# AI Based Dynamic Lane Management

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***Abstract*—This paper presents a comprehensive review of strategies employed in AI-based dynamic lane management systems, focusing on Dynamic Lane Reversal (DLR) and Dynamic Lane Assignment (DLA). By synthesizing findings from various scholarly sources, we aim to elucidate the effectiveness and drawbacks of these strategies in optimizing traffic flow and enhancing roadway safety.We begin by contextualizing the importance of dynamic lane management in addressing the challenges of urban congestion and improving transportation efficiency. Subsequently, we delve into the diverse methodologies and algorithms utilized in existing research, ranging from rule-based systems to machine learning and deep learning approaches.Through a systematic analysis of empirical studies and theoretical frameworks, we highlight the key findings regarding the performance and applicability of dynamic lane reversal and usage control techniques. Furthermore, we discuss the implications of these strategies on traffic throughput, travel time, environmental impact, and user experience.Our review identifies notable trends, advancements, and limitations in the field, providing valuable insights for policymakers, urban planners, and transportation engineers. We conclude by outlining potential avenues for future research and development, emphasizing the need for interdisciplinary collaboration and real-world validation of AI-based dynamic lane management solutions.**

***Index Terms*—AI, dynamic lane management, lane reversal, lane usage control, traffic optimization, transportation efficiency.**

## I. Introduction

Urban traffic congestion is a pervasive issue plaguing cities worldwide, leading to myriad negative consequences such as increased fuel consumption, extended waiting times, heightened pollution levels, and impeded movement of emergency vehicles [1]. In response to this pressing challenge, the integration of artificial intelligence into dynamic lane management systems has emerged as a promising solution to mitigate various traffic conditions effectively.

Dynamic lane management systems, enhanced by IoT integration and real-time traffic flow analysis, offer an innovative approach to continuously optimize urban traffic flow [1]. By leveraging IoT sensors and sophisticated algorithms, these systems can dynamically adjust lane configurations and traffic signal timings, thereby enhancing vehicle security and minimizing citywide congestion. Additionally, advancements in AI-driven autonomous vehicles have paved the way for automated lane-shifting mechanisms, enabling safer and more efficient traffic management [3].

Traditional traffic control strategies often rely on fixed lane grouping approaches, which may prove ineffective in accommodating fluctuating traffic demands [3]. In contrast, dynamic lane grouping strategies, a hallmark of Intelligent Transportation Systems (ITS), dynamically allocate lanes based on real-time movement demand, thus offering a more flexible and adaptive solution to traffic management challenges [3].

In light of these advancements, this paper aims to explore the effectiveness of integrating dynamic lane assignment strategies with AI-driven signal optimization at signalized intersections [3]. Through a comprehensive review of existing literature, this paper endeavors to contribute to the growing body of knowledge surrounding AI-based dynamic lane management in urban traffic systems. By elucidating the benefits and challenges associated with these innovative approaches, this research seeks to inform future endeavors aimed at optimizing traffic flow and enhancing urban mobility.

## II. Workflow of AI-Based Dynamic Lane Management

To enhance city transportation and reduce traffic congestion, dynamic lane management systems utilize interconnected methods, facilitated by the Internet of Things and Artificial Intelligence algorithms. A more effective transportation system may be achieved via this tech-driven strategy, which integrates sensors, communication networks, data processing, and instantaneous decision-making [1].

### *Step 1:*

IoT sensors are initially placed at strategic points, comprising cameras, lidar, radar, and others. These sensors continuously observe and collect data on vehicle counts, speeds, and traffic congestion levels As they operate, simultaneous exchange of location, velocity, and trajectory data between the central infrastructure and linked Vehicle-to-Infrastructure (V2I) communication technologies exists. The system's intelligence relies on this constant stream of data, which provides insights about the flow of traffic and possible bottlenecks [1].

### *Step 2:*

The brain of this whole system is the control center, where the collected data is ingested and then sent through specialized communication networks like cellular or dedicated short-range communication (DSRC) systems. Depending on the variable conditions different algorithms like Dynamic Lane switching, Dynamic Lane Reversal, Dynamic Lane Usage Control, etc are brought into consideration [1].

***Step 3:***

The control system sends changes to lane allocation to electronic signs and traffic lights along the roads. Whether it's a lane closure, lane change, or other traffic instruction, these signals provide that information to cars in real-time. In the event of an accident on a certain lane, for instance, the system might quickly reorganize adjacent lanes to reroute traffic and assist in removing the accident site, reducing the disruption to traffic flow. Simultaneously, the system also evaluates dynamic routing options for individual automobiles. This entails offering alternate routes to drivers depending on the real-time traffic situations and lane layouts. Connected vehicles may get these route suggestions via their communication technology, enabling them to make informed choices that improve traffic efficiency [1].

These are the basic steps involved in DLM with AI, further, let's talk about how and which strategies have an impact on traffic congestion.

## III. Strategy 1: Dynamic Lane reversal

Dynamic Lane Reversal is a sophisticated traffic management technique employed to enhance road network efficiency and alleviate congestion during peak traffic periods. This strategy involves dynamically altering the direction of lanes on roads or highways to accommodate the predominant flow of traffic. By reallocating lanes to accommodate higher volumes of vehicles in a particular direction, Dynamic Lane Reversal optimizes traffic flow and minimizes congestion. This process is facilitated through the use of advanced traffic control systems, which monitor real-time traffic conditions and implement lane reversals as needed. Dynamic Lane reversal is instrumental in mitigating traffic congestion and enhancing overall transportation efficiency, thereby improving the commuting experience for motorists.

A promising way for cities to tackle congestion is to transcend the limits of "traditional" static urban design and utilize systems that dynamically allocate street space according to the prevailing conditions [4].

A popular concept in the "family" of dynamic space allocation, aiming at reducing congestion in intelligent traffic systems, is that of Dynamic Lane Reversal, first introduced by [5]. It entails the reversal of traffic flow along a lane to temporarily increase the capacity of congested edges at the expense of under-utilized ones [5].

