Received 24 March 2024, accepted 22 April 2024, date of publication 25 April 2024, date of current version 17 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3393640

APPLIED RESEARCH

Game Scheduling for Vehicle Platoons at Autonomous Intersection Accommodating Priority Passage Requests

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This work was supported in part by the National Key Research and Development Program of China under Grant 2022YFB2502904, in part by the Natural Science Foundation of Hubei Province for Distinguished Young Scholars under Grant 2022CFA091, and in part by Wuhan Science and Technology Major Project under Grant 2022013702025184.

ABSTRACT Addressing the human-centric needs in vehicle scheduling at intersections poses a significant challenge. In this paper, we propose a game scheduling method to address the problem of platoon scheduling while considering priority passage requests. Firstly, we construct a coalition game-based platoon scheduling model. Within this model, a kernel function searches for the optimal coalition group within the kernel set to ensure that participants, such as platoons, gain higher payoffs by joining the coalition than they would individually. The coalition payoff function determines the optimal passage order. Secondly, we design a baseline strategy where the payoff and action obtained by the priority passage platoon in the coalition game serve as the baseline values. Finally, based on this strategy, we develop a bargaining game model where the priority passage platoon acts as the bargainer, while other platoons act as the other party, with baseline payoff and action serving as constraints. The Nash equilibrium identifies the optimal passage order for the priority passage platoon. We conduct 3 experiments: experiment 1 evaluates the effectiveness of the coalition game model; experiment 2 tests the effectiveness of the bargaining game model; and experiment 3 assesses the effectiveness of the game scheduling method in reducing vehicle travel costs and compares it with existing methods. The results demonstrate that our proposed game scheduling method not only reduces the travel costs of the priority passage platoon but also minimizes its impact on other vehicles to the greatest extent possible.

INDEX TERMS Autonomous intersection, baseline payoff, game scheduling, priority passage request, vehicle platoon.

I. INTRODUCTION

Research consistently indicate that Connected and Autonomous Vehicle (CAV) has the potential to reduce traffic conflicts by approximately 90%. This reduction is attributed to their ability to interact with their surroundings through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications and this ability is attributed to the advanced wireless communication and Internet technologies. The technologies mentioned above not only enhance the safety and efficiency of transportation users but also address human-centric needs. For instance, emergency vehicles like rescue, fire, and ambulance vehicles require priority passage for urgent tasks, while regular vehicles may need priority passage for daily activities such as commuting to work or urgent travel. With these advancements, the traffic control system

The associate editor coordinating the review of this manuscript and approving it for publication was Eyuphan Bulut.

will become more flexible and capable of better serving users across different industries.

Intersections serve as the primary bottleneck in road traffic systems, emphasizing the critical role of effective intersection management in alleviating congestion. Autonomous intersection management offers several advantages over signal control [1], reducing green time losses and enhancing traffic schedule efficiency. In autonomous intersections, vehicles are not bound by traditional traffic signals, which presents a scheduling challenge. Various rules have been proposed or employed to tackle this issue, including the First Come First Served (FCFS) strategy [2], the First in First out (FIFO) strategy [3], and the auction strategy [4]. However, these fixed rules govern the processing of all vehicles, limiting their adaptability to fluctuating traffic conditions.

Several research have introduced optimization strategies to further improve intersection performance, including bi-level programming [5], [6], tree search [7], and machine learning [8], [9], [10], [11], reservation optimization [12], other strategies [13], [14], yielding satisfactory schedule results. However, Lioris et al. [15] found that increasing intersection capacity is feasible when vehicles traverse intersections as platoons rather than individually. Kumaravel et al. [16] reframed the vehicle platoon scheduling problem as a job-shop scheduling problem, providing a comprehensive proof. However, their research did not consider platoon formation within the scheduling process, focusing primarily on entire platoons. In response to this limitation, some research have addressed platoon formation when tackling scheduling problems. For example, Zhao et al. [17] developed criteria to identify compatible platoons in entrance lanes. Similarly, Li et al. [18], [19] utilized the deep Q-network method to determine the optimal platoon size before the scheduling process. Jiang et al. [20] formulated a mixed-integer linear programming model to optimize the passing order and size of platoons. Similarly, Deng et al. [21] devised a traffic schedule model to coordinate platoons, introducing platoon formation decision variables. Similar research endeavors can be found in the literatures [19], [22], and [23].

Some research focuses on game theory and explores its application in solving scheduling problems. Optimization strategies aim to achieve globally optimal results by considering the overall payoff of all participants. Unlike optimization strategies, game theory offers greater flexibility and can be categorized into cooperative and non-cooperative games. Cooperative games aim to maximize the total payoff of all gamers, while non-cooperative games focus on Nash equilibrium states, where each gamer's payoff is maximized. Cheng et al. [24] proposed a non-cooperative game-based vehicle passing intersection model where the payoff function includes safety, speed, and comfort. Each vehicle aims to maximize its own payoff, leading to the attainment of Nash equilibrium. Yang et al. [25] introduced a cooperative game driving model considering different drivers' characteristics and employed a zero-mean normalization method to enhance the computational efficiency of the game model. Elhenawy et al. [26] presented a cooperative control algorithm based on the chicken game model to minimize vehicle delay and ensure safe crossing at intersections, achieving an 89 percent reduction in vehicle crossing delay. Lu et al. [27] proposed a distributed cooperative route planning algorithm based on evolutionary game theory to coordinate vehicles in a network, achieving satisfactory delay performance and computational efficiency. Wang et al. [28] proposed a game-based hierarchical control strategy comprising negotiation, bargaining, and optimization layers. The negotiation model optimizes vehicle passing sequences, the bargaining model enhances traffic efficiency through cooperative processes, and the model predictive control (MPC) method is utilized in the optimization layer to track vehicle speeds while considering comfort indicators. Sun et al. [29] investigated the game relationship between pedestrians and vehicles at autonomous intersections to reduce the risk of conflict between them. Jia et al. [30] designed a multi-factor-enabled interactive decision-making method based on dynamic game theory to address vehicle passing conflicts. This method enables vehicles to make decisions consistent with human logic, interact with surrounding vehicles, and switch game modes to address failures in the game. Hang et al. [31] developed a trajectory planning model based on differential game theory to resolve conflict trajectories at intersection conflict zones. They also designed a collision risk assessment model for the game process to ensure passing safety. Additionally, they also [32] proposed a trajectory planning model based on fuzzy coalitional game theory to address the social and individual benefits between vehicles. Similar research endeavors can be found in the literature [33], [34], [35].

