Multi-agent Signal-less Intersection Management with Dynamic Platoon Formation

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ABSTRACT

We propose a novel mechanism to manage platoons of autonomous vehicles at traffic intersections. Our mechanism optimises the formation forming vehicle platoons to minimises overall waiting time, allowing the optimal platoon size to be determined dynamically, thus minimising overall travel time. In addition, we introduce a conflict resolution algorithm, which dynamically authorises multiple platoons to manoeuvre even when the majority are single vehicles. Our empirical evaluation shows that, for single intersections, our mechanism can reduce the average travel time by up to ≈65% compared to conventional fixed-time traffic signals and up to ≈4% compared to advanced non-platoon-based signal-less first-come-first-served approaches. Moreover, from the corridor-level aspect, our mechanism can reduce the weighted average trip duration up to ≈22% compared to the fixed-time traffic signals and up to ≈45% compared to the signal-less first-come-first-served approaches.

KEYWORDS

Intersection Management; Connected and Autonomous Vehicles; Multi-agent System; Platoon; and Microscopic Traffic Simulation

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1 INTRODUCTION

Traffic congestion is one of the key causes of air pollution and losses in economic efficiency, having wider impacts on health and climate change [26]. In the UK alone, traffic congestion cost the drivers around £6.9 billion in 2019 [11]. With the impending deployment of connected and autonomous vehicles (CAVs)[1], there is an opportunity to make a step-change from the status quo (i.e. traffic signals) to mitigate carbon emissions from road transportation. As these vehicles will be powered either by electricity (potentially from carbon-emitting sources) or by carbon-based sources, it will be crucial to utilise their autonomy and connectivity to improve traffic flow, minimising start-stop behaviours typically lead to congestion.

To this end, work in the AI community has sought to address the problem of intersection management with CAVs since the early 2000s, following the seminal work by Dresner and Stone (2008). They proposed a grid model of an intersection and a simple heuristic following the First Come First Served (FCFS) principle, allocating paths and time-slots to the incoming vehicles. Since their work, a number of alternative approaches have emerged in the field [6, 12, 21, 24, 32, 40]. In general, these approaches consider two objectives: (i) to optimise the flow at an intersection, as expressed by relevant metrics, such as traffic throughput (either based on incentives or waiting time); and (ii) to scale up the solution to consider multiple intersections or large numbers of vehicles. These approaches also consider a centralised controller and do not allow for any communication between vehicles.

In our work, we remove the latter constraint as vehicles are increasingly being connected through radio vehicle-to-vehicle communications. The goal is to allow them to dynamically form platoons of multiple vehicles. Several studies suggest that travelling in a platoon can significantly improve the efficiency of traffic, e.g., [10, 22, 23, 36–38]. However, these studies have only minimally considered the delays caused/mitigated by platooning at road intersections. Furthermore, these approaches have only considered synthetic scenarios. In our work work, we look to use real-world traffic data and real road intersection structures to stress test platoon formation techniques.

Against this background, this paper proposes a new resource reservation mechanism for signal-less intersection management, which forms platoons dynamically. The mechanism optimises platoon formation by calculating and balancing individual platoons' waiting time cost at the intersection. In so doing, our mechanism can minimise the overall travel time despite the large time slots reserved by platoons. Our mechanism is tested using real-world data on a real eight-intersection urban corridor microscopic simulation model. In more detail, our contributions are as follows:

[1]CAVs are vehicles that are capable of driving themselves without human interference and wirelessly exchange information with other devices (e.g. vehicles and external networks) [27].

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(1) We introduce a novel waiting-time-based platoon formation algorithm that allows the IMA to grant multiple platoon formations dynamically considering their utility, weighing the potential waiting time cost created by the platoons.
(2) We improve the state-of-the-art decentralised resource reservation algorithm in [35] accounting for platoons to cover extra space and time-slots and ensure multiple platoons' safe crossing even when most reservations are single CAVs.
(3) We present a realistically-calibrated traffic model of a real-world eight-intersection corridor using the Simulation of Urban MObility (SUMO) [14] tool by reproducing traffic demand with heterogeneous vehicle types according to the pNEUMA dataset, which comprises traffic data collected by drones in Athens, Greece [1].
(4) We extensively test and evaluate the mechanism through several scenarios on the calibrated simulation. The results show that FCFS performs especially poorly under extreme traffic conditions (poorer than conventional traffic signals), while our approach demonstrates superior performance in corridor-level aspect.

The rest of this paper is structured as follows. Section 2 provides an overview of related literature. Section 3 presents the model description and relevant definitions and assumptions. The formulation of our dynamic platoon formation algorithm and the resource reservation mechanism is provided in Section 4. Then, our algorithm is evaluated against conventional traffic lights and non-platoon-based signal-less FCFS approach in Section 5. Lastly, Section 6 conclude the paper and outline future work.

2 RELATED WORK

In the past decades, a number of approaches have been proposed to reduce traffic congestion by utilising intelligent and adaptive traffic control. It has been shown that the performance of conventional traffic signal programs can be significantly improved using various approaches such as fuzzy logic [7], machine learning [18], and multi-agent systems [8]. However, the traffic signals themselves may not be the most efficient method for the not-to-distant future, where CAVs become extensively used, as they rely on drivers and/or vehicles making visual contact with the signal head. A signal-less controller, on the other hand, which can directly communicate with the vehicle and transmit signal indications to it, can much better nurture the full potential of vehicle connectivity technology.