Through the implementation of Dynamic Lane Reversal schemes, urban centers can optimize their street infrastructure utilization, effectively responding to fluctuations in traffic demand over the course of the day. Dynamic Lane Reversal systems enable municipalities to address network disruptions swiftly and efficiently, facilitating seamless adaptation to critical events and emergency evacuations autonomously, without reliance on manual intervention. Dynamic Lane Reversal schemes necessitate access to real-time traffic data encompassing metrics such as traffic volumes, queue lengths, and travel speeds, alongside the implementation of a proficient algorithm to ascertain the optimal timings for lane adjustments. Furthermore, a lane evacuation protocol has been devised to expedite evacuation processes while minimizing the disruption caused by lane-changing behaviors. The devised methodology is trained within the SUMO (Simulation of Urban Mobility) microscopic simulation package, a renowned tool within the transportation domain. Subsequently, rigorous testing is conducted under diverse traffic scenarios to evaluate its efficacy and robustness.

### *1. Literature Review*

The nascent stages of dynamically allocating space within urban road networks initiated with the introduction of Intermittent Bus Lanes (IBL) [6].

In addition to transit priority schemes, urban spatial allocation efforts have been directed towards Reversible Lane Systems (RLS) [7].

These systems offer the advantage of augmenting roadway capacity with minimal investment in infrastructure. By utilizing underutilized one-way lanes and redirecting traffic flows from opposing directions, RLS aims to optimize roadway capacity. Widely adopted globally, RLS serve to enhance directional roadway capacity during peak commuting hours, network disturbances, emergencies, and evacuation scenarios. However, their deployment is restricted to predetermined locations and schedules, primarily reliant on manual control by traffic enforcement personnel. Consequently, RLS are characterized by inefficiencies, cost-ineffectiveness, and operational complexities [5]. By capitalizing on the capabilities of autonomous vehicle technology, they [5] presented a conceptual framework for DLR wherein lane orientations are swiftly and autonomously adjusted based on real-time traffic data collected by traffic sensors. They framed the challenge of assigning traffic flow directions to individual lanes within a road network as a multi-commodity flow optimization dilemma. To address this, they proposed both an integer programming model and a two-level programming model supplemented by a solution methodology employing genetic algorithms. Many existing methodologies for determining optimal lane allocation rely on Integer Linear Programming (ILP) or Mixed Integer Linear Programming (MILP) optimization algorithms. However, these approaches often overlook or simplify the effects of lane reversals, which can lead to unrealistic assumptions. Moreover, the computational demands of these algorithms are substantial, particularly because they necessitate solving the optimization problem at each timestep. Consequently, their application in real-world scenarios, especially those involving large-scale traffic networks, is challenging due to computational complexity and resource requirements.

After thorough research, the paper referenced at [1] was identified as the most prominent one for Dynamic Lane Reversal. Hence, everything in that paper is analyzed and interpreted in this DLR strategy.

### 2. Methodology

The methodologies employed in this [4] study encompass three key components: the simulation environment, the lane reversal strategy, and the reinforcement learning (RL) agent.

Firstly, a simulation environment was constructed using the SUMO framework, featuring a 4-way intersection with specific lane configurations and traffic signal control based on gap-based actuated signal strategy.

Secondly, a lane reversal strategy was devised to efficiently manage traffic flow in the reversible lane. Initially, vehicles were restricted from entering the reversible lane, allowing its evacuation before accommodating oncoming traffic. To mitigate disruption and minimize evacuation time, a novel lane reversal strategy was implemented. This strategy involved creating dynamic special zones within the reversible lane, prompting vehicles to change lanes strategically to minimize disruption.

Thirdly, a reinforcement learning (RL) agent was employed to dynamically control lane reversals at the intersection. The RL agent, utilizing the Double Deep Q-Network (DQN) algorithm with a dueling architecture and an e-greedy exploration strategy, made decisions every five minutes based on the observed state of the intersection. The state included information on the current direction of the reversible lane, average waiting times, and vehicle counts in each lane.

In summary, the study utilized a simulation environment, a novel lane reversal strategy, and an RL agent to optimize traffic flow and reduce congestion at the intersection, with the aim of improving overall transportation efficiency. A deeper analysis of methodologies and results of the study are discussed below:

***A. Simulation Environment:*** In this study [4], the SUMO simulation framework was employed to model a simulated traffic scenario. The simulation environment featured an artificial 4-way intersection, as illustrated in Figure 1 from [4]. This intersection comprised a 2-lane main artery extending 500 meters in each direction, alongside a dynamic reversible middle lane designed without left turns. Additionally, secondary streets were represented by static 1-lane roads extending 500 meters in each direction. Traffic signal control at the intersection adhered to a gap-based actuated signal control strategy, as referenced in prior literature [8].

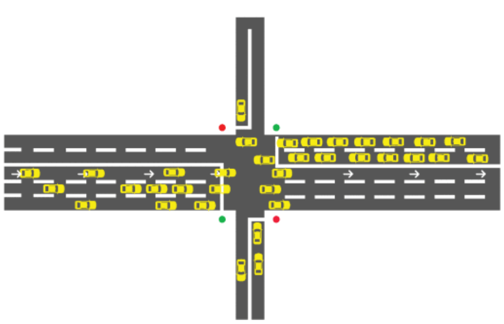

Fig. 1. Intersection environment

***B. Lane Reversal Strategy:*** A reinforcement learning approach implemented initially involved restricting access to the reversible lane and preventing vehicles from entering it from other lanes. Before allowing traffic from the opposite direction to utilize the lane, evacuation was ensured. However, this traditional approach resulted in significant disruption to overall traffic flow, primarily due to the emergence of lane-changing behavior as vehicles attempted to vacate the reversible lane, coupled with the period during which the lane was inaccessible to traffic. To mitigate these negative effects, a novel reversible lane evacuation strategy was devised. This strategy [4] introduced dynamic special zones within the lane undergoing evacuation: a zone adjacent to the neighboring lane queue and a fixed-length buffer zone behind it. Vehicles positioned in the reversible lane prior to the buffer zone were directed by an intelligent traffic management system to change lanes. If a vehicle fell within either of these designated zones, the lane change instruction was annulled, and the vehicle was instructed to proceed straight ahead to avoid disrupting other traffic. Once a vehicle transitioned to the downstream reversible lane, it was instructed again to change lanes. This strategy aimed to guide lane changes to areas with greater vehicle spacing, facilitating smoother transitions and thereby mitigating adverse effects. After experimentation with various buffer zone lengths, a length of 50 meters was determined to be the most effective in optimizing traffic flow.

