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A Practical Decentralized Access Protocol for Autonomous Vehicles at Isolated under-Saturated Intersections

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Abstract

The majority of research efforts in the field of access control of autonomous vehicles at intersections are geared towards fully connected vehicles. The underlying assumptions for such efforts are active vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), infrastructure-to- vehicle (I2V) communications, and/or presence of a central controller. Though efficiency is proven to be significantly enhanced, the assumptions face inherent security and privacy obstacles and require high infrastructure costs. In previous work, the authors designed and demonstrated a simpler, less costly, and more secure approach to autonomous vehicle management at intersections. The approach allows vehicles to make autonomous decisions at intersections based solely on sensing and/or beacon information with no V2V or V2I communications required. This paper extends our model to account for various vehicle classes, all possible turns at the intersection with corresponding safe turning speeds, and various intersection geometries. Compared to a fully actuated signal controller, the proposed and improved model is again proven operationally more efficient, as it reduced the average delay per vehicle by at least 21% and up to 51% for the various simulated scenarios. After 40 million seconds of simulation, the proposed model proved collision free operations.

Key words: autonomous vehicles, intersection control, decentralized, intersection access

1 Introduction

In 2014, there were approximately 6.06 million vehicle crashes in the United States leading to 32,675 traffic related deaths and 2.34 million injuries (NHTSA, 2015). In addition, the accidents accounted for more than $242 billion in damaged property. Among other contributing factors, human error is leading when it comes to the overwhelming majority (more than 90 percent) of vehicle crashes. Human error can be in the form of driver distraction, misjudgment, speeding and/or impairment (Maddox, 2012). In addition, the National Highway Traffic Safety Administration (NHTSA) states that more than 50 percent of all crashes occur at or around intersections (NHTSA, 2015). Besides the high crash rates at or near intersections, the latter are the main cause of delay and congestion in urban areas. In 2014 alone, Americans have suffered an estimated 6.9 billion hours of congestion time, 3.1 billion gallons of wasted fuel, and $160 billion in combined delay and fuel costs (Schrank, Eisele, Lomax, & Bak, 2015). With the projected increase in urbanized density, prohibitively expensive and limited right-of-way, environmental and societal constraints, and ever increasing construction costs, this burden is expected to intensify.

The recent technological advances in the vehicle industry, the global positioning system (GPS) accuracies, the wireless communication speeds, the artificial intelligence (AI) protocols, the high definition (HD) digital cameras, radar and sensing technologies have paved the way for accelerated deployment of autonomous vehicles on the road (Ozbay, Ban, & Yang, 2018). The main goal behind the rush for autonomous vehicle operations is the desperate need for improved road safety and mobility, which lead to wider benefits including lower travel costs, improved fuel efficiency and consumption, reduced air pollution and increased labor productivity (Fernandes & Nunes, 2012) (Milakis, van Arem, & van Wee, 2017). Several research groups have presented models of autonomous vehicle operations, specifically at intersections, that demonstrate drastic improvements over current operations (Olia, Razavi, Abdulhai, & Abdelgawad, 2018) and safety performance (Rios-Torres & Malikopoulos, 2016). The AI lab in the Computer Science Department at the University of Texas at Austin developed a safe and efficient multi-agent protocol and simulator that manages autonomous vehicles at intersections (Dresner & Stone, 2005). They called it the Autonomous Intersection Management (AIM). The protocol is based on a centralized controller managing the speed profiles and trajectories of autonomous vehicles approaching intersections. All vehicles are assumed to use Vehicle-to-Intersection (V2I) communications, with which they send a request to the central controller to reserve space and time to pass through the intersection. The controller uses Intersection-to-Vehicle (I2V) communications to inform the respective vehicles whether their requests were accepted or denied. Zhu et al. (2009) devised a centralized controller which evaluates the total vehicle delay given all requests, whether granted or postponed, in an attempt to minimize delay. Zohdy, Kamalanathsharmaand, and Rakha (2012) similarly presented a central management protocol and an in-house developed simulator to synchronize vehicle trajectories while maintaining safety and reducing total intersection delay. The same group also used game theory to manage vehicles, equipped with cooperative adaptive cruise control, at isolated intersections (Zohdy & Rakha, 2016) and expanded that approach to include connected automated vehicles (CAVs) (Elhenawy, Elbery, Hassan, & Rakha, 2015). Recently, Feng, Head, Khoshmagham, and Zamanipour

(2015) presented an algorithm, which adaptively allocates signal phases in real time, (and simulator) in which connected vehicles broadcast their information to the roadside infrastructure, such as a controller. The controller then uses the information to optimize phase sequence and duration to minimize total vehicle delay and queue lengths. Also, B. Yang and Monterola (2016) proposed a signal control algorithm for simple intersections with three vehicle categories: conventional vehicles, connected vehicles (those able to communicate with the central controller), and automated vehicles (whose trajectory can be fully controlled by the central controller). The proposed algorithm minimizes the total vehicle delay by finding the optimal departure sequence, and for automated vehicles, the optimal trajectory as well.

Other research teams focused on decentralizing control at the intersection, but requiring all vehicles to communicate with each other at every time step, some with various levels of automation. VanMiddlesworth, Dresner, and Stone (2008) presented a decentralized methodology assuming full vehicle-to-vehicle (V2V) communications between autonomous vehicle approaching and crossing small intersections. Also, Carlino, Boyles, and Stone (2013) devised a decentralized methodology to cross intersections based on auction strategies. The aim behind the latter protocol was to promote fairness among the different approaches to the intersection. Lu et al. (2014) also discussed a decentralized protocol relying on (V2V) to exchange information and follow predefined rules to eliminate conflicts at the intersection. Similarly, Makarem and Gillet (2012) proposed a distributed management scheme allowing for fluent coordination of connected vehicles at inter- sections. W. Wu, Zhang, Luo, and Cao (2015) presented another decentralized approach where vehicles compete to cross the intersection, by sharing their projected arrival times. Assuming full (V2V) communications, the latter approach permits simultaneous crossing of vehicles traveling on non-conflicting lanes, without optimizing a specific performance measure (Rios-Torres & Malikopoulos, 2016). X. Yang and Recker (2006) presented a simulation-based framework to study a distributed traffic information system that makes use of V2V communications. In this framework, vehicles share information with one another to allow for independent route optimization, creating a self-organizing traffic network that adapts to real-time and historical traffic information. This leads to reduced travel times, but requires full communication and a relatively high penetration rate. Alonso et al. (2011) proposed a scenario where three connected vehicles (two operated by human drivers and one autonomous) arrive at an intersection at the same time. They used this scenario to test two decision algorithms for priority conflict resolution for mixed-flow (autonomous and non-autonomous) conditions. The scenario requires no infrastructure modification or centralized controller but counts on the connected vehicles to make independent decisions. K. Yang, Guler, and Menendez (2016) proposed a decentralized intersection control scheme that requires the majority of the vehicles to be able to automatically accelerate or brake while having V2I communications. The proposed scheme assumes that the intersection sends traffic information (I2V) to all vehicles, which then make independent decisions based on the received information. However, a human's attention is still required to steer the wheel as the algorithm only controls acceleration or deceleration. Ahmane et al. (2013) proposed an approach for controlling traffic at isolated intersections in a decentralized manner without requiring autonomous vehicles or invasive changes to the vehicles. This is done by equipping vehicles with an Intelligent Transport System (ITS) station that allows them to communicate with each other. Additionally, vehicles are equipped with an on-board signalization that shows a red or green light indicating the right of way. Vehicles arriving at the intersection may go through when the on-board signalization shows a green light. While this depends on the human drivers abiding by the shown signal and speed limits, the proposed solution is more efficient than traditional traffic lights.

