension of our preliminary work [5], [6], the state of the global traffic network at time t is redefined and upgraded as follows:

$$S_t = \{s_{i,t}\}_{i=1}^{|\mathcal{V}|} = \langle \Upsilon_{i,t}^{TF}, \Psi_{i,t}^{TS} \rangle \tag{1}$$

where $\{s_{i,t}\}$ is the state of the intersection i at time t which is the heterogeneous observation of traffic states from all approaches, and $\mathcal{V}$ is the set of intersections in the road network,

$$\Upsilon_{i,t}^{TF} = \langle \ \langle \delta_{l,i,t}^{VT}, \delta_{l,i,t}^{PV} \rangle_{l=1}^{K_{\phi,i}} \rangle_{\phi=1}^{F_i} \tag{2}$$

and

$$\Psi_{i,t}^{TS} = \langle \phi_{i,t}^{S}, \ \phi_{i,t}^{D}, \ \phi_{i,t}^{PS}, \ \phi_{i,t}^{MinG}, \ \phi_{i,t}^{MaxG} \rangle. \tag{3}$$

In Equation (2), F_i represents the number of phases at intersection i, and $K_{\phi,i}$ denotes the number of approaching links at phase ϕ_i. Each observation for an approaching link l in phase ϕ_i includes vehicle traffic state $\delta_{l,i,t}^{VT}$ which includes vehicle presence time in the detector zone, average waiting time, average delay, average speed, and pedestrian volume $\delta_{l,i,t}^{PV}$.

In Equation (3), variables like $\phi_{i,t}^{S}$, $\phi_{i,t}^{D}$, and $\phi_{i,t}^{PS}$ denote the current phase status, duration, and pedestrian serving status. $\phi_{i,t}^{MinG}$ indicates fulfillment of minimum green time or pedestrian serving in the current phase, while $\phi_{i,t}^{MaxG}$ signals if the current phase duration has reached the maximum green serving time. Pedestrian recall activation prompts monitoring of the maximum green serving time, allowing vehicles priority until this limit is reached, after which pedestrians are served based on traffic conditions.

B. Action Space

The action of an agent at intersection $a_{i,t}$ is defined as either 0 or 1. When $a_{i,t} = 0$, the current signal phase is maintained. When $a_{i,t} = 1$, it indicates a transition to the next phase, governed by minimum green time to ensure safety and efficiency. The revised action formulation is:

$$a'_{i,t} = \begin{cases} a_{i,t}, & \text{if } (\phi_{i,t}^{MinG} \parallel \phi_{i,t}^{MinPW}) \\ 1, & \text{if } (\phi_{i,t}^{MaxG} \ \& \ \phi_{i,t}^{PR}) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Where $\phi_{i,t}^{MinG}$ indicates the minimum green time has been served. If the current phase is non-pedestrian and pedestrian recall $\phi_{i,t}^{PR}$ is enabled, the minimum green time serves as the pedestrian serving time $\phi_{i,t}^{MinPW}$. If $a_{i,t} = 1$, the action is evaluated against the minimum green time constraint based on the phase duration $\phi_{i,t}^{D}$. If the constraint is met, the final action is $a'_{i,t} = 1$, and the agent selects the phase with the highest traffic demand based on both pedestrians waiting time and vehicles' presence time. Before switching the next phase to green, the yellow and red clearance timings are served. If $a_{i,t} = 0$, the agent refrains from action. In pedestrian crossing phases, the agent forces the final action to be $a'_{i,t} = 1$ and switches to the non-pedestrian phase as $\phi_{i,t}^{MaxG}$ approaches, ensuring pedestrian safety. Pedestrian serving time ϕ_{i}^{EPW} is estimated based on pedestrian traffic demand,

$$\phi_{i,t}^{MinPW} = \phi_{i}^{MinSW} + \phi_{i}^{MinFDW} + \phi_{i}^{EPW} \tag{5}$$

where ϕ_{i}^{MinSW} is minimum solid walk time, ϕ_{i}^{MinFDW} is flashing don't walk time, and ϕ_{i}^{EPW} is,

$$\phi_{i}^{EPW} = \phi_{i}^{MinFDW} * N_{i,t,ped} \tag{6}$$

where $N_{i,t,ped}$ is the number of pedestrians waiting. This dynamic approach prioritizes both vehicular and pedestrian traffic, reducing waiting times and enhancing signal timing efficiency.