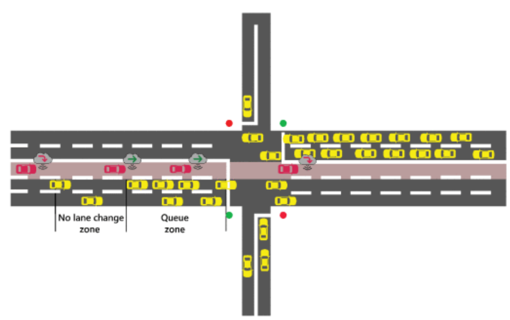


Fig. 2. Initialization of reversible lane evacuation

***C. Reinforcement learning agent:*** In this work a reinforcement learning agent controls the lane reversal dynamically in the described intersection every t steps, which was set to be 5 minutes. This value was chosen by taking into consideration the literature which suggests that lane changes at intervals shorter than 5 minutes do not yield significant benefits [9]. The architecture of the RL agent as well as the state, action and reward design, and the parameters values that were used are outlined below.

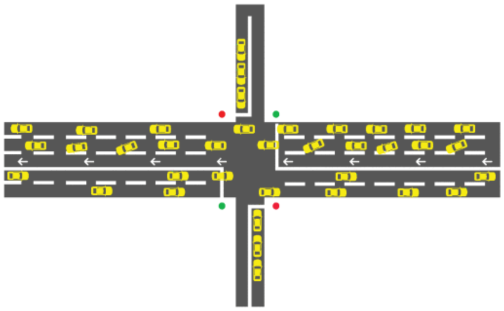

Fig. 3. Finalization of lane reversal

### 3. Components

***A. RL Architecture:*** The RL agent utilized in this [4] study follows a specific setup known as the DQN algorithm, incorporating a dueling architecture. This design aids the agent in discerning valuable actions across various scenarios. Additionally, it employs an exploration strategy termed e-greedy with exponential decay, striking a balance between trying out new actions and adhering to known effective actions [10], [11].

***B. State:*** The state includes a one-hot vector that describes the current direction of the reversible lane ($d_{\text{east}}$, $d_{\text{west}}$), the average waiting time of vehicles in the eastbound and westbound edges (($wt_{\text{east}}$, $wt_{\text{west}}$) as well as the number of vehicles per lane in those edges ($\frac{v_{\text{east}}}{l_{\text{east}}}$, $\frac{v_{\text{west}}}{l_{\text{west}}}$). All the observations were aggregated over the predefined step duration. The state space can be described in [4] as:

$$s = \{d_{\text{east}}, d_{\text{west}}, wt_{\text{east}}, wt_{\text{west}}, \frac{v_{\text{east}}}{l_{\text{east}}}, \frac{v_{\text{west}}}{l_{\text{west}}}\}$$

***C. Action:*** The RL agent has a binary action space, choosing between two actions: either reversing the lane direction (1) or maintaining the current direction (0). When opting to reverse the lane, the action is executed only once the reversible lane is entirely evacuated [4].

***D. Reward:*** The "reward" ($r_i$) is a metric of the RL agent's performance, defined as the negative sum of the average wait times for vehicles on both the eastbound and westbound edges: $r_i = -(wt_{\text{east}} + wt_{\text{west}})$. These equations provide a clear understanding of the components and mechanisms underlying the RL system utilized in the study.

### 4. Results and Conclusions

In this study [4], the researchers designed and evaluated a Dynamic Lane Reversal scheme to optimize traffic flow under varying demand conditions. To thoroughly assess the scheme's effectiveness, they created seven distinct scenarios, each representing different frequencies and intensities of demand variations along the main artery. The RL algorithm, crucial for controlling the DLR scheme, underwent training exclusively on the most demanding scenario, termed in Scenario 1 from [4]. This scenario was carefully crafted to mimic alternating peak demands, alternating between 1400 vehicles per hour and 600 vehicles per hour every 15 minutes over a 2-hour simulation period. Meanwhile, the demand for other intersection movements, such as West-to-South or North-to-South, remained constant at 140 vehicles per hour throughout the simulation. Importantly, the total demand for both directions remained constant over the entire simulation duration, ensuring a fair comparison between the Dynamic Lane Reversal scheme and a static lane configuration. The subsequent scenarios, labeled 2 through 6, followed a similar logic to Scenario 1 from [4], with variations in the frequency and intensity of demand changes as detailed in 7 from [4]. Additionally, Scenario 7 simulated the morning and afternoon peak hours of a city's transportation system demand, further expanding the scope of the study. By systematically varying the demand conditions across these scenarios, the researchers aimed to comprehensively evaluate the Dynamic Lane Reversal scheme's performance under different traffic conditions. This approach allowed them to assess the scheme's adaptability and effectiveness across a range of realistic scenarios, providing valuable insights into its potential real-world applicability and benefits.

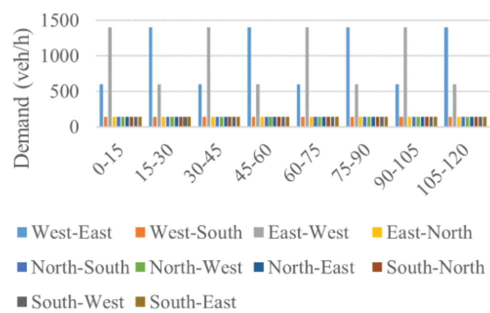


Fig. 4. Scenario 1- Severe demand change every 15 minutes

| Parameter | Value |
|---|---|
| Number of episodes | 4000 |
| Experience replay size | 100000 |
| Discount factor gamma | 0.85 |
| Batch size | 32 |
| Interpolation parameter tau | 0.001 |
| Learning rate | 0.0001 |
| Number of steps before NN weight update | 4 |

Fig. 5. Table 1: Parameter Values of Dueling-DDQN Agent

In the analysis of simulation outputs, it was found that the developed Dynamic Lane Reversal scheme consistently outperformed the static lane configuration with actuated traffic signal control across all scenarios, as detailed in 8 from [4]. This observation underscores the robustness and effectiveness of the proposed DLR scheme and highlights its excellent transferability across varying demand conditions. Moreover, the Dynamic Lane Reversal scheme demonstrated notable improvements in key metrics such as average trip duration, fuel consumption, and emissions of CO2, CO, and NOx. These findings suggest that implementing the Dynamic Lane Reversal scheme can lead to significant enhancements in traffic efficiency and environmental sustainability compared to static lane configurations. As anticipated, the most substantial benefits from the Dynamic Lane Reversal scheme were consistently observed in scenarios characterized by severe demand changes. This reaffirms the scheme's efficacy in dynamically adapting to fluctuating traffic conditions and mitigating congestion effectively. Furthermore, the analysis revealed that scenarios with lower frequencies of demand changes yielded greater benefits from the Dynamic Lane Reversal scheme. This is attributed to the reduced negative impact of lane reversals, such as disruptions and non-utilization periods, in scenarios with less frequent demand changes.