Based on the above discussion, we can conclude the following research gap:

- current research in addressing the platoon scheduling problem typically assumes an ideal scenario without considering human-centric requirements. Consequently, the platoon scheduling problem involving vehicles with priority passage requests remains unresolved.

Therefore, this paper proposes a game scheduling model based on game theory. The contributions of this paper are as follows:

- We have designed a new baseline strategy that transforms the platoon scheduling problem with priority passage requests into a two-stage game problem.
- In the first stage, we design a coalition game model to solve the cooperative scheduling problem among platoons. In the second stage, we design a bargaining game model to address the non-cooperative scheduling problem among platoons.

The remainder of this paper is organized as follows. Section II addresses a scheduling problem. Sections III and IV introduce the coalition game model and bargaining game model, respectively. Section V presents a new platoon management method. Section VI presents a game

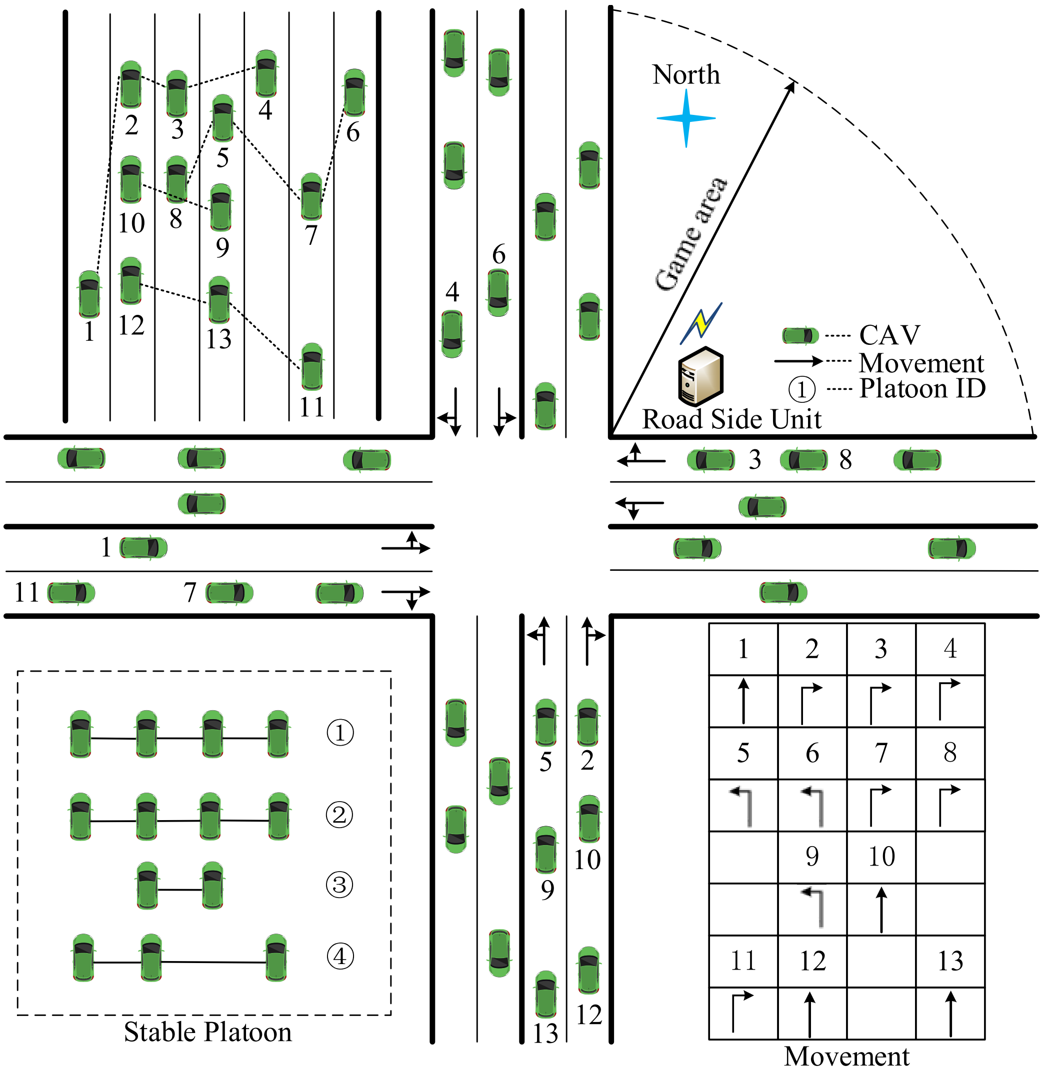

FIGURE 1. Studied scenario.

schedule flowchart. Section VII conducts experimental tests, and Section VIII provides the conclusion for this paper.

II. PROBLEM STATEMENT

We initially provide a description of the studied scenario, as illustrated in Fig. 1. Upon entering the game area, vehicles traverse the intersection in the form of vehicle platoons, where vehicles within the same platoon are devoid of collision relationships. When the platoon is stable, vehicles within it can pass through conflict zones simultaneously. However, not all vehicle platoons can reach a stable state due to differences in each vehicle's position and speed. Data exchange between platoons can be facilitated through the road side unit. From Fig. 1, we can infer that the platoon size is determined by the geographical characteristics of the intersection, ranging from 1 to 4; thus, we do not consider the optimal size in the game process. Additionally, we do not consider failures and packet losses in the communication process.

This paper addresses the optimal scheduling of platoons in the presence of priority passage requests. Existing research has shown remarkable success in enhancing overall traffic efficiency for multiple vehicles. However, the challenge lies in ensuring efficient passage not only for vehicles with priority passage requests but also for others during the scheduling process. In other words, the challenge needs to minimize the impact on other vehicles affected by the priority passage requests. We aim to tackle this challenge using game theory, determining the appropriate game strategy to construct a scheduling model that fulfills these objectives. It's important to note that we focus on regular vehicles in this context, excluding emergency vehicles. According to traffic regulations, emergency vehicles such as police cars, ambulances, fire engines, and disaster relief vehicles have absolute priority.