Additionally, multi-intersection networks have been analyzed to optimize autonomous vehicles flow using green-wave progression and assuming infrastructure-to-infrastructure communications (I2I) (Li & Wang, 2006; J. Wu, Abbas-Turki, Correia, & Moudni, 2007; Yan, Dridi, & Moudni, 2009; Perronnet, Abbas-Turki, & Moudni, 2014). Du, HomChaudhuri, and Pisu (2017) presented a scheme with multiple intersections and full communications (V2V, V2I and I2I) in which each intersection has a controller which assigns appropriate velocities to approaching vehicles. Each intersection controller solves an optimization problem to improve fuel efficiency and balancing density, while avoiding collisions. Bazzan, de Brito do Amarante, and Costa (2012) proposed an agent-based approach and compared a centralized implementation of this approach to a decentralized one with V2V communications. They find that even though a centralized approach is feasible, communication, reliability and fault-tolerance are aspects that should not be neglected (Kim, Hobeika, & Jung, 2018).

The mentioned research approaches are based on the premise of either centralized control, full V2V, V2I and/or I2V communications, as summarized in (Shladover, 2017). For such protocols to work, efficient, reliable and secure communications network needs to be in place, and is ready to safely and securely deliver such massive communications data in real time with little to no delay (Khoury & Khoury, 2014). Several technical obstacles still need to be resolved before CAVs become a reality, including the availability of a dedicated Radio Frequency (RF) for such communications. The RF spectrum should be able to withstand a wide range of contention scenarios, ranging from low to high (Khoury & Khoury, 2014). Second, the communications infrastructure must be secured to avoid inherent vulnerability to jamming and cyber-attacks and to protect user privacy (Petit & Shladover, 2015). Given the criticality of the V2V and V2I communications, system security is estimated to be the most critical item of the infrastructure (US Government Accountability Office, 2013; Petit & Shladover, 2015).

In a recent paper, we investigated a fully *decentralized* approach to manage access of autonomous vehicles through isolated intersections (Khoury & Khoury, 2014). The management scheme does not rely on V2V or V2I communications nor does it centralize control of vehicles' speeds and trajectories through an intersection manager (Khoury & Khoury, 2014). The proposed Decentralized Autonomous Intersection Access Control (DAIAC) methodology allows approaching vehicles to make their own decisions locally based on sensing information only. By doing so, the privacy concerns of V2V and V2I communications are eliminated. Additionally, the security concerns of the massive communications needed for V2V and V2I are also mitigated, as the proposed DAIAC protocol only requires securing the beacon signal (one dimension). The idea behind the access protocol was presented in Khoury and Khoury (2014), where vehicles approaching an isolated intersection sense a beacon signal that is emitted by the infrastructure. The signal is being emitted irrespective of the presence of vehicles. Based on the signal, the vehicle is able to tell whether there are other contending vehicles at or near the intersection and takes the decision to continue or give way to other vehicles

(Khoury & Khoury, 2014). A simplified scenario is tested using the DAIAC protocol and simulated using the AIM platform. The results proved zero collisions at the intersection. The results showed significant improvement in intersection operations over a fully actuated signal controller, but were less efficient than a central controller, as anticipated.

In this paper, we propose DAIAC3, which is a significant extension of the original DAIAC, yet still maintains its core spirit and advantages. Those can be summarized by the three main goals behind the research effort. The first is to allow autonomous vehicles to safely, practically and privately access an intersection. The second is to do so in a decentralized environment, where there is no need for a central controller and thus eliminates the single point of failure. The third goal is to reduce the infrastructure cost (compared to current schemes) by not relying on V2V and V2I communications (Khoury & Khoury, 2014). DAIAC3 addresses several simplifying assumptions made in the original version of DAIAC, all of which are important for practical deployment, including:

- *Only Passenger Cars*: DAIAC3 accounts for a range of vehicle classes as specified in the AASHTO *Green Book* (AASHTO, 2011)
- *No Turns*: DAIAC3 accommodates all possible vehicle turns at the intersection
- *Turn Speed*: DAIAC3 handles reduced vehicle speeds for safe left and right turns
- *One Flow Rate*: DAIAC3 allows the user to specify a different flow rate for every approach
- *One Lane per Approach*: DAIAC3 allows the user to specify different intersection geometries to model intersections between major and minor roads

The paper outline is as follows. Section 2 presents the extended intersection model given the upgraded DAIAC3 scheme. The revised algorithm as part of DAIAC3 is detailed in Section 3. Section 4 evaluates the operational results and Section 5 presents our conclusions and directions for future work.

2 Intersection and Traffic Models

For demonstration purposes, we model one major road intersecting one minor road for a total of 4 approaches, as shown in Figure 1. The eastbound and westbound approaches are major and contain 2 lanes each, while the northbound and southbound approaches are minor and contain 1 lane each. Turn percentages and allowed movements per lane are shown in Figure 1. Note that with the upgraded DAIAC3 model, various intersection geometries are easily modeled.

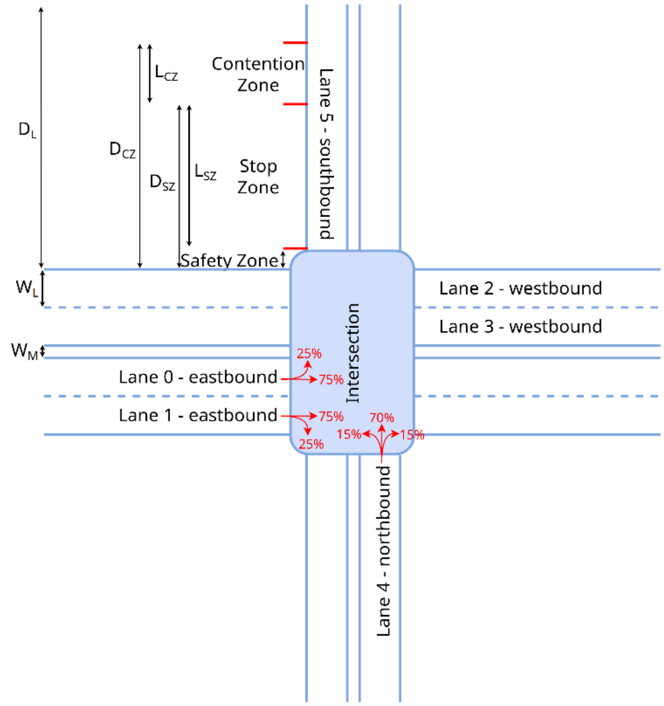

Figure 1: Intersection Model

Specific lengths D_L and widths W_L are assigned to the four approaches, to delineate the intersection environment. A median also exists between the opposing lanes of width W_M. For each lane per approach, three non-overlapping zones are delineated: a *contention zone*, a *stop zone*, and a *safety zone* (Khoury & Khoury, 2014). Each zone is defined by two parameters: its distance from intersection, and its length. For example, the *contention zone* has a distance from the intersection D_{CZ} and length L_{CZ}. The distances and lengths of the other two zones are similarly set as: D_{SZ}, L_{SZ}, $Dsafe$ and L_{safe}. Since the *safety zone* is right at the intersection, D_{safe} is equal to L_{safe}. The *safety zone* is analogous to the crosswalk space, delineated at the end of each approach to the intersection beyond the stop bar.