C. Reward Function

The reward function balances vehicular and pedestrian traffic needs using the vehicle Eco_PI metric to assess performance, considering stops and delays based on the fuel consumption model in [7], [8]. Stops are counted when vehicles halt while approaching the intersection, and stop delay is the time vehicles spend stationary in the queue. Additionally, the reward function includes pedestrian and driver waiting times. Pedestrian waiting time is the sum of the differences between each pedestrian's arrival time and their waiting time to cross, while driver delays mirror vehicle delays.

The immediate reward $r_{i,t}$ for each traffic movement at intersection i is computed using the following equations:

$$r_{i,t} = - \left[\frac{\alpha * \delta_{i,t}^{Eco\_PI} + \beta * \delta_{i,t}^{DD} + (1 - \alpha - \beta) * \delta_{i,t}^{PWT}}{\delta_{i,t}^{Eco\_PI} + \delta_{i,t}^{DD} + \delta_{i,t}^{PWT}} \right] \tag{7}$$

where $(\alpha, \beta) \in [0, 1]$ weights the significance of vehicle waiting, driver waiting, and pedestrian waiting timings, which ensures a balanced focus on both vehicular and pedestrian movements by normalizing the reward components. And $\delta_{i,t}^{Eco\_PI}$ is vehicles Eco_PI, $\delta_{i,t}^{DD}$ is vehicle driver delay, which is the vehicle stop delay $\delta_{i,t}^{SD}$, and $\delta_{i,t}^{PWT}$ is pedestrian waiting time. This study uses $\alpha = 0.4, \beta = 0.3$ to prioritize reducing vehicle delays while accounting for pedestrian waiting times. The reward function normalizes the contributions of pedestrian, driver, and vehicle waiting times proportionally. In addition, vehicle Eco_PI is calculated as

$$\delta_{i,t}^{Eco\_PI} = \sum_{l=1}^{L_i} \delta_{i,l,t}^{SD} + (\delta_{i,l,t}^{SK} * \delta_{i,l,t}^{NS}) \tag{8}$$

where $\delta_{i,l,t}^{SD}$ is the stop delays that occurred in link l_i, $\delta_{i,l,t}^{NS}$ is the number of stops, and $\delta_{i,l,t}^{SK}$ is the stop penalty penalized for every stop [14], [15]. The pedestrian waiting time is calculated as,

$$\delta_{i,t}^{PWT} = \sum_{l=1}^{L_i} [\sum_{n=1}^{N_{i,l,ped}} (t_{i,l} - tped_{i,l,n})], \tag{9}$$

where $N_{i,l,ped}$ is the number of pedestrians waiting, $t_{i,l}$ is the time that pedestrians are allowed to cross the street, and $tped_{i,l,n}$ is the n-th pedestrian's arrival time. The optimization of each agent's policy, represented by i, intends to maximize the global long-term return $E[R_0^\pi]$, where $R_{i,t}^\pi = \sum \tau^T \gamma^{\tau - t} r_{i,t}$ denotes the return at time t, with γ being the discount factor. By incorporating pedestrian and driver waiting time into the reward function, the study seeks to achieve a more comprehensive and balanced optimization approach that considers both vehicular and pedestrian performance in signal timing decisions.

D. The Proposed RL Algorithm

The algorithm 1 outlines signal timing optimization with vehicles and pedestrian states, using reinforcement learning for an optimal policy. It dynamically adapts signal timing based on real-time vehicular and distributed pedestrian traffic to enhance traffic flow efficiency and pedestrian safety.

