Decentralized Management of Road Intersections without Communication

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***Abstract*—**

I. Introduction

Efficient management of unsignalized intersections is crucial for smooth undisrupted traffic flow. An inadequately managed unsignalized intersection can affect the network's signalized intersections as well as intelligent transportation systems (ITS) and may eventually lead to congestion and road accidents. In accordance with the data provided by the Ministry of Road Transport and Highways, India (MORTH), in 2021, a staggering 98,571 accidents were related to intersections, with a vast majority of 74.21% (i.e., 73,155) occurring at uncontrolled intersections [1].

In many towns and cities, uncontrolled intersections lacking proper infrastructure are common, particularly in areas with low traffic density. The absence of infrastructure can lead to safety issues and traffic flow disruptions. To mitigate these problems, the installation of the required infrastructure is imperative. As autonomous vehicles become more accessible, it is possible that intersections will be managed autonomously through a command center in the near future. Nevertheless, even with technological advancements, some infrastructure, such as a traditional traffic signal or a command center, will still be necessary for uncontrolled intersections. However, from an economic standpoint, building such infrastructure may come with exorbitant costs that may not justify its utility.

Given the potential risks associated with uncontrolled intersections, it is crucial to find effective ways of managing them. This question of intersection management becomes even more pressing with the increasing prevalence of autonomous vehicles. However, it remains unclear how such vehicles can navigate uncontrolled intersections without the aid of infrastructure or communication protocols like V2X/V2I/V2V (vehicle-to-everything/vehicle-to-infrastructure/vehicle-to-vehicle).

In this paper, we propose a novel framework for fully autonomous vehicles to navigate intersections. The algorithm is designed to provide real-time output without relying on any infrastructure or communication protocols. The framework is specifically tailored for intersections where installing traffic signals or any other infrastructure is redundant due to low traffic density.

II. Related work

Over the last decade, the development of Autonomous Intersection Management (AIM) has gained significant attention due to the pressing issues of traffic growth and on-road safety at intersections. With the increasing number of vehicles on the road and rising concerns over accidents and delays, AIM offers a promising solution to optimize traffic flow and minimize collisions through the integration of advanced sensors, algorithms, and communication technologies into connected vehicles and autonomous vehicles. According to recent data from the USA and India, intersections account for the majority of road accidents, highlighting the urgent need for innovative intersection management solutions like AIM [1], [2].

Traffic lights have been a commonly used tool for regulating traffic flow at intersections for many years. In most cases, the signal phase timings are determined using various parameters such as traffic density (PCUs/hr) and queue length. For instance, the Traffic Signal Timing manual by NCHRP provides guidelines for optimizing signal timings based on these factors [3]. However, despite their widespread use, traffic lights have been shown to be inefficient when it comes to minimizing waiting times at intersections. Prolonged waiting times lead to increased fuel consumption, resulting in higher levels of harmful emissions. Over the last decade, researchers have utilized data collection technologies (viz. connected autonomous vehicles (CAVs), mobile sensing, etc.) to gather real-time traffic data and optimize traffic phase timings based on parameters such as flow volume, travel time, queue length, and shockwave boundary [4].

The literature on intersection management classifies approaches into two main segments: V2I (vehicle-to-infrastructure communication), known as the Centralized approach, and V2V (vehicle-to-vehicle communication), referred to as the Distributed approach [5]. In the Centralized approach, a roadside infrastructure communicates with vehicles, performs necessary computations, and guides them safely through intersections. This method is particularly effective for high-traffic density intersections, as the infrastructure can handle heavy computational loads and periodically store traffic information, eliminating the need for continuous information broadcasting by vehicles [6], [7], [8]. However, a failure in the roadside infrastructure can lead to a breakdown of the entire system, which is not the case in the Distributed approach. In the Distributed approach, computations are either performed on the vehicles themselves or a designated vehicle assumes a leadership position and carries out the required computations[9], [10], [11]. This approach creates a more robust and scalable system, making it well-suited for low to medium-traffic density intersections. However, it relies on limited computational resources at the vehicle end and requires high communication and computational bandwidth to reach a

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consensus.

Two prominent approaches for intersection management are space-time reservation and trajectory planning. In a space-time reservation system, the intersection is divided into an occupancy grid, ensuring that no two autonomous vehicles (AVs) occupy the same grid cell at the same timestamp. Resources are allocated based on scheduling or priority policies. The First Come First Serve (FCFS) policy has proven to be effective, where vehicles communicate their arrival time to the infrastructure or other vehicles, and priority is given to the one with the shortest travel time. Various heuristic and optimization-based algorithms exist for scheduling and reservation.

