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COORDINATION OF CONNECTED AND AUTOMATED TRUCKS FOR PLATOONING CONSIDERING TURNING ALONG AN ARTERIAL CORRIDOR

Final Report

by

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DISCLAIMER

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EXCUTIVE SUMMARY

Freight traffic affects the performance of the road network in a sensitive and significant way. When it's significant in proportion, the coordination of signals could fail according to the research of FMRI's first-year project. Trucks need extra distance and time for deceleration and acceleration. A traffic bottleneck appears more easily on a road segment or intersection where freight traffic is significant. To address these problems, strategies have been developed in the FMRI first and the second-year project to formulate multiple trucks' trajectories to pass consecutive signals individually and cooperatively considering mixed traffic conditions. The stability problem of vehicle streams has been studied in the third-year project. In an urban arterial corridor, turnings could happen frequently, which is different from that on a highway. Considering the turning vehicles that join into the corridor from either a midblock or intersection in this problem is the main concern of this year's project.

On an arterial corridor, when freight traffic is significant, a truck-only lane is assigned. This project investigates the method for truck platooning on the truck-only lane allowing the turnings. Ensuring a safe turning maneuver when truck platooning is on the corridor has led to a coordination problem for vehicle maneuvers. Current methods for coordinating CAVs at intersections do not consider the signals in urban intersections and the truck platoon in a truck-only lane. This research model the maneuvers of CAVs as time-discrete events and provide an analytical solution that scheduling time of CAV trucks to pass an intersection or join into the platoon in the corridor given their sequences. The objective is to ensure the safe maneuvers of all CAVs.

The project focuses on the planning and coordination of vehicles on corridors, which is a critical area of research for connected and automated vehicles, especially when turning movements from side streets are permitted. The challenge in involving signals is that the relationship between signal status and the initial sequences of vehicles can lead to various planning scenarios. To address this challenge, this project proposes a model that analyzes and optimizes the sequences and time instances of vehicle passage at signalized intersections, to minimize total travel time. The model also considers the duration of signals as a variable and analyzes signal control strategies such as red truncation and green extension. The results show the effectiveness of the proposed method in minimizing total travel time by providing optimal final sequences and arrival times, irrespective of the sequence and initial appearing time of vehicles. Moreover, the model is with an option to determine the red truncation and green extension, resulting in travel time savings ranging from 8.77% to 20.69%. Besides, the method can also define suitable speed control for side street vehicles, leading to travel time savings ranging from 8.85% to 11.86%. Overall, this work provides a valuable contribution to the planning strategies for connected and automated vehicles at signalized intersections.

1. INTRODUCTION

In the last decades, Connected and Automated Vehicles (CAVs) have been an important subject of research for their potential to provide safer and more eco-friendly travel in urban areas. Due to that the majority of application scenarios of CAVs are located in urban streets, one area of investigation has been the longitudinal control of CAVs and the planning of CAV trajectories along the network with traffic signals. The coordination of CAVs has become a hot topic, supported by the technology of Vehicle-to-Vehicle (V2V) communication, Vehicle-to-Infrastructure (V2I) communication, and other relative technologies.

Several studies have investigated CAV coordination. For instance, (Zhu and Ukkusuri, 2015) studied a linear programming formulation for autonomous intersection control while (Wu et al., 2019) developed an autonomous intersection management (AIM) to model the sequential movements of CAVs without a signal at a decentralized coordination using multi-agent learning method. A multi-agent artificial intelligence -based algorithm was developed for CAV coordination at an intersection (Dresner and Stone, 2008). A comprehensive survey by (Rios-Torres and Malikopoulos, 2016) reviewed various approaches to coordinate CAVs at intersections, on-ramps. The methods include both centralized and decentralized techniques, using either heuristic rules or optimization and control algorithms to minimize travel time, fuel consumption, or other metrics. According to a comprehensive survey by (Gholamhosseinian and Seitz, 2022), various strategies for cooperative intersection management has been reviewed including reservation-based approaches, auction-based approaches, and decentralized approaches. Coordination at both signal and non-signal is studied considering a fully cooperative intersection management (CIM) that contributes to both traffic safety and efficiency (Chen and Englund, 2015). The way to model interaction include space and time discretization and trajectory Modeling.

The issue of CAVs making turns at signalized intersections remains a problem since when turning movements from side streets are permitted, the involvement of signals, together with the relationship between signal status and the initial sequences of vehicles can lead to various planning scenarios. Developing a unique model to analyze this issue is a significant step in understanding of coordinating CAVs, which is the first contribution of this work. In response to this challenge, this work presents an optimization model that provides descriptive analytics, which is another notable contribution.

Centralized methods, such as (Li and Wang, 2006) have investigated the coordination and planning of vehicles at blind crossings by representing vehicle sequences as spanning trees. (Yan et al., 2009) proposed a dynamic programming algorithm to authorize vehicles with precise time instances to cross intersections by applying V2V information to minimize the time of evacuating time of CAVs while optimizing vehicle passing order. (Zohdy et al., 2012) used a Cooperative Adaptive Cruise Control based method to manage vehicles to avoid collisions and minimize intersection delay. Similarly, (Jin et al., 2012) studied the multi-agent intersection management system (MAS) for CAVs by optimizing the departure sequence at an intersection and reducing the number of stops and travel time significantly compared to the traditional FIFO (first-in-first-out) approach. Other concerns, such as minimizing vehicle overlap, have also been addressed in several studies (Lee et al., 2013; Lee and Park, 2012). Some researchers have also focused on controlling actual trajectories to ensure that vehicles stick to planned ones, including (de Campos et al., 2013; Kamal et al., 2013; Hafner et al., 2013; Dai et al., 2016).

In contrast, some decentralized methods have been applied to coordinate vehicles at intersections, such as the virtual vehicle for vehicle merging control proposed by (Uno et al., 1999). The concept has been in modeling CAVs merging, including (Lu et al., 2000; Lu and Hedrick, 2003; Lu et al., 2004; Chen et al., 2021). The coordination of CAVs based on fuzzy logic was also studied by (Milanés et al., 2009, 2011) and a critical set was used to avoid collision in the planning and control (Hafner et al., 2011, 2013).

Many previous studies in the field of intersection coordination have considered both signal and non-signal. However, most of the studies focused on the optimization of signal itself. For instance, (Miculescu and Karaman, 2019) used a coordination control method with an event-triggered algorithm to plan vehicles at an intersection, assuming stochastic arrival times with no traffic signals. (Kumaravel et al., 2021) used a two-level optimization to coordinate CAV platoons at a signal-free intersection, which overcome the baseline of n first-come-first serve and longest queue first rule. (Lee and Park, 2012) proposed a Cooperative Vehicle Intersection Control (CVIC) system that enabled traffic composed of fully automated vehicles without signals, including system failure cases. (Chen et al., 2022) developed a reservation-based method using rapid check criterion to ensure a conflict-free time slots for CAVs at a non-signalized intersection.

Another way to categorize coordination or planning methods for CAVs is to divide them into reservation-based methods and optimization-based methods. Reservation-based methods use a reservation system to allocate time slots for vehicles to pass through intersections. Vehicles submit a request and the system approves the request if there is no conflicts (Bian et al., 2019). Optimization-based methods use optimization to minimize travel time, fuel consumption, or emissions for vehicles while avoiding collisions (Lee and Park, 2012). These methods should account for all constraints, such as vehicle dynamics and signal logic.

The planning strategy for coordinating CAVs at signalized intersections is a complex task due to the need to consider both the relationship between vehicles and the logic of signals, as stated before in the publications (Xiao et al., 2021, 2023). Moreover, the vast number of potential scenarios makes it infeasible to model all possible combinations. Additionally, incorporating common operations such as a signal or speed control further complicates the optimization model.

This work aims to address these challenges by proposing a model that optimizes the sequences and timing of vehicle movements at intersections with turning movements to minimize total travel time while considering signals. Furthermore, the study seeks to analyze speed control and signal control strategies, such as red truncation and green extension, and their impact on the model. The primary objectives or motivations are: first, to develop a model to minimize total travel time considering signals by describing the sequences and timing of vehicles passing through with turning movements; and second, to analyze speed control or signal control strategies such as red truncation and green extension, with the signal duration as a variable in the model.

2. METHODOLOGY

2.1 PROBLEM STATEMENT AND MATHEMATICAL REPRESENTATION

The focus is the planning problem of connected and automated vehicles (CAVs) at signalized intersections when the vehicles can turn from side streets into the mainstream. The primary objective of the study is to optimize the sequence and timing of vehicle movements through the intersection to minimize the total travel time.