In this environment, each intersection hosts an A2C reinforcement learning agent, denoted as i. At each time step t, agent i observes vehicular state features, including vehicle presence time in the detector, current signal state through offline DT data collection, and pedestrian arrivals through random distribution. It collaborates with neighboring agents $\mathcal{N}_i$ via message passing to exchange and receive their states. Agent i processes its updated state $s'_{i,t}$ using actor and critic neural networks to derive the optimal policy π_i and control the signal phase ϕ_i. Agent i validates actions against physical constraints. If the phase is non-pedestrian-crosswalk, the minimum serving time is set as the estimated pedestrian walk time ϕ_i^{EPW}; otherwise, it uses the phase's configured minimum green time. No actions are applied back to the offline DT if the agent stays in the current green phase. Otherwise, agent i selects a phase ϕ_j with higher upcoming traffic demand and applies the signal phase change action to the signal controller in offline DT. After applying the action, agent i observes pedestrians' waiting time $pd_{i,wt}$ and vehicles' Eco_PI, estimating the current reward r_i based on the new traffic state $s_{i,t+1}$. The current reward and new state are stored in the experience replay buffer. The agent learns from this buffer to minimize critic loss $L(\omega_i)$ and actor loss $\hat{J}(\theta)$ (lines 9-10). Agent i repeats these processes to identify an optimal policy, improving vehicular traffic Eco_PI and pedestrian waiting time. This iterative learning allows for dynamic signal timing adaptation, optimizing traffic flow efficiency, and enhancing pedestrian safety during crossings.

Algorithm 1 Signal timing optimization with vehicles and pedestrian state using A2C reinforcement learning

Ensure: Initialize graph $G(\mathcal{V}, \mathcal{E})$, agent $i \in \mathcal{V}$, link $l_i \in \mathcal{E}$, physical constraints i_c.

Ensure: Initial signal timing for the intersection i, minimum green time $\phi_{i,t}^{MinG}$, yellow time $\phi_{i,t}^{y}$, red clearance time $\phi_{i,t}^{r}$, maximum green time $\phi_{i,t}^{MaxG}$, pedestrian minimum solid walk time ϕ_i^{MinSW}, and flashing don't walk time ϕ_i^{MinFDW}.

1: For each episode with T simulation period, each agent learns and optimizes the model parameter through multi-threading with the following steps iterative.
2: Measure the pedestrian volume at intersection i and include it in the state $s_{i,t}$ along with the vehicular traffic state.
3: Observe and perform message passing.
4: Obtain policy, action and value.
5: Evaluate action with constraints $a'_{i,t} = (a_{i,t}|i_c)$.
6: Take action $a'_{i,t}$ in offline DT if constraint evaluation is success.
7: Calculate reward $r_{i,t}$ and observe new state $s'_{i,t+1}$.
8: Store State and Reward in Replay buffer D.
9: Learn from experience if $t >=$ sample batch_size.

In a distributed agent environment, each agent makes context-specific decisions based on local observations and information from neighboring agents. The convergence of an optimal policy can vary among agents, leading to increased learning efficiency. The distributed nature of the agents improves overall learning performance, contributing to finding improved signal timing strategies tailored to their specific traffic conditions.

V. Experimental Evaluation

This study evaluates different traffic signal timing strategies using real-time vehicular and randomly distributed pedestrian traffic data, comparing them to an actuated signal timing plan with pedestrian recall. Scenarios include real-time signal timing with pedestrian recall, automated pedestrian traffic detection, dynamic adjustment of pedestrian signal phase timing based on demand, and assessment of automated pedestrian traffic detection with dynamic signal timing alongside push buttons. Additionally, monetary analyses of fuel expenses and salary losses due to waiting times are conducted.