Vehicles approaching the intersection, while in the contention zone, determine if other vehicles are contending for use of the intersection space. Contending vehicles are able to stop safely in the stop zone if the decision was to do so. To eliminate the probability of two vehicles reaching the intersection space and not triggering contention, we sized the contention zone L_{CZ} to be the length of the longest vehicle plus the longest intersection length (the intersection length varies depending on the direction of travel, along the major or minor road). $L_{CZ} = L_{LongestVehicle} + max\,[L_{Intersection}]$. So, for the geometric scenario described in Figure 1, $L_{CZ} = L_{LongestVehicle} + 4 \times W_L + W_M$. This ensures that any two approaching vehicles on a colliding path trigger contention while at least one of them is in the contention zone. Vehicles whose decision is to stop will actually do so right before entering the *safety zone*. The logic behind the localized-decentralized decision process is briefly reiterated in Section 3 and detailed in (Khoury & Khoury, 2014). DAIAC3 scheme is based on the following practical assumptions:

- Only vehicles coming from the same approach can be in the intersection at the same time. For an approach with one lane (the minor road), vehicles following each other can be inside the intersection space at the same time (they keep following each other). For an approach with more than one lane (major road), vehicles from both lanes can be inside the intersection at the same time as their paths do not conflict (referring to Figure 1).

- Vehicles driving straight travel at a constant speed of *v* m/sec, the lane's speed limit (autonomous vehicles logically obey the speed limit). While turning, vehicles reduce their speed to the specified safe turning speed.

At the spawn instant, vehicles are assigned specific characteristics based on their selected vehicle class. Based on the U.S. national vehicle composition, given by the *Vehicle inventory and use survey* and the *Office of the Highway Policy* (US Census Bureau, 2004), three vehicle classes are used for the simulation with their percentages as follows: 91% small (passenger car), 5% medium (single-unit truck), and 4% heavy (conventional school bus) vehicles. The corresponding vehicle characteristics are based on AASHTO standards (AASHTO, 2011), as shown in Table 1 detailing realistic/design vehicle specifications such as:

- Length: the length of the vehicle, in meters.
- Width: the width of the vehicle, in meters.
- Front overhang: the distance from the front axle to the front bumper, in meters.
- Rear overhang: the distance from the rear axle to the rear bumper, in meters (the front and rear overhang lengths are used to calculate the vehicle wheelbase).
- Max steering angle: the maximum angle away from the center to which the front wheels can be turned, in radians.
- Acceleration and deceleration rates were assumed based on data averaged from U.S. urban cities, using the U.S. FTP-72 (Federal Test Procedure) cycle, also referred to as Urban Dynamometer Driving Schedule (UDDS).

Table 1: Vehicle characteristics, dynamics, and percentages

	Small	**Medium**	**Heavy**
Length (m)	5.79	9.14	12.19
Width (m)	2.13	2.44	2.44
Front overhang (m)	0.92	1.22	2.13
Rear overhang (m)	1.52	1.83	2.44
Max steering angle (radian)	0.55	0.56	0.60
Acceleration (m/s^2)	2.5	2.25	2.0
Deceleration (m/s^2)	2.5	2.5	2.5
Percent of traffic	91	5	4

The vehicle characteristics are also consistent with those used in standard traffic micro-simulation tools. To spawn vehicles, DAIAC3 generates flows proportional to the vehicle class percentages. As to the flow rate per approach lane, we modeled it as a random

Poisson process using rate parameter λ vehicles/hour/lane (vphpl). Once it is spawned, a vehicle is assigned a destination and characteristics depending on its class. The percentages of vehicles going through, right, and left from the approaches of the minor and major roads are shown in Figure 1. Different percentages are easily modeled but those were selected based on normal real-life traffic patterns. To simulate realistic vehicle operations, vehicles turning left or right have to slow down to vturn, a speed lower than vmax. Several studies focused on the speed profiles of vehicles making turns at signalized intersections (Chan, 2006; Viti, Hoogendoorn, van Zuylen, Wilmink, & van Arem, 2008). For the purpose of our study, the left turn speed is set to a maximum of 8 m/sec and to 5 m/sec for right turning vehicles (right turn radius is tighter than left turn radius) to match the preset turning speeds used by standard micro-simulation software such as SimTraffic 9.0 of the Synchro software (TrafficWare, 2018). Throughout the turning trajectory, a vehicle maintains the respective turning speed and is then allowed to accelerate back to v_{max} once its rear bumper clears the intersection. For safe car-following behavior and collision-free access to the intersection, DAIAC3 assumes vehicles to be equipped with several sensors. Those include a sensor that determines the distance to the rear bumper of the vehicle in front. Another sensor allows the autonomous vehicle to determine its location with respect to the intersection (*dist2Intesection*). Another sensor specifies the current zone that the vehicle is traversing (*inCtnZone*, *inStopZone*, *inIntersection*) (Khoury & Khoury, 2014).

DAIAC3 also assumes that the intersection infrastructure includes sensors that provide information to approaching vehicles through the emitted beacon signal. Approach lanes to the intersection are assumed to be equipped with presence sensors to detect if vehicles are present within a certain zone. While approaching the intersection, vehicles are also expected to receive the current time, the *lane ID* that the vehicle is currently in, and the per lane presence sensor values. This information will allow autonomous vehicles to detect contention. We previously presented two methods to expose the information to all vehicles. The first approach relies on visually exposing this information (potentially to the side of the road) where vehicles detect it in real time using HD video/image processing (Gavrila, Franke, Wohler, & Gorzig, 2001; Chen, Yang, Zhang, & Waibel, 2004; W. Wu, Chen, & Yang, 2005; Ellahyani, Ansari, & Jaafari, 2016). Vehicles use the GPS to synchronize their clocks. This approach is consistent with our proposed decentralized and minimal communication scheme. Yet, the preferred approach depends on sensing a beacon signal rather than counting on image processing, which might pose issues related to processing speed or during inclement weather conditions. At every time step, the intersection infrastructure is expected to send a beacon signal to all vehicles within the defined zones, using short range I2V communication. Vehicles use the beacon messages to synchronize their clocks, using common wireless network techniques described in the 802.11 standard (IEEE Computer Society, 2012). It is crucial that approaching vehicles synchronize their clocks so that they take the right decision at every time step, as it is highlighted in Section 3. Note that the intersection infrastructure does not need to centrally store or process any vehicle information for future computations, which makes it more practical and resilient to hacking/failures, compared to centralized controllers.