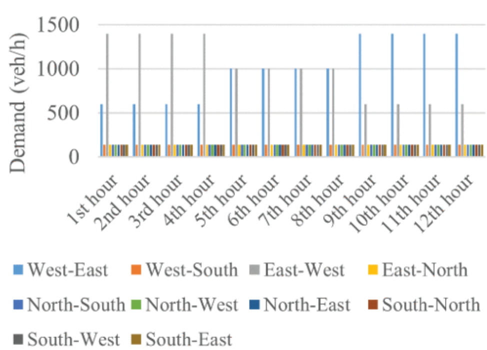


Fig. 6. Scenario 7- Morning and evening peak

| Scenario | Demand changes | Duration |
|---|---|---|
| 1 | Every 15 minutes : 600 – 1400 veh/h | 2 Hours |
| 2 | Every 15 minutes : 800 – 1200 veh/h | 2 Hours |
| 3 | Every 30 minutes : 600 – 1400 veh/h | 2 Hours |
| 4 | Every 30 minutes : 800 – 1200 veh/h | 2 Hours |
| 5 | Every 60 minutes : 600 – 1400 veh/h | 2 Hours |
| 6 | Every 60 minutes : 800 – 1200 veh/h | 2 Hours |
| 7 | Every 4 hours : 600 – 1000 - 1400 veh/h | 12 Hours |

Fig. 7. Table 2: Demand Patterns of the Different Scenarios

| Scen. | Aver. Trip Dur. | Total Fuel Cons. | Total CO2 Emis. | Total CO2 Emis. | Total NOx Emis. |
|---|---|---|---|---|---|
| 1 | -9.1% | -8.7% | -8.7% | -17.4% | -9.6% |
| 2 | -2.0% | -1.9% | -1.9% | -4.3% | -2.1% |
| 3 | -12.2% | -11.3% | -11.3% | -21.1% | -12.4% |
| 4 | -2.4% | -2.4% | -2.4% | -5.2% | -2.7% |
| 5 | -19.9% | -16.4% | -16.4% | -30.6% | -18.1% |
| 6 | -4.7% | -4.7% | -4.7% | -10.1% | -5.3% |
| 7 | -17.7% | -15.1% | -15.1% | -29.6% | -16.7% |

Fig. 8. Table 3: DLR Scheme Results Compared to Static Lane Configuration

Scenarios 1-7 provide a visual representation of the timings of lane reversals across various scenarios, along with their correlation with the accumulation of vehicles on westbound and eastbound edges. Remarkably, the behavior of the RL agent appears consistent and accurate throughout, as evidenced by the alignment of blue peaks with blue shaded areas and red peaks with red shaded areas. This consistency indicates that the RL agent was effectively trained and capable of responding efficiently to different scenarios without the need for retraining.It's important to note that the accumulation of vehicles on a road with a dynamic lane configuration is directly influenced by this configuration. Consequently, determining the optimal timings for lane reversals is a complex task that goes beyond a simple comparison of westbound and eastbound accumulations. The results from the figures are promising, demonstrating that the developed Dynamic Lane Reversal scheme promptly reacts to changes in demand without unnecessary actions in between. However, there were a few instances of reversals, particularly in scenario 7, where the effectiveness of these actions wasn't certain. To address this, future research could explore the introduction of penalties in the reward function of the RL algorithm for frequent lane reversals. This could potentially mitigate the occurrence of unnecessary reversals and further enhance the efficiency of the Dynamic Lane Reversal scheme.