A. Experiment Design

This study utilizes real-world data from the PM-peak hour scenario of December 15, 2022, obtained from the MLK Smart Corridor [16], [17]. The dataset encompasses transportation and vehicular traffic data, along with randomly distributed pedestrian data recorded every second. The proposed model is trained with training comprising 15 episodes for different scenarios, each episode consists of 3600-second simulation steps and learning from 240 batch sizes of experience replay. The model assigns coefficient values to reward components: 0.4 for vehicle Eco_PI, 0.3 for drivers' waiting time, and 0.3 for pedestrian waiting time, with plans for dynamic adjustment during future training. Comparisons are made between the performance of DGMARL with both pedestrian and vehicular traffic signal timing plans and the baseline MLK Smart Corridor vehicle-actuated signal timing plan. Additionally, push-button requests are randomly generated with probabilities ranging from 0.25 to 0.75 to analyze automated pedestrian traffic detection. By precisely considering pedestrian arrivals, waiting times, and push-button requests, DGMARL-based signal control systems prioritize safer pedestrian crossings and improve vehicular traffic flow. This holistic optimization approach enhances traffic flow and promotes a safer road environment for all users.

The experimental setup utilized a real-world dataset collected by the Department of Computer Science and Engineering at the University of Tennessee, Chattanooga, USA [16]. It includes data from a corridor connecting 11 intersections on the MLK Smart Corridor with bidirectional traffic in multiple directions (East-West, West-East, North-South, and South-North). The dataset includes intersection geometry, traffic signal timing plans, camera and zone-detecting device parameters, Signal Phase and Timing (SPaT) messages, vehicle flow, speed, and vehicle presence time in the detector. Each intersection features a diverse phase setup with different signal light configurations. The simulation model for the 11 intersections on the MLK Smart Corridor in offline DT follows network creation guidelines [18], [19]. It incorporates vehicular data from archived one-minute volume counts at network entry edges for December 15, 2022, 10-minute turn percentages at each intersection approach, and signal timing plans from the city. Pedestrian data is randomly generated based on the assumption of a 1% pedestrian volume probability during the simulation at every second for each intersection's signal phase with pedestrian phase crossing enabled.

B. Results and Discussion

In this experiment, the PM-peak hour model with a one-hour simulation is used to perform the test runs. A total of 458 pedestrians and 2825 vehicles were active on the road, as shown in Table I, which presents the state of traffic and the average serving times for pedestrians in both the actuated and DGMARL scenarios. The observations reveal that DGMARL with dynamic pedestrian signal timing efficiently adjusts pedestrian serving times while adhering to minimum serving time constraints. Figure 3 displays

TABLE I
OVERALL TRAFFIC AND SERVING STATE

Performance Measurement	Value
Total no. of pedestrians arrived	458
Total no. of vehicles traveled	2825
Actuated: Avg. of peds. serving time	22.51s
DGMARL PedRecal: Avg. of peds. serving time	22.51s
DGMARL Automated: Avg. of peds serving time	21.84s

variations in vehicle Eco_PI, stops, delay, and pedestrian waiting time across different scenarios: actuated signal timing with pedestrian recall, automated detection with pedestrian recall, automated detection with dynamic estimated pedestrian signal timing, and automated detection with push-button timing. Results show that DGMARL combined with automated detection and dynamic timing, including push-button activation, improves vehicle Eco_PI by 27.14%, reduces delay by 58.72%, and decreases pedestrian waiting time by 60.62% on average compared to both actuated signal timing with pedestrian recall and DGMARL signal timing with pedestrian recall. In DGMARL with pedestrian recall scenarios, vehicle stops increase by 4.67% on average, compared to only 0.97% with automated detection and dynamic timing. Figure 4 shows that the DGMARL model, with automated pedestrian traffic detection and dynamic signal timing, adjusts pedestrian serving based on demand. This reduces pedestrian waiting time by 60.55% compared to actuated signal timing with pedestrian recall and by 49.46% compared to DGMARL with pedestrian recall. Additionally, Figure 5 demonstrates that DGMARL, with automated pedestrian traffic detection and dynamic signal timing, reduces Eco_PI by 28.29% and driver waiting time by 55.74% compared to actuated signal timing with pedestrian recall. It also reduces Eco_PI by 9.08% and driver waiting time by 21.64% compared to DGMARL with pedestrian recall.