3 DAIAC Algorithms

Given the intersection environment described in Section 2, autonomous vehicles are able to locally decide on the next action without V2V or V2I communications using DAIAC3 algorithms. Three main algorithms control a vehicle's travel behavior as it traverses the predefined zones and crosses the intersection. Recall from Khoury and Khoury (2014) that the infrastructure sends beacon messages to the vehicles every time step comprising: a time-stamp now indicating the current time, the index (*id*) of the current lane *lane_id*, the zone presence information per lane where $presence_S[lane\_id]$ indicating whether vehicles are present within the stop zone of the lane indexed by *lane_id*, similarly, $presence_C[lane\_id]$ indicates whether vehicles are present within the contention zone of *lane_id*, a configured *green* duration indicating the duration of a green interval, and similarly *all_red* duration indicating the duration of the *all-red* interval.

Algorithm I allows each vehicle to locally compute a signal phase simulating a signal with two phases: a *GREEN* phase for a fixed duration of *green* sec (while assigning red to other lanes), and a *RED* phase assigns a red signal to all lanes for a duration of *all_red* seconds (to clear the intersection). Note that all vehicles synchronize their clocks as they enter the contention zone, making the signal consistent among all approaching vehicles. The computed signal is used by Algorithm III to determine whether to stop or proceed, while the vehicles are traversing the stop zone. If the computed signal is visibly exposed by the infrastructure to all vehicles, then the case of mixed operations, autonomous and traditional driver-based vehicles, can be accommodated through the intersection. A flowchart of Algorithm I is shown in Figure 2. Algorithm II, detailed in Khoury and Khoury (2014) and shown in Figure 3, allows only vehicles in the contention zone to check if other vehicles are present in the contention or stop zones of other lanes, using $presence_C[lane\_id]$ and $presence_S[lane\_id]$ to declare contention or not. Algorithms I and II are maintained from Khoury and Khoury (2014).

Algorithm III, which is the core of DAIAC3, uses the output of the previous two algorithms to safely decide whether to stop or cross the intersection at a safe speed, if the vehicle is to make a turn. Algorithm III was completely upgraded to accommodate DAIAC3 realistic improvements. Algorithm III is locally executed by every vehicle at every time step allowing the vehicle to respond to the current situation. If a vehicle applies the brakes within the stop zone, *slowedDownBeforeIntersection* returns true. If the vehicle needs to make a turn to reach its destination (assigned when it was spawned), *SLOWFORTURNS()* of Algorithm III determines if and when it should slow down prior to reaching the intersection to reach a safe turning speed, described in Section 2. Flowcharts of the two main subroutines comprising Algorithm III are shown in Figures 4 and 5.

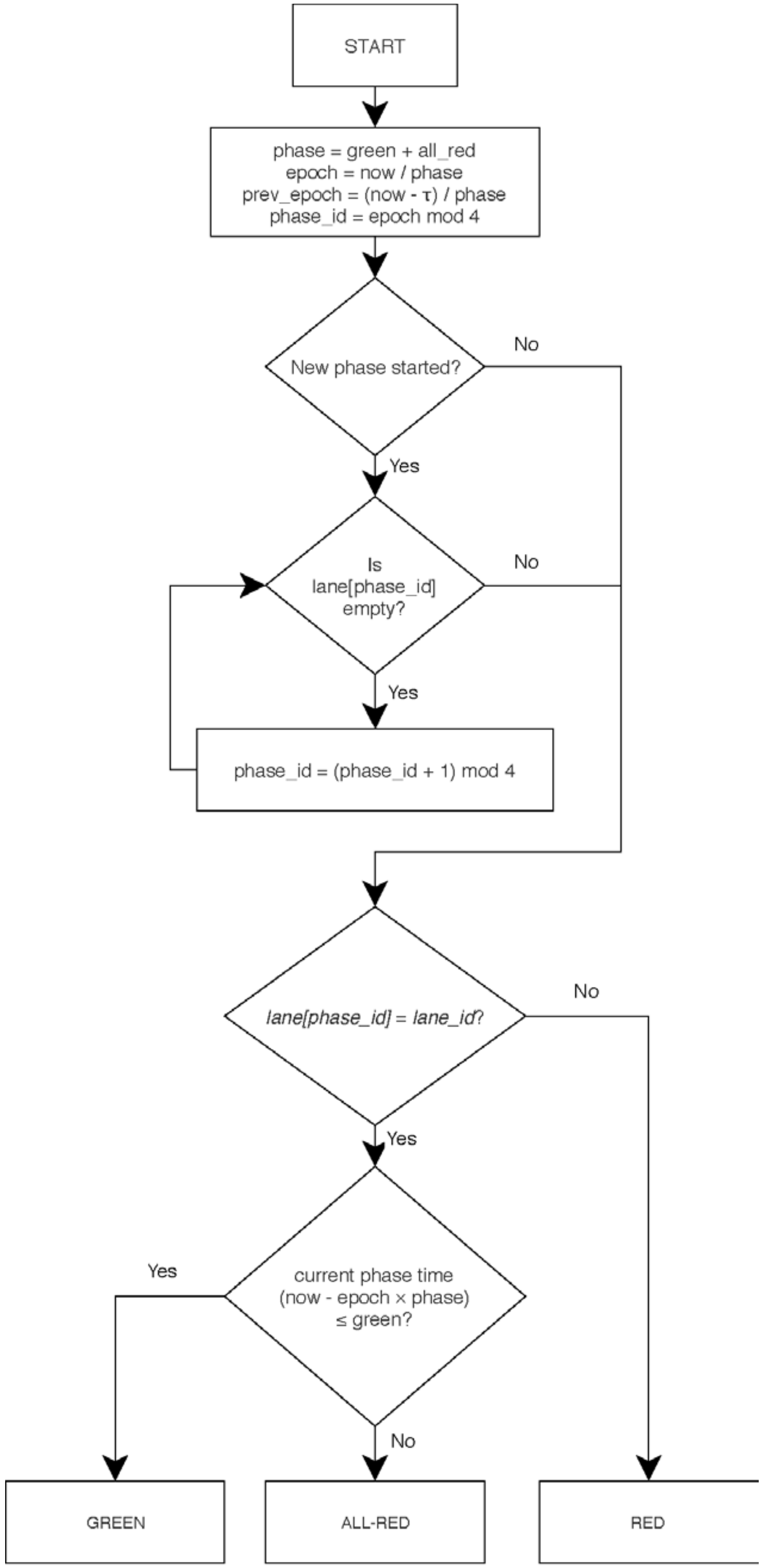

Figure 2: Algorithm I: algorithm executed by a vehicle for simulating an actuated signal