On the other hand, in trajectory planning, vehicles follow predetermined paths to safely navigate the intersection. The trajectory planning layer considers parameters such as acceleration/deceleration, travel time, and the arrival of other vehicles to plan the optimal trajectory for each vehicle.

In the past decade, several surveys have been published, shedding light on various aspects of intersection management. Qureshi and Abdullah [12] delve into intelligent intersection management technologies and their practical applications. Li et al. [13] explore the relationship between traffic control systems and vehicular communication, comparing three pairs of control strategies: Big-Data-Based Versus Concise-Data-Based Controls, Model-Based Versus Simulation-Based Predictive Controls, and Planning-Based Versus Self-Organization-Based Controls. Turning to signalized and unsignalized intersections, Chen and Englund [14] provide a comprehensive review, emphasizing trajectory planning, virtual traffic light, and space-time reservation methods. On a related note, Ross-Torres and Malikopoulos [15] delve into heuristic and optimization-based scheduling policies from both centralized and decentralized control perspectives. Furthermore, Guo et al. [4] conduct an extensive examination of signalized intersection management using connected autonomous vehicles, addressing aspects such as flow estimation and the optimization of traffic signal timings. Namazi et al. [16] undertake a systematic review focused on signalized and unsignalized four-way intersection management, including a comparative analysis of goal satisfaction among different methods. Khayatian et al. [5] adopt a different perspective, discussing intersection management from multiple key angles and shedding light on the limitations associated with each approach. Their analysis provides valuable insights into the challenges and potential drawbacks of different intersection management strategies. Zhong et al. [17] survey autonomous intersection management, categorizing prior research into three hierarchical layers: corridor coordination, intersection management, and vehicle control. They also delve into the transition from signalized intersection management to autonomous intersection management, addressing challenges such as computation, collision avoidance, and priority policies. Finally, Gholamhosseinian et al. [18] conducted a thorough survey on various intersection management architectures, covering signalized, unsignalized, and hybrid intersections. Their analysis is based on the intersection of management goals like efficiency, safety, infotainment, and environmental considerations.

III. Problem Formulation

Consider an unsignaled intersection with medium to low traffic density. The objective is to autonomously navigate the intersection without utilizing any vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), or vehicle-to-everything (V2X) communication. The intersection can have multiple connected roads, but to formulate the problem, we focus on a 4-way intersection as depicted in Figure 1; 3-way and 5-way intersections are discussed later. Since the intersection has low traffic density, it is reasonable to assume that each road at the intersection consists of one incoming lane and one outgoing lane. The vehicles approaching the intersection indicate their intentions using turn signals (left, right, or none for going straight).

At each incoming lane, there are three distinct zones: *the red zone*, *the yellow zone*, and *the green zone*. To ensure that vehicles can stop if necessary, we define *the red zone*, where vehicles decelerate to a speed of 20 km/hr. The length of *the red zone* depends on the average speed of approaching vehicles. Given that this intersection scenario is designed for low to medium-traffic situations, the length of *the red zone* is set to five times the length of a vehicle (i.e., 20 meters). In *the yellow zone*, vehicles are able to observe other vehicles present at the intersection. The length of *the yellow zone* is assumed to be 1.5 times the length of a vehicle. If more than half of a vehicle has crossed into *the green zone*, it is not required to stop and can proceed through the intersection. An illustration of this concept is provided in Figure 1.

To enable each lane is identified by a lane id (a,b,c ..., refer figure 1) in a clockwise direction starting from absolute north. The letter also denotes the lane priorities, i.e., lane a has higher priority than lane b, and so on. A vehicle maneuver is denoted using 1,2,3 for left, straight, and right maneuvers, respectively. Refer to figure 1 for illustration. V_j^i denotes a vehicle in lane $i \in a, b, c, \dots$ with future maneuver $j \in 1, 2, 3$.

Assumptions The problem is formalized with the following assumptions:

- The intersection does not have a traffic signal or roundabout. The traffic volume is low/medium.
- All vehicles at the intersection indicate their intended motion through the indicator.
- The autonomous cars are able to perceive the intent of other vehicles once inside *the yellow region*.
- Vehicles do not take U-turns at the intersection
- Pedestrians and other uncertainties of the environment are not considered.