In this vein, [9] introduced FCFS, the first to signal-less multi-agent intersection control algorithm. This algorithm introducing a resource reservation mechanism with a central agent, suggesting conflict-free time-slots for vehicle agents to cross the intersection. Due to its flexibility and adaptability, this seminal work has been extended by many studies. Notably, [6] introduces an auction-based approach allowing the driver to bid for their time-slots, showing a reduction in the overall waiting time. Similarly, [32] proposed a market-inspired approach assuming different drivers have different bidding power, imitating human society. Different approaches that mainly focus on improving the intersection efficiency and scaling up their studied areas can also be seen, such as token-based reservation [24], Distributed Constraint Optimisation Problem (DCOP) approaches [33], and deep reinforcement learning [12].

Meanwhile, there have been considerable developments in the field of vehicle automation. Most notably, several cars nowadays are equipped with Adaptive Cruise Control (ACC), a smart radar-based system allowing cars to automatically maintain a safe gap to the car or vehicle in front, which has demonstrated benefits in terms of increasing road capacity, reducing delays and decreasing pollutant emissions and fuel consumption [25]. An improved version of ACC is Cooperative Adaptive Cruise Control (CACC), where automation is combined with connectivity and vehicles communicate their intention, speed and routes among themselves in order to behave as a group – *platooning*. This has additional positive impacts involving, not least, a reduced communication overhead due to the controller only needing to pass signal indications to a single vehicle rather than multiple ones, e.g., [5, 10, 19, 20, 22, 23, 29, 36–38]. ACC and CACC have been explored within the context of various traffic management applications. For instance, [22] integrates platooning into a network of 16 intersections, showing an improvement up to 300% increase in traffic capacity (compared to fixed-time traffic lights). Similarly, a study in [5] conducts a field test on five consecutive traffic lights, showing an average of 5% reduction in travel times.

Due to these promising results, many researchers in modelling automated intersection for CAVs have turned their attention towards platooning, due to its cooperative controls. For example, [13] propose a heuristic platoon reservation method, and their simulation results show a significant reduction in the average travel time by $\approx$ 8% compared to [9]. In the same vein, [2] propose a stop-sign algorithm that allows platoons to cross the intersection one at a time, reducing the fuel consumption by up to 13%, and [3] advance the prior work by giving priority to the platoon that has the highest waiting time. Furthermore, [17] propose a coordinator that optimises the platoons' arrival time (by accelerating/decelerating) in order to avoid unnecessary queuing delays and fuel consumption.

However, the aforementioned studies are usually simulated and evaluated in highly stylised and idealised scenarios, which are rarely seen in real-world traffic. Several essential elements are rarely considered, including road geometry, turning manoeuvres, realistically high traffic demand, heterogeneous vehicle types, and a variation in vehicle speed. For example, in [13], the studied intersection is an artificial 2-way-1-lane simulating relatively low traffic demand. Similarly, [3] use a 4-way-1-lane intersection with pre-generated platoons assuming the groups have been formed as arrival with unchangeable size. In addition, [2–4, 13, 17, 39] implicitly and unrealistically assume that vehicles are identical. Moreover, many studies still have not scaled up their works to cover multiple intersections. Thereby, the impact of platooning in a bigger aspect has not been extensively explored. As such, while several studies have shown that platooning works well in idealised and deterministic intersection management scenarios, it is unclear whether it works equally well in practice, especially when platoons contain longer vehicles that take up more time and space when crossing the intersection.

Against this background, we present a multi-agent intersection management algorithm with a platooning mechanism, where the platoons are formed dynamically. Our flexible mechanism allows multiple platoons to be formed and existing platoons to be extended as long as they reduce the overall waiting time of the intersection.

Moreover, we carefully consider the dynamism of real-world scenarios by testing and evaluating our approach on a calibrated microscopic traffic simulation model of a real-world case study with real traffic data. In this way, we can realistically evaluate our approach and demonstrate a broader impact of platooning.

3 THE CALIBRATED TRAFFIC MODEL

We base our model on the original FCFS model [9] that considers a road intersection managed by an *Intersection Manager Agent* or IMA[2]. The IMA can grant its resource (time-slotted space in the intersection) to each vehicle—*Driver Agent* or DA—to coordinate each vehicle's movement. We next describe how the intersection and the vehicles are modelled.

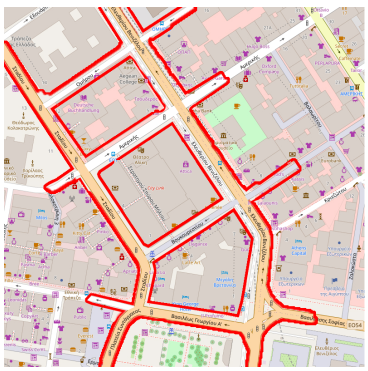

Figure 1: The corridor in Athens, Greece, used in this study, comprising of eight intersections (within the solid enclosure).