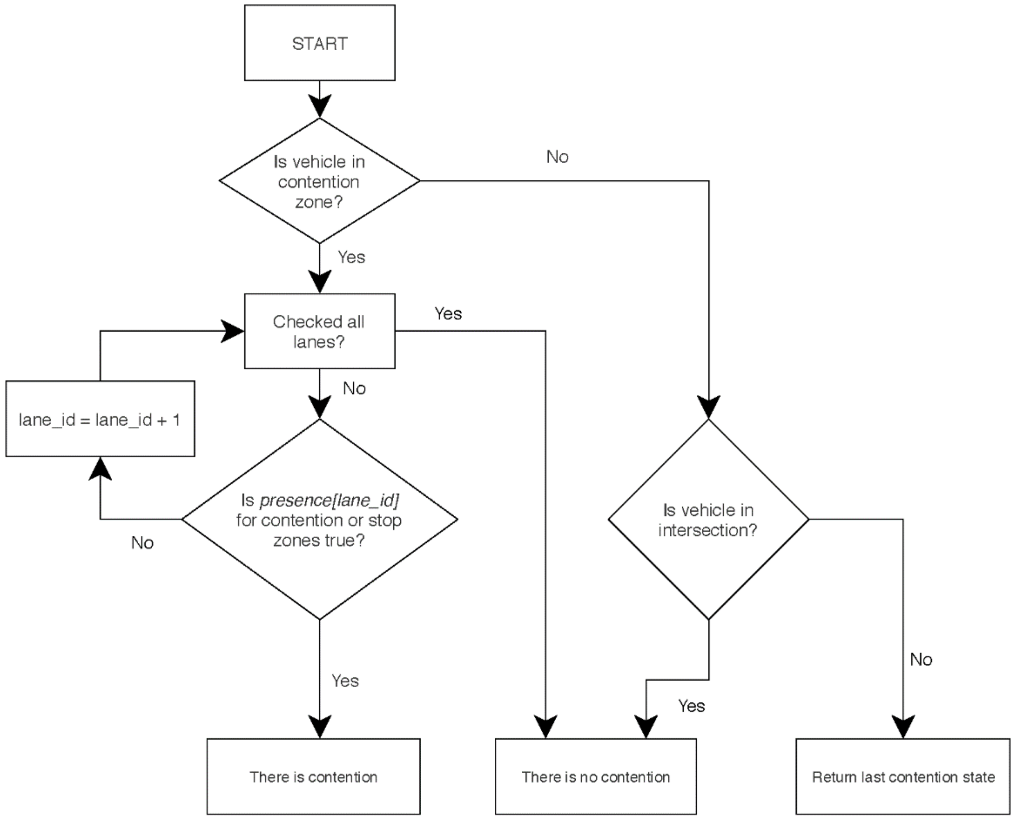

Figure 3: Algorithm II: algorithm executed by vehicle to determine whether there is contention

4 Evaluation

The open source AIM simulator presented in (Dresner & Stone, 2005) was used as the platform to run the DAIAC3 algorithms. However, we have significantly extended and revised AIM to support decentralized operations with real-life vehicle characteristics and movements, including vehicle classes, dimensions, dynamics, and performance. The revised simulator was used to assess one main performance measure to evaluate the efficiency of DAIAC3 versus a fully actuated signal controller. The main measure is the average vehicle delay in seconds (as specified by the Highway Capacity Manual (HCM) (TRB, 2010)). To compare the performance of DAIAC3, we modelled a matching intersection setup using SimTraffic 9.0 of the Synchro software (TrafficWare, 2018). All input parameters (e.g. vehicle dimensions, percentages, acceleration, deceleration, lane length and width, turning percentages, turning speeds, phasing times/cycles, etc.) matched the values used in DAIAC3, as presented in this paper. The delay of a specific vehicle is defined as the difference between the actual time it takes the vehicle to cross the intersection under prevailing conditions and the hypothetical free-flow time it would have taken the vehicle without the presence of the intersection (i.e. does not slow down). The sum of the individual delays divided by the total number of vehicles served through the intersection is then the average vehicle delay.