To achieve this objective, a mathematical expression that utilizes mixed integer programming has been proposed. The model considers the objective of minimizing the total travel time for all vehicles that pass through the intersection. The constraints are divided into two categories: reachability constraints and conditional constraints. The reachability constraints ensure that each vehicle can pass through the intersection. The conditional constraints consider the relative positions of the vehicles and the possible passing movements at a signal.

The model has considered speed and signal duration as variables in its variant or extension. To address the conditional constraints, we have employed big-M method to convert these constraints into regulatory constraints, which are easier to understand mathematically and can be handled in optimization software.

The intersection considered in this work involves vehicles approaching from two directions. Specifically, the vehicles on a West-East street move in a longitudinal direction from West to East, while the vehicles on the side street move from South to North to make a right turn. Vehicles that make a right turn from the side street can pass the intersection while the main street has a red signal. They can also turn while the main street has a green signal only if there is enough gap. To provide a clear and concise understanding of the scenario, the study lists a set of assumptions. Firstly, V2V communication is assumed to be active as soon as a vehicle enters the intersection area. Secondly, CAVs can receive timing information, such as the expected starting time of red, the duration of red, and cycle length, without delay. Thirdly, the vehicles from the same direction will maintain their initial sequences throughout the whole process. Fourthly, the lane-changing and overtaking behavior of a vehicle are not considered in the scope of concerns. Therefore, the baseline case follows the rule of first-in-first-out (FIFO) rule at this intersection.

2.2 MODELING USING MIXED INTEGER PROGRAMMING

Denote vehicles from the main street as $i, i+1, \dots, i+n$ and denote vehicles from the main street as $j, j+1, \dots, j+m$, the objective is to minimize the total travel time for all vehicles:

$$min \sum_{i \in I} T_i + \sum_{j \in J} T_j \quad (1)$$

Where i is the index of vehicles from main street and j from side street. T shows the total travel time for a vehicle. The constraints are divided into three categories: (i) individual vehicle reachability constraints, (ii) vehicle sequence conditional constraints.

Individual vehicle reachability constraints

In order to ensure a realistic and feasible model, the travel time for any vehicle should be constrained to be greater than or equal to the time it takes to travel the distance from its initial position to the intersection area at its maximum speed.
It is assumed that all vehicles approach the intersection at a constant speed, and thus the travel time cannot be less than the time it takes to cover the distance D_i or D_j at the respective speeds of vehicles v_i or v_j. Furthermore, let t_i and $t_j$denote the initial time instances when vehicles i and j start to approach the intersection area, respectively.

$$T_i \geq \frac{D_i}{v_i}, T_j \geq \frac{D_j}{v_j} \quad (2)$$

$$F_i = t_i + T_i, F_j = t_j + T_j \quad (3)$$

$$T_i \geq \frac{D_i}{v_i}, T_j \geq \frac{D_j}{v_j} \quad (4)$$

The final time for vehicles traveling on the main street can only be located in the green period. Specifically, for the current cycle under consideration, this green period is bounded between the end of the red signal and the start of the next red signal. This constraint ensures that vehicles on the main street can pass through the intersection during the allotted green time to obey the traffic law.

$$F_i \in (R_{end}, R_{start}) \quad (5)$$

It is assumed that the vehicles traveling on the same approach will maintain their initial sequence throughout the planning process, meaning that no overtaking or lane-changing behavior will happen.

$$F_i < F_{i+1}, F_j < F_{j+1} \quad (6)$$

Conditional constraints

To further clarify the impact of the initial appearing time on the final arrival time of each vehicle, certain additional conditional constraints have been introduced. Various combinations of initial appearing time at the intersection for vehicles as been identified. For each combination, we must formulate a set of conditional constraints using an if-then approach. These have led to nested constraints, where the constraints for each combination are dependent on the values of the previous combination.

To solve this, a branch and bound approach is used to divide scenarios based on the initial appearing time. Specifically, these constraints are designed to ensure avoidance of collisions at the intersection, given the initial appearance sequence of the vehicles. To facilitate the expression of these constraints, the numberings 1, 2, 3, and 4 are used for vehicles. Recalling that there is an assumption that no overtaking will occur between two vehicles occupying the same dedicated lane, a series of scenarios to show the relation between the initial appearing time and final arrival time to account for the need to maintain collision-free conditions at the intersection.

Considering the scenario where the initial time follows $t_1 < t_2 < t_3 < t_4$, a side street vehicle is permitted to make a right turn at a red signal if the main street vehicle is expected to pass. This logic is represented by the following two constraints as described in (7). Other scenarios with inequality expressions follow the similar logic.

Scenario 1 if $t_1 < t_2 < t_3 < t_4$:

$$\begin{gathered} F_3 > F_2 + h \; if \; F_3 > R_{end} \\ F_4 > F_2 + h \; if \; F_4 > R_{end} \end{gathered} \tag{7}$$

Scenario 2 if $t_1 < t_3 < t_2 < t_4$:

$$\begin{gathered} F_2 > F_3 + h \; if \; F_3 > R_{end} \\ F_3 > F_1 + h \; if \; F_3 > R_{end} \end{gathered} \tag{8}$$

Scenario 3 if $t_1 < t_3 < t_4 < t_2$:

$$\begin{gathered} F_2 > F_4 + h \; if \; F_4 > R_{end} \\ F_3 > F_1 + h \; if \; F_3 > R_{end} \end{gathered} \tag{9}$$

Scenario 4 if $t_3 < t_1 < t_2 < t_4$:

$$\begin{gathered} F_1 > F_3 + h \; if \; F_3 > R_{end} \\ F_4 > F_2 + h \; if \; F_4 > R_{end} \end{gathered} \tag{10}$$

Scenario 5 if $t_3 < t_4 < t_1 < t_2$:

$$F_1 > F_4 + h \; if \; F_4 > R_{end} \tag{11}$$

Scenario 6 if $t_3 < t_1 < t_4 < t_2$:

$$\begin{gathered} F_4 > F_1 + h \; if \; F_4 > R_{end} \\ F_1 > F_3 + h \; if \; F_3 > R_{end} \\ F_2 > F_4 + h \; if \; F_4 > R_{end} \end{gathered} \tag{12}$$

When the sequence of initial appearing time is determined, one set of conditional constraints is utilized in the programming problem.

Speed as variable

Incorporating additional variables such as the constant speed of side street vehicles can extend the model. This is important since speeds from side street vehicles are assumed to be changeable to adapt to the coordination, and optimizing speed control can effectively reduce travel time. Furthermore, the variation in speed of side street vehicles will influence the overall sequences of vehicles. Here lower and upper bounds are assigned to the speed:

$$T_j \geq \frac{D_j}{{v_j}^*}, {v_j}^* \in (V_{min}, V_{max}) \tag{13}$$

Signal duration as a variable

In traffic signal operation, there are two commonly used approaches for setting signal priority: red truncation and green extension. Red truncation is ending the red phase earlier than planned, while the green extension is extending the current green phase. However, simply extending the green phase does not necessarily lead to a reduction in total travel time. This is because adding green time to allow more vehicles from the main street to pass may also at the same time affect the vehicles from the side street.

To analyze and find an optimal solution, these two values are set as control variables length of red truncation (rt) and length of green extension (ge) with a limited range. These two variables influence the signal and thus also could affect the final results.

The new red ending time is determined by subtracting the length of red truncation from the planned red ending time, while the new green ending time or red starting time in the next cycle is determined by adding the length of the green extension to its planned value:

$$R^*_{end} = R_{end} - rt, rt \in (0, rt_{max}) \tag{14}$$

$$R^*_{start} = R_{start} + ge, ge \in (0, ge_{max}) \tag{15}$$

In the problem, when the choice of a signal control is active, the two variables will be included in the constraints. Other variables and constraints in the problem remain the same as in the previous problem.

Solutions to conditional constraints

An if-then constraint is split into two sets of constraints linked by logic OR. Taking the inequality $F_3 > F_2 + h \; if \; F_3 > R_{end}$ as an example, the conditional constraints raise ahead can be solved as follows:

The origin constraint is

$$\text{if } F_3 - F_2 - h > 0 \quad \text{then } F_3 - R_{end} > 0 \tag{16}$$

This can be expressed as:

$$(F_3 - F_2 - h\ >\ 0\ and\ F_3 - R_{end}\ >\ 0\ )\text{ or }(\ F_3 - F_2 - h <\ 0\ ) \tag{17}$$

$$(0\ <\ F_3 - F_2 - h\ and\ 0\ <= F_3 - R_{end}\ )\text{ or }(\ F_3 - F_2 - h\ < 0\ ) \tag{18}$$

Then, to solve the nested constraints, a big M method is employed. Let the binary integer term is $z\ =\ \{0, 1\}$, and we add M1, M2, and M3 which are with large enough values:

$$0\ <\ F_3 - F_2 - h +\ M1 * z \tag{19}$$

$$0\ <\ F_3 - R_{end} +\ M2 * z \tag{20}$$

$$F_3 - F_2 - h\ <\ 0\ +\ M3 * (1 - z) \tag{21}$$

By doing so, the previously nested conditional constraints are transformed into conventional constraints, allowing for the use of standard optimization techniques to solve the problem. It should be noted that if z=1, then constraints (19) and (20) become redundant, and constraint (19) can be removed. Therefore, only constraints (20) and (21) are required in this case.