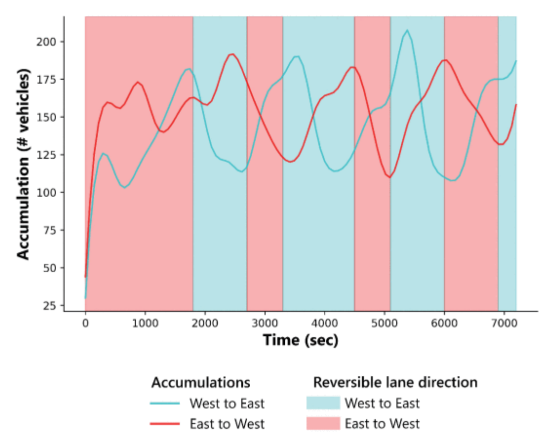


Fig. 9. Scenario 1- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

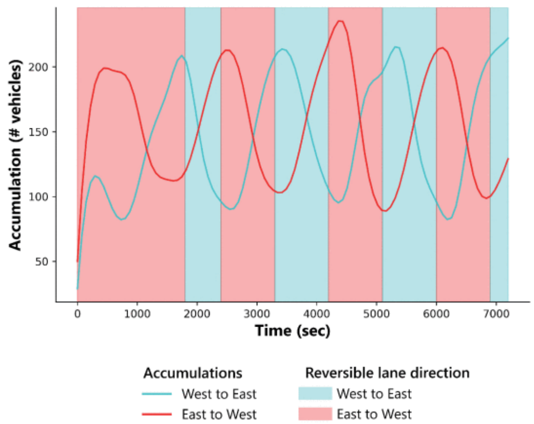


Fig. 10. Scenario 2- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

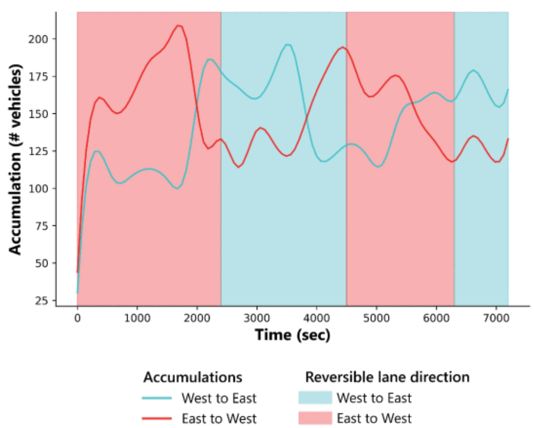


Fig. 11. Scenario 3- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

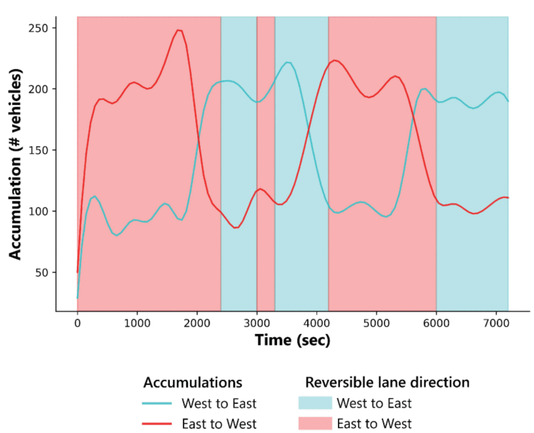


Fig. 12. Scenario 4- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

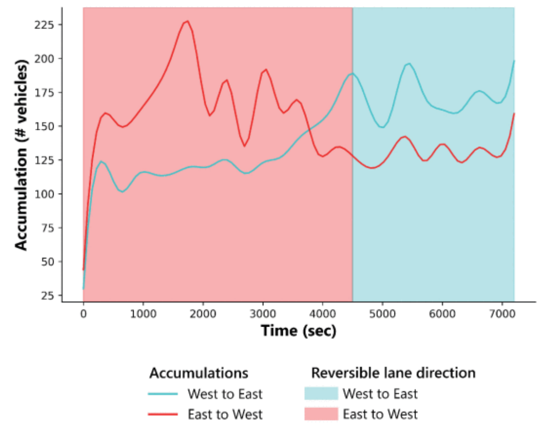


Fig. 13. Scenario 5- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

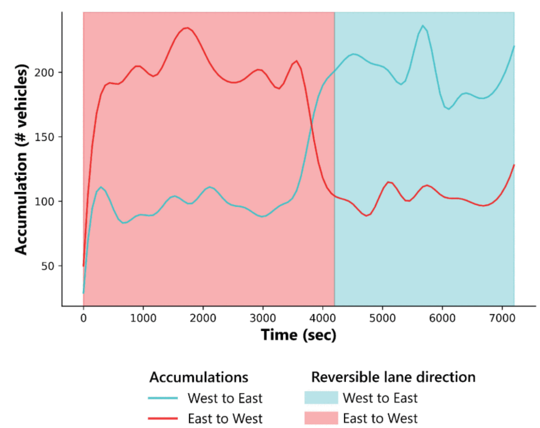


Fig. 14. Scenario 6- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

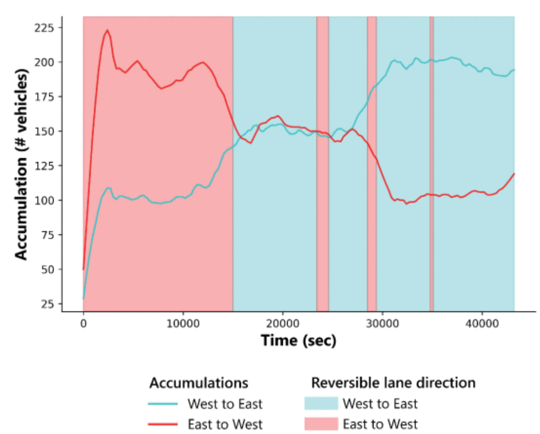


Fig. 15. Scenario 7- Timings of lane reversal with respect to accumulations on Westbound and Eastbound edges

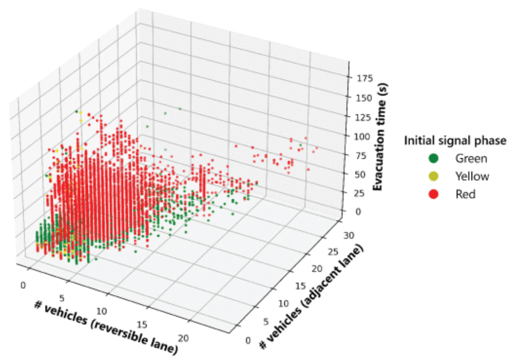


Fig. 16. Impact of traffic signal phase during initialization of lane reversal to evacuation time

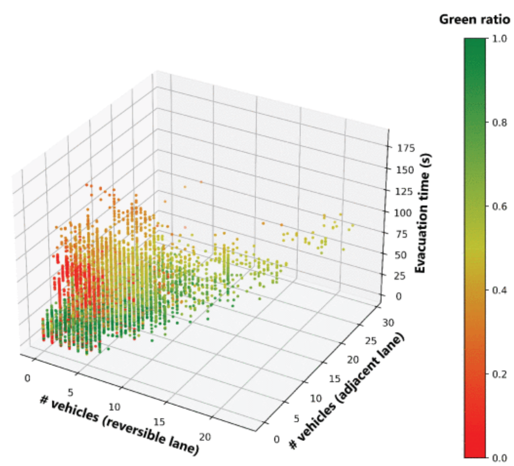


Fig. 17. Impact of ratio of green time during lane evacuation to evacuation time of reversible lane

### *5. Future Work*

In this study [4], a novel Dynamic Lane Reversal scheme is presented, leveraging Reinforcement Learning in conjunction with a lane evacuation strategy to optimize lane reversals in intersections experiencing fluctuating demand. Despite training the RL agent on a single extreme demand scenario, the results across all tested scenarios underscore its remarkable transferability, efficiency, and effectiveness in reducing both average trip duration and greenhouse gas emissions.

Moving forward, there are several avenues for future research. Firstly, exploring a wider range of scenarios will help delineate the boundary conditions under which such a strategy proves beneficial. Additionally, investigating alternative evacuation strategies could enhance the scheme's performance further. Dissecting the timesteps associated with the RL formulation would empower the agent to act more flexibly. Moreover, delving into the realm of multi-agent reinforcement learning could facilitate cooperation between the traffic signal and the Dynamic Lane Reversal scheme. Lastly, scaling up to a corridor and network level would offer insights into the scheme's applicability and efficacy in larger transportation systems.