The problem statement can be defined as follows,

Problem III.1 (Autonomous Intersection Management)**.** *Given an un-signaled intersection I_n with n approaching lanes and a set of vehicles intending to cross the intersection, find a time-optimal strategy to allow the vehicles to pass the intersection without collision.*

IV. Decentralized Intersection Management

In this section, we present a solution algorithm to tackle problem III.1. The problem is addressed using a harmony

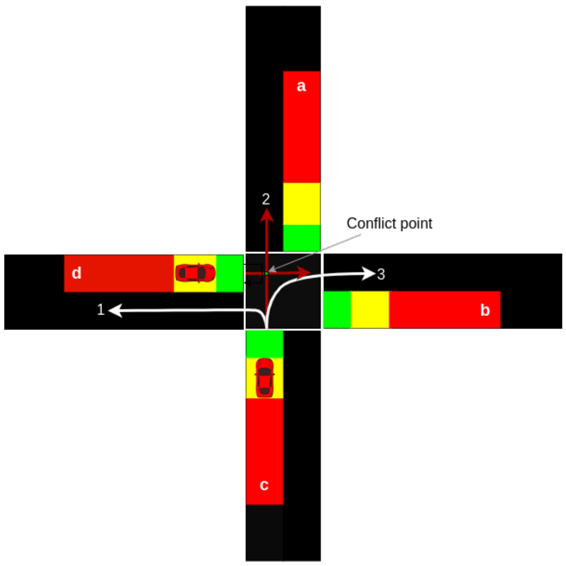


Figure 1: A 4-way intersection is described with the associated notations used in the paper. The white arrows represent the possible maneuver and red arrow represents the intended maneuver of the vehicle. The vehicle in lane ‘a’ and lane ‘b’ have conflicting maneuvers and the green dot represents the conflict point.

matrix for an intersection. A harmony matrix encompasses all feasible combinations of two maneuvers that can be executed simultaneously, ensuring coexistence. An example of a harmony matrix for a four-way intersection is illustrated in table I.

Consider an n-way intersection with n incoming lanes. In this scenario, up to n vehicles will be present at the intersection, and a unanimous decision is required to determine the right of way. To identify the optimal combination of vehicles that can pass simultaneously, we construct a graph with n nodes, where the harmony matrix defines the connections between these nodes. The search for the best possible combination corresponds to finding the largest fully connected sub-graph, a well-known problem in graph theory referred to as the *Maximal Clique Problem*. Explain this

Whenever a vehicle approaches the intersection, the algorithm 1 is invoked. Initially, the vehicle enters the *Red Zone* of the intersection and reduces its speed to 20km/hr. Upon entering the *Yellow Zone*, the vehicle utilizes its camera to observe the surrounding vehicles and their intended maneuvers. Based on this information, a graph is constructed using the harmony matrix. The best possible combination of vehicles is determined by solving the maximal clique problem on the created graph. Various algorithms exist to solve this problem, and in our implementation, we utilize the *networkx* package. The vehicles identified in the solution are granted the right of way. This process is repeated until the vehicle successfully crosses the intersection.

If there exist multiple cliques of the same length, then the clique containing the higher priority lane is given the preference. The absolute lane priorities are defined as given in

