

Article

An Innovative Cooperative Driving Strategy for Signal-Free Intersection Navigation with CAV Platoons

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Abstract: We present an innovative cooperative driving strategy known as Dynamic Resequencing and Platooning (DRP) designed to ensure the safe and efficient traversal of Connected and Automated Vehicles (CAVs) through signal-free intersections. By employing a Resequencing and Platooning Algorithm (RPA) grounded in state transition networks and CAV platooning, the optimal crossing sequence for CAVs is ascertained within a finite time. Through the utilization of a decentralized energy-optimal control framework, optimal trajectories are devised for CAVs, thereby facilitating optimal coordination among them. Simulation results underscore the substantial performance benefits of the DRP strategy compared to traffic light, First-In-First-Out (FIFO), and Local Dynamic Resequencing (LDR) strategies, with notable reductions observed in both travel delay and fuel consumption.

Keywords: signal-free intersection; connected and automated vehicles; hybrid electric vehicles; cooperative driving strategies



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1. Introduction

Urban intersections often suffer from severe congestion, yet they play a crucial role in allocating conflicting streams of traffic. Traditional intersection management relies on static signal traffic lights coordinated through timers [1]. However, this strategy, which is solely based on predefined time cycles, overlooks variations in actual vehicle density and travel velocities on the road, potentially leading to ineffective responses to diverse traffic demands [2]. With the rapid advancement of electric and autonomous vehicles, Connected and Automated Vehicles (CAVs) hold promise for revolutionary changes in traffic networks, substantially enhancing network performance [3,4]. By harnessing Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, CAVs can access real-time travel data from adjacent vehicles and interact with infrastructure, thus enabling the possibility of signal-free intersections [5,6]. Effectively and securely coordinating CAVs through signal-free intersections necessitates the formulation of diverse cooperative driving strategies. These strategies typically optimize one or more objectives by orchestrating the crossing sequence and travel trajectories of all CAVs, thereby addressing the Crossing Sequence Problem (CSP) and the Trajectory Optimization Problem (TOP) for CAVs.

Certain studies have deemed the First-In-First-Out (FIFO) strategy as a feasible approach to cooperative driving. Under this paradigm, the resolution of the CSP directly hinges upon the sequence of entry of each CAV into the intersection zone [7,8]. Relative to the conventional traffic light strategy, the FIFO strategy exhibits noteworthy reductions in travel delay, thereby emerging as a robust mechanism for mitigating traffic congestion. Researchers have developed a decentralized energy-optimal control framework to precisely compute the controllable arrival times and optimal control inputs for each CAV, thereby offering a solution to the TOP [9]. Augmenting this framework with safety distance constraints and considerations for passenger comfort can augment the robustness

of strategies [10]. Nonetheless, contemporary research underscores a principal constraint of the FIFO strategy, particularly its incapacity to dynamically reconfigure the sequencing of CAVs' crossings [11]. This limitation is acutely evident in scenarios of heightened traffic demands, curtailing further enhancements in intersection capacity and impeding the maximal utilization of CAV capabilities in addressing traffic congestion. Consequently, in the pursuit of more sophisticated cooperative driving strategies, prioritizing investigations into the CSP is imperative.