III. COALITION GAME MODEL

A game model includes five parts: gamer set G, payoff set P, strategy set O, Nash equilibrium strategy Θ^*, Nash equilibrium payoff P^*, denoted as Eq.(1), where N is number of gamers, M is number of strategy in O, o is the strategy conducted by gamer, Θ is combination strategy for all gamers, Ω is combination strategy space and is denoted as $\Omega = \{\Theta_1, \Theta_2, \Theta_3, \ldots, \Theta_i, \ldots\ldots, \Theta_{M^N}\}$, i and j are index, $p(o_1, o_2, o_3, \ldots, o_i, \ldots, o_{N-1}, o_N)$ is the payoff function of a gamer under combination strategy Θ conducted by all gamer, p_1 is the payoff of the first gamer, p_2 is payoff of the second gamer, p_3 is payoff of the third gamer, Nash equilibrium strategy Θ^* means all coalition gamers conduct Nash equilibrium action o^* simultaneously, Nash equilibrium payoff P^* means $\sum_i^n p_i^*$ is maximum compared to any combination strategy Θ.

The Eq.(1) provides a basic description of a game. The first problem need to be consider how to construct a coalition group. There may exist some gamers that do not share their sources to participate this coalition game because their acquired payoff in game process is not satisfactory. The platoon state is first defined by following Eq. (2) if its size is $n_{size} = 3$,

$$\begin{cases} G = \{g_1, g_2, g_3, \ldots, g_i, \ldots, g_{N-1}, g_N\} \\ P = \begin{Bmatrix} p_1(o_1, o_2, o_3, \ldots, o_i, \ldots, o_{N-1}, o_N) \\ p_2(o_1, o_2, o_3, \ldots, o_i, \ldots, o_{N-1}, o_N) \\ p_3(o_1, o_2, o_3, \ldots, o_i, \ldots, o_{N-1}, o_N) \\ \cdots \\ p_N(o_1, o_2, o_3, \ldots, o_i, \ldots, o_{N-1}, o_N) \end{Bmatrix} \\ \Theta^* = \{o_1^*, o_2^*, o_3^*, \ldots, o_i^*, \ldots, o_{N-1}^*, o_N^*\} \\ P^* = \{p_1^*, p_2^*, p_3^*, \ldots, p_i^*, \ldots, p_{N-1}^*, p_N^*\} \end{cases} \tag{1}$$

$$s_p^i = \left\{(\bar{s}/\tilde{s}, n_c)_0, (t_{in}, v, d)_1, (v, d, \Delta t_f)_2, (v, d, \Delta t_f)_3\right\} \quad i \in (1, N^+) \tag{2}$$

where $o_i \in O$, $\Theta_j \in \Omega$, $i \in (1, M)$, $j \in (1, M^N)$, N^+ is number of platoons that need the scheduling requirement, i is platoon index, $(\cdot)_1$ is leading vehicle state and include t_{in}, v and d, t_{in} is timestamp allowed for passing through the intersection, v is current speed, d is current position, different from leading vehicle state, $(\cdot)_{2-3}$ is following vehicle state and extra include the headway between preceding vehicle Δt_f, $(\cdot)_0$ is vehicle distribution state and include $\bar{s}$ or $\tilde{s}$, n_c, denoted as

$$(\cdot)_0 = \begin{cases} (\bar{s}, n_c)_0, & \text{if } n_c = n_{size} - 1 \\ (\tilde{s}, n_c)_0, & \text{if } n_c < n_{size} - 1, \end{cases} \tag{3}$$

where n_c is the number of following vehicles that can catch up with leading vehicle, $\bar{s}$ is the compact state which means platoon can achieve formation before arriving at the intersection and $n_c = n_{size} - 1$, $\tilde{s}$ is the slack state which means platoon cannot achieve formation when arriving at the intersection and $n_c < n_{size} - 1$. Under compact sate, $\forall \Delta t_f = 0$, that is, the headway does not exist. To provide a detailed explanation of Eq.(3), we construct a state judgement function for platoon, denoted as

$$\begin{cases} J(i) = \min\left\{J | J = t_{in} - t_{in}^{1 \le i \le n_{size}}\right\} \\ (\cdot)_0 = \begin{cases} (\bar{s}, n_c)_0, \text{ if } J(i) \ge 0 \\ (\tilde{s}, n_c)_0, \text{ if } J(i) < 0 \end{cases} \end{cases} \tag{4}$$

where i is vehicle index, t_{in}^i the arrival time of nth vehicle, if $J \ge 0$, J is the delay time of nth vehicle, $J < 0$ means that the vehicle can arrive at the intersection after t_{in} and the delay time is 0. t_{in}^i can be calculated by $t_{in}^i = d_i/v_i + t_c$, where t_c is current timestamp.

Based on Eq.(2)-Eq.(4), the timestamp for platoon completion passage is calculated by

$$t_{out} = \begin{cases} t_{in} + \max\{\Delta t_1, \Delta t_2, \Delta t_3, \ldots, \Delta t_{n_{size}}\}, & \text{if } (\bar{s}, n_c)_0 \\ t_{in} + d_l/v_l - (t_{in} - t_c) + \Delta t_l, & \text{if } (\bar{s}, n_c)_0, \end{cases} \tag{5}$$

where Δt is the time interval of each vehicle passing conflict zone, Δt_l is the time interval of last following vehicle passing conflict zone, $d_l/v_l - (t_{in} - t_c)$ is headway difference, t_c is current timestamp. The headway difference is time interval that the last following vehicle takes to travel to the stop bar at t_{in}. Therefore, we can acquire $[t_c, t_{out}]$.

Next, we require a payoff function for each gamer, i.e., each platoon. As described in Section II of the problem statement, the platoon scheduling issue at autonomous intersections pertains to resolving driving conflicts at conflict zone and ensuring the safety of each platoon. Additionally, this problem involves optimizing the passing efficiency of all platoons. Both safety and efficiency are crucial for the scheduling process. The payoff function for each gamer is denoted as:

$$p = p_s(\kappa(i)) + p_e(\Theta) \quad \begin{cases} p_s(\kappa(i)) \in \{0, -\infty\} \\ p_e(\Theta) = Eq.(2-5) \\ i \in [1, N], \Theta \in \Omega, \end{cases} \tag{6}$$

where p is payoff and has two different forms: p^c and p^{n-c}, p^c is coalition game payoff, p^{n-c} is non-coalition game payoff, p_s is driving safety payoff and only take two values: 0 and $-\infty$, p_e is efficiency payoff and calculated by Eq.(2)-Eq.(5), κ is conflict index variable and i is platoon index. If the platoon does not participate coalition game, its payoff is p^{n-c} and p^c is 0. If the platoon participate coalition game, its payoff is p^c and p^{n-c} is 0, p_e is the function of combination strategy Θ and Θ can determine $[t_c, t_{out}]$ directly. If the platoon does not participate coalition game, p_e is only determined by Eq.(5). Regardless of whether the platoon participates in the coalition game or not, its payoff consists of p_s and p_e. p_s is function of conflict index variable $\kappa(i)$, κ can be denoted as

$$\kappa_1(i) = (i, j), j \in [1, N] \ \textit{and} \ j \ne i \tag{7}$$

or

$$\kappa_2(i) = (i, j), j = \left\{j | d_j \le d_i, j \in [1, N^+]\right\}, \tag{8}$$

where j is also platoon index. If the platoon participates game, conflict index variable is $\kappa_1(i)$. If it does not participate game, conflict index variable is $\kappa_2(i)$.