3.1 The Intersections

While [2, 13] only consider ideal intersection geometry, we consider more practical intersections and use the SUMO simulation tool to model these. Specifically, our study is modelled after a road network in Athens, Greece, as it is a focus area in [1], which uses an array of drones to capture real-world traffic data providing precise vehicle movements. However, for the system's simplicity and to save up the simulation runtime, only two out of ten focus areas are used, covering a corridor of eight intersections (see Fig. 1).

Additionally, another element that highly impact the realism of the model is intersection geometry. Even though SUMO can import a road network from OpenStreetMap directly, information is partially inaccurate, e.g,. the number of lanes per road, free-turn lanes, public transport lanes, and the possible driving direction of each lane. To rectify this, TraVia [30], a traffic data visualisation tool, allows us to reproduce the vehicle movements in pNEUMA and adjust the road corridor accordingly and practically. Moreover, as we also consider the actual fixed-time traffic signal program, the red and green times or phases are extracted through TraVia instead of using SUMO's pre-generated signal programs.

Furthermore, for the intersection access, an individual vehicle or a platoon is scheduled based on a cell-based reservation mechanism similar to [9, 35]. To be specific, the centre of the intersection is discretised into a grid of cells. These cells indicate DAs' occupancy and time-slots according to their manoeuvring paths. They are also used to prevent conflicts among DAs' reservations (see Fig. 4).

[2]The IMA typically sits within the infrastructure at the intersection and communicates with nearby vehicles using typical radio frequency communications.

3.2 Vehicles

Let $A_t = \{a_1 ... a_I\}$ denote the set of DAs in the system at time t. Each $a_i \in A_t$ has the following properties: position pos_i^t, velocity v_i^t, orientation θ_i^t, length l_i, width, and type $type_i$. All agents in A_t have the same minimum gap between each agent (2.5 m) but different maximum velocity v_i^{max} and accelerating rate α_i^{max} depending on their type. To simulate the most practical environments, the dataset in [1] is derived to specify a population of vehicle types, acceleration, and also a deviation in maximum speed. In particular, the maximum speeds are assigned using a normal distribution given minimum and maximum values of 95% spread (z=1.96). The full details of the vehicle properties can be seen in Table 1.

Moreover, to model platoons, we use $status_i$ to represent/label one of three states of a vehicle, which are:

(i) $leader$ – A leader of a platoon.
(ii) $follower$ – A follower in a certain platoon.
(iii) $null$ – An ordinary DA that does not belong to any platoon, henceforth referred to as a *standalone* DA.

Unlike existing work by [2, 3, 13] where all vehicles are labelled as they enter the IMA's communication range, in our approach, platoons are formed dynamically only when they are queuing and meet certain conditions ensuring the benefits to the overall system. These conditions will be specified in Section 4.

Table 1: Vehicle properties, including share, length, acceleration, and maximum velocity based on their type.

Type	Share	Length	α^{max}	v^{max} (m/s)	
		(m)	(m/s^2)	avg	SD
Bus	2.2%	12	2.90	9.98	2.33
Delivery	4.1%	6.5	3.03	10.91	3.01
Motorcycle	33.2%	2.1	4.14	13.90	3.95
Private	43.8%	5	3.32	12.09	3.25
Taxi	16%	5	3.10	11.5	3.03
Truck	0.7%	7.1	2.80	9.01	3.65

3.3 Traffic Demand

The most crucial element in the calibrated model is reproducing the ground-truth traffic demand. Particularly, the pNEUMA dataset provides vehicles' latitude and longitude position as a snapshot per time step (0.04 sec, 25 FPS), from staring point to the end of route. We project these positions on the road corridor, recreating vehicles' trajectory individually and acquiring their explicit route. In doing so, a few discontinuities can be seen as several vehicles disappearing and reappearing at certain spots. This is due to blind-spots, where drones lose track of the vehicles moving behind tall buildings. In turn, all the routes passing these blind-spots are carefully reconnected to ensure their continuity. Consequently, we acquire the pattern of ground-truth traffic demand, in a series of routes:

$$Route_x = < \{road_k, ..., road_K\}, ratio > \tag{1}$$

denoting route $x \in X$ (total route) with a specific departure at $road_k$ travelling to $road_K$ through $road_{k+1}, ..., road_{K-1}$, while $ratio$ refers to the ratio of the number of vehicles travelling on route x to the total number of vehicles. We next describe our core algorithm that dynamically form platoons in consideration of their utility cost.

4 MULTI-AGENT INTERSECTION MANAGEMENT WITH DYNAMIC PLATOON FORMATION

Having defined the model elements, we next define our intersection management mechanism that dynamically forms platoons while minimising overall waiting time and continue describing the safe passage reserving process for standalone DAs and platoons.

Due to the platoon synchronisation movements, follower DA(s) can cross the intersection in a less interrupted manner than standalone ones, reducing unnecessary braking and accelerating. Thus, the travel time and delays are reduced cumulatively with every platoon formed. The larger the platoon size, the greater the reduction. However, by doing this, the system may suffer cumulative delays elsewhere, i.e. so-called *externalities.* For instance, as the platoon requires large reserved space and time-slots, forming one on a lane may prolong any future reservations and cause multiple DAs to wait, leading to substantial delays to the flow. Therefore, forming a platoon greedily, i.e. as soon as a DA enters the communication range (as in [13]), is unlikely to be optimal or beneficial. To alleviate this issue, we propose a dynamic platoon formation to ensure the *cost* efficiency of every platoon formed.