## IV. Strategy 2: Dynamic Lane Assignment

Signalized intersections play a pivotal role in transportation networks, often serving as crucial nodes that significantly influence overall network performance. Particularly in urban areas, congestion during peak hours is a common occurrence at these intersections. One major contributor to congestion is the fluctuation of traffic demand throughout the day.Traditional signal control strategies typically revolve around adjusting signal timing to accommodate varying traffic demand. This optimization process involves modifying parameters such as green time and cycle length to improve traffic flow at the intersection. However, conventional methodologies often assume fixed lane assignments (FLA) at intersection approaches throughout the day. In other words, the number of lanes designated for each movement remains constant. This fixed lane assignment approach can lead to poor lane utilization, ultimately undermining intersection performance. As a result, it becomes imperative to explore alternative strategies, such as dynamic lane assignment, to effectively address congestion and optimize traffic flow at signalized intersections.

DLA strategy is a rational and reasonable Intelligent transportation system technique that can provide a better space allocation at intersection approaches by dynamically assigning lanes to each movement according to traffic demand [3].In DLA, the number of lanes for each movement (left, through and right) depends mainly on the real time traffic demand for that movement. For instance, if there is a huge demand for left turn movement during a specific period, more lanes will be assigned for left turn traffic while the remaining lanes will be assigned for the other turning movements (through and right) [12]. Variable message signs VMS synergizes the effective application of DLA through providing the driver with clear information about the lane utilization as he approaches the signal [13]. One application of DLA is the Dynamic Lane Management , which allows utilization of hard shoulders for freeway traffic at rush hours. It has been successful in many situations in reducing delay and enhancing safety [14]

### *1. Literature Review*

In the study [15], three selection criteria were employed to assess potential intersections for the application of Dynamic Lane Assignment. These criteria included the volume change criterion, which gauges traffic fluctuation throughout the day, the volume per lane criterion, and the volume per capacity criterion. The case study outcomes highlighted the volume per capacity criterion as the most effective in pinpointing suitable intersection candidates for DLA implementation. This criterion likely considers the intersection's capacity to handle traffic, making it a reliable indicator of where DLA could offer the most significant benefits.Furthermore, the results indicated that implementing DLA resulted in a noteworthy reduction of overall intersection delay, with a 15 percent decrease observed. This finding underscores the effectiveness of DLA in optimizing traffic flow and mitigating congestion at intersections, offering promising implications for traffic management strategies.

In their study, Zhang et al. [16] introduced a mathematical programming optimization model aimed at determining the most efficient lane assignment at signalized intersections. Their approach focused on minimizing the critical lane flow ratio, calculated as the volume divided by the lane saturation flow ratio. Through analysis of four distinct case studies, the researchers observed that implementing DLA notably improved traffic operations at the designated intersection. This enhancement was evidenced by reductions in both the critical lane flow ratio and average intersection delay. These findings underscore the effectiveness of DLA in optimizing traffic flow and reducing congestion at signalized intersections, highlighting its potential for improving overall transportation efficiency.

In Another study [17] the impact of DLA has been investigated at one approach of a signalized intersection. A model for optimizing a time-space combination was proposed. The analysis results revealed the proposed method produces the optimum benefit scheme.Previous studies have primarily focused on evaluating the operational advantages of Dynamic Lane Allocation when implemented at signalized intersections. However, there appears to be a gap in the existing literature regarding practical guidelines for implementing DLA techniques in real-world scenarios. Additionally, the DLA techniques documented in the literature often necessitate extensive delay calculations for all potential lane configurations to determine the optimal setup based on traffic volume. This process is time-consuming and may diminish the agility and efficiency of DLA when applied in practical settings. Thus, there is a need for research that not only explores the operational benefits of DLA but also provides practical insights into its implementation to enhance its real-world applicability and effectiveness.

Following extensive research, [12] emerged as a pivotal reference for Dynamic Lane Assignment strategies. This paper's significance lies in its development of an Artificial Neural Network (ANN) model designed to swiftly predict the optimal lane assignment—specifically, determining the appropriate number of lanes for each turning movement—at signalized intersections, regardless of the volume combination. Consequently, every aspect of this paper has been meticulously analyzed and interpreted within the framework of our DLA strategy.

### *2. Methodology*

In this study [12],a MATLAB model previously developed [3] was employed, which generated a hypothetical dataset of turning movement volumes along with the corresponding optimal lane assignments. The aim was to train and test the proposed Artificial Neural Network (ANN) model for optimizing Dynamic Lane Assignment (DLA) at intersections. Our objective was to minimize vehicle delay, with delay calculations based on the methodology outlined in the Highway Capacity Manual [18]. A minimum cycle length of 60 seconds was considered, ensuring pedestrian safety.

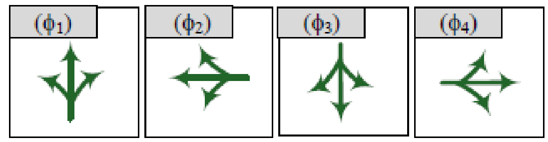


Fig. 18. Approach-based phasing scheme

The DLA model was formulated with specific constraints. We adopted an approach-based phasing scheme, allocating one phase to each approach to accommodate all movements (left, through, right). Additionally, we focused solely on protected left turns, assuming full protection without opposing traffic conflicts.

Our DLA model is adaptable to varying lane and approach configurations, assuming an equal number of approaching and exit lanes. We utilized a dichotomous variable to represent permissible movements from each approach.

The algorithmic steps for determining the optimal lane assignment are illustrated in figure 8 from [12]. Equations (1)-(4) (mentioned below) describe the mechanism used to adjust traffic demand at each approach independently. Left turn and through movements were modified without altering the overall approach demand, ensuring flexibility in demand adjustments while maintaining system integrity.

$$\mathrm{V_i = V_{iLT} + V_{iTH} + V_{iRT}} \tag{1}$$
$$\mathrm{V_{iLT} = 0.1 \text{ to } 0.7V_i} \tag{2}$$
$$\mathrm{V_{iTH} = 0.1\ V_i \text{ to } (0.8V_i - V_{iLT})} \tag{3}$$
$$\mathrm{V_{iRT} = V_i - V_{iLT} - V_{iTH}} \tag{4}$$

$V_{i,LT}$: Left turning volume at approach $i$.
$V_{i,T}$: Through volume at approach $i$.
$V_{i,RT}$: Right turning volume at approach $i$.

In the cited study [12], a comprehensive examination was conducted at a 4-leg intersection in Dhahran city, Saudi Arabia. The intersection utilized a pre-timed signal with an approach-based phasing scheme for efficient intersection control. The specific layout of the intersection, along with lane configurations at each approach, were meticulously detailed in figure 19 from [12].