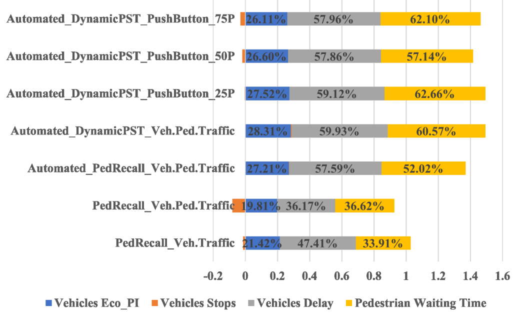

Fig. 3. Automated pedestrian traffic detection with dynamic pedestrian signal timing performance improvements compared to pedestrian recall. PST - Pedestrian Serving Signal Time.

Lastly, a monetary analysis, referencing 2022 Chattanooga salary data from [20], is conducted to assess pedestrian and driver waiting times' impact on productivity. With actuated signal timing, the average salary loss was 1.29%, decreasing to 0.97% with DGMARL optimizing both vehicular and

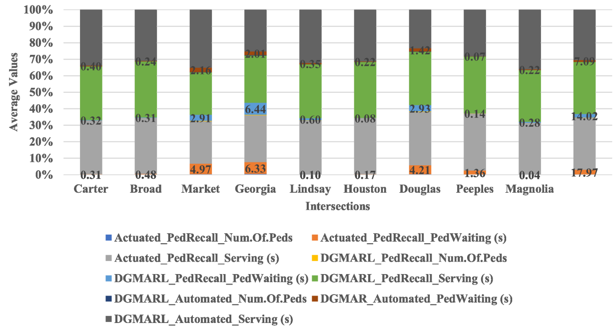

Fig. 4. Pedestrian traffic, waiting time, and serving time comparison.

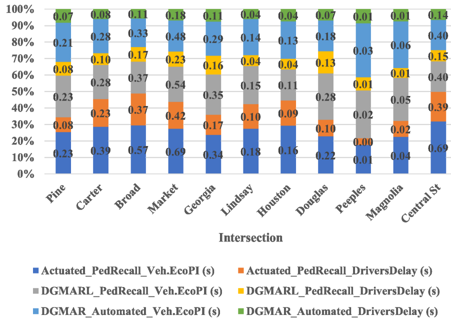

Fig. 5. Vehicles Eco_PI and drivers waiting time comparison.

pedestrian traffic signal timing. Furthermore, referencing 2022 gas costs in Chattanooga, Tennessee, from [21], DGMARL signal timing reduced gas expenses by 24.51% compared to actuated signal timing.

VI. Conclusion

In conclusion, this study explored automated pedestrian traffic detection coupled with dynamic pedestrian serving time, optimizing both pedestrian and vehicular traffic signal timings using Decentralized Graph-based Multi-Agent Reinforcement Learning. The model significantly improved traffic flow efficiency, reduced fuel consumption, enhanced pedestrian safety, and minimized waiting times. The study demonstrates that decentralized multi-agent models enable effective traffic flow improvements by allowing agents to adapt to changing traffic conditions. Future research will involve testing the model with real-world pedestrian data.

Acknowledgment

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy under the Award Number DE-EE0009208. This manuscript has been partly authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy (DOE). The publisher acknowledges the US government license to provide public access under the DOE Public Access Plan (https://energy.gov/downloads/doe-public-access-plan).