4.1 Dynamic Platoon Formation

The *cost* in our study refers to the overall waiting time across the intersection, which is greatly affected by the existence of platoons. Specifically, the effect is categorised into two types: (i) the reduction of waiting time λ_{plt} and (ii) the increase in waiting time T_{plt}. As a platoon forms, the reduction comes from the reduced stop-and-go movements, while the increase comes from the cumulative delays of multiple DAs on the other inbound lanes.

By virtually grouping consecutive queuing DAs into multiple groups and calculating their λ_{plt} and T_{plt}, the algorithm can decide on platoon formation in real-time. If any groups of DAs make the reduction higher than the increase, i.e., $\lambda_{plt} > T_{plt}$, those DAs will be logically merged together, effectively forming a platoon. DAs in a platoon will adjust their driving behaviour according to $status_i$ (see later Section 4.2). It should be noted that merging can be done only in two scenarios: merging two standalone DAs together and creating a new platoon, or merging a standalone DA with an existing platoon, thus making it longer. We emphasise that, using our approach, the platoon size is non-static and can be *extended* dynamically as long as a net benefit is obtained (unlike [2, 3, 13]).

Example cases of platoon formation can be seen in the left part of Fig. 2. Here, lane01 shows a typical case where two vehicles are one possible platoon. In lane02, the IMA is considering extending the size of an existing platoon by including the vehicle behind. In lane03, the vehicle with granted reservation is no longer considered in the platoon formation while the rest still do. Lastly, in lane04, the IMA considers vehicles even when they are still moving. Furthermore, the right hand side of Fig. 2 shows the overall process of DAs handling platoon formation, including sharing some basic information with the IMA, retrieving a labelling response from the IMA, and adjusting their driving behaviour.

Next, we explain how the IMA calculates the cost of platoon formation, starting with the reduction of waiting time, λ_{plt}.

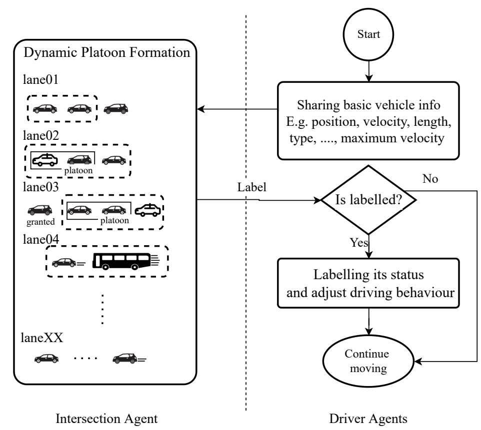

Figure 2: The interaction between the IMA and DAs where vehicle icons represent DA in certain lanes. Dashed rectangles represent a group of DAs possible for platoon formation, while the solid rectangles represent DAs that are already in platoons. Square dots represent additional lanes and DAs being considered in the platoon formation algorithm.

4.1.1 *Calculating the Reduction of Waiting Time.*

Whenever a platoon *can* be formed, i.e. a DA approaches another queuing DA that shares a similar route, the IMA can suggest two possible choices:

(i) Merging the approaching DA with its preceding one(s) into a platoon.
(ii) Doing nothing, and leaving the approaching DA as a standalone one.

Assuming the platoon cooperate via CACC, as suggested in [28], the follower DAs only follow the trajectory and speed recommended by their leader. Once the leader acquires a reservation, in situation (i) the follower DAs are less likely to perform stop-and-go movements to cross such intersection, which is where the reduction in waiting time comes from. In situation (ii), the approaching DA must slow down and wait for its reservation slots, which is more time-consuming. Therefore, the amount of reduced waiting time is the travel time difference between situations (i) and (ii).

To calculate this time difference, an estimated time of arrival (ETA) and estimated clearance time (ECT) – the amount of time vehicles need to manoeuvre and completely leave the intersection – will be used. We first focus on computing the travel time between two points, that incorporates ETA and ECT.

DA Travel Time: We build on [13] to calculate the time that the DA requires to travel a certain distance without exceeding v^{max}. The function, called $cruise(d, a_i)$, is defined as:

$$cruise(d, a_i) = \frac{v_i^{max} - v_i^t}{\alpha_i^{max}} + \frac{1}{v_i^{max}} \left[d - \frac{\left((v_i^{max})^2 - (v_i^t)^2 \right)}{2 \cdot \alpha_i^{max}} \right] \quad (2)$$

where d is the travel distance, and v_i^t is the velocity of an input DA a_i at time t. The first term denotes the acceleration time, and the second term denotes the time that vehicle travels a constant speed (v_i^{max}). We next expand on this to compute the ETA and ECT.