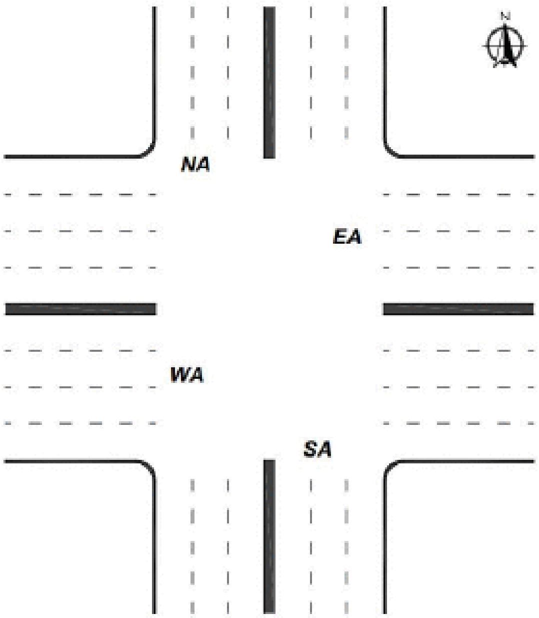


Fig. 19. Geometric layout of the study intersection

To better understand traffic dynamics, approach volumes were meticulously recorded during both AM and PM peak hours on a typical weekday, as highlighted in figure 21 from [12]. For analytical simplicity, it was assumed that only outer lanes could serve as shared lanes, leading to the identification of all feasible lane group combinations (LGCs) for both 4-lane and 3-lane legs, as depicted in figure 20 from [12].

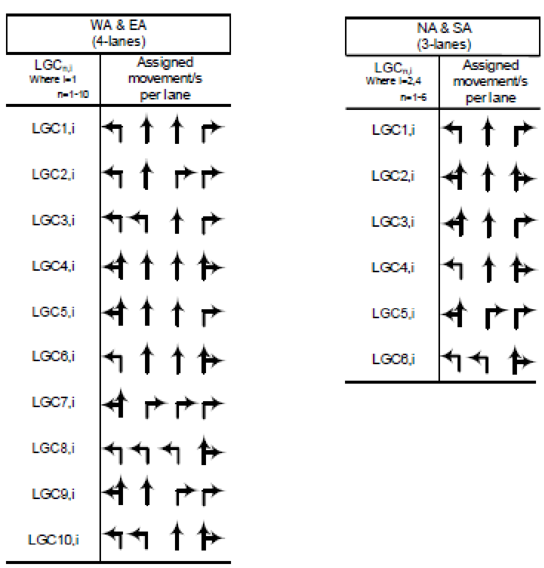


Fig. 20. Lgcs considered in the developed model

| Period | Observed approach volumes (vehicle/hr.) | | | | Intersection Volume |
|---|---|---|---|---|---|
| | WA | NA | EA | SA | |
| AM peak 6:30-7:30 | 1628 | 474 | 1462 | 80 | 3644 |
| PM peak 16:00-17:00 | 2199 | 669 | 1921 | 525 | 5314 |

Fig. 21. Table 1: Approach-based phasing scheme

These recorded approach volumes were instrumental in executing the Dynamic Lane Assignment model, illustrated in figure 22 from [12]. Real-world traffic volume data were collected from an intersection experiencing varying traffic demand throughout the day. Subsequently, these data were utilized to generate hypothetical datasets representing various turning movement combinations, following a predefined logic.

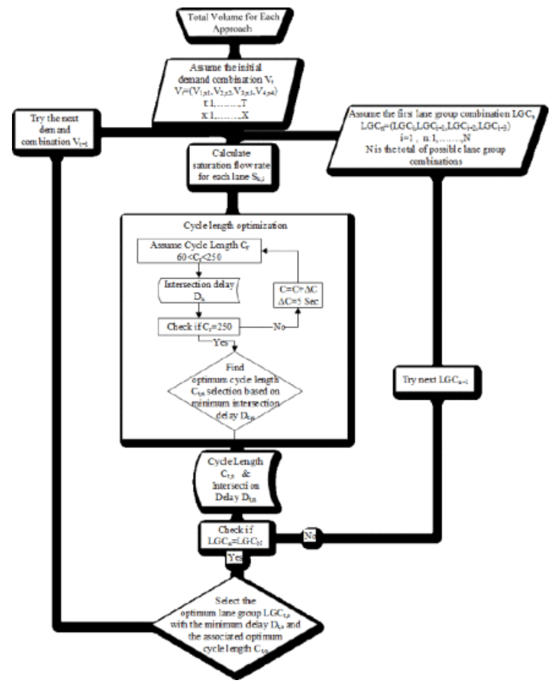


Fig. 22. Flowchart for the developed DLA model

With a 10 percent incremental adjustment applied to the percentage of turning volumes, over 600,000 turning volume combinations were generated for each peak hour (AM and PM). Each combination underwent analysis with the DLA model to determine the optimal lane assignment for all approaches of the intersection, resulting in datasets comprising turning volume combinations paired with corresponding optimal lane assignments.

These datasets were subsequently leveraged to both train and test the proposed Artificial Neural Network (ANN) model, designed to optimize DLA at intersections. The subsequent section delves into the detailed methodology employed, providing valuable insights into the data collection process, model development, and the underlying rationale guiding the study's approach.

### 3. ANN Model Development

ANN, or Artificial Neural Network, is a technique rooted in Artificial Intelligence (AI). It works by mimicking the way the human brain learns from past experiences. Just like our brains can learn from information and make sense of it, artificial neurons in ANN can also learn from data they're given and understand the connections between different pieces of information.Currently, ANNs are used to solve complicated transportation problems because they can handle nonlinear relationships without a pre-assumed relationship between input and output [18]–[21].

This study [12] uses a feedforward neural network, which is designed to imitate the structure of the human brain. The network is composed of three types of layers: the input layer, hidden layer, and output layer, illustrated in 23 from [12]. Each layer contains multiple processing units known as neurons. These neurons receive signals, including variables, weights, and biases, from all the neurons in the preceding layer. The number of neurons in the input and output layers matches the number of input and output variables, respectively.