According coalition game, we need to guarantee the stability of coalition group, we denote a coalition group as

$$\Xi = \{g_1\} \cup \{g_2\} \cup \{g_3\} \tag{9}$$

where $\cup$ is coalition operation, $\{g_1\} \cup \{g_2\}$ means gamer g_1 and gamer g_2 reach an coalition agreement and group a coalition group $\{g_1, g_2\}$. It's easy to envision a scenario where a gamer opts to join a coalition group only if the payoff they receive in a non-coalitional game is inferior to what they would gain in a coalition game. Eq.(10) gives an example

$$\sum\nolimits_{1}^{3} p_i^* > \sum\nolimits_{1}^{2} p_i^* + p_3^{n-c} \tag{10}$$

if Eq.(10) holds, it means that $p_3^{n-c} + \forall p_{1\le i\le 2}^* < \sum_2^3 p_i^*$ and $p_3^* > p_3^{n-c}$, g_3 will participate the coalition Ξ. On the other hand, if $\sum_1^3 p_i^* = \sum_1^2 p_i^* + p_3^{n-c}$ or $p_3^* = p_3^{n-c}$, we consider g_3 will not participate the coalition Ξ. For a N gamers, a kernel set is denoted as

$$\begin{cases} K = \{\Xi_1, \Xi_2, \Xi_3, \ldots, \Xi_N\} \\ \forall \Xi \neq \emptyset, \mathcal{N} \le N^+ \end{cases} \tag{11}$$

In K, $\Xi_i \neq \Xi_j$ and $i \neq j$, which means that the size of groups are various. The small groups and large groups may exist in K simultaneously. From Eq.(10) we know that all gamers participate the optimal coalition group to improve its payoff, so some optimal coalition group will grow up gradually. In other word, the larger the size of the group, the more gamers will benefit from it. To identify optimal coalition groups, the general formation of kernel function is derived from Eq.(10) and denoted as

$$\max : F_K = \sum\nolimits_{1}^{\forall n} p_i^* - \left(\sum\nolimits_{1}^{\forall n-1} p_i^* + p_{\forall}^{n-c} \right)$$
$$\textit{subject to Eq.}(2-11),\ 1 < \forall n < N^+, \tag{12}$$

optimal kernel set K can be acquired by calculating Eq.(12), for a certain group, $p_\forall$ is the payoff of an arbitrary gamer.

Based on the above discussion about coalition game, we give the coalition payoff under Eq.(11) and denoted as Eq.(13)

$$\max : \sum\nolimits_{i}^{n} p_i$$
$$\textit{subject to Eq.}(2-12) \tag{13}$$

IV. BASELINE METHOD

Merely constructing a coalition game model is insufficient for solving the platoon schedule problem with personalized demands. Building upon the outcomes of coalition game, in this section, we propose a baseline strategy and construct the bargaining game model.

For the platoon with a personalized request, it is crucial to enhance the platoon's traffic efficiency and determine an appropriate level of enhancement. We have devised a baseline strategy. This strategy posits that in the coalition game mode, the platoon with personalized demand can attain baseline payoff. The baseline payoff refers to the basic payoff obtained by the coalition member when not considering the individualized request of member. We use mathematical language to describe this strategy in terms of baseline payoff and baseline action. Assume *ith* platoon has priority passage request, Θ^* can be rewritten as

$$\Theta^* = \left\{ o_1^*, o_2^*, o_3^*, \ldots, o_i^b, \ldots, o_{N-1}^*, o_N^* \right\}, \tag{14}$$

where o_i^b is baseline action, i.e., ordinal number. P^* can be rewritten as

$$P^* = \left\{ p_1^*, p_2^*, p_3^*, \ldots, p_i^b, \ldots, p_{N-1}^*, p_N^* \right\}, \tag{15}$$

where p_i^b is baseline payoff. In fact, the payoff obtained by coalition member after proposing personalized request must surpass this baseline payoff. We define a new action set and denote as

$$\left\{ o | 1 \le o_i \le o^b \right\}, \tag{16}$$

action o_i is needed to be determined again for *ith* platoon. The action is smaller than o^b to achieve an improved payoff.

We need to construct bargaining game model to determine o_i. There only exist two gamers, the one is the gamer with priority passage request, denoted as g_1, i.e., *ith* platoon, the other is the remaining gamers in the above coalition group, denoted as gs_2. Their strategy sets are Eq.(16). g_1 want to improve its payoff based on the p_i^b and o_i^b maximally. Θ^* need to be updated to support g_1, g_1 needs to acquire higher priority than the platoons ahead of it, inevitably reducing the benefits of gs_2. The bargaining process between them need to be divided into three cases for discussion:

Case1: If $o^b = 1$, the bargaining game will not happen. The gamer is allowed to first pass intersection according to coalition game stage, the p^b is maximum and potential for improvement is 0. That is, *ith* platoon does not bargain with other platoon, which is not contradictory with coalition group depicted in Eq.(10). Coalition game considers driving safety payoff p_s and passage efficiency payoff p_e, bargaining game only focus on p_e.

Case2: when $o^b = 2$, the equilibrium solution is not improved. If the value of o changes from 2 to 1, the payoff of g_1 improves but the payoff of gs_2 decreases directly. If we consider $o^b = 2$ as equilibrium solution for bargaining game, the payoff of g_1 does not improve, that is, priority passage request is not achieved. In this case, we consider $o = 1$ as the equilibrium solution to achieve the priority passage request.

Case3: If $o^b > 2$, we conduct bargaining game to acquire Nash equilibrium solution. The Nash equilibrium payoff $p_1(\Theta^*(o))$ and $p_2(\Theta^*(o)) = \sum_i^{N-1} (t_{out} - t_c)^i$ of g_1 and gs_2 can be calculated based on Eq.(2)-Eq.(5) and o^b. Noted that driving safety payoff is not considered.

$$\begin{cases} \max : p_1(\Theta^*(o)) \times p_2(\Theta^*(o)) \\ \textit{subject to Eq.}(2-5) \textit{and Eq.}(14-16) \end{cases} \tag{17}$$

The emphasis here is that, in the process of bargaining games, the focal point of gs_2 will shift from the Nash equilibrium strategy Eq.(14) to the strategy set Eq.(16). In other words, the passage order of the remaining gamers in the above coalition group remains unchanged.