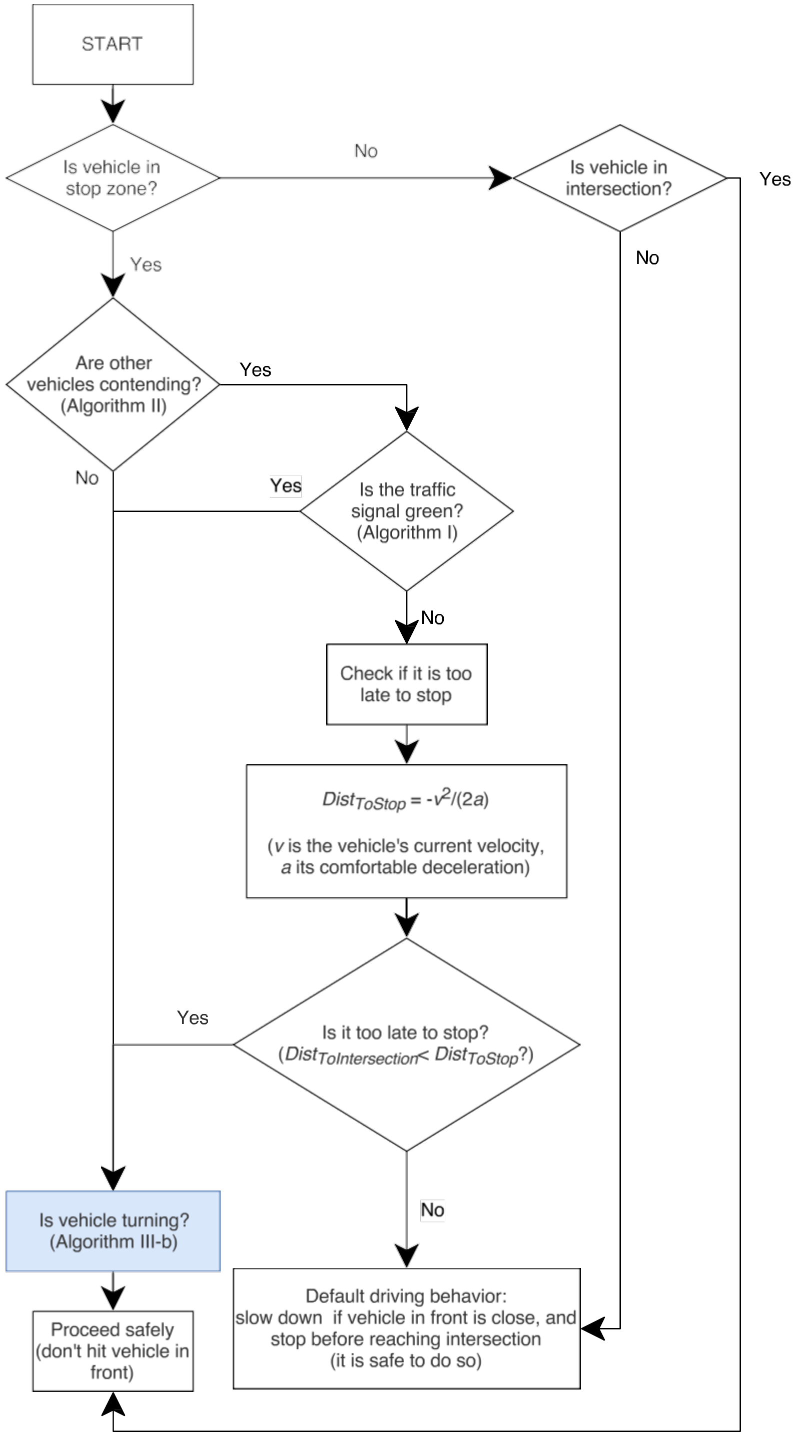

Figure 4: Algorithm III-a: safe distributed decision process

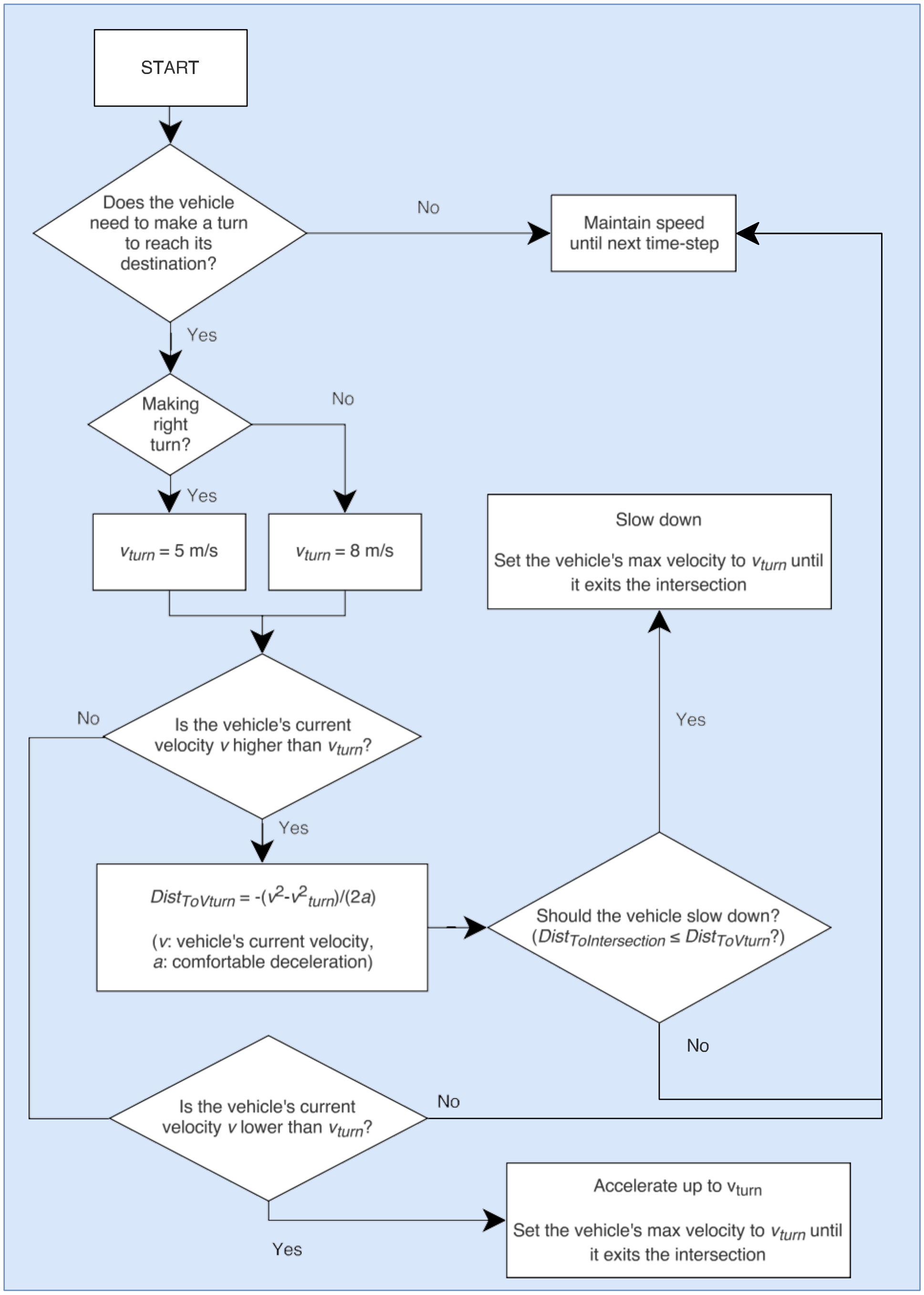

Figure 5: Algorithm III-b: safe turn protocol

A sketch of our extended AIM simulator in action is shown in Figure 6.

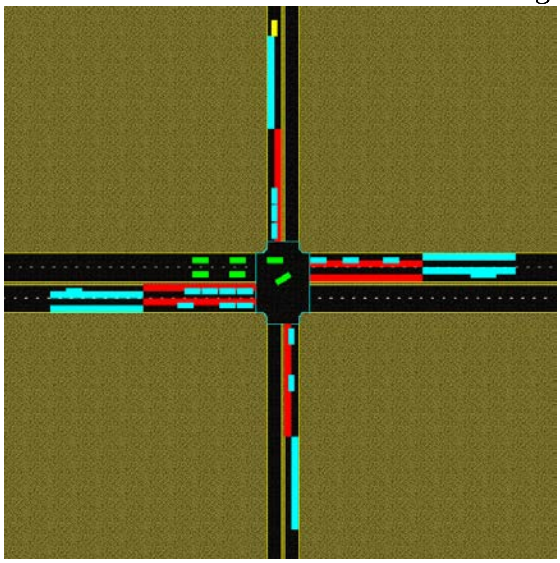

Figure 6: Simulator Snapshot: vehicles in yellow are approaching the intersection; vehicles in green have been served; vehicles in cyan are contending; during contention, the stop zone color is either Green or Red depending on the computed signal; the contention zone is colored cyan when any of the approaching vehicles is contending.

The following parameters were fixed during the simulation:

1. The time step $\tau = 0.02$ sec
2. $D_{CZ} = 77$ m, $L_{CZ} = 33$ m, $D_{SZ} = 44$ m, $L_{SZ} = 40$ m, $D_{safe} = 4$ m, $L_{safe} = 4$ m, $W_L = 5$ m, $W_M = 1$
3. The lane speed limit is $v_{max} = 10$ m/sec
4. The *all_red* safety phase was set to 4.58 sec
5. The *green* duration is taken as 5 or 10 seconds depending on traffic flow

For higher demands per lane, queues are expected to form. Thus, the green time was increased when the demands increased to allow for efficient queue dissipation. The *all_red* phase time was calculated to be 4.58 seconds to account for the worst case scenario. We describe this worst case scenario and how the *all_red* time was derived in detail here, given that it is key to avoiding collisions. Analyzing all possible intersection access scenarios, the worst case is found to be when a heavy vehicle that is approaching the intersection at a velocity v_{heavy}, just passes the point-of-decision (POD) within the stop zone while having green signal. Right then, the signal turns red for this approach, meaning that the heavy vehicle should stop. We define the POD as the point at which any vehicle will have to decide to stop or continue at constant speed, when contention is declared. It is located at a known distance from the *safety zone* (given that we assumed constant comfortable deceleration rate to allow for safe stopping). Once a vehicle passes the POD, the vehicle is bound to continue irrespective of the signal indication. This is consistent with current vehicle operations through intersection dilemma zones. Vehicles deciding to stop will only start braking at the POD to minimize vehicle delay. Vehicle delay increases when vehicles are driving below the speed limit, v_{max}. Since the heavy vehicle passed the POD, it will not be able to stop in time before entering the *safety zone*, and is thus bound to continue. The *all_red* phase needs to clear the intersection of this heavy vehicle before switching green for another approach. The heavy vehicle in this scenario is turning left (longer trajectory within the intersection). At the same time, there is a small vehicle, which usually has the highest acceleration rate, waiting at the stop bar of the next clockwise-conflicting approach (shortest distance to the turning path of the heavy vehicle refer to schematic shown in Figure 7).