ETA: In [13], a vehicle's ETA does not account for any braking, as the focus was only on a two-way intersection with light traffic. Our model involves more complex situations with higher traffic volumes, where vehicles regularly slow down approaching a stop line. Hence, a DA's ETA has to account for braking. Let d_i^{line} be the distance between the stop line and the front bumper of a_i, d^{brake} be the braking distance (to stop before the stop line) and t_i^{brake} be the braking time. The DA's and platoon's ETA are given by:

$$t_i^{EA} = cruise\left(d_i^{line} - d^{brake}, a_i\right) + t_i^{brake} \tag{3}$$

$$t_{plt}^{EA} = cruise\left(d_i^{line}, a_{lead}\right) \tag{4}$$

respectively. In the case of the platoon's ETA (t_{plt}^{EA}), the preceding agent can be either an ordinary agent or a member in the platoon. The input a_{lead} in Equation (4) is the actual platoon's leader of a new platoon or the *extended* one assuming the DA joins with another preceding it.

ECT: Let d_{line,a_i}^{trg} and $d_{line,a_{lead}}^{trg}$ be the distance between the target lane and the stop line of a_i and a_{lead} respectively, $l_{plt} = \sum_{j=1}^{N-1} h_j + l_N$ be the total length of the platoon where h_j is the headway distance between the j-th vehicle's front bumper and the $(j+1)$-th vehicle's front bumper and l_N be the length of the last DA of the platoon with N size. In a respective order, the DA's and platoon's ECT are given by:

$$t_i^{EC} = t_i^{EA} + cruise\left(l_i + d_{line,a_i}^{trg}, a_i\right) \tag{5}$$

$$t_{plt}^{EC} = t_{plt}^{EA} + cruise\left(l_{plt} + d_{line,a_{lead}}^{trg}, a_{lead}\right) \tag{6}$$

Lastly, the platoon's reduction in waiting time, λ_{plt}, is given by:

$$\lambda_{plt} = t_i^{EC} - t_{plt}^{EC} \tag{7}$$

Next, we proceed to calculate the effects of a platoon in terms of increasing the waiting time for the rest of the intersection.

4.1.2 Calculating the Increase of Waiting Time. Due to the large reserved space and time-slots of the platoon, waiting time can gradually build up for multiple DAs. Here, we introduce a method to calculate the waiting time across all DAs.

By projecting the platoon's path and other DAs' paths on the intersection, the conflict points/areas between the platoon's path and the DAs' paths can be located. Assuming the platoon is crossing, other DAs have to wait for a certain amount of time until these conflict areas become unoccupied, which means more *cost* to the platoon formation. We denote these conflict areas between the platoon and the DAs by placing virtual circles with a predefined diameter (one lane's width) on these intersecting points (see Fig. 3).

Given one particular circle, we can specify two occupancy time periods generated by both the platoon and a DA. The overlap between these two time periods represents the increased waiting time

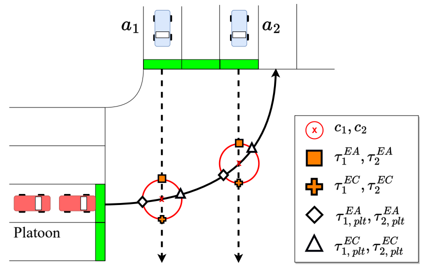

Figure 3: The example situation when the platoon's path (solid line) cuts through several DAs' paths (dashed lines); the vehicles on the left represent the platoon, while the rest are standalone DAs, and the circles represent the conflict areas between the platoon and DAs.

of this DA. However, one platoon's path usually overlaps with multiple DAs, causing an cumulative increase in waiting time across the intersection. We next explain how to calculate the increase from multiple DAs using the ETA and ECT.

Let $A_{ovp} \subset A_t$ be a set of DAs having paths that overlap with the platoon's path, $A_{ovp} = \{a_1 ... a_M\}$. Each overlapping DA is denoted as $a_m \in A_{ovp}$, while c_m denotes the circle area at the point where the platoon's path and the a_m's path overlap. Additionally, d_{line,a_i}^m and $d_{line,a_{lead}}^m$ is the distance from the edge of c_m to the stop line respect to a_i and a_{lead}. For a better understanding of terms representation, please see Fig. 3 accordingly.

Then, the DA a_m's ETA on c_m and the platoon's ETA on c_m are calculated as follows:

$$\tau_m^{EA} = t_m^{EA} + cruise\left(d_{line,a_i}^m, a_m\right) \tag{8}$$

$$\tau_{m,\,plt}^{EA} = t_{plt}^{EA} + cruise\left(d_{line,a_{lead}}^m, a_{lead}\right) \tag{9}$$

Similarly, the DA a_m's ECT on c_m and the platoon's ECT on c_m are calculated as follows:

$$\tau_m^{EC} = \tau_m^{EA} + cruise\left(2r_m + l_m, a_m\right) \tag{10}$$

$$\tau_{m,\,plt}^{EC} = \tau_{m,\,plt}^{EA} + cruise\left(2r_m + l_{plt}, a_{lead}\right) \tag{11}$$