V. PLATOON MANAGEMENT METHOD

After determining the passage order of platoons, the acceleration profile of each platoon can be calculated through the following optimization problem

$$\begin{aligned} &\min_{u_i(t)} \quad \frac{1}{2}\int_{t_i^1}^{t_i^2} u_i(t)^2 \\ &\textit{subject to}: u_{\min} \le u_i(t) \le u_{\max} \\ &\qquad v_{\min} \le v_i(t) \le v_{\max} \\ &\qquad p_i\left(t_i^1\right) = p_i^1, v_i\left(t_i^1\right) = v_i^1 \\ &\qquad p_i\left(t_i^2\right) = p_i^2, v_i\left(t_i^2\right) = v_i^2 \\ &\qquad t \in \left[t_i^1, t_i^2\right], \end{aligned} \tag{18}$$

where t_i^1 and t_i^2 are current timestamp and exit timestamp of *ith* platoon, $u(t)$ is acceleration, $u_{\min}$ and $u_{\max}$ are minimum acceleration and maximum acceleration, $v_{\min}$ and $v_{\max}$ are minimum speed and allowed maximum speed, v^1 and p^1 are current speed and position, v^2 and p^2 are exit speed and terminal position.

The consensus control method [36], [37] is employed to execute the planned trajectory. According consensus control method, the control input is influenced by the tracking error, potentially resulting in prolonged control convergence time due to notable position and speed discrepancies. These disparities stem from the individual positions and speeds of each vehicle. When a platoon does not reach the stability, the substantial gap between vehicles diminishes passage efficiency. Consequently, this section proposes a platoon management method grounded in Euler tour theory (PE).

The platoon management problem needs to be divided into two sub-problems: the vehicle collision problem and the platoon assignment problem. As depicted in Figure 1, vehicles are grouped into platoons, ensuring that vehicles within the same platoon do not conflict with each other, thus preventing vehicles with collision relationships from coexisting in the same platoon. A platoon set includes all platoons, and for a fixed number of vehicles, there exist some platoon sets. An optimal platoon set is sought by enumerating all possible platoon sets. A platoon management method is devised to compute the optimal platoons for each vehicle, as illustrated in **Algorithm 1**.

The PE method takes a sequence of vehicle information within the scheduled area as input and produces the optimal platoon set for these vehicles as output. It operates by iteratively assigning vehicles to possible platoons and verifying their conflict relationships. The method computes the feasible platoons for all vehicles. In this study, each vehicle is conceptualized as a node, with an edge between two vehicles denoting their proximity. The absolute differences in position and speed between two vehicles serve as the weight of this edge. Thus, each platoon represents a Euler tour. The PE method seeks the optimal platoon set, consisting of several Euler tours. The optimal set exhibits two primary characteristics: firstly, it contains fewer platoons, and secondly, it maintains a lower average weight. Three **for** loops are employed to search for the optimal platoon set in **Algorithm 1**. Once the optimal platoons are determined, they will remain unchanged.

Algorithm 1 PE

Initialization Set $PPS = []$ and$OPS = []$ OPS to store all possible platoon sets and the optimal platoon set. Set *pps* to store a possible platoon set. Set ε to be the stop criterion. Set $w_{\max}$ and b to be average weight and the number of platoons in a platoon set. Set $a = size\,(PPS)$.

While $\varepsilon < 5$ **do**
  Enumerate a platoon set and store it in *pps*.
  if *pps* in *PPS*: **then**
    $\varepsilon = \varepsilon + 1$
  else:
    Store *pps* in *PPS* and $\varepsilon = 0$
  end if
end while

---

for $a = 1$ **A do**
  $b = size\,(PPS[a])$
  if $b < b_{\min}$: **then**
    $b_{\min} = b$
  end if
end for

---

for $a = 1$ **A do**
  if $size\,(PPS[a]) > b_{\min}$: **then**
    Delete $PPS\,[a]$ from *PPS*
  end if
end for

---

for $a = 1$ **A do**
  Calculate the average weight w of $PPS\,[a]$.
  if $w < w_{\max}$: **then**
    $w_{\max} = w$ and $OPS = PPS[a]$
  end if
end for

VI. GAME SCHEDULING METHOD

In the third and fourth sections, we design a baseline strategy and construct a coalition game model and a bargaining game model, respectively. The baseline strategy serves as a bridge between the two game models, providing a baseline payoff for the bargaining game. This enables prioritization of gamers' passage requests while minimizing the impact on other gamers' payoffs. To further clarify the game scheduling method, named COBB, we present the flow in Fig. 2.

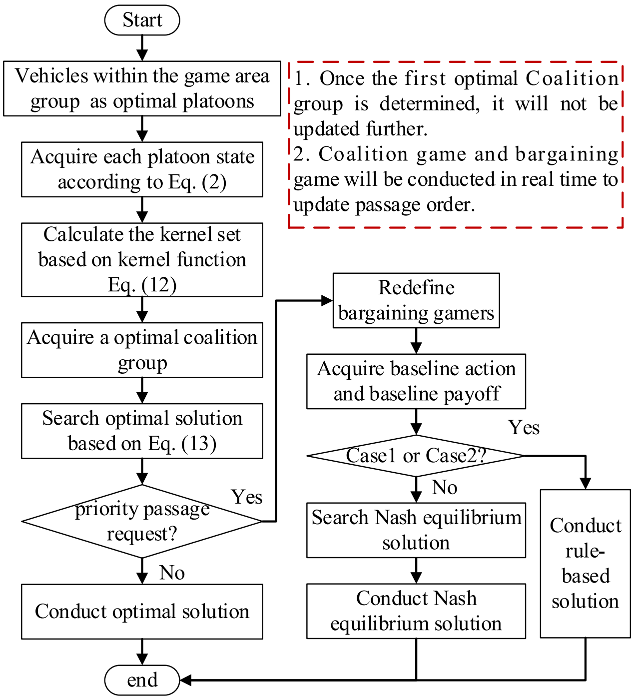

FIGURE 2. COBB method flowchart.