3. EXPERIMENTS AND RESULTS

3.1 SIMULATION SETUP

The proposed method was implemented using Python, and the numerical simulations are presented below. The method was validated using six different cases, where the initial time instances to approach the intersection were varied. In the space-time figures, the red line represents the red-light duration on the main street. Vehicles 3 and 4 are allowed to turn onto the main street and pass during red (for main street) or when there is a feasible gap. The simulation parameters are shown in Table 1:

Table 1 Parameters used in simulation

Initial spacing (meters)	450
Initial speed (m/s)	20
Number of vehicles from main street	2
Number of vehicles from side street	2
Minimal acceptable headway (sec)	1.8
Red duration (sec)	25
Red starting time (sec)	18
Maximum red truncation (sec)	5
Maximum green extension (sec)	5

In this study, the term 'initial sequence' refers to the order of the initial appearing time of each vehicle approaching the 450 meters range of this intersection, arranged from smallest to largest. It is worth noting that, even for the same sequence, different values of initial appearing time can impact the final results for vehicles to pass through the intersection. Therefore, the case study categorizes the cases according to the variation in both the initial sequence and the initial appearing time values.

For vehicles with initial appearing time instances of 1, 0, 2, and 3 (secs) in the intersection range, the corresponding sequence is V2 V1 V3 V4. The same sequence is identified by the same case number, while the difference in initial appearing time is indicated by a decimal number. For instance, for vehicles with an initial appearing time of 1, 2, 4, 5, in this intersection range, the sequence is V1 V2 V3 V4, denoted as Case 1 or Case 1.1. Case 1.2 is used to represent the combinations of the same vehicle sequence with varying initial appearing times such as 0, 2, 4, 5.

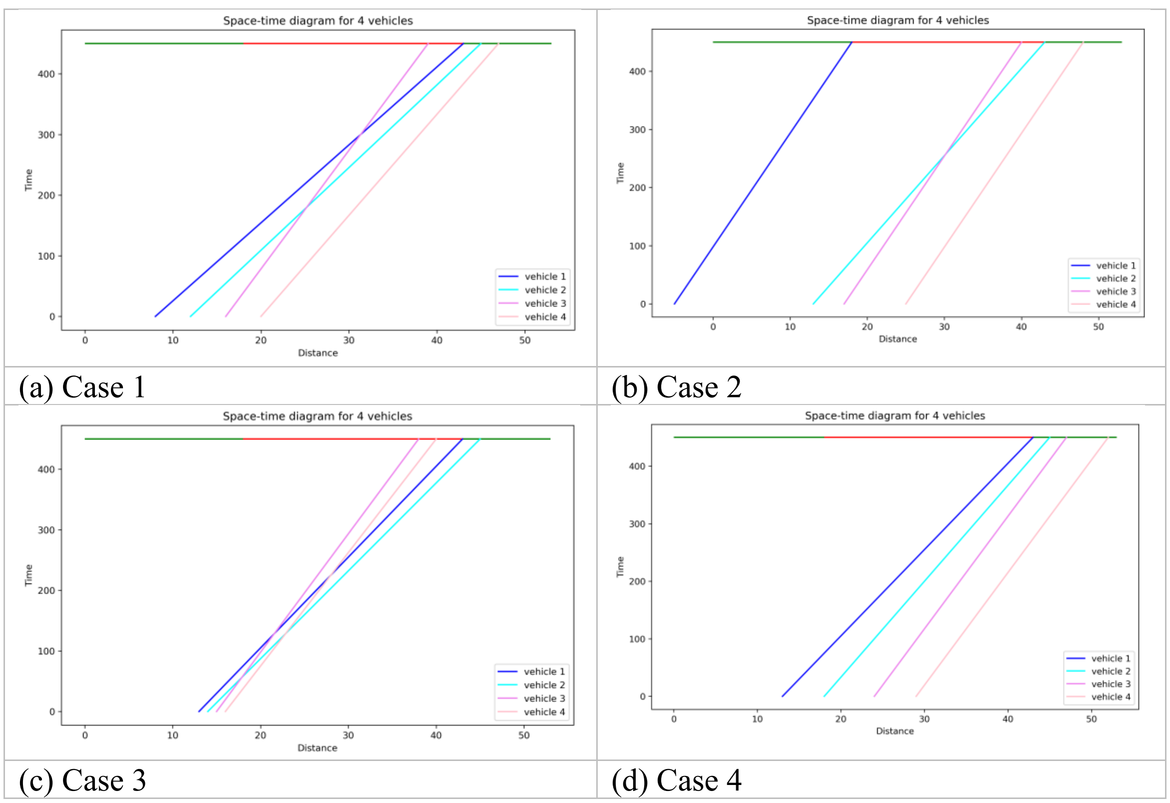
The proposed method is denoted as the baseline method and then two extended versions (adding signal control and speed control) were utilized for comparison purposes.

3.2 CASE STUDY: VEHICLE PLANNING WITH SAME INITIAL SEQUENCES

The first case demonstrated how varying initial appearing times, even with the same sequence, can lead to different sequences of final arrival times. This is illustrated by comparing cases 1.1, 1.2,1.3, and 1.4 which have the same vehicle sequences but different specific initial appearing times.

Table 2 Initial appearing time of vehicles (with same initial sequences) and Optimized travel time

Initial time instances (sec)	Case 1.1	Case 1.2	Case 1.3	Case 1.4
t_1	8	-5	13	13
t_2	12	13	14	18
t_3	16	17	15	24
t_4	20	25	16	29

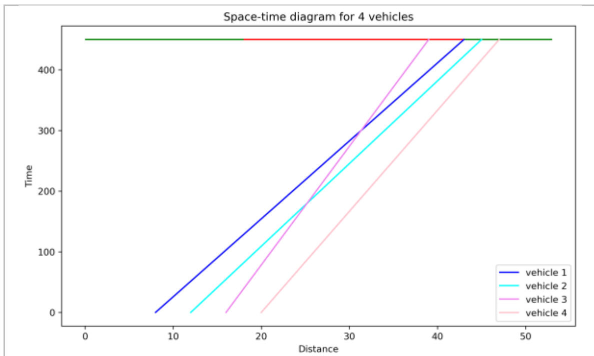


(a) Case 1 (b) Case 2

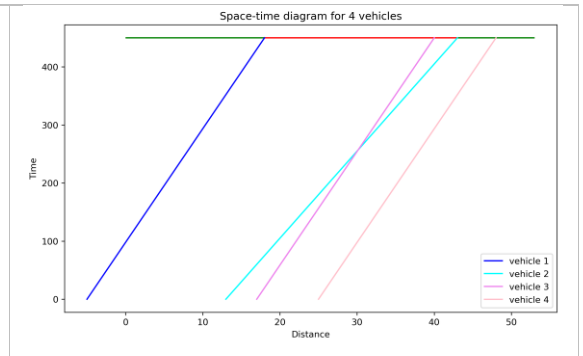
(c) Case 3 (d) Case 4

Figure 1 Planning of CAVs at signalized intersection with same sequences of initial appearing time

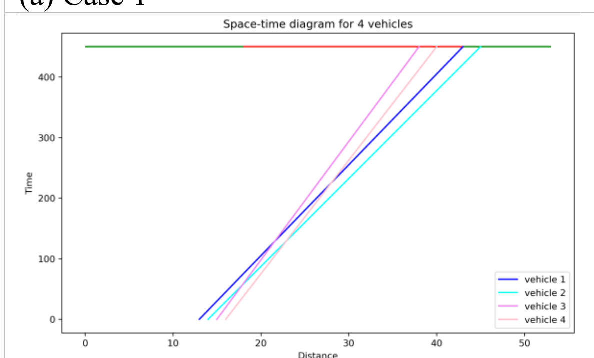
In (a), it showed that vehicle 3 arrived at the intersection while the main street was still displaying a red light so it made a turn before the light turned green. Following this, vehicle 1 passed the intersection upon the green light appearing, followed by vehicle 2. Finally, vehicle 4 approached the intersection and made a turn after vehicle 2. In (b), vehicle 1 had an early appearing time before the red signal and passed through the intersection before the light turned red. Vehicle 3 arrived and made a turn immediately since no vehicle was allowed to pass from the main street. When the light turned green, vehicle 2 passed. Finally, when vehicle 4 arrived at the intersection, it turned immediately despite the red light being active for the side street as there were no vehicles approaching from the main street at that moment.