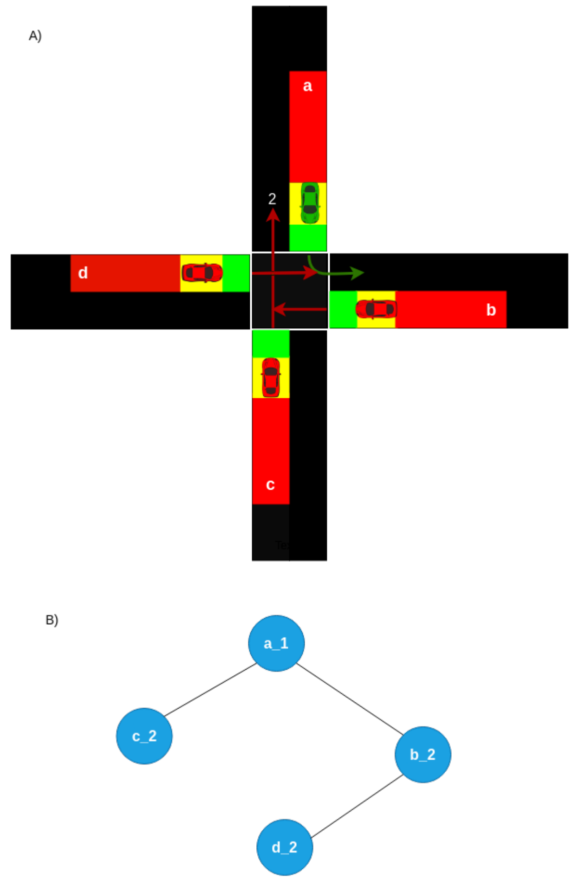


Figure 2: A) A scenario of 4 crossing vehicles with conflicting movements B) A graph generated using harmony matrix based on vehicle movements

Algorithm 1 Intersection management

Input: $\mathcal{M} \leftarrow$ *Harmony Matrix*

while $vehicle\ at\ intersection$ **do**
    if $vehicle\ in$ *Red Zone* **then**
        $Reduce\ Speed\ 20km/h$
    else if $vehicle\ in$ *Yellow Zone* **then**
        $IVehs \leftarrow Get\_Vehicles\_and\_their\_intent()$
        $Graph \leftarrow Create\_graph(IVehs, \mathcal{M})$
        $ROD \leftarrow Solve\_max\_clique\_prob(Graph)$
        if $Vehicle\ in\ ROD\ and\ No\ vehicles\ crossing$ **then**
            $cross\ the\ intersection$
        end if
    else if $vehicle\ in$ *Green Zone* **then**
        $cross\ the\ intersection$
    end if
end while

section III.

A. Deadlock Analysis

The proposed algorithm is designed to ensure deadlock-free operation during vehicle navigation through the intersection.

Table I: Harmony matrix for a four-way intersection. In the matrix, 0 stands for conflict and 1 for harmony/coexistence

	V_1^a	V_2^a	V_3^a	V_1^b	V_2^b	V_3^b	V_1^c	V_2^c	V_3^c	V_1^d	V_2^d	V_3^d
V_1^a	0	0	0	1	1	1	1	1	0	1	0	1
V_2^a	0	0	0	0	0	0	1	1	0	1	0	0
V_3^a	0	0	0	1	0	0	0	0	1	1	0	0
V_1^b	1	0	1	0	0	0	1	1	1	1	1	0
V_2^b	1	0	0	0	0	0	0	0	0	1	1	0
V_3^b	1	0	0	0	0	0	1	0	0	0	0	1
V_1^c	1	1	0	1	0	1	0	0	0	1	1	1
V_2^c	1	1	0	1	0	0	0	0	0	0	0	0
V_3^c	0	0	1	1	0	0	0	0	0	1	0	0
V_1^d	1	1	1	1	1	0	1	0	1	0	0	0
V_2^d	0	0	0	1	1	0	1	0	0	0	0	0
V_3^d	1	0	0	0	0	1	1	0	0	0	0	0

Several key measures are incorporated to prevent the occurrence of deadlocks.

Firstly, the algorithm is activated only when a vehicle enters the intersection, and it terminates as soon as the vehicle obtains the right of way and successfully crosses the intersection. By limiting the algorithm's execution to the precise moment when the vehicle is actively engaged in the intersection, the likelihood of deadlocks occurring is greatly reduced. Furthermore, in situations where there are multiple cliques of the same length that can potentially pass, the algorithm takes into account lane priorities to select the optimal combination. This intelligent selection process helps avoid any eternal wait for a vehicle and eliminates the possibility of deadlocks arising from conflicting priorities.

Through extensive simulations and evaluations, it has been demonstrated that the algorithm effectively manages traffic flow without encountering deadlocks. Although vehicles with lower lane priorities may experience slightly longer waiting times, these delays are finite and do not lead to deadlocks or gridlock scenarios. The robustness of the algorithm has been validated through various real-world simulations, ensuring an efficient traversal of vehicles through the intersection while guaranteeing deadlock-free operation.