Here, r_m is the radius of c_m, equal to half of lane's width. If a_m is a platoon, the l_m will be this platoon length. Any DA that has τ_m^{EA} (ETA on c_m's) overlapping with $\left(\tau_{m,\,plt}^{EA}, \tau_{m,\,plt}^{EC}\right)$, in other words, about to overlap with platoon's time slot. will receive some increase in waiting time, δ_m, that can be calculated as:

$$\delta_m = max(0, \tau_{m,\,plt}^{EC} - \tau_m^{EA}) \tag{12}$$

If τ_m^{EA} does not fall in this interval, δ_m will be 0 rather than a negative value. This means no extra *cost* caused by the DA a_m. Now, as a platoon's path can overlap with multiple DAs, all the DAs in A_{ovp} need to be considered and calculate the cumulative waiting time caused by the platoon, T_{plt}, which is equal to:

$$T_{plt} = \sum_{m=1}^{M} \delta_m \tag{13}$$

Consequently, having the reduction of waiting time and the cumulative increase in waiting time computed, we can calculate the *cost* efficiency of forming a platoon, β, as follows:

$$\beta = \lambda_{plt} - T_{plt} \tag{14}$$

If β is positive, the platoon will be formed. Note that β can be a negative value, representing an increase in overall waiting time. This situation usually occurs when the DA is about to join a large platoon (four to five vehicles long), causing more delays on the others, i.e. more externalities, while reducing only a fair amount of stop-and-go movements. We next explain how the DAs and platoons secure their reservations with the IMA.

4.2 The Resource Reservation Mechanism

This section introduces our reservation-based management mechanism, which supports the dynamic platoon formation approach from the previous sections. Next, we describe the DAs' and the IMA's protocols.

4.2.1 Driver Agents Protocols. The DAs in our system behave differently depending on their label, $status_i$. While the protocols of the *leader* and the standalone DAs are straightforward, *follower* DAs need to consider more parameters while crossing the intersection. As followers need to synchronise their movements as a group, the followers' speed cannot exceed the speed computed by the car-following model, maintaining the minimum gap with their preceding DAs. Therefore, the speed of any followers at time t is:

$$v_n^t = min(v_n^{t-1} + \alpha^{max}, v^{cf}) \tag{15}$$

where v^{cf} indicates the speed of the car-following model [16] used by SUMO, and $n \in \{1, \ldots, N\}$ is the position of a follower DA in a size-N platoon. With this speed computed, the follower DAs will not request a reservation with the IMA while the standalone and leader DA still have to.

Specifically, any leader or standalone DA has to execute the following operations to reserve the time-slotted space:

(1) Request information of the target lane (for path prediction), and the reservation map (i.e. previously occupied cells) from the IMA once it enters the communication range.
(2) Execute a path prediction process calculating a potential trajectory given the target lane. This process provides a path vector $p_i = \{< pos_i^{t+1}, \theta_i^{t+1} >, ..., < pos_i^{t+s}, \theta_i^{t+s} >\}$, where $t + 1$ and $t + s$ is the start and end timestamp of this path.
(3) Resolve any conflicts of p_i that may arise due to overlapped reservations by postponing its reservation time in case of conflict, utilising the reservation map in (1).
(4) Send a request message containing the required path and DA properties to the IMA and then wait for a confirmation.
    - If reject, repeat from step (1) again.
    - If confirm, begin the crossing.
(5) Notify the IMA that it has completely executed the manoeuvre and has left the intersection.

Note that, in step (3), the cell-based method that we build upon the work [35] is not designed to handle vehicles crossing as a group, which requires more space and longer time-slots. When an DA arrives as the platoon's leader, extra cells are explicitly required for the followers. These extra cells are calculated by assuming a trace that the leader leaves behind (see Fig. 4). In essence, this trace behaves as the followers covering additional space. The length of this trace (including the leader's length) is equal to l_{plt}.

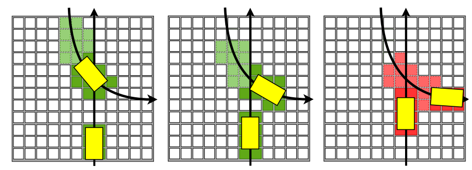

Figure 4: A example conflict between two paths where one DA is the platoon's leader that leaves its trace behind, represents occupying cells.

4.2.2 Intersection Manager Agent Protocols. Even though IMA will directly receive the conflict-free path through the request message, the IMA cannot approve the path/request immediately due to concurrency issues that occur in practice. For example, the IMA may have already accepted a request from a_i and updated the reservation map, and, later, a request message by a_{i+1} constructed with an out-of-date reservation map arrives. To ensure safety and the agents' synchronisation, the IMA must verify the validity of the requested path against the current state of the reservation map.

Specifically, the IMA cross-checks all the movements of the requesting DA against previous reservations in the reservation map. If no conflict is found, the IMA will update the reservation map accordingly and send an approval message to the requesting DA with reservation details. Otherwise, the request will be rejected; in such a case, the requesting DA has to perform the path prediction and conflict resolution again using the updated reservation map.

5 EMPIRICAL EVALUATION

This section describes how our proposed mechanism's performance is evaluated with simulation, along with the simulation setup and results. Specifically, we use the traffic simulator SUMO version 1.6.0 [15]. The client-server-based Traffic Control Interface (TraCI) [34] available in SUMO enables the coordination between the DAs and the IMA, and so both FCFS and our method can be implemented.