The resequencing strategy aims to optimize the crossing sequence of CAVs. This approach employs a Resequencing Algorithm (RA) to address the CSP, generating multiple feasible crossing sequences for each CAV and selecting the optimal sequence. Throughout this process, maintaining the relative crossing sequence among CAVs is crucial while accommodating the insertion of newly entering CAVs [12]. However, this strategy is constrained to adjusting the crossing sequence of the most recently entered CAV, resulting in suboptimal sorting outcomes. To enhance the effectiveness of sorting results, the Dynamic Resequencing (DR) strategy proposes a comprehensive and independent re-evaluation of the crossing sequences of all CAVs each time a new CAV enters the intersection zone [13]. Although this approach may enhance sorting accuracy, it also significantly prolongs the runtime of the RA. In response to this challenge, the Local Dynamic Resequencing (LDR) strategy has been introduced, effectively reducing the number of CAVs requiring crossing sequence adjustments and thus shortening the runtime of the RA [14]. However, it is important to note that these strategies are predominantly event-triggered, leading to frequent updates of the optimal crossing sequence derived from the RA. This frequent updating elevates the risk of the RA becoming trapped in local optima [15], thereby complicating the search for a globally optimal solution. Our study observes that when transitioning the DR strategy to a time-triggered approach, the involvement of CAVs in crossing sequence adjustments is confined within a finite range. At this juncture, the CSP bears a striking resemblance to the Car Reordering Problem (CRP) encountered in automotive paint shops. Both seek to minimize the cost associated with a specific sequence dependency within a finite retrieval sequence [16]. Drawing upon the methodology of the CRP, we establish a centralized CSP model and introduce state transition networks to centrally enhance the RA, effectively mitigating the challenge of local optima. Expanding on this, we integrate the enhanced RA with the Platoon Forming Algorithm (PFA) to formulate the Resequencing Platoon Algorithm (RPA). This innovative approach allows CAVs to pre-organize batches, enabling the formation of CAV platoons capable of collectively navigating intersections [17]. During the calculation of the optimal crossing sequence for CAVs, the RPA extensively leverages historical computation results, thereby minimizing unnecessary crossing sequence updates and further evading local optima traps.

Addressing the TOP, we persist in employing a decentralized energy-optimal control framework, refining the recursive algorithm for controllable arrival times to accommodate the requirements of CAV platoons. This innovative strategy is designated as the Dynamic Resequencing and Platooning (DRP) strategy, presenting fresh perspectives and methodologies for alleviating traffic congestion.

This paper is organized as follows. Section 2 delves into the design of signal-free intersections and outlines the framework of the DRP strategy. It establishes both a centralized CSP model and a decentralized TOP model. Section 3 introduces an enhanced RA that capitalizes on state transition networks. This algorithm is amalgamated with the PFA to devise the RPA, aimed at achieving the global optimal solution for the centralized CSP within a finite time. In Section 4, an improved recursive algorithm is proposed for determining controllable arrival times tailored to CAV platoons. This algorithm imposes temporal constraints to address the energy-optimal control problem [18] while solving the TOP. Section 5 presents a series of experiments comparing the performance and fairness of CAVs at both traditional intersections and signal-free intersections under various strategies: the traffic light strategy, FIFO strategy, LDR strategy, and DRP strategy. Subsequent to this, a detailed analysis and discussion of each strategy's performance ensue. Finally, in Section 6,

the paper culminates with a comprehensive summary, offering research conclusions and outlining avenues for future exploration and development.

2. Framework of DRP Strategy and Problem Formulation

This section will delineate the configuration of signal-free intersections, introduce the specific framework of the DRP strategy, and establish mathematical models for centralized CSP and decentralized TOP. These efforts lay the foundation for the subsequent sections.

Figure 1 illustrates a symmetrical cross intersection comprising two dual lanes, each with a width of S . This intersection operates without signal control and features a coordination unit at its center, capable of interacting with adjacent CAVs, allowing only CAVs to pass through. In accordance with existing research perspectives [19,20], the intersection area is divided into three subareas. The central square region, with a side length of S , designated as the Merging Zone (MZ), serves as the primary area for CAV merging and is thus prone to collisions. Surrounding the MZ is the Control Zone (CZ), with a distance of L from its entrance to the MZ entrance, where the coordination unit transmits control information to CAVs within this area. The outermost zone is the Organizing Zone (OZ), with a distance of H from its entrance to the CZ entrance, primarily serving as a buffer zone for organizing the crossing sequence and travel trajectories of CAVs. In this study, we assume that all CAVs are configured as Series Hybrid Electric Vehicles (HEVs) with identical physical properties and enter the intersection area with the same initial velocity v_0 .