B. Safety Analysis

Ensuring safety is crucial when vehicles cross an unsignaled intersection. The proposed algorithm prioritizes non-conflicting vehicles, significantly reducing the risk of accidents. As the crossing process is fully autonomous and adheres to the designed path, deviations are unlikely. However, to further enhance safety, a safety monitor can be implemented to address any potential discrepancies during the intersection crossing. A safety monitor continuously assesses the safety of the vehicle's trajectory while a motion planner guides the car's movements. If the safety monitor detects a potential danger, it assumes control and steers the vehicle to safety. The monitor utilizes data-driven human models to evaluate safety. In cases where there might be inaccuracies in the human models, the safety monitor tends to be more conservative, leading to frequent interventions.

To address this, a confidence-aware safety monitor has proven to be beneficial. Tian et al. [19] demonstrate the successful application of such a monitor for merging on roundabouts, particularly when involving human drivers.

V. Simulation Setting

The efficacy of the developed algorithm is assessed by conducting comprehensive simulations that replicate real-world scenarios. In order to simulate realistic traffic conditions, we employ the Simulation of Urban MObility (SUMO) [20]. SUMO is an open-source traffic simulator renowned for its ability to handle large-scale traffic simulations. Within SUMO, the built-in functions are leveraged to facilitate motion planning, enabling seamless evaluation of intersection management algorithms. To facilitate real-time control of vehicles, the Traffic Control Interface (TraCI), a Python API specifically designed for SUMO, is utilized.

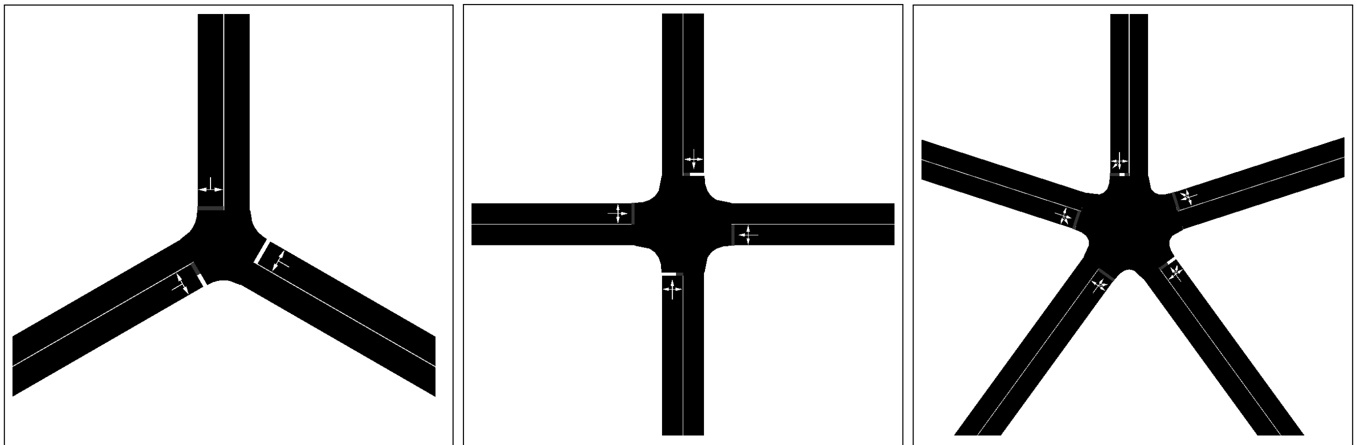
The developed algorithm is subjected to a simulation duration of 1 hour under conditions of low to medium traffic density. To determine the appropriate range for low to medium traffic density, we refer to the Manual on Uniform Traffic Control Devices (MUTCD), specifically Chapter 4 [21], which states that a traffic signal is warranted if the traffic volume on a single-lane road reaches 500 PCUs per hour or above for both directions. Thus, we conduct simulations across a spectrum of values: 150, 200, 250, 300, and 350 PCUs/hour/lane.

A. Intersection Types

The algorithm's robustness is evaluated on various types of intersections, including a three-way intersection with a 'Y' shape, a four-way junction, and a five-way junction. These intersections are characterized by roads extending up to 500m, each with a single incoming and outgoing lane. Figure 3 provides a visual representation of the three junctions that are considered for testing the algorithm's performance.