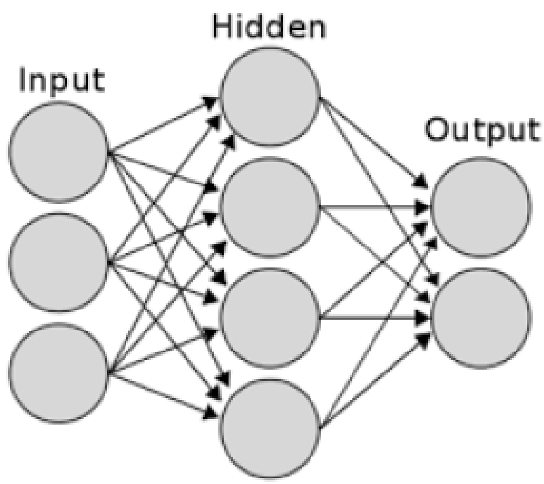


Fig. 23. Example of 2-layered network

Determining the topology of the neural network has been the subject for many studies [22], [23]. These studies haven't really nailed down a specific method for figuring out the best setup for an Artificial Neural Network (ANN). So, most of the time, people just try different configurations and see what works best for the particular problem they're tackling. In trial and error approach, a systematic procedure is followed starting with a small number of hidden layers and then building it larger until an acceptable accuracy is achieved without causing overfitting [12].

The connection between the optimal lane assignment and variations in demand appears to be nonlinear and uncertain. Consequently, an Artificial Neural Network (ANN) was employed to address this challenge. Developed within the MATLAB environment, the ANN model aimed to predict the best lane arrangement for a solitary signalized intersection based on traffic volumes. The model comprises 12 inputs representing approach volumes and 4 outputs corresponding to the optimal lane assignment for each approach. To train and test the ANN model, a subset of 75,000 turning volume combinations was randomly selected from the total of 600,000 for each peak hour. These samples, totaling 150,000 turning volume combinations, were partitioned into 75 percent for training and the remaining 25 percent for testing.

Several training algorithms were evaluated for constructing the ANN model, including Levenberg-Marquardt, Resilient Backpropagation, Scaled Conjugate Gradient, BFGS Quasi-Newton, Bayesian regularization backpropagation, and Variable Learning Rate Backpropagation. Among these options, the Bayesian regularization backpropagation algorithm was selected for this study due to its superior classification accuracy compared to other algorithms. The Bayesian regularization backpropagation algorithm employs Levenberg-Marquardt optimization to update weight and bias values. It is capable of generating a network that generalizes well by determining the appropriate combination of squared errors and weights. In this process, the term ”back-propagation” denotes the backward propagation of errors from the model output to the hidden layer. This involves updating weights and biases based on optimization algorithms to minimize the sum of errors, ultimately enhancing the accuracy of predictions.

In this study, the trial and error procedure was followed in determining the optimum topology for the ANN model until reaching a point at which the ANN model can predict the optimal lane assignment combinations with reasonable accuracy. Levenberg-Marquardt algorithm was chosen as the training algorithm as it resulted in the highest prediction accuracy compared to the other training algorithms. ANN model with three hidden layers, with 14 neurons in each of them, was found to be the best combination with an average testing accuracy of 92 percent [12].

### 4. Conclusion

The functionality of signalized intersections profoundly influences the overall operational characteristics of a transportation network. Dynamic Lane Assignment (DLA) is an Intelligent Transportation System (ITS) technique utilized to optimize traffic operations at signalized intersections by efficiently utilizing available space. With DLA, the allocation of lanes for specific movements dynamically adjusts based on real-time traffic demand.

In this study, the authors adopted a DLA model, developed by themselves and others, to generate hypothetical datasets of turning movement volumes along with corresponding optimal lane assignments. Traffic counts were conducted at a four-leg intersection experiencing fluctuating traffic throughout the day to capture approach volumes during both morning (AM) and evening (PM) peak hours. These approach volumes served as inputs for the DLA model to generate hypothetical turning movement volume datasets.

By systematically adjusting the percentage of turning volumes in increments of 10 percent, over 600,000 turning volume combinations were generated for each peak hour. For each combination, the DLA model determined the optimal lane assignment for all intersection approaches. Subsequently, these datasets were utilized to train and test an Artificial Neural Network (ANN) model.

From each dataset, a random sample of 75,000 turning volume combinations was selected, totaling 150,000 combinations. Among these, 75 percent were allocated for training the ANN model, while the remaining 25 percent were used for testing. The ANN model was constructed following a systematic approach, ultimately comprising three hidden layers, each with 14 neurons. This configuration yielded an average testing accuracy of 92 percent.

The developed ANN model by [12] proves to be a versatile algorithm capable of accurately identifying the optimal lane combination, showcasing its potential for enhancing traffic management and operations.

### *5. Future Work*

Moving forward from the study's findings on the effectiveness of the Dynamic Lane Assignment (DLA) model, future research endeavors could focus on several critical areas to advance the implementation and understanding of DLA techniques in optimizing signalized intersections.

Firstly, there's a pressing need for real-world validation of the developed DLA model. Transitioning from hypothetical datasets to actual implementation in real-world scenarios is essential to ascertain the model's effectiveness and practicality. Conducting field studies and pilot implementations at real intersections experiencing varying traffic conditions would offer invaluable insights into the model's performance in practical settings.

Parameter optimization within the DLA model presents another promising avenue for future research. Fine-tuning parameters such as the percentage increments for adjusting turning volumes could lead to more effective lane assignment strategies. Exploring the impact of different parameters based on empirical data and traffic flow dynamics could significantly enhance the accuracy and efficiency of the DLA model.

Moreover, the exploration of advanced machine learning techniques beyond Artificial Neural Networks (ANN) holds potential for further optimizing lane assignments at signalized intersections. Deep Learning algorithms or Reinforcement Learning approaches could offer alternative strategies worth investigating. Comparing the performance of different machine learning models within the context of DLA would provide insights into their respective strengths and limitations.

Additionally, evaluating the DLA model across various intersection configurations is essential to understand its applicability in diverse transportation networks. Analyzing its performance under different geometries and traffic flow patterns would offer a comprehensive understanding of its effectiveness across various contexts.

Lastly, assessing the long-term impacts of implementing DLA strategies on traffic flow patterns, congestion levels, and overall network performance is crucial. Conducting longitudinal studies to monitor changes in traffic dynamics post-implementation would provide insights into the sustained benefits of DLA techniques in optimizing signalized intersections.

By addressing these areas in future research endeavors, stakeholders can further leverage Dynamic Lane Assignment techniques to enhance the efficiency, safety, and sustainability of urban transportation networks.


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