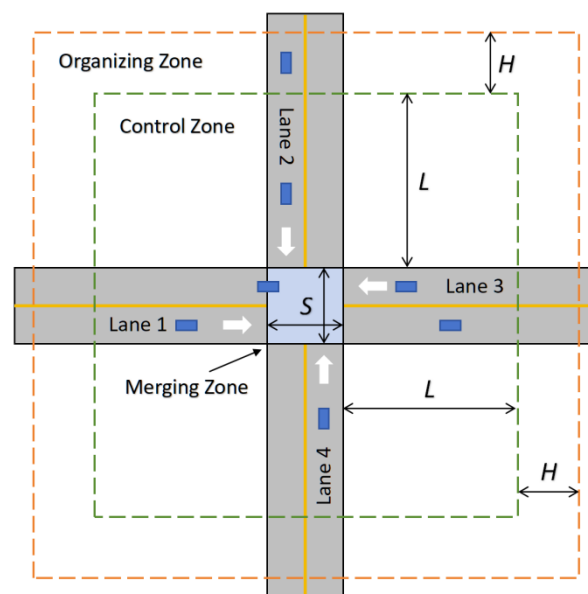


Figure 1. Signal-free intersection with CAVs.

2.1. Framework of DRP Strategy

Figure 2 illustrates the framework of the DRP strategy, which comprises three stages based on the positioning of CAVs within the area.

- Stage One: Upon CAV i entering the OZ, it transmits pertinent information, including the current time t_i^e , to the coordination unit. Every 2 s, the coordination unit invokes the RPA based on state transition networks and CAV platooning to resolve the centralized CSP, orchestrating the crossing sequence and platoon formation for all CAVs in the OZ. Subsequently, employing the decentralized energy-optimal control framework to tackle the TOP problem, optimal travel trajectories are charted for the CAVs in the OZ. CAV i maintains its initial velocity v_0 while traversing the OZ.
- Stage Two: Upon ingress into the CZ, CAV i receives the optimal travel trajectory and platoon formation prescribed by the coordination unit and autonomously adheres to

the commanded velocity. Once established, the trajectory remains unchanged unless there exists a collision risk.

- Stage Three: Upon entering the MZ, CAV i travels at a consistent velocity v_i^m to ensure stability and safety throughout the journey.

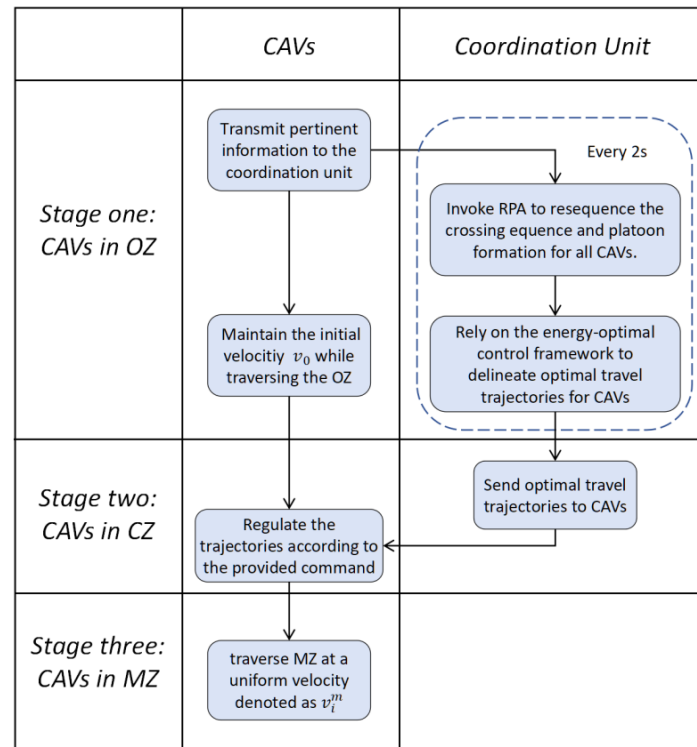


Figure 2. Framework of DRP strategy.

2.2. Centralized CAVs Crossing Sequencing Problem Formulation

We designate the segments within the OZ as organizing segments and regard them as conveyors, with the MZ at the center of the intersection viewed as a processing point. At this point, leveraging the methodology of the CRP problem, a centralized CSP can be established.