B. Real-world traffic modeling/distribution

The assumption of a uniform distribution of incoming vehicles is not realistic in real-world scenarios. To model the arrival



(a) Three-way ('Y') Intersection (b) Four-way Intersection (c) Five-way Intersection

Figure 3

of vehicles more accurately, we employ a *Poisson Distribution*. The Poisson Distribution, represented by equation 1, describes the probability of an event occurring a certain number of times within a fixed time interval.

$$P(k) = \frac{\lambda^k e^- \lambda}{k!} \tag{1}$$

In the equation, $P(k)$ denotes the probability of the event occurring k times, while λ represents the average number of events in the fixed time interval t. The Poisson distribution is particularly useful for modeling independent and random events, given the knowledge of the average occurrences within a specific time interval. In our context, we utilize the Poisson distribution to estimate the probability of incoming vehicles. We determine the average number of vehicles per lane per hour, which is 250 PCUs for low-density traffic and 500 PCUs for medium-density traffic. These values serve as the average rate of events in the Poisson distribution, allowing us to calculate the probability of different numbers of vehicles arriving in a given time period.

VI. Results and Discussion

A. Evaluation Metrics

The performance of the intersection management algorithm is assessed based on two primary metrics: travel time and average waiting time.

1) Travel Time: Travel time is defined as the duration it takes for a vehicle to traverse a road segment extending 500 meters from the center of the intersection on each side. It encompasses the time from when a vehicle arrives at the intersection until it completely passes through the specified road segment.

2) Average Waiting Time: Average waiting time measures the duration that vehicles spend in a queue at the intersection before being able to proceed. It represents the average time a vehicle has to wait before entering the intersection and beginning its traversal through the road segment. The waiting time is calculated by summing up the waiting times of all vehicles in the queue and dividing it by the total number of vehicles.

By considering travel time and average waiting time, the evaluation provides a comprehensive understanding of the algorithm's impact on traffic flow, congestion, and overall intersection efficiency.

B. Comparison Models Reasoning

To assess the algorithm's effectiveness, we perform a comparative study using non-communicative and communicative methods defined below. The comparative study consists of two types of traffic distribution: 1. Balanced traffic and 2. Unbalance traffic. In balanced traffic, the traffic density is equal in all lanes, and in unbalanced traffic, the traffic densities are distributed non-uniformly, and the lane priorities are set accordingly.

1) Fixed-Time Traffic Signal: A fixed-time traffic signal is the most common method to control junction traffic. In a fixed-time traffic signal, the green time is fixed and does not change with respect to time. Webster's formula [22] is often used to determine the optimal cycle length and effective green time.

$$Optimal\ cycle\ length\ (Co) = \frac{1.5 * L + 5}{1 - y} \tag{2}$$

$$Effective\ Green\ Time\ (Ga) = \frac{ya/y}{Co - L} \tag{3}$$

Where L represents the total lost time, including all red time, we set $L = 2n$, where n is the number of incoming lanes. y is the sum of critical ratios for each lane, which is the ratio of observed volume to saturation flow. Saturation flow refers to the maximum number of PCUs that can pass per hour. To establish the saturation flow, we refer to an empirical study by Kumar et al. [23]. In their study, they observed a busy three-legged junction in Vellore, India, and noted a peak traffic of 7573 PCUs per hour at the junction. Since the three-legged junction has 5 incoming lanes, we consider a saturation flow of approximately $7573/5 \approx 1500$ in our case. Table II displays phasing timings for the respective observed volumes. During the simulation, we utilize a 4-phase traffic signaling approach since there is a single incoming lane, and all movements are required during the green time.

Table II: Signal phase timing for fixed-time signal

Traffic Density	Green time(s)	Amber time(s)
150	5	2
200	7	2
250	10.75	2
300	19.75	2
350	61.75	2

2) Adaptive Traffic Signal: Adaptive traffic signals dynamically adjust to traffic demands, enhancing traffic flow. Real-time data is gathered through traffic sensors or cameras, and algorithms then adapt signal timings according to this data. We employ a delay-based algorithm developed by Oertel and Wagner[24] for comparison. This algorithm modifies green times based on queue sizes, adhering to maximum and minimum green time bounds. In practice, the algorithm is given fixed-time signals as per table II, and then the algorithm modifies them.

3) Intersection Management using V2I protocols: We also conduct a comparison between our strategy and an algorithm that employs communication for intersection management. Li and Liu [6] utilize vehicle-to-infrastructure communication to gather data. Using this collected data, conflicts are identified through a predefined conflict matrix, and the infrastructure provides arrival times to vehicles. Vehicles then adapt their speeds based on these arrival times, ensuring a seamless passage through the intersection.