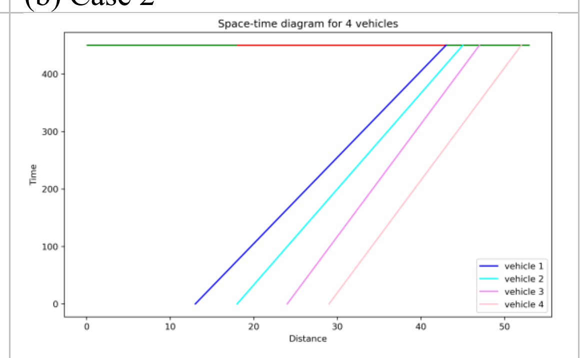
(a) Case 1



(b) Case 2



(c) Case 3



(d) Case 4

Figure 2 planning of CAVs at signalized intersection with same sequences of initial appearing time

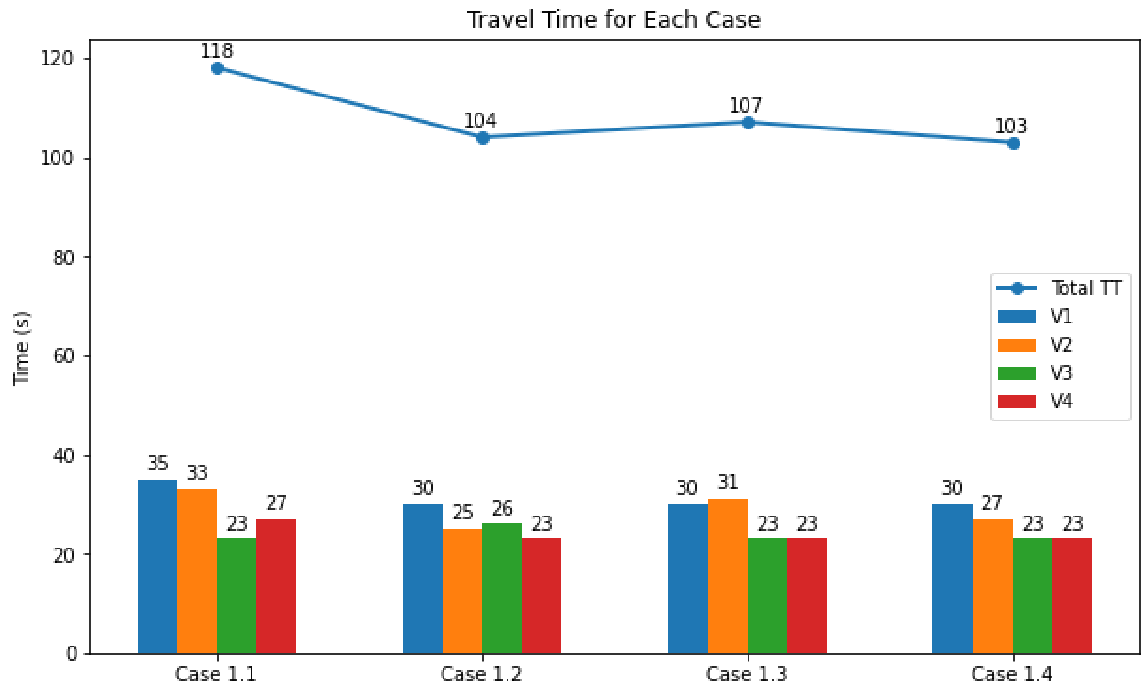


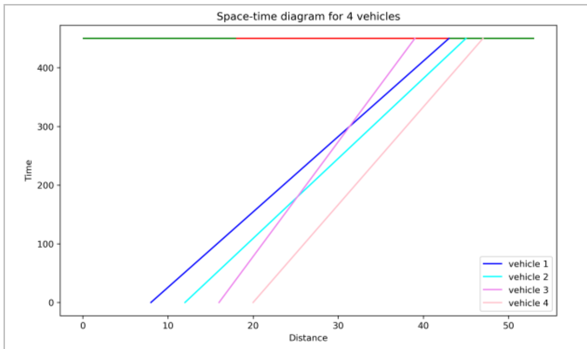
Figure 3 Optimized travel time for each vehicle and total minimized travel time (with same initial sequences)

3.3 CASE STUDY: VEHICLE PLANNING WITH VARYING INITIAL SEQUENCES

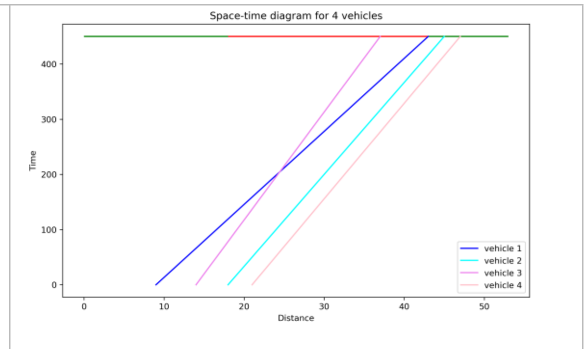
The second case examined the planned results when the sequence of initial appearing times of vehicles was different. It demonstrated that varying the sequences of initial appearing time can result in different sequences of final arrival time.

Table 3 Initial appearing time in each case (with different initial sequences)

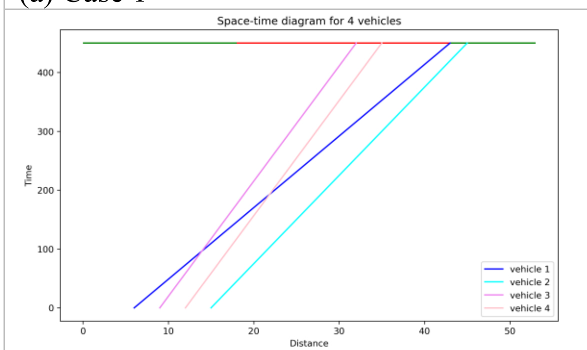
Case/ Time (sec)	V1	V2	V3	V4
Case 1	8	12	16	20
Case 2	9	18	14	21
Case 3	6	15	9	12
Case 4	7	14	4	11
Case 5	12	17	5	9
Case 6	11	19	8	15



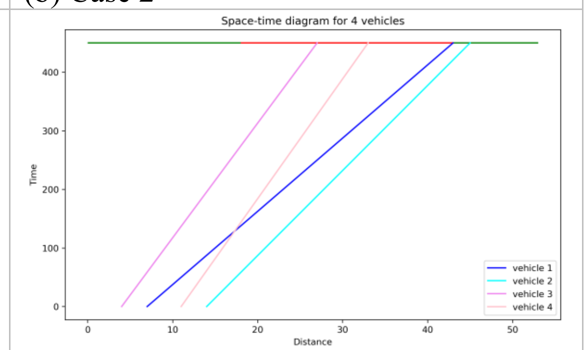
(a) Case 1



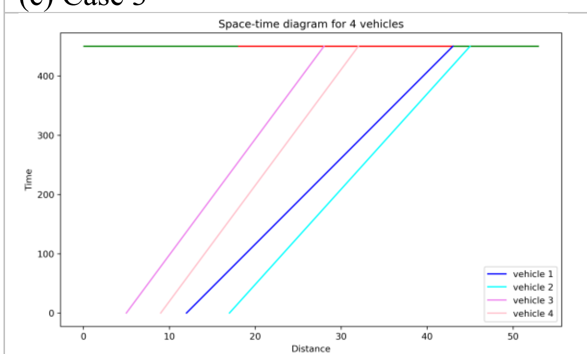
(b) Case 2



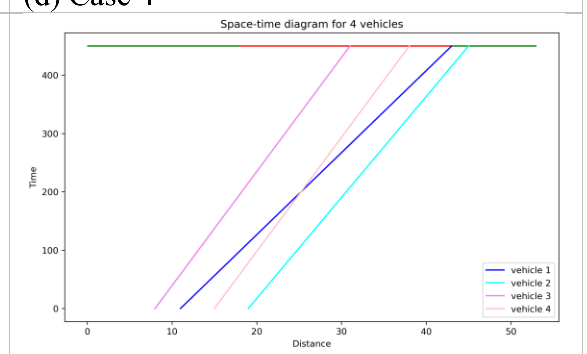
(c) Case 3



(d) Case 4



(e) Case 5



(f) Case 6

Figure 4 Planning of CAVs at signalized intersection with varying sequences of initial appearing time, optimized sequences.