Figure 3 depicts how a signal-free intersection can be transformed into a storage system consisting of a set of organizing segments and a group of CAVs. Let $M = \{1, 2, 3, 4\}$ denote the identification of organizing segments, $N = \{1, \dots, n\}$ represent the identification of CAVs, and $n \in \mathbb{N}^+$ denote the total number of CAVs on the four organizing segments. For organizing segment $k \in M$, $n_k \in \mathbb{N}^+$ denotes the number of CAVs on it, and the identification of the $j \in [1, n_k]$ -th CAV on organizing segment k is denoted as $\sum_{i=1}^{k-1} n_i + j$. It is important to note that there is no strict precedence between the sequences of CAVs entering the MZ from different organizing segments. However, considering that overtaking increases travel delay [21], each organizing segment operates internally following the FIFO principle. Therefore, if there is more than one CAV on organizing segment k , the $p \in [1, n_k]$ -th CAV on the segment should enter the MZ before the $q \in [p, n_k]$ -th CAV on the same organizing segment. When two consecutive CAVs, i and j , entering the MZ pose a potential collision risk, a collision avoidance cost $C_{i,j}$ is incurred, measured in seconds, with the specific calculation method detailed in reference [22]. On the other hand, when CAV i and CAV j do not pose a collision risk, no collision avoidance cost is incurred. Based on this assumption, we further propose that, for any three distinct CAVs x , y , and z , the sum of their collision avoidance costs satisfies the inequality $C_{x,y} + C_{x,z} \geq C_{y,z}$. Therefore, the key to the CSP lies in adjusting the sequence of CAVs entering the MZ to minimize the total collision avoidance cost.

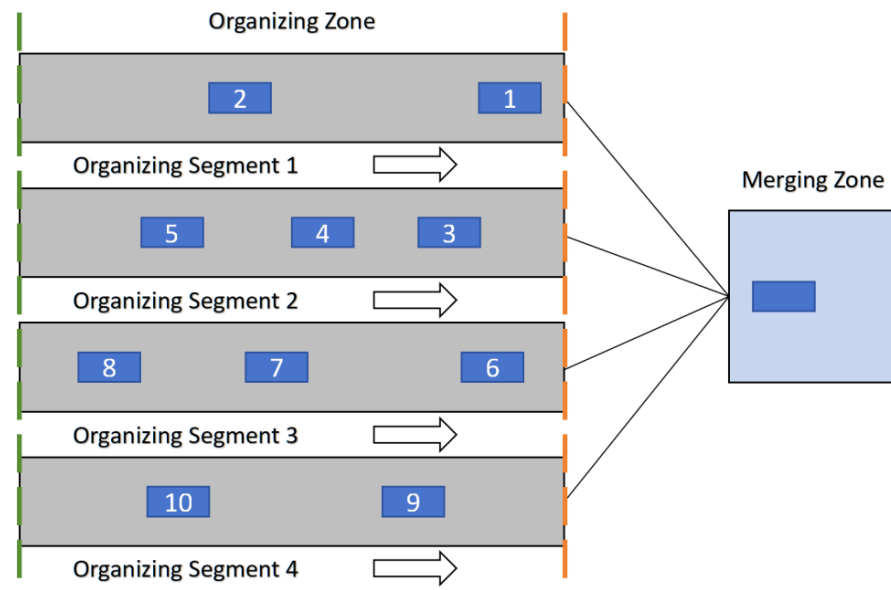


Figure 3. Configuration of CAVs storage system.