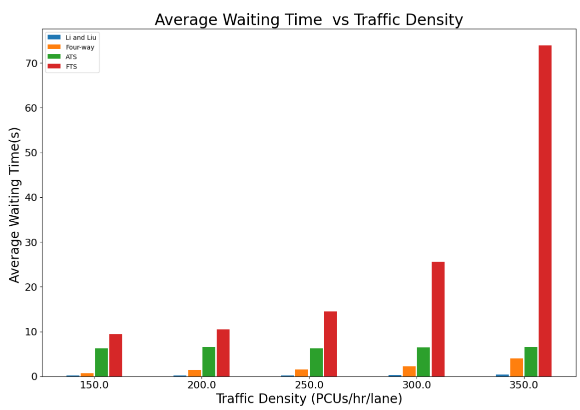


Figure 4: Comparative study on average Waiting Time(s) vs Traffic Density (PCUs/hour/lane) for balanced traffic

Figure 4,5 shows the comparison study between the 4 algorithms for Balanced traffic. The waiting time delay of our approach is lower than fixed-time traffic signals (FTS) and adaptive traffic signals (ATS) and comparable to Li and Liu at lower traffic densities. A similar trend is observed in travel time. At a traffic density of 350 PCUs/hr/lane, Li and Liu's waiting time and travel time are 11.8 and 1.4 times lower than ours respectively, but considering the fact that they have used V2I communication for management, it is expected. On

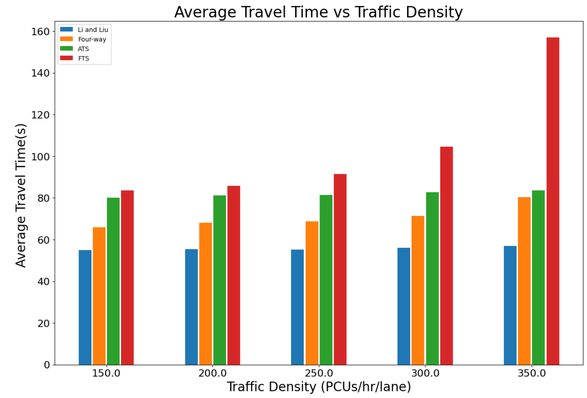


Figure 5: Comparative study on average Travel Time(s) vs Traffic Density (PCUs/hour/lane) for balanced traffic

the contrary, our algorithm provides comparable results at low traffic densities without using any infrastructure.

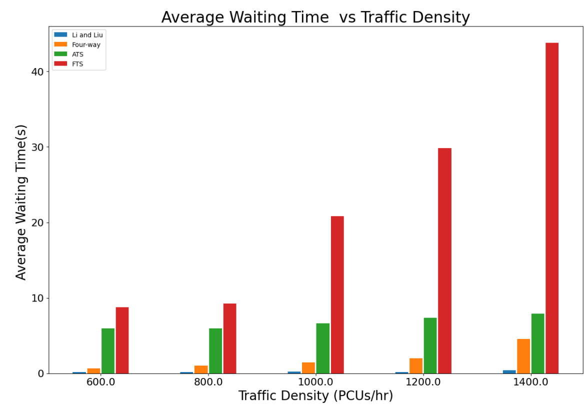


Figure 6: Comparative study on average Waiting Time(s) vs Traffic Density (PCUs/hour/lane) for unbalanced traffic

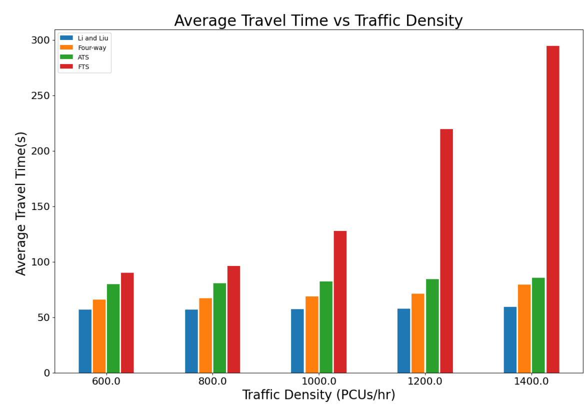


Figure 7: Comparative study on average Travel Time(s) vs Traffic Density (PCUs/hour/lane) for unbalanced traffic

In unbalanced traffic density, the total traffic density is divided in the ratio of 4:3:2:1, and the lane priorities are set accordingly. Figure 6 and 7 show the average waiting time and average travel time for unbalanced traffic. The performance of fixed-time and adaptive traffic signals declines, whereas our algorithm's performance is improved compared to balanced traffic. This is due to the fact that we use absolute lane priorities, which results in queuing in the least priority lanes for balanced traffic, whereas the queue length in unbalanced traffic is lower and large amount of traffic is resolved faster by assigning higher priority to lane. The highest average travel time is within the bound of 50% of Li and Liu's algorithm with communication infrastructure.