The rolling strategy is employed in optimization-based methods to reduce computation resource consumption in solving the optimization problem. Similarly, we use the rolling strategy to determine the coalition kernel set. The rolling horizon is denoted as ΔT, and its value is not fixed. Initially, all vehicle states entering the game area are gathered to compute the kernel set and optimal coalition groups. Then, the group that is closest to the intersection conduct the coalition game. When the remaining vehicles in the scheduling area increase to the previous quantity, the new optimal coalition group is recalculated once again.

It's important to highlight that coalition games fall within the realm of cooperative games, unlike non-cooperative games. The disparities between the two are evident in two key aspects. Firstly, non-cooperative games are marked by their competitive nature, prioritizing individual gains for gamers. While reaching a Nash equilibrium state can maximize each gamer's payoff, the collective sum may not necessarily be optimized. Secondly, coalition games lack this competitive nature, instead emphasizing cooperative relationships among gamers and maximizing the overall payoff of coalition group. Therefore, the cooperative game method is more suitable for solving scheduling problems. Based on the above discussion, we have designed the baseline method and considered the payoff of the gamer with a priority passage request in the coalition game process as a measure for how to address priority passage requests.

VII. EXPERIMENT TEST

To validate the effectiveness of the COBB method proposed in this paper, we conducted several comparative experiments.

TABLE 1. Simulation parameters.

Parameter	Value
Game range	$300m$
Simulation time	$500s$
Free flow speed	$10m/s$
Maximum acceleration	$3m/s^2$
Minimum acceleration	$-6m/s^2$
Maximum left turning speed	$10m/s$
Maximum straight speed	$10m/s$
Free flow speed	$10m/s$
Maximum speed	$11m/s$
Maximum traffic demand	$500veh/l/h$
Minimum traffic demand	$100veh/l/h$

Additionally, we performed a comparative analysis on the experimental results.

First, we construct an experimental environment, the about parameters are listed in Table 1. Experiment time is conducted for $500s$. The free flow speed is specified within the range of $10m/s$, and the maximum speeds for left-turn, straight-through, and right-turn movements are uniformly set at $10m/s$. The maximum traffic demand is established at 500 vehicles per lane per hour, with a minimum threshold of 100 vehicles per lane per hour. Maximum acceleration is $3m/s^2$ and minimum acceleration is -$6m/s^2$.

In this section, we use travel cost as the criterion for the performance evaluation. Inspired by Ma et al. [38] and Yu et al. [39], who quantified the cost of vehicle delay at $6\$/hour$, we employs $6\$/hour$ and $1.5\$/L$ as the unit travel cost for delay and fuel consumption, respectively. An instantaneous fuel consumption model is used to assess the vehicles' fuel consumption during travel, which can be represented

$$f = \begin{cases} \lambda, & a(t) \le \dfrac{R_a(t) + R_r(t)}{M_a} \\ \lambda + \theta_1 R_T(t) v(t), & a(t) \in \left(-\dfrac{R_a(t) + R_r(t)}{M_a}, 0\right) \\ \lambda + \theta_1 R_T(t) v(t) + \dfrac{\theta_2 M_a a(t)^2 v(t)}{1000}, & a(t) \ge 0, \end{cases} \tag{19}$$

where f is the fuel consumption, λ is the fuel consumption rate during idle state, θ_1 and θ_2 are power parameters, M_a is the average vehicle mass, R_a is the air resistance, R_r is the rolling resistance, and R_T is the vehicle tractive force. R_a can be calculated by $R_a(t) = \frac{\rho}{2} D_c F_a v(t)^2$, where ρ is the air density, D_c is the air resistance coefficient, and F_a is the average frontal cross-sectional area of the vehicle. R_r can be calculated by $R_a(t) = 0.01 \frac{1+v(t)}{44.73} M_a g$, where g is gravity acceleration. R_T can be calculated by $R_T = M_a a(t) + R_a(t) + R_r(t) + R_g(t)$, the experiment only considers vehicles traveling on flat roads and does not account for the effect of road gradient on vehicle fuel consumption, so $R_g(t) = 0$.

To show the performance, proposed game schedule method is compared with some existing methods in the literature:

ASC method: The Adaptive Signal Control (ASC) method utilizes sensors, cameras, radar, and other devices to monitor traffic flow, vehicle density, driving speed, and other information. It analyzes this data to determine the optimal signal phase timing. The advantage of this method lies in its ability to flexibly adjust parameters such as signal phase cycles, duration of passage phases, and phase differentials according to actual conditions. This minimizes traffic congestion, reduces wait times, and maximizes vehicle passage efficiency.

FCFS method [2]: The First Come First Served (FCFS) method is a rule-based scheduling method where vehicles and road side units communicate to exchange data. Road side units sort the information provided by vehicles based on the order of arrival and allocate passage time for vehicles accordingly.

LQF method [40]: The Longest Queue First (LQF) method is a rule-based scheduling method. It assigns a weight to each lane based on the platoon length of each lane, with lanes capable of simultaneous passage being assigned equal weights. During the scheduling process, the weights of each lane are periodically updated, and the lane with the highest weight is granted priority passage rights.

OC method [16]: The Optimal Coordination (OC) method is designed based on the earliest deadline first principle. It has been proven to achieve the globally optimal solution. Therefore, it is not a rule-based scheduling method.

DDQN method [41]: The Double Deep Q-Network (DDQN) method is a machine learning method that trains neural networks by setting states, actions, and rewards. This enables the network to make optimal decisions for the task at hand.

The ASC method treats traffic signals as passage cues without requiring communication and interaction between vehicles and road side units. Therefore, this method can only achieve single-vehicle scheduling, and the issue of vehicle trajectory planning is not addressed in the scheduling process. For the FCFS, LQF, OC, and DDQN methods, vehicle trajectory optimization can be achieved. Once the optimal coalition group is determined, these methods replace the game method and are executed to decide the passage order for the platoons. On the other hand, if there exists a platoon with a priority passage request in the group, it can pass the intersection first, and the remaining platoons comply with the scheduling result determined by the four methods.

The DDQN learning model requires training to achieve optimal decision-making capabilities. Consequently, it's essential to define suitable observation states, action spaces, and reward functions tailored to the scheduling problem. The action space of the learning model should encompass all possible passage order for the scheduled platoons, making it discrete. It can be denoted as $A = \{a_1, a_2, a_3, \ldots, a_n\}$, where $n!$ represents the number of discrete actions contained in the action space. The reward can be set as the average

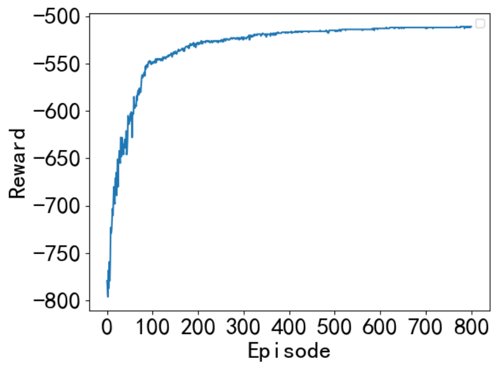

FIGURE 3. History reward curve.