In the subsequent step, we define a directed network wherein each node V_i corresponds to a CAV i on the organizing segments, thereby constituting the node set $V_{OS} = \{V_1, \dots, V_n\}$. We delineate $R = \{V_j \in V_{OS} | j = \sum_{i=1}^{k-1} n_i + 1, \forall k \in M\}$ as the assortment of nodes corresponding to the nearest CAVs on each organizing segment to the MZ, and $E = \{V_j \in V_{OS} | j = n_k + \sum_{i=1}^{k-1} n_i, \forall k \in M\}$ as the collection of nodes associated with the farthest CAVs on each organizing segment from the MZ. Specifically, R_k and E_k symbolize the nodes aligned with the closest and farthest CAVs from the MZ on organizing segment k , respectively. Subsequently, we establish a collection of directed arcs, denoted as A_{OS} . An arc (V_i, V_j) exists within A_{OS} if CAV j can promptly succeed CAV i into the MZ, for instance, when CAV i and CAV j are proximate or situated on distinct organizing segments. The cost attributed to arc (V_i, V_j) equals the collision avoidance cost $C_{i,j}$ between CAV i and CAV j . Additionally, we introduce a virtual node V_s and two arrays of virtual arcs, namely A_r and A_e . $A_r = \{(V_s, V_j) | V_j \in R\}$ symbolizes the arcs originating from V_s to each node within R , whereas $A_e = \{(V_j, V_s) | V_j \in E\}$ represents the arcs from each node within E to V_s . The expenses associated with these virtual arcs are established at 0. In recapitulation, the CSP quandary can be articulated as the quest for the minimum-cost pathway within the directed network $G = (V, A)$, depicted in Figure 4, where $V = \{V_s\} \cup V_{OS}$, $A = A_{OS} \cup A_r \cup A_e$. Employing these symbols and definitions, the CSP is amenable to representation as an integer programming paradigm:

$$\min \sum_{(V_i, V_j) \in A} C_{i,j} x_{i,j} \quad (1)$$

$$\text{subject to } \sum_{(V_i, V_j) \in A} x_{i,j} = 1, V_i \in V, \quad (2)$$

$$\sum_{(V_i, V_j) \in A} x_{i,j} = 1, V_j \in V, \quad (3)$$

$$l_i - l_j + |V| x_{i,j} \leq |V| - 1, V_i, V_j \in V, V_j \neq V_s, \quad (4)$$

$$l_s = 1, \quad (5)$$

$$2 \leq l_i \leq |V|, V_i \in V, V_i \neq V_s, \quad (6)$$

$$l_i < l_{i+1}, V_i \in [R_k, E_k), k \in M, \quad (7)$$

$$l_i \geq 0, V_i \in V, \quad (8)$$

$$x_{i,j} \in \{0, 1\}, V_i, V_j \in V. \quad (9)$$

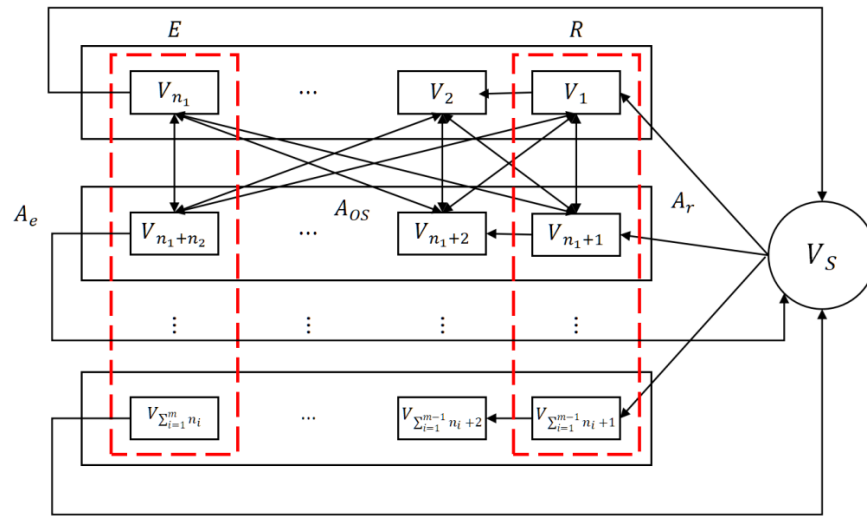


Figure 4. Network representation of centralized CSP.

The decision variable $x_{i,j}$ is a binary variable indicating whether the arc (V_i, V_j) is selected. It is set to 1 if CAV j follows CAV i into the MZ; otherwise, it is set to 0 for all other arcs (V_i, V_j) . The positional variables l_i represent the position of the node V_i corresponding to CAV i in the path. Constraints (2) and (3) ensure the uniqueness of the paths for entering and leaving any node V_i , thereby avoiding path duplication and intersection. Constraint (4) ensures the absence of subpaths within the path. Constraint (5) stipulates that the position of the virtual node V_S must be 1. Constraint (6) ensures that the positions of nodes corresponding to CAVs in the path range from 2 to $|V|$. Finally, constraint (7) ultimately mandates the precedence relationship among nodes corresponding to CAVs situated on the identical organizing segment.