References

[1] S. INRIX, "Inrix 2022 global traffic score card," 2022.
[2] J. Babatunde, O. A. Osman, A. Stevanovic, and N. Dobrota, "Fuel-based nash bargaining approach for adaptive signal control in an n-player cooperative game," *Transportation Research Record*, p. 03611981231161623, 2023.
[3] X. Zhang and G.-l. Chang, "Optimal control strategies with an extended cell transmission model for massive vehicular-pedestrian mixed flows in the evacuation zone," *Journal of advanced transportation*, vol. 48, no. 8, pp. 1030–1050, 2014.
[4] C. Yu, W. Ma, K. Han, and X. Yang, "Optimization of vehicle and pedestrian signals at isolated intersections," *Transportation Research Part B: Methodological*, vol. 98, pp. 135–153, 2017.
[5] V. K. Kumarasamy, A. J. Saroj, Y. Liang, D. Wu, M. P. Hunter, A. Guin, and M. Sartipi, "Integration of decentralized graph-based multi-agent reinforcement learning with digital twin for traffic signal optimization," *Symmetry*, vol. 16, no. 4, p. 448, 2024.
[6] ——, "Traffic signal optimization by integrating reinforcement learning and digital twins," in *2023 IEEE Smart World Congress (SWC)*, 2023, pp. 1–8.
[7] A. Stevanovic, S. A. Shayeb, and S. S. Patra, "Fuel consumption intersection control performance index," *Transportation research record*, vol. 2675, no. 9, pp. 690–702, 2021.
[8] S. A. et al., "Investigating impacts of various operational conditions on fuel consumption and stop penalty at signalized intersections. international journal of transportation science and technology," 2022.
[9] X. Liang, S. I. Guler, and V. V. Gayah, "Traffic signal control optimization in a connected vehicle environment considering pedestrians," *Transportation Research Record*, vol. 2674, no. 10, pp. 499–511, 2020.
[10] A. M. Roshandeh, H. S. Levinson, Z. Li, H. Patel, and B. Zhou, "New methodology for intersection signal timing optimization to simultaneously minimize vehicle and pedestrian delays," *Journal of Transportation Engineering*, vol. 140, no. 5, p. 04014009, 2014.
[11] X. Liang, S. I. Guler, and V. V. Gayah, "Decentralized arterial traffic signal optimization with connected vehicle information," *Journal of Intelligent Transportation Systems*, vol. 27, no. 2, pp. 145–160, 2023.
[12] Z. Li, H. Yu, G. Zhang, S. Dong, and C.-Z. Xu, "Network-wide traffic signal control optimization using a multi-agent deep reinforcement learning," *Transportation Research Part C: Emerging Technologies*, vol. 125, p. 103059, 2021.
[13] P. Group, "Ptv vissim," 2022. [Online]. Available: "https://www.ptvgroup.com/en/solutionsproducts/ptv-vissim/"
[14] A. Stevanovic and N. Dobrota, "Impact of various operating conditions on simulated emissions-based stop penalty at signalized intersections," 2021.
[15] S. Alshayeb, A. Stevanovic, and B. B. Park, "Field-based prediction models for stop penalty in traffic signal timing optimization. energies," 2021.
[16] A. Harris, J. Stovall, and M. Sartipi, "Mlk smart corridor: An urban testbed for smart city applications," in *IEEE International Conference on Big Data*, 2019, pp. 3506–3511.
[17] T. V. Tran, S. Khaleghian, J. Zhao, and M. Sartipi, "Simcal: A high-performance toolkit for calibrating traffic simulation," in *2022 IEEE International Conference on Big Data (Big Data)*, 2022, pp. 2895–2902.
[18] GDOT, "Vissim simulation guidance," 2021-06-01, FHWA-GA-21-1833, 18-33. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/60642
[19] A. J. Saroj, S. Roy, A. Guin, and M. Hunter, "Development of a connected corridor real-time data-driven traffic digital twin simulation model," *Journal of Transportation Engineering, Part A: Systems*, vol. 147, no. 12, p. 04021096, 2021.
[20] S. I. Office, "Occupational employment and wages in chattanooga," U.S. BUREAU OF LABOR STATISTICS, Tech. Rep., 2022. [Online]. Available: https://www.bls.gov/regions/southeast/news-release/occupationalemploymentandwages_chattanooga.htm
[21] EIA, "Weekly u.s. regular all formulations retail gasoline prices," U.S. Energy Information Administration, Tech. Rep., 2022. [Online]. Available: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPMR_PTE_NUS_DPG&f=W