TABLE 2. The experimental results of DDQN method, OC method and CO method.

Demand $(veh/h/lane)$		100	200	300	400
DDQN	Delay(s)	4.0	4.3	4.4	4.4
	Fuel(ml)	14.1	14.3	14.5	15.2
CO	Delay(s)	4.2	4.0	4.1	4.6
	Fuel(ml)	14.7	14.8	15.1	15.3
OC	Delay(s)	4.13	4.2	4.2	4.9
	Fuel(ml)	14.9	14.7	15.4	15.1

vehicle delay under the passage sequence outputted by the model. The observed states of the model can be defined as the timestamp at which each platoon passes through the intersection at its current speed and the time points at which passage is allowed. Figure 3 illustrates the reward history during the learning process, and it shows convergence in the $500th$ episode.

To verify the decision-making capabilities of the DDQN learning model and the effectiveness of the coalition game component (CO) in the COBB method, we conducted separate implementations of the DDQN method, CO method, and OC method, presenting the experimental results in Table 2. The data in Table 2 indicates that the performance of the DDQN method in terms of delay and fuel consumption is comparable to that of the OC method. Additionally, the CO method demonstrates satisfactory decision-making capabilities, with the coalition game primarily focusing on overall interests.

Table 3 illustrates the test results of all methods across traffic demands ranging from 100 to 500 vehicles per hour per lane. AV denotes all vehicles passing through the intersection, while PV represents vehicles requesting priority passage. We recorded their passage delay and fuel consumption separately. If one vehicle in a platoon requests priority passage, then all vehicles in that platoon belong to PV. Only one platoon is allowed priority passage in a coalition group. The ASC method cannot accommodate vehicle priority passage requests, and Table 6 does not offer a comparison of the handling of PV by the ASC method and the COBB method. Clearly, the performance of the COBB method surpasses that of the ASC method under varying levels of traffic demand, mainly for two reasons: First, the ASC method cannot

TABLE 3. The experimental results of all methods under different demands.

Demand $(veh/h/lane)$			100	200	300	400	500
ASC	AV	Delay(s)	5.8	13.8	45.0	43.7	82.2
		Fuel(ml)	21.9	26.3	40.0	40.2	59.9
	PV	Delay(s)	N/A	N/A	N/A	N/A	N/A
		Fuel(ml)	N/A	N/A	N/A	N/A	N/A
FCFS	AV	Delay(s)	5.4	5.7	5.6	5.6	6.9
		Fuel(ml)	15.1	15.3	15.2	15.2	16.4
	PV	Delay(s)	1.3	1.9	3.0	2.9	4.6
		Fuel(ml)	11.9	12.8	13.7	13.1	14.8
LQF	AV	Delay(s)	6.2	5.6	6.1	6.5	7.0
		Fuel(ml)	15.7	15.2	16.0	16.2	16.3
	PV	Delay(s)	1.6	1.2	2.3	3.6	4.9
		Fuel(ml)	12.2	12.2	13.4	13.9	14.8
OC	AV	Delay(s)	5.2	4.6	5.0	5.8	6.4
		Fuel(ml)	15.4	15.5	15.3	16.6	17.0
	PV	Delay(s)	1.2	1.0	1.3	2.5	3.6
		Fuel(ml)	12.7	12.8	12.7	14.2	14.3
DDQN	AV	Delay(s)	4.8	4.6	5.0	5.4	6.5
		Fuel(ml)	15.3	15.3	15.8	16.0	17.5
	PV	Delay(s)	1.1	1.1	1.5	2.5	4.0
		Fuel(ml)	12.6	12.7	12.5	13.2	15.5
COBB	AV	Delay(s)	4.2	4.3	5.0	4.6	6.1
		Fuel(ml)	14.6	15.3	15.8	15.4	17.4
	PV	Delay(s)	1.5	1.8	1.1	2.3	4.1
		Fuel(ml)	12.6	13.3	12.4	13.4	15.3

schedule vehicles in the platoon form, resulting in a larger time gap for vehicles passing through the intersection. Smaller time gaps under the same vehicle passage demand translate to higher passage efficiency. Additionally, this method, along with FCFS and LQF, falls under rule-based methods, unable to make optimal decisions based on real-time changes in traffic flow. Second, the ASC method cannot intervene with vehicles using longitudinal trajectory planning during the scheduling process, leading to many vehicles idling outside the intersection, awaiting passage. This contributes to its higher fuel consumption compared to other methods.

Tables 5 and 4 respectively provide comparison results of the FCFS method and the LQF method with the COBB method. A common feature of these two methods is that when the traffic demand level is low, their PV travel costs are lower than those of the COBB method, but as demand increases, their PV travel costs become higher than those of the COBB method. In FCFS scheduling and LQF scheduling, we allow PV to have absolute priority passage rights. While absolute priority passage rights may not have a negative impact on subsequent vehicles passage under lower traffic demand, as demand increases, this operation may increase the passage delay for subsequent vehicles. Tables 4 and 5 indicate that under a demand of 300-500 vehicles per hour per lane, the COBB method reduces the travel costs of PV without increasing the travel costs of AV, indicating the effectiveness of the baseline strategy we designed.

Tables 7 and 8 respectively provide comparison results of the OC method and the DDQN method with the COBB method. Similar to the FCFS and LQF methods, under traffic demands of 100-200 vehicles per hour per lane, the PV travel costs of the COBB method are higher than those of the OC method and the DDQN method. However, under a demand of 300-500 vehicles per hour per lane, the PV travel costs of the OC method and the DDQN method narrow the gap with the COBB method, and even at a demand of 500 vehicles per hour per lane, the PV travel costs of the OC method are lower than those of the COBB method. Two reasons account for this phenomenon: Firstly, both methods belong to optimization-based strategies, maximizing traffic efficiency compared to rule-based methods. Secondly, both methods enhance traffic efficiency while eliminating the impact of absolute priority passage rights on other vehicles, a feat the FCFS and LQF methods cannot achieve.

The aforementioned experimental results demonstrate that the COBB method exhibits satisfactory performance compared to other methods. To confirm the effectiveness of this method in managing PV vehicles, we also provide the travel costs of PV vehicles after implementing the COBB method under dynamic demand.