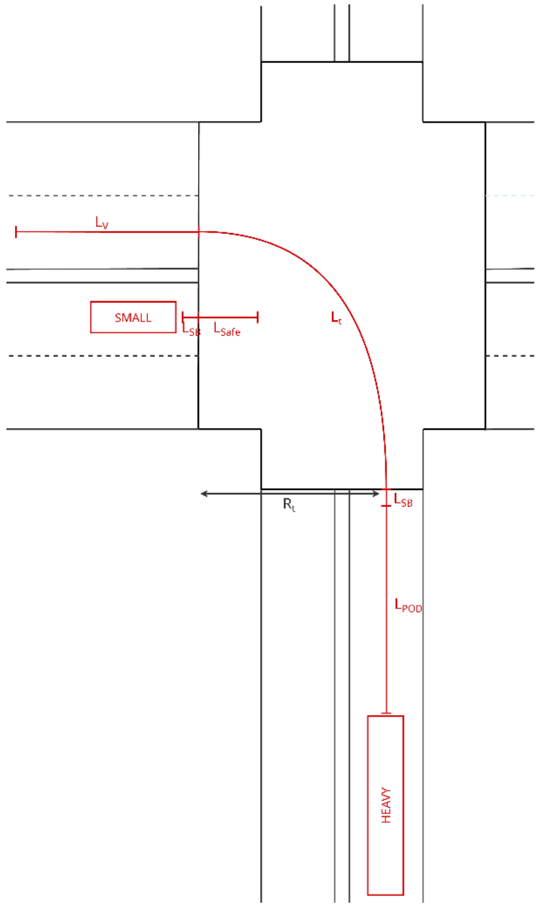

Figure 7: Sketch of worst case scenario to clear intersection

Two time values are computed: (1) time that the small vehicle needs to enter the intersection after accelerating from stop; and (2) time that the heavy vehicle needs to clear the intersection from the *POD*. A vehicle clears the intersection when the rear bumper clears the intersection space, to account for the vehicle length. The time difference between the two is the *all_red* needed to clear the intersection space without collision. We define the following new parameters (all others are defined earlier):

- R_t : the radius of the left turn that the heavy vehicle will make,

- L_t: the arc-length of the left turn,
- L_{SB}: the length of the stop bar zone (all vehicles bound to stop will do so before this zone), and
- L_{POD}: the length from the *POD* to the stop bar zone.

We consider three sub-cases. Note that, in all three cases, once the vehicle clears the intersection, it will accelerate again until it reaches v_{max}.

1. If initial v_{heavy} is greater than v_{turn}, the vehicle keeps going for the longest distance possible and only decelerates for the exact amount of distance required to go from v_{heavy} to v_{turn} before reaching the turning point inside the intersection.
2. If v_{heavy} is equal to v_{turn}, the vehicle keeps going at the same speed.
3. If v_{heavy} is less than v_{turn}, the vehicle will accelerate until it reaches v_{turn}.

Knowing constant-comfortable acceleration and deceleration rates apply, the time necessary for the small vehicle to reach the intersection is calculated as follows:

$$Time_{SmallToIntersection} = \sqrt{2 \times \frac{L_{Safe} + L_{SB}}{a_{small}}}$$

The time needed for the heavy vehicle to traverse the intersection can be described under Case 1 or Case 3 above (Case 2 where $v_{heavy} = v_{turn}$ is a boundary condition (applies to the two other cases) as the heavy vehicle does not need to adjust its speed to complete the turn). Common equations that apply to all cases include:

$$R_t = 2 \times W_L + W_L \times 0.5 + W_M + L_{safe} \tag{1}$$

$$L_t = R_t \times \frac{\pi}{2} \tag{2}$$

$$L_{POD} = \frac{v_{heavy}^2}{2 \times d} \tag{3}$$

$$Time_{ToVturn} = \frac{Dist_{ToVturn}}{\langle v_{turn} + v_{heavy} \rangle} \tag{4}$$

$$Dist_{ToVmax} = \frac{v_{max}^2 - v_{turn}^2}{2 \times a_{heavy}} \tag{5}$$

$$Time_{ToVmax} = \frac{Dist_{ToVmax}}{\langle v_{max} + v_{turn} \rangle} \tag{6}$$

$$Dist_{AtVmax} = L_v - Dist_{ToVmax} \tag{7}$$

$$Time_{AtVmax} = \frac{Dist_{ToVmax}}{v_{max}} \tag{8}$$

The equations that apply to Case 1 where, $v_{heavy} > v_{turn}$:

$$Dist_{ToVturn} = \frac{v_{turn}^2 - v_{heavy}^2}{2 \times d_{heavy}} \tag{9}$$

$$Dist_{AtVheavy} = L_{POD} + L_{SB} - Dist_{ToVturn} \tag{10}$$

$$Time_{AtVheavy} = \frac{Dist_{AtVheavy}}{v_{heavy}} \tag{11}$$

$$Dist_{AtVturn} = L_t \tag{12}$$

$$Time_{AtVturn} = \frac{Dist_{AtVturn}}{v_{turn}} \tag{13}$$

$$\begin{aligned} all\_red = {} & Time_{AtVheavy} + Time_{ToVturn} + Time_{AtVturn} \\ & + Time_{ToVmax} + Time_{AtVmax} \\ & - Time_{SmallToIntersection} \end{aligned} \tag{14}$$

The equations that apply to Cases 2 and 3 where, $v_{heavy} \leq v_{turn}$:

$$Dist_{ToVturn} = \frac{v_{turn}^2 - v_{heavy}^2}{2 \times a_{heavy}} \tag{15}$$

$$Dist_{AtVturn} = L_t + L_{POD} + L_{SB} - Dist_{ToVturn} \tag{16}$$

$$Time_{AtVturn} = \frac{Dist_{AtVturn}}{v_{turn}} \tag{17}$$

$$\begin{aligned} all_{red} = {} & Time_{ToVturn} + Time_{AtVturn} + Time_{ToVmax} \\ & + Time_{AtVmax} - Time_{SmallToIntersection} \end{aligned} \tag{18}$$

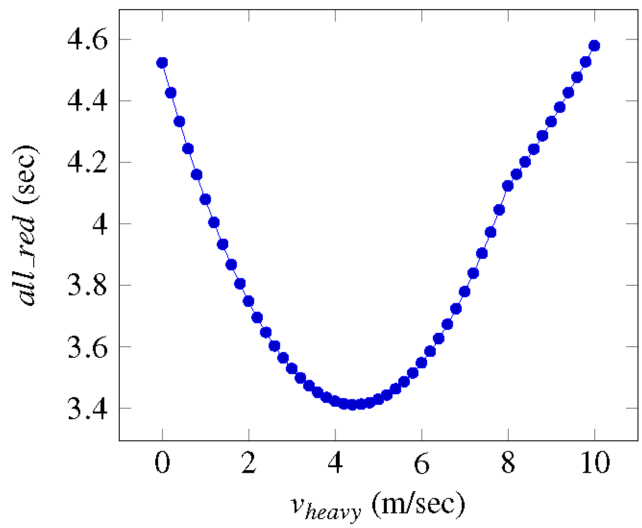

Figure 8: Plot of *all_red* times corresponding to different heavy vehicle speeds at the *POD*

Using equations (14) or (18), we calculate the necessary *all_red* time that ensures collision-free access. We do so for all possible values of v_{heavy} between 0 and v_{max} (accounts for all three cases). Note that Case 2, ($v_{heavy} = v_{turn}$), connects the linear line (Case 1) to the hyperbolic curve (Case 3), as shown in Figure 8. The maximum *all_red* time needed to clear the intersection for the worst case is found to be 4.58 seconds for $v_{heavy} = v_{max}$ = 10 m/sec.