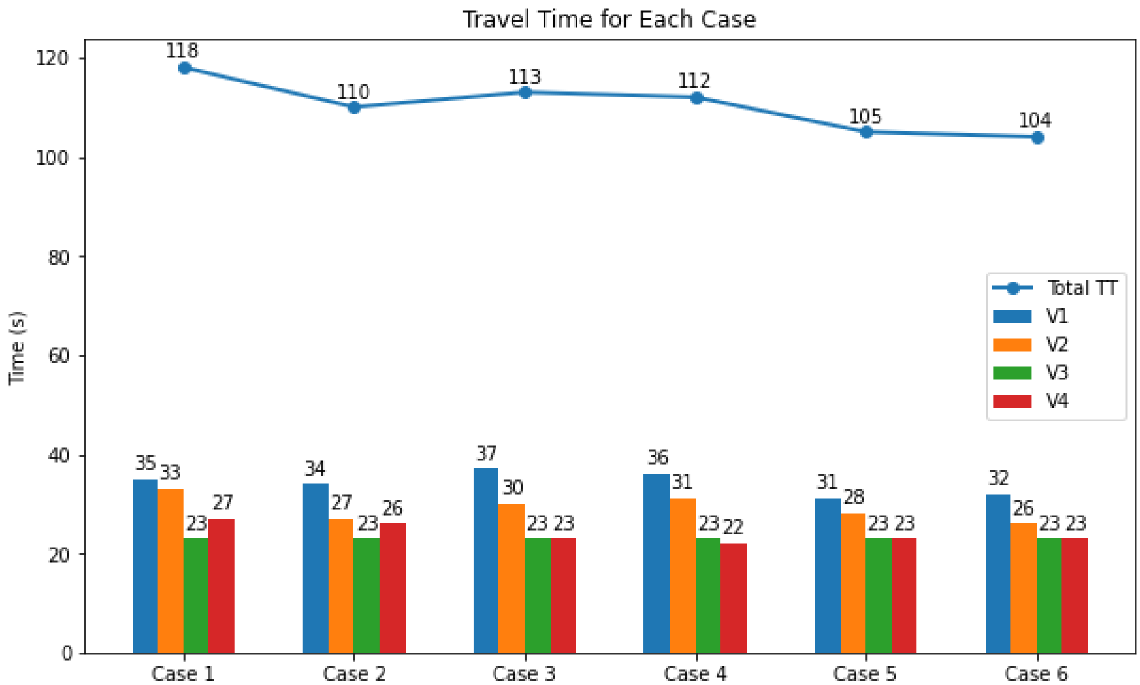


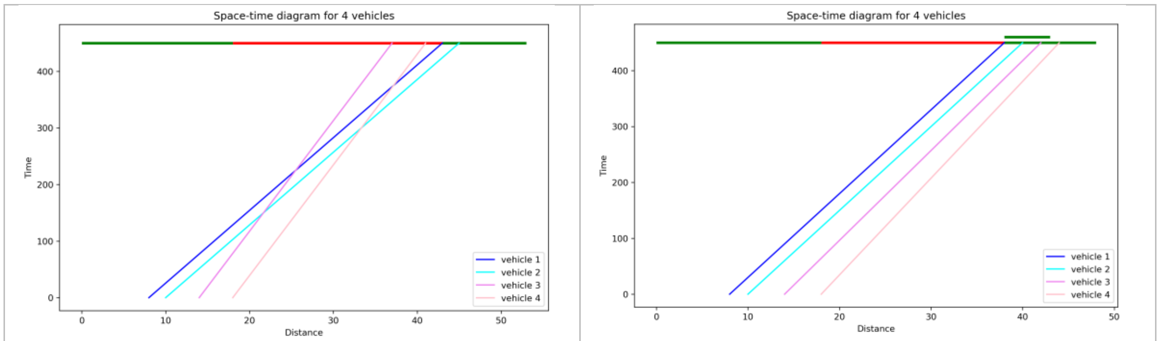
Figure 5 Optimized travel time for each vehicle and total minimized travel time (with different initial sequences)

Figure 4 illustrates the planned results when the initial appearing time sequences of vehicles are varied. Figure 5 shows the optimized travel time for each vehicle and the total travel time. The diagrams demonstrate that the proposed method can provide optimal final sequences and a final arrival time that minimizes total travel time, even with different initial sequences. In (a), vehicle 3 made a turn before the main street turned green, followed by the other three vehicles in their initial sequences. The same results were obtained in (b), even though the initial time of vehicle 2 was later than that of vehicle 3. This is because vehicle 3 was so close to the intersection that it could make a turn at red without considering the vehicles from the main street, which would be blocked by the red light. In (c), (d), (e), and (f), both vehicle 3 and vehicle 4 were close enough to the intersection to turn before the main street turned green. The key factor is whether the vehicle from the side street can turn during red. If not, the vehicles on the main street will have priority and become new constraints for the side street vehicles.

3.4 CASE STUDY: SIGNAL DURATION AS A VARIABLE

The initial appearing time is unchanged using **Error! Reference source not found.**.
Figure 6 demonstrates how the proposed method automatically assigns the red truncation given the initial inputs. As a result, the travel time for vehicles 3 and 4 increased from 23 sec to 28 sec and 26 sec respectively, while the travel time for vehicles 1 and 2 decreased from 35 sec to 30

sec. The total travel time for all vehicles decreased from 116 sec to 114 sec by applying an optimized value for red truncation of 5 sec and green extension of 5 sec. In this case, vehicles from the side street yielded at the intersection, allowing vehicles 1 and 2 to pass first. Although they did not pass immediately during the red for the main street, the total travel time for all vehicles was reduced.



(a) Before red truncation / green extension | (b) After red truncation / green extension

Figure 6 Planning of CAVs at signalized intersection with red truncation or green extension

Although the proposed method offers several signal operation options, it may not always result in red truncation for minimizing the total travel time. As demonstrated in Figure 7, when the constant speeds of the vehicles are different, the best strategy for providing minimal travel time for all vehicles is not applying any signal control. This highlights the significance of incorporating the proposed method, which could achieve the most efficient and effective solution while reducing the cost of signal control.

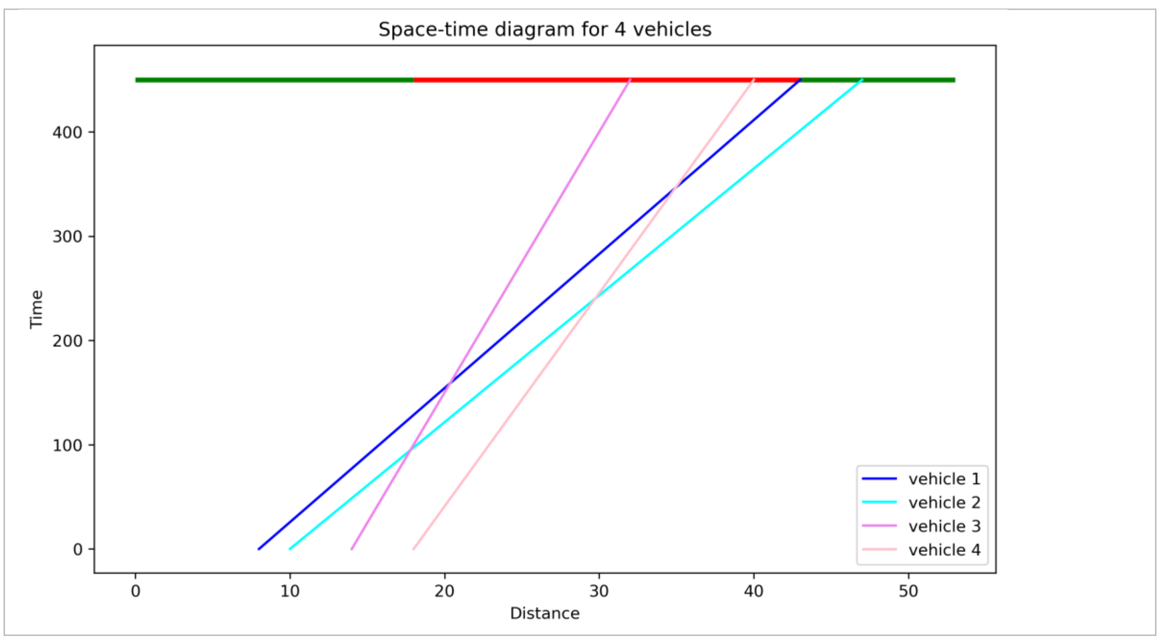
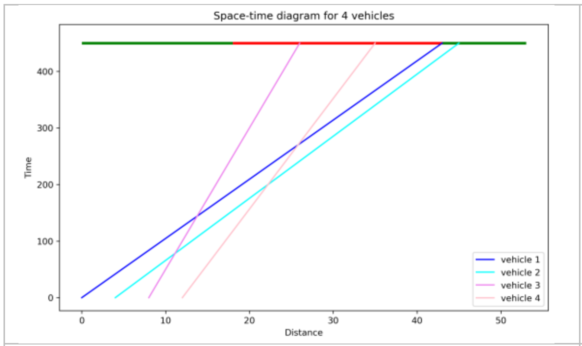
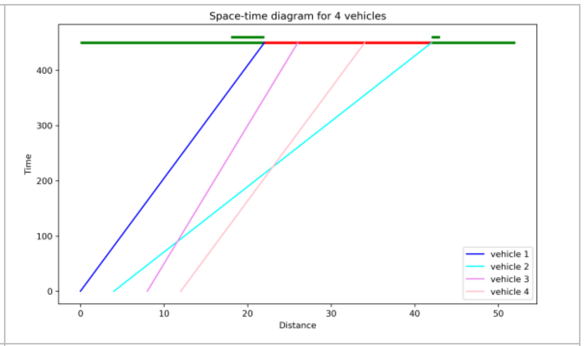