Table 9 presents dynamic demand data, while Tables 10 and 11 respectively showcase the experimental and comparative results of the COBB method and the CO method. The CO method solely incorporates the coalition game component, with no execution of requests from PV vehicles. It's evident that compared to the CO method, the COBB method has reduced PV travel costs by 5.0% to 33.3%, while increasing AV travel costs by 3.8% to 5.6%. This indicates that bargaining in the game somewhat sacrifices the interests of AVs to prioritize PV travel requests. The reason for this phenomenon is that bargaining games aim to maximize the

TABLE 4. The Comparison results of LFQ method and COBB method.

Demand	LQF		COBB	
$(veh/h/lane)$	AV($/hr)	PV($/hr)	AV(%)	PV(%)
100	26.8	3.1	-14.6%	**+3.2%**
200	50.8	6.1	-6.1%	**+11.5%**
300	81.0	10.7	-6.0%	-14.0%
400	111.0	16.0	-12.2%	-10.6%
500	142.6	22.5	**+0.6%**	-1.8%

TABLE 5. The comparison results of FCFS method and COBB method.

Demand	FCFS		COBB			
$(veh/h/lane)$	AV($/hr)	PV($/hr)	AV($/hr %)		PV($/hr %)	
100	25.0	3.0	22.9	-8.4%	3.2	**+6.7%**
200	51.3	6.7	47.7	-7.0%	6.8	**+1.5%**
300	76.2	11.4	76.1	-0.1%	9.2	-19.3%
400	101.6	14.6	97.5	-4.0%	14.3	-2.1%
500	142.6	22.2	143.4	**+0.6%**	22.1	-0.5%

TABLE 6. The comparison results of ASC method and COBB method.

Demand $(veh/h/lane)$	Delay (%)	Fuel (%)	ASC ($/hr)	COBB ($/hr %)	
100	-27.6%	-33.3%	33.7	22.9	-32.0%
200	-68.8%	-41.8%	98.4	47.7	-51.5%
300	-88.9%	-60.5%	316.8	76.1	-76.0%
400	-89.5%	-61.7%	416.7	97.5	-76.6%
500	-92.6%	-71.0%	885.5	143.4	-83.8%

TABLE 7. The comparison results of OC method and COBB method.

Demand	OC		COBB	
$(veh/h/lane)$	AV($/hr)	PV($/hr)	AV(%)	PV(%)
100	25.1	3.1	-8.8%	**+3.2%**
200	49.0	6.2	-2.7%	**+9.7%**
300	74.3	9.5	**+2.4%**	-3.2%
400	109.4	15.2	-10.9%	-5.9%
500	143.0	20.4	**+0.3%**	**+8.3%**

TABLE 8. The comparison results of DDQN method and COBB method.

Demand	DDQN		COBB	
$(veh/h/lane)$	AV($/hr)	PV($/hr)	AV(%)	PV(%)
100	24.5	3.1	-6.5%	**+3.2%**
200	48.5	6.2	-1.6%	**+9.7%**
300	76.1	9.5	0.0%	-3.2%
400	104.4	14.3	-6.6%	0.0%
500	146.6	22.2	-2.2%	-0.5%

TABLE 9. Dynamic traffic demands.

1	Period(s)	[0, 200]	[200, 300]	[300, 400]	[400, 500]	N/A
	Demand $(veh/h/lane)$	50	150	350	200	N/A
2	Period(s)	[0, 100]	[100, 200]	[200, 500]	N/A	N/A
	Demand $(veh/h/lane)$	150	50	500	N/A	N/A
3	Period(s)	[0, 50]	[50, 200]	[200, 350]	[350, 400]	[400, 500]
	Demand $(veh/h/lane)$	500	300	50	200	150
4	Period(s)	[0,100]	[100,150]	[150,300]	[300,400]	[400,500]
	Demand $(veh/h/lane)$	50	250	300	150	500

benefits of the involved gamers but fail to increase the total sum of benefits for all gamers. Gratifyingly, under demand 3, the COBB method not only reduces PV travel costs but also decreases AV travel costs.

TABLE 10. The experimental results of CO method and COBB method under dynamic demands.

		Demad1		Demand2		Demand3		Demand4	
		AV	PV	AV	PV	AV	PV	AV	PV
CO	Delay(s)	4.2	4.7	5.0	5.2	4.5	5.8	4.7	4.6
	Fuel(ml)	15.0	15.2	15.7	15.8	16.1	16.1	15.3	15.5
COBB	Delay(s)	4.9	2.0	5.6	4.0	4.8	1.7	5.2	2.0
	Fuel(ml)	15.4	13.2	16.1	15.5	15.3	12.9	15.6	14.1

TABLE 11. The comparison results of CO method and COBB method.

Demand Level	CO		COBB			
($veh/h/lane$)	AV($/hr)	PV($/hr)	AV($/hr %)		PV($/hr %)	
Demand1	35.2	7.2	36.8	**+4.5%**	4.8	-33.3%
Demand2	85.6	16.0	90.4	**+5.6%**	15.2	-5.0%
Demand3	85.6	16.8	83.2	-2.8%	11.2	-33.3%
Demand4	62.4	12	64.8	**+3.8%**	9.6	-20.0%

VIII. CONCLUSION

In this paper, we propose a game scheduling (COBB) method to tackle the platoon scheduling problem of priority passage requests at autonomous intersections. To prevent adverse effects on other vehicles while implementing priority passage for certain vehicles, we divide the game process into two stages: coalition game and bargaining game. In the coalition stage, all platoons cooperate to maximize overall payoff. We design a baseline strategy considering the payoff obtained by platoon applying for priority passage requests in the coalition game as their baseline payoff. In the bargaining game, the gamer bargains with other, ensuring not to fall below the baseline payoff, to maximize its own payoff. Experimental results demonstrate that compared to other methods, this COBB method can effectively minimize the negative impact of priority passage request vehicles on other vehicles and reduce travel costs for both PV and AV in certain traffic demands.

Next, based on the findings of this study, we discuss future research directions. Firstly, this paper focuses solely on platoon scheduling decisions without considering longitudinal trajectory planning. Integrating trajectory planning into the game scheduling model is crucial. Secondly, the paper assumes that game participants are connected autonomous vehicles and does not consider human-driven vehicles. Although human-driven vehicles can interact with surrounding connected autonomous vehicles or road side units, human drivers cannot make precise game decisions like connected autonomous vehicles. Constructing a game model that accounts for human drivers is essential.

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