Table 2 compares the traffic operations results of the proposed DAIAC3 protocol versus those of a fully actuated signal controller. Demand increments of 50 vehicles per hour per lane (vphpl) were simulated starting at 50 and ending at 300, as shown in the table. The average delay per vehicle (seconds per vehicle) crossing the intersection is adopted as the main performance measure for comparison.

Table 2: Average vehicle delay (sec) comparison of DAIAC3 versus fully actuated signal

Flow (vph)		**Signal**	**DAIAC3**	**% Reduction**
Low to Medium (Green = 5)	50	13.0	3.8	70.8
	100	18.7	9.7	48.1
	150	25.7	16.1	37.4
High (Green = 10)	200	31.8	26.5	16.7
	250	58.7	40.3	31.3
	300	195.8	131.6	32.8

An intersection with the same geometry controlled by a fully actuated signal is simulated using the well-known market software, SimTraffic 9.0 of the Synchro Software (TrafficWare, 2018), as shown in Figure 9. Multiple replications of the models (both Synchro and DAIAC3) were created and averaged to account for the randomness in Poisson arrivals. Parameters used in the DAIAC3 and Synchro simulators are consistent. Those parameters include geometric characteristics of the intersection, approach length and lane width, vehicle dimensions, percentages, acceleration, deceleration, turning percentages, turning speeds, phasing times/cycles. The comparison differentiates between operations under low to medium traffic flows (approach demands less than 200 vphpl, using *green* = 5) and operations at higher demands (higher than 200 vphpl, using *green* = 10). Note that a traffic flow of 300 vphpl means a total of 1800 vph going through the intersection given the intersection layout shown in Figure 1. For demands between 50 and 150 vphpl, the DAIAC3 scheme shows, on average, a reduction of 51% in average vehicle delay compared to the fully actuated signal controller. As for the higher approach demands (between 200 and 300 vphpl, using green = 10), the DAIAC3 scheme shows an average reduction of 27% in vehicle delay compared to the fully actuated signal. Note the high delay per vehicle as the approach demands reach 300 vphpl, as shown in the last row of Table 2. For the latter scenario, the demands obviously exceeded the capacity of the intersection (given the modelled geometry and assigned *green* = 10 per phase). Long queues were observed in both the DAIAC3 and SimTraffic simulation models. We used the HCM methodology to calculate the cycle length that minimizes the average vehicle delay for optimal operations. We did that using Synchro 9.0 and reran the SimTraffic model to get a reduced average delay of 69.4 sec/veh. The optimized cycle length for the 300 vphpl demand flows was found to be 100 sec (i.e. using *green* = 20).

The average delay per vehicle was then reduced, given the optimized green, from 195.8 to 69.4 seconds, which represents great improvement in intersection operations. This is logical, since more green time is needed per approach to allow for the long queues to dissipate. Consequently, we implemented this optimized cycle information into the DAIAC3 model. The resulting average delay was found to be 54.7 seconds (a big reduction from 131.6 seconds, shown in Table 2). Again, DAIAC3 outperformed even an optimized signal controller by more than 21%. We might be able to further optimize DAIAC3 by incorporating variable green times based on demands to optimize intersection operations; however, this might prove challenging while keeping the system decentralized and mostly passive (no information stored at the controller or infrastructure).

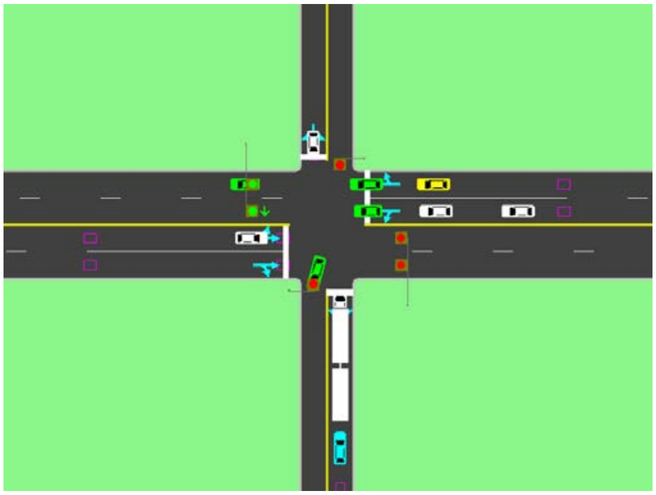

Figure 9: Snapshot of SimTraffic model simulating a fully actuated signal

Finally, different demand volumes per approach were simulated using the upgraded DAIAC3 scheme. The eastbound, westbound, southbound and northbound demand volumes were arbitrarily set to 120, 150, 100, and 80 vphpl, respectively. The latter scenario was replicated using a fully actuated signal controller modelled using SimTraffic 9.0. Consistently, DAIAC3 provided more than 38% reduction in average vehicle delay (12.5 sec/veh versus 20.3 sec/veh for a fully actuated Signal).

5 Conclusion and Future Work

A different perspective to managing access of autonomous vehicles at isolated under-saturated intersections is presented. The approach is mainly decentralized, where vehicles make decisions locally with little information. The model has been simulated for more than 40 million seconds and proved collision free; also validated through the analytical derivation presented in Section 4. An operational analysis comparing the DAIAC3 scheme to a fully actuated signal controller proved that DAIAC3 clearly outperforms the controller in terms of average vehicle delay through the intersection. Results show that the average delay using the DAIAC3 scheme is at least 35% lower than a fully actuated signal operation. The results showed consistently better operations using DAIAC3 for all tested traffic demands per approach.

The proposed DAIAC3 scheme is operationally better than current signal controllers. The main advantages of DAIAC3 are inherent in addressing the three main research goals. The first is to allow autonomous vehicles to safely, practically and securely access an intersection. The second is to do so in a decentralized environment without the need for a central controller, which eliminates the single point of failure. The third goal is to reduce the infrastructure layers by not relying on V2V and V2I communications.

A practical, feasible and fully decentralized access protocol is presented in this paper. Future work will include expanding DAIAC3 capabilities to account for the following scenarios: inclement weather conditions and the associated impacts on the vehicles' speed profiles, accommodating emergency vehicle priority treatments and accident response and management, higher fidelity vehicle dynamics using variable power/acceleration/deceleration models, access through multiple intersections in a corridor or grid system, and various levels of vehicle automation including human operated vehicles.

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