Figure 7 Planning of CAVs at signalized intersection with red truncation or green extension options, speed speed1 = 20 m/s, speed2 = 12 m/s, speed3 = 25 m/s, speed4 = 20 m/s.

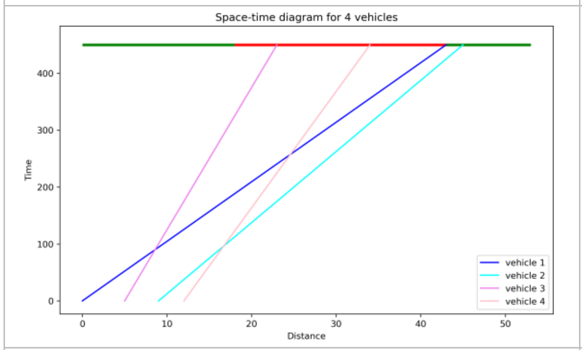
To investigate the impact of signal control options on the final sequences, the red truncation and green extension as control variables were used to test on multiple cases. The results for each case were then presented in
Figure 8. It was observed that for case 1, case 2, and case 3, the influence of these control variables was more significant in changing the final arrival sequences of the vehicles. Specifically, both green extension and red truncation were active according to the model, but with different values for each case. While for cases 4-6, only red truncation was active. This finding suggests that the choice of signal control options can have a significant impact on the optimization results.



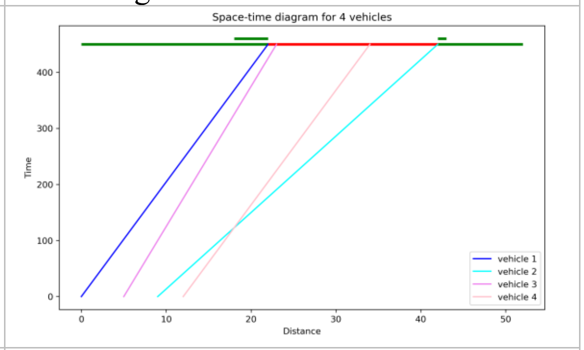
Case 1 baseline



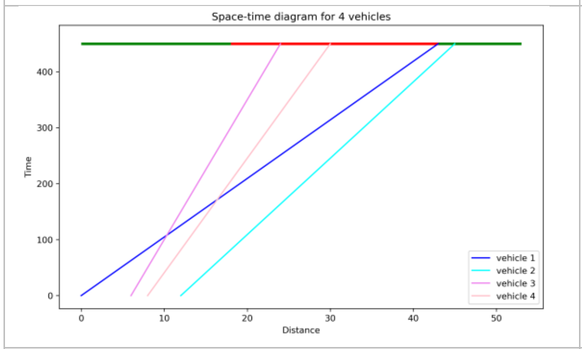
Case 1 signal control



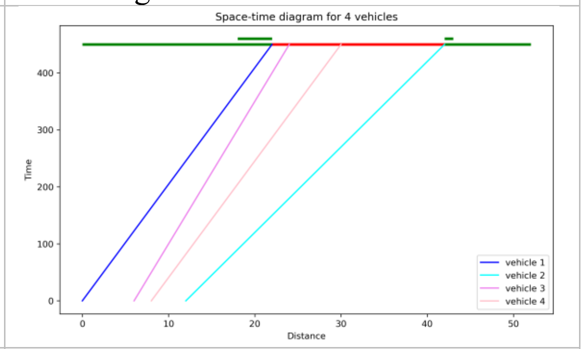
Case 2 baseline



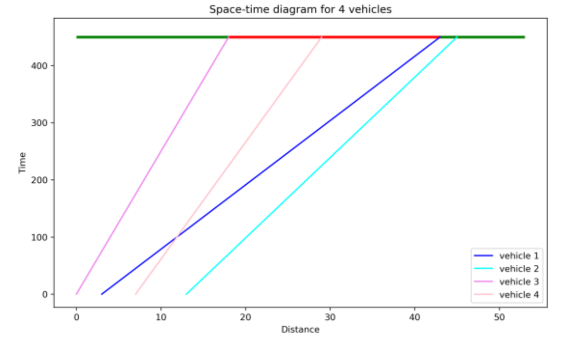
Case 2 signal control



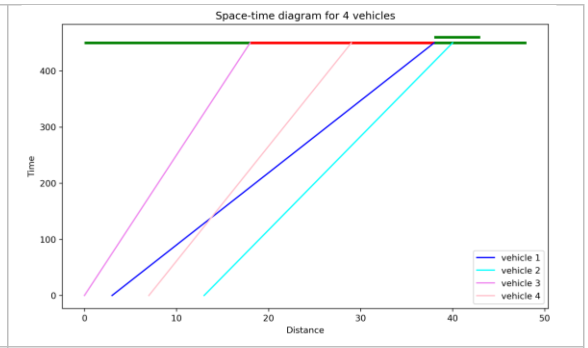
Case 3 baseline



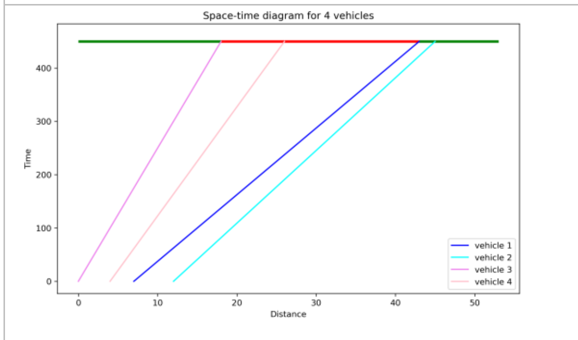
Case 3 signal control



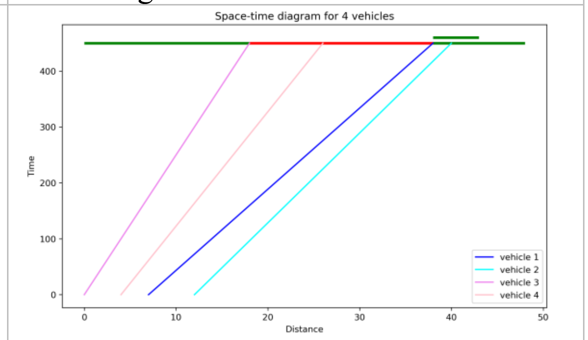
Case 4 baseline



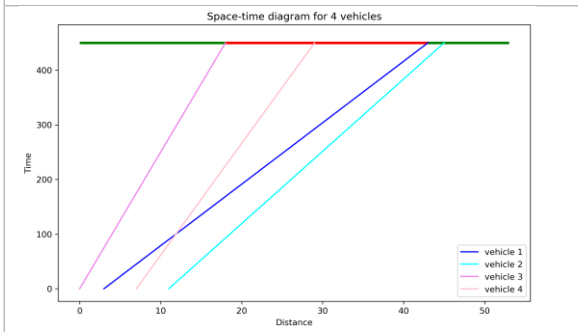
Case 4 signal control



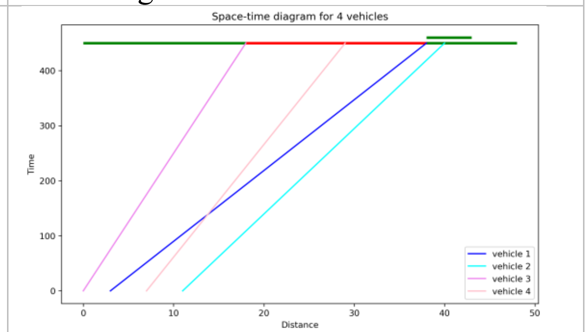
Case 5 baseline



Case 5 signal control



Case 6 baseline



Case 6 signal control

(a) Before red truncation / green extension | (b) After red truncation / green extension

Figure 8 Planning of CAVs at signalized intersection with both red truncation and green extension options, each control variable is ranging from 0 sec to 5 sec.