Based on the simulation outputs, we compare our proposed method against FCFS and fixed-time traffic signals (TFL) in terms of two average values: intersection delay and trip duration. The purpose of evaluating using these two values is to demonstrate the performance of each intersection control in different aspects. Specifically: the intersection delay expresses the performance at the level of individual intersections; whereas the trip duration reflects the performance from a higher perspective at the network or corridor level, where the whole trip through a network is considered instead. Note that, to see the change in values over time, the intersection delay results are captured in 15-minute intervals (simulation time) with a time step of 0.25 seconds.

5.1 Simulation Setup

To evaluate our method, we examined five traffic volume scenarios, from 6,000 to 14,000 veh/hr (increasing by 2,000 veh/hr). In particular, traffic volumes 6,000 - 10,000 veh/hr represent light traffic,

Table 2: The table shows the highest results of intersection delay of different intersection controls: TFL, FCFS and our platooning mechanism. The plus and minus indicate 95% confidential interval. The bottom part compares the difference in percentage, where negative and positive values indicate a decrease and increase, respectively.

Intersection delay

Methods & comparison	Traffic volumes (veh/hr)				
	6,000	8,000	10,000	12,000	14,000
TFL	17.06 ±2.56	19.19 ±1.86	23.83 ±3.91	25.35 ±2.62	38.18 ±4.72
FCFS	10.04 ±0.27	10.38 ±0.32	11.13 ±0.63	12.58 ±1.77	13.08 ±0.9
Platoon	10.1 ±0.34	10.38 ±0.53	10.89 ±0.45	11.99 ±1.04	13.25 ±1.27
TFL vs FCFS	-41.15%	-45.91%	-53.29%	-50.37%	-65.74%
TFL vs Platoon	-40.80%	-45.91%	-54.30%	-52.70%	-65.30%
FCFS vs Platoon	0.60 %	0.00 %	-2.16 %	-4.69 %	1.30%

similar to what is usually encountered in early mornings or inter-peaks. On the other hand, traffic volumes between 12,000 - 14,000 veh/hr represent heavy traffic, similar to morning and evening peak times. Each traffic volume scenario was simulated over 20 runs.

The purpose of having multiple scenarios is not only to represent traffic at different times of the day but also to demonstrate the impact of our dynamic platoon formation under different conditions. For example, in light traffic, the resource reservation mechanism alone can resolve the waiting vehicles effectively and constantly maintain a short queue. On the other hand, in heavy traffic the resource reservation mechanism can no longer maintain the short queue due to the increase in the number of vehicle arrivals. As the queue grows longer, the platoon has a higher chance of forming, but the externalities' cost of the platoon increases as well. Therefore, we can evaluate how our method performs both in simple scenarios when the externalities are relatively low and in more challenging conditions, where the externalities are substantially higher.

Note that, a similar pattern of the ground-truth demand can be achieved as the *ratio* of each route remains unchanged (see Equation 1). For example, in a 10,000 veh/hr scenario, when $Route_1$ has a ratio of 5%, the number of vehicles using this route will be 500 vehicles. We next describe our evaluating results, which are intersection delays and trip duration.

5.2 Intersection Delay Results

We measured the intersection delay through the average travel time (in seconds) on the inbound roads over eight intersections and compared our method against TFL and FCFS. It is noted that the term "travel time" refers to the amount of time that DAs need before accessing one intersection within a time interval, not the amount of time DAs need from all passing intersections within their routes, thereby it only captures the performance per intersection. Additionally, the outbound roads of one intersection can be the inbound roads of its nearby intersections.

In light traffic scenarios, FCFS and our mechanism can shorten the intersection delay by up to 53-54% compared to TFL. Likewise, FCFS and our mechanism still outperform TFL by reducing the intersection delay by up to 65% even with heavy traffic scenarios. In comparison with non-platoon mechanism, our platoon mechanism slightly outperforms FCFS in only few scenarios, decreasing the delay by 2.16% at 10,000 veh/hr and 4.69% at 12,000 veh/hr. The full results of the different mechanisms can be seen in Table 2.

However, the results here only reflect the performance at the single intersection level. We next continue to evaluate our proposed mechanism from the higher point of view.

5.3 Trip Duration Results

To evaluate our method further, we also measured the average trip duration on all vehicles. The trip duration measures (in seconds) how long vehicles take to drive from their departure to their destination, in other words, completing their designated trips. This means that the queuing delays are also accumulated as they journey through intersection(s), expressing the performance of the whole network. It should be noted that the average results here are weighted averages, as vehicles in our simulation are heterogeneous. Results are weighted using an estimation of passengers/loads according to the cost-effectiveness study in [31]. To be precise, estimated values are 20.80 passengers on buses, 1.56 on deliveries, personal & taxis, 1.186 on motorcycles, and 3.07 tons on trucks.

However, the trip duration results alone do not completely record the actual trip duration. During simulation, as the traffic volumes increase, some vehicles cannot depart according to their schedule due to unavailable space preventing them from entering the network. These vehicles are kept delayed outside of the simulation area, waiting to depart when the space becomes available. The issue is that SUMO starts capturing the trip duration only when vehicles enter the simulation, meaning that any prior departure delays are entirely ignored. According to this, the trip duration does not indicate the actual time of each journey. To cope with this issue, we consider additional output value named trip departure delay, which indicates "the time the vehicle had to wait before it could start his journey" according to SUMO manual[3]. In this way, the journey's departure delay is not overlooked.