C. Intersections types

The versatility of the algorithm allows for seamless extension to intersections with n number of incoming lanes by adjusting the conflict matrix. In this section, we showcase the algorithm's performance across 3-way, 4-way, and 5-way intersections. Figures 8 and 9 illustrate the average waiting time and average travel time for varying traffic densities, respectively.

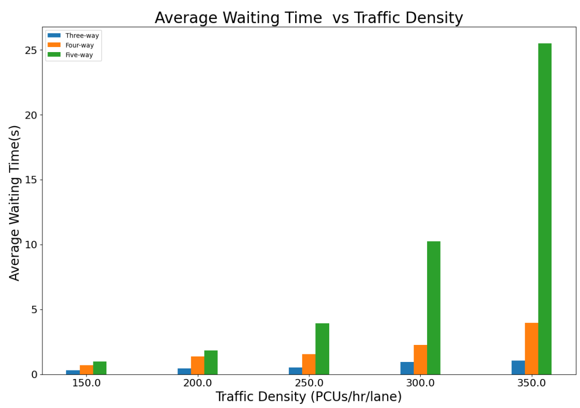


Figure 8: Average Waiting Time(s) vs Traffic Density (PCUs/hour/lane) for different intersections

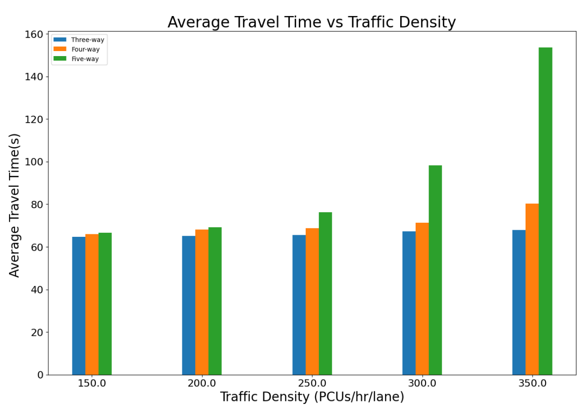


Figure 9: Average Travel Time(s) vs Traffic Density (PCUs/hour/lane) for different intersections

The average waiting time increases with the number of incoming lanes as the traffic density is directly proportional to incoming lanes. The average time delay does not vary as much as the average waiting time but shows a similar trend. This is because the queue length in the least priority lane increases, leading to a higher waiting time for vehicles in the lane.

Table III: Lane-wise waiting time and travel time for 3-way, 4-way, 5-way intersections

Traffic Density	3-way	4-way	5-way
lane 'a'	0.4606	0.8660	1.0970
lane 'b'	0.9275	1.7263	2.0858
lane 'c'	1.6415	2.8863	4.2837
lane 'd'	N/A	10.2094	13.3636
lane 'e'	N/A	N/A	146.1092

Table III shows the average waiting time for each lane at a traffic density of 350 PCUs/hr/lane. It can be clearly observed that the values for the least priority lane (alphabetical priority is used as defined in problem formulation) values increase exponentially.

VII. Conclusion and Future works

In this paper, we presented a novel framework for fully autonomous cars to navigate unsignalized intersections with low traffic density. The algorithm refrains from using any dedicated infrastructure or communication protocols for intersection management and relies only on sensory inputs to navigate the intersection safely. The efficacy of the algorithm was evaluated through a number of traffic simulations in SUMO against existing methodologies. It was observed that our algorithm performs better than current non-communicative methods (FTS and ATS) and provides comparable results to the communicative method (Li and Liu [6]). The algorithm is more suitable for unbalanced traffic environments due to its prioritizing nature. This approach can provide the solution to the uncontrolled intersections where basic infrastructure installation is also wasteful.

The future work can be pursued in a multitude of directions. We aim to take it forward by integrating the algorithm with a safety monitor and testing with the Carla simulator. With safety monitors in place, experiments can be carried out with mobile robots along with sensory inputs from camera to identify other vehicle intents.

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