Figure 9 presents the total travel time between the baseline and proposed method. It illustrates that the travel time savings range from 8.77% to 20.69%. The travel time savings shows that the proposed method has a significant impact on reducing travel time for all vehicles for different scenarios.

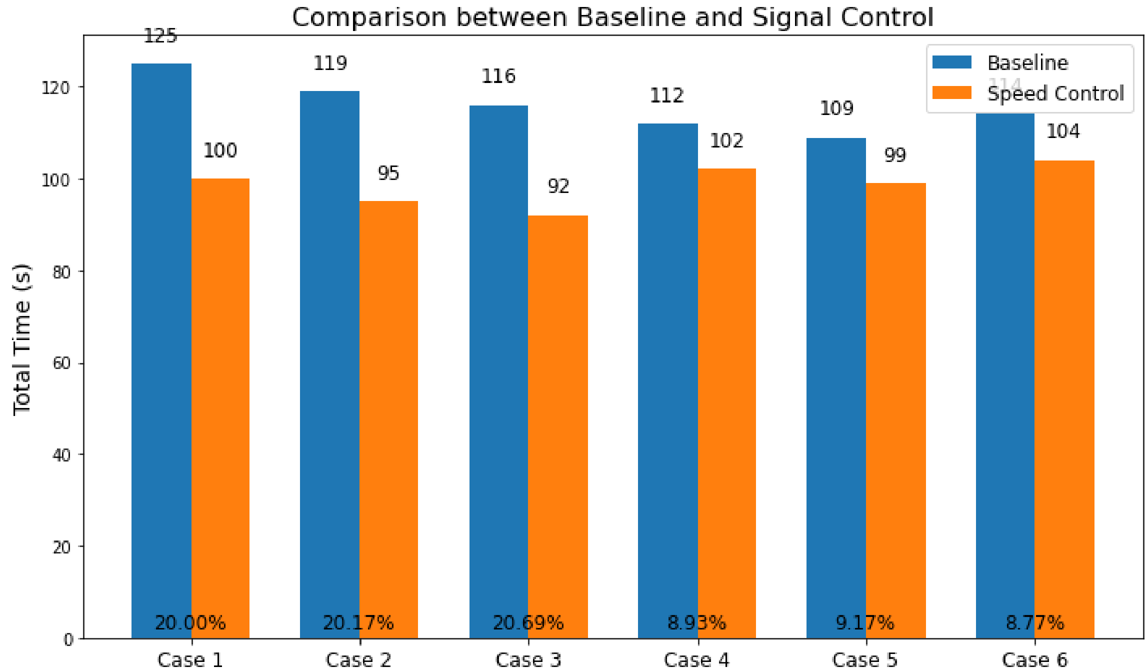
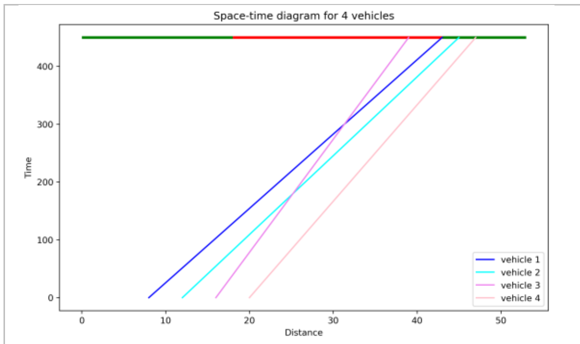


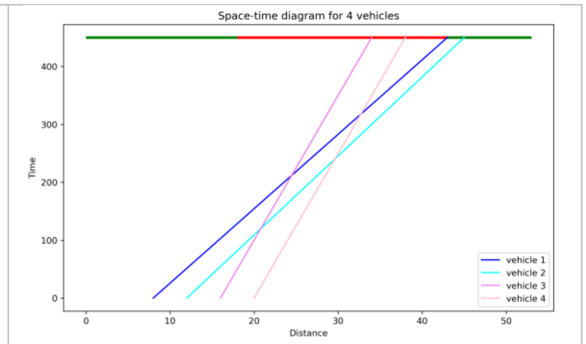
Figure 9 Comparison between the proposed method with its signal control extension.

3.5 CASE STUDY: SPEED AS A VARIABLE

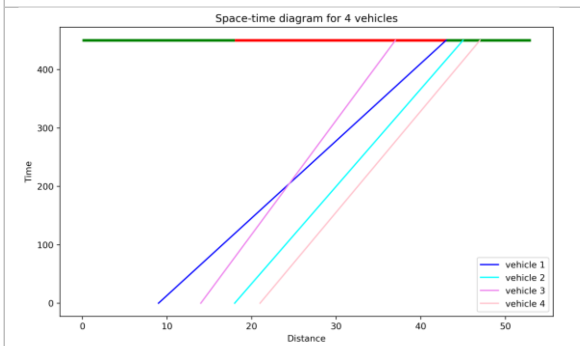
In this case, the speeds of two vehicles from the side street were taken as variables. The model then calculated the optimal speed and arrival time for each vehicle, aiming to minimize the total travel time. The corresponding trajectories of the vehicles are demonstrated in Figure 10. Figure 11 presents the travel time savings with the proposed method, ranging from 15.12% to 24.22% in comparison to the baseline, where the proposed method is applied but speeds are not variables. These results show the effectiveness of considering the speed in the proposed method in reducing travel time in different scenarios.