Therefore, to fully cover all the usage time, the sum of trip duration and trip departure delay is used instead, which we refer to as "total trip duration". The weighted average of the total trip duration is shown in Table 3. It can be seen that, in light traffic scenarios, FCFS can outperform TFL by up to 20.77%, and, similarly, platooning can also outperform TFL even by up to 22.35%. On the

[3]https://sumo.dlr.de/docs/Simulation/Output/TripInfo.html

Table 3: This table shows the weighted average total trip duration results of different intersection controls: TFL, FCFS and our platooning mechanism. The plus and minus indicate 95% confidential interval. The negative values here indicate a decrease while positive values indicate an increase.

Total trip duration

Methods & comparison	Traffic volumes (veh/hr)				
	6,000	8,000	10,000	12,000	14,000
TFL	63.4 ±0.53	66.89 ±0.21	70.68 ±0.2	76.97 ±0.16	125.46 ±0.46
FCFS	51 ±0.12	52.48 ±0.12	56 ±0.16	111.2 ±1.24	154.9 ±1.08
Platoon	50.8 ±0.16	52.6 ±0.2	54.88 ±0.13	61.04 ±0.2	112.9 ±0.78
TFL vs FCFS	-19.56%	-21.54%	-20.77%	44.47%	23.47%
TFL vs Platoon	-19.87%	-21.36%	-22.35%	-20.70%	-10.01%
FCFS vs Platoon	-0.39%	0.23%	-2 %	-45.11%	-27.11%

other hand, in heavy traffic, FCFS cannot outperform TFL and even increases the total trip duration by up to 44.47%. In contrast, our platooning can reduce the total trip duration by 20.7% compared to TFL. Moreover, our proposed mechanism also outperforms the FCFS, decreasing the total trip duration by up to 2% with light traffic and by 45% with heavy traffic.

5.4 Discussion

By evaluating a range of settings, and comparing both platooning and non-platooning-based mechanisms, we gain several insights. Initially, from the intersection delay aspect, FCFS works well in many scenarios and significantly outperforms TFL. However, the trip duration results, which express the performance in a corridor aspect, show otherwise. As the traffic becomes considerably high, FCFS starts to perform poorly and cannot even outperform TFL.

In more detail, the downside of FCFS is that it prioritises the sequence of releasing DAs over the impact on the intersection as a whole. The FCFS principle always grants reservations in order of arrival regardless of whether it creates significant delay costs to the other DAs (i.e., the externalities). The amount of delay may seem relatively small and negligible as FCFS can still achieve good performance over conventional traffic lights, as shown in many studies, especially in light traffic or idealised predictable situations. However, under realistically-high traffic and more dynamic situations, the delays become more noticeable, and they negatively affect the traffic flow, as highlighted by our findings.

On the other hand, the advantage of our method lies in the core algorithm that minimises the externalities across the intersection while reducing unnecessary vehicle movements in the form of platooning. As a result, our method can significantly improve the performance from the network-level aspect and outperform both TFL and FCFS, even when traffic volumes increase. To demonstrate that the performance improvement is the results of our platoon formation, we provide the average number of platoon formed during the experiment in Table 4.

However, in the intersection-level aspect, despite our attempt to minimise the externalities caused by platoons, they still causes a slight negative effect to the intersection (see 14,000 veh/hr Table 2). Apparently, small externalities are unavoidable in exchange for forming platoons. They seem significant enough to create chain delays to the end of the queue, increasing the average travel time delays, especially in such extreme traffic. Moreover, this issue also cause a performance drop in the network-level aspect.

Table 4: This table shows the average number of platoon formed and average number of vehicles per platoon in different traffic volume scenarios.

	Traffic volumes (veh/hr)				
	6000	8000	10,000	12,000	14,000
Platoon	11.6	53.66	244.6	748.14	1105.5
Vehicles per platoon	2.06	2.09	2.23	2.41	2.47

6 CONCLUSION AND FUTURE WORK

In this paper, we presented a multi-agent intersection management algorithm with a systematic dynamic platoon formation that avoids collisions with other DAs and aims to minimise intersection delay and improve trip duration. Our empirical evaluation on a realistic microscopic traffic simulation model shows that, from the intersection perspective, FCFS and our platooning can reduce the intersection delay by up to 53-54% with light traffic and by up to 65% with heavy traffic. However, by considering the weighted average trip duration results that capture performance throughout the network, FCFS cannot even outperform TFL and actually increases the trip duration by up to 44%. While our platooning, which ensures minimal impact on the intersection in every platoon formed, can outperform the traffic lights and FCFS in any scenario. Specifically, our platooning can decrease the trip duration by up to 22% compared to TFL and by up to 45% compared to FCFS.

Future work will investigate chain delays caused by the externalities and the addition of pedestrians to intersections, which is essential for deploying autonomous intersection controls in many urban areas. We plan to optimise the platooning performance containing crosswalk phases by considering different parameters such as the estimated number of pedestrians, walking speed, and the cost of each phase. In this way, the algorithm will be more practical and able to adapt to dynamic real-world situations.

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