2.3. CAVs Trajectory Optimization Problem Formulation

Upon establishing the sequence of all CAVs entering the MZ, additional computation of the arrival times of CAVs at the MZ, symbolized as $t^m \in \mathbb{R}^+$, becomes imperative to furnish essential temporal constraints for tackling the TOP. By taking into account the arrival time t_j^m of the preceding CAV j in the sequence at the MZ, along with the collision avoidance costs $C_{j,i}$ between CAVs j and i , recursively determining the arrival time t_i^m of CAV i at the MZ emerges as a straightforward and efficient approach [8].

Following this, to derive the precise trajectories of the CAVs, it is essential to establish the corresponding models. To accomplish this, we postulate that the movement of each CAV is subject to second-order dynamics:

$$\dot{p}_i = v_i(t), \quad \dot{v}_i = u_i(t) \quad (10)$$

Here, $p_i(t)$, $v_i(t)$, and $u_i(t)$ correspond to the position (the distance traveled upon entering the CZ), velocity, and acceleration (control input) of CAV i . To ensure that the velocity and control input of CAV i remain within acceptable ranges, constraint (11) is imposed:

$$0 \leq v_{\min} \leq v_i(t) \leq v_{\max} = v_0, \quad u_{\min} \leq u_i(t) \leq u_{\max}, \quad \forall t \in [t_i^0, t_i^x] \quad (11)$$

These constraints are effective within the interval $[t_i^0, t_i^x]$, where t_i^0 and t_i^x denote the instants when the CAV i enters the CZ and exits the MZ, respectively. In accordance with the assumptions outlined in Section 2.1, all CAVs traverse the OZ at a consistent velocity v_0 and maintain a uniform velocity v_i^m upon entering the MZ. Given the arrival time t_i^e of any

CAV i in the OZ, the time t_i^0 when CAV i enters the CZ can be ascertained by incorporating the respective travel time to t_i^e . Similarly, the departure time t_i^x when CAV i exits the MZ can be directly computed by adding the travel time to t_i^m , as illustrated in the ensuing equation:

$$t_i^0 = t_i^e + \frac{v_0}{H}, \quad t_i^x = t_i^m + \frac{v_i^m}{S} \quad (12)$$

A primary focus of research in TOP is the reduction in energy consumption [9]. For HEVs, scholarly investigations have proposed leveraging Pontryagin's minimum principle for analysis and resolution, effectively converting electrical energy into prospective fuel consumption equivalents [23]. As indicated by the study cited in [24], the energy consumption rate of CAV i is contingent upon its control input $u_i(t)$, exhibiting a monotonic increase with the augmentation of $u_i(t)$. By amalgamating the aforementioned studies, TOP can be reformulated into the subsequent energy-optimal control problem for each CAV i [9]:

$$\min_{u_{\min} \leq u_i(t) \leq u_{\max}} \int_{t_i^0}^{t_i^m} C_i(u_i(t)) dt \quad (13)$$