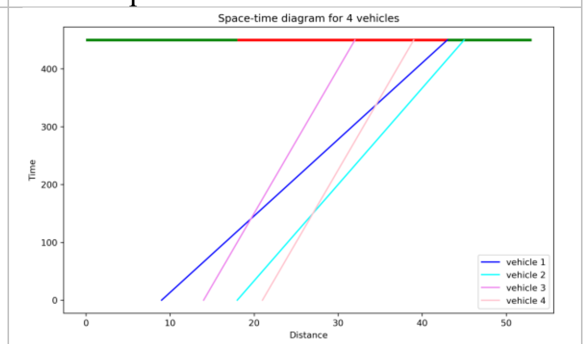
Case 1 baseline



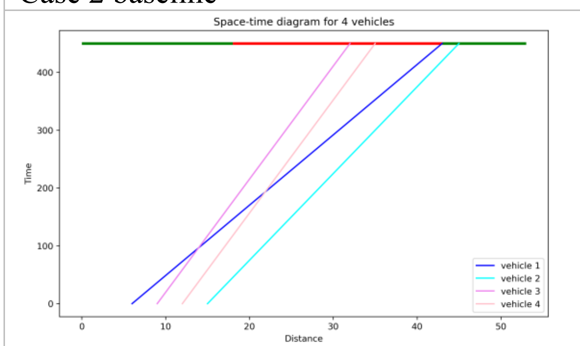
Case 1 speed control



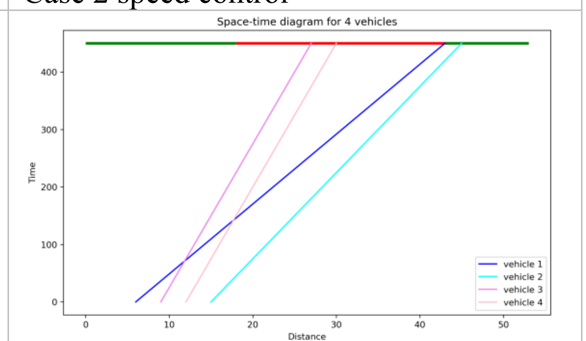
Case 2 baseline



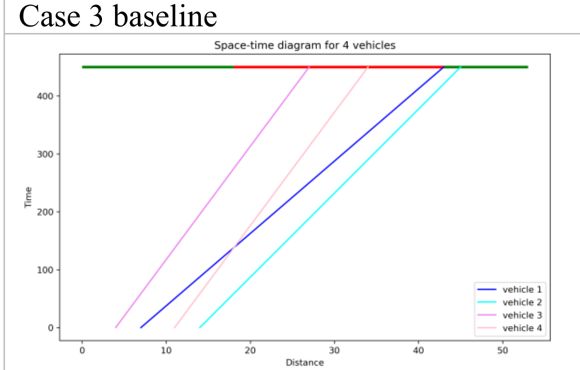
Case 2 speed control



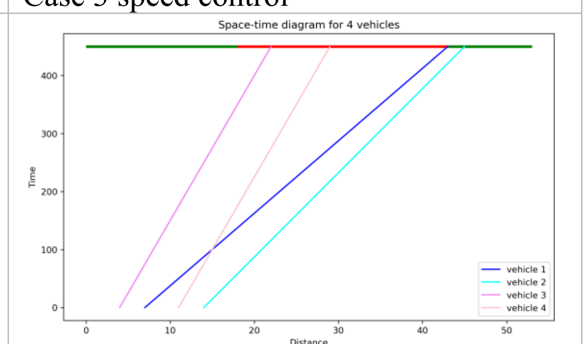
Case 3 baseline



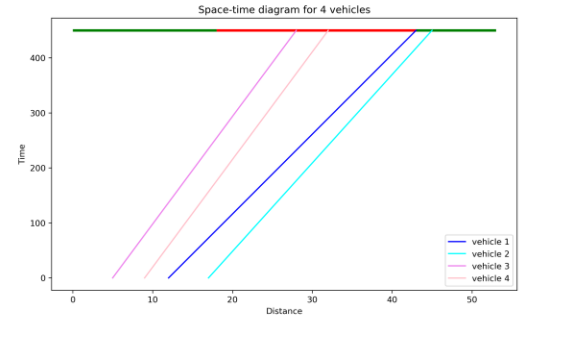
Case 3 speed control



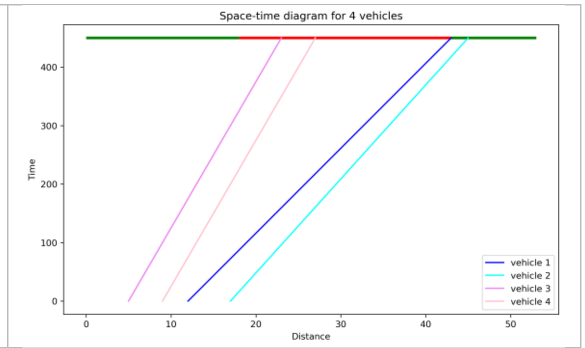
Case 4 baseline



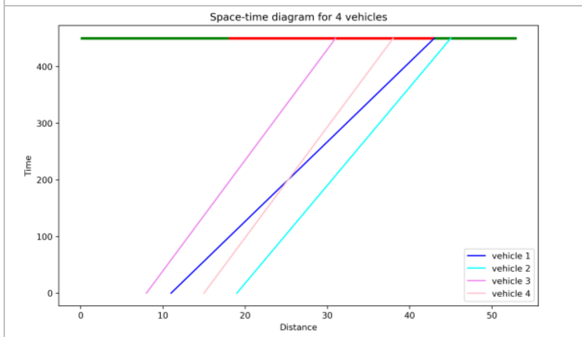
Case 4 speed control



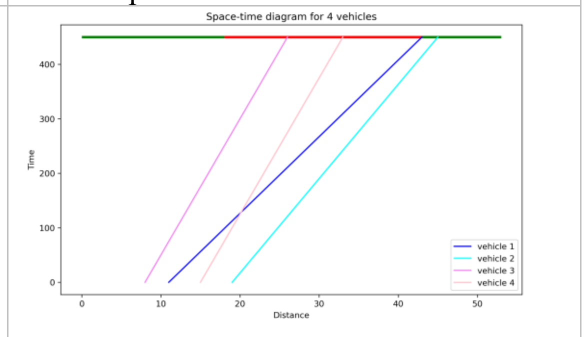
Case 5 baseline



Case 5 speed control



Case 6 baseline



Case 6 speed control

(a) Before speed control	(b) After speed control

Figure 10 Planning of CAVs at signalized intersection with speed control for case 1-6, speed3 and speed4 are variable ranging from 20m/s to 25m/s

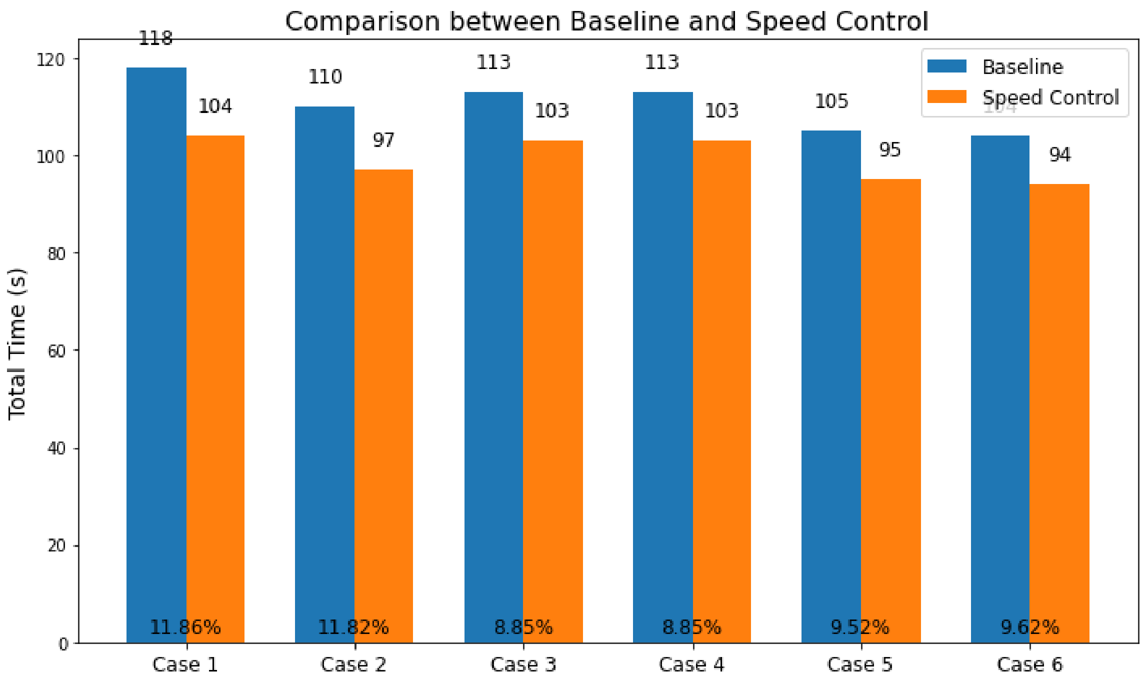


Figure 11 Comparison between the proposed method with its speed control extension.

Figure 11 shows the travel time (TT) for different cases with and without speed control. In all cases, the total travel time is reduced by implementing speed control, with TT savings ranging from 8.85% to 11.86%. For individual vehicles, the largest travel time saving is observed in case 1, where vehicle 4 has a saving of 33.33. Speed control is effective but not benefiting all vehicles such as vehicle 1 and 2, especially in cases where the baseline travel time is already low.

4. CONCULSION

This work investigated the planning of CAVs at signalized Intersections to enable safe and efficient turn movements considering possible solutions using signal control and speed control. The results demonstrate that both signal control and speed control can lead to significant travel time savings for vehicles.

The results showed that collision-free results can be assigned to CAVs when final sequences are fixed. When final sequences are not fixed: 1. When the sequence of the initial appearing time of vehicles was fixed, the proposed method may plan vehicles to lead to varying sequences of final arrival time 2. Even with different sequences, the proposed method could provide optimal final sequences and a final arrival time that can minimize total travel time. 3. The proposed method can also help to determine an optimal signal control strategy of red truncation and green extension to minimize total travel time for all vehicles, with a travel time saving ranging from 8.77% to 20.69%. The method can also determine the speed control of vehicles at signals to save travel time from 8.85% to 11.86%. The proposed method can also help to determine an optimal strategy of signal control such as applying red truncation and green extension to save total travel time for all vehicles. In general, this study makes a valuable contribution to the knowledge development of CAV planning by providing a solution for addressing issues CAVs have at signalized intersection in urban areas.

The model assumptions used in the study may not fully capture the complexities of real-world coordination, as stated in the introduction, there are numerous combinations of situations. To address the problem thoroughly by providing a general solution is the future study of the authors. Besides, the study uses travel time as the performance metric, while other metrics such as fuel consumption, and emissions can be also implemented in the future.

One limitation of this method is the need for precise control over the movements of CAVs to successfully execute the planned maneuvers. However, efficient communication between CAVs and signals and the development of robust control algorithms can adapt to unpredictable scenarios. Advancements in control methods in the state-of-the-art may offer feasible solutions to meet the requirements.

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