subject to (10), (11),

$$p_i(t_i^0) = 0, \quad p_i(t_i^m) = L, \quad v_i(t_i^0) = v_0. \quad (14)$$

Here, $C_i(u_i(t))$ represents the energy consumption rate functional, and, when $C_i(u_i(t)) = \frac{1}{2} u_i^2(t)$, the goal of problem (13) is to minimize transient engine operation [11,12]. Since internal combustion engines achieve their maximum efficiency at steady-state operating points [24], pursuing this objective directly leads to advantages in terms of fuel consumption and emissions [19]. Problem (13) is subject to multiple constraints, encompassing vehicle dynamics (10) and velocity and control input (11). In our investigation, $p_i(t)$, $v_i(t)$, and $u_i(t)$ are defined to denote the position (the distance traveled upon entering the CZ), velocity, and acceleration (control input) of CAV i , respectively. Additionally, t_i^0 and t_i^m signify the times at which CAV i enters CZ and exits MZ, respectively. The distance from the entrance of CZ to the entrance of MZ is L , and CAVs traverse OZ and enter CZ at a constant velocity v_0 . Therefore, problem (13) is also subject to initial and final state constraints (14). Through the application of Hamiltonian functions [19], we can obtain the optimal control input function $u_i^*(t)$ for CAV i , thereby devising a trajectory that minimizes energy consumption while adhering to the specified arrival time at the MZ as t_i^m .

3. Resequencing and Platooning Algorithm for Solving CSP

In order to tackle the centralized CSP as described by the integer programming model (1), this section introduces an enhanced RA founded on state transition networks. Through the amalgamation of the refined RA with a PFA, an RPA is established, aiming to achieve the global optimal solution of the centralized CSP within a finite time. Figure 5 delineates the comprehensive procedure of the RPA.

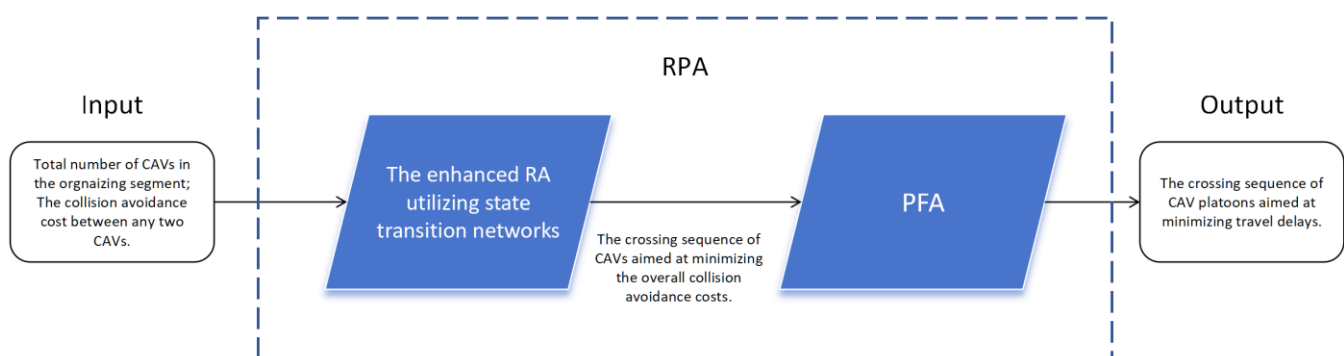


Figure 5. The procedure of RPA.

3.1. Resequencing Algorithm based on State Transition Network

To enhance the performance of the RA, we have introduced state transition networks [16]. For the research object composed of four organizing segments, a state vector $\mathbf{st} = [st_1, st_2, st_3, st_4, k_{st}]$ has been defined to represent the current state ST . Each element $st_k \in [0, n_k]$ in $\mathbf{st}$ denotes the number of CAVs sorted on organizing segment k , while k_{st} identifies the segment where the sorted CAV is located when transitioning from the previous state ST' to the current state ST . Taking the state vector $\mathbf{st}' = [st'_1, st'_2, st'_3, st'_4, 4]$ representing the state ST' as an example, suppose that, in this state, a CAV on organizing segment 3 has been sorted. Then, the correspondence between the state vector $\mathbf{st}$ of the new state ST and $\mathbf{st}'$ is $st_1 = st'_1, st_2 = st'_2, st_3 = st'_3 + 1, st_4 = st'_4, k_{st} = 3$. This state transition process incurs a transition cost $C(ST', ST)$, which equals the collision avoidance cost between the CAV currently being sorted and the last sorted CAV, identified as $\sum_{i=1}^3 n_i + st'_4$ and $\sum_{i=1}^2 n_i + st'_3 + 1$.

To enhance the intuitive understanding of the state transition network, we categorize the states ST into different stages $h = \sum_{k \in M} st_k$ based on the total number of sorted CAVs. Since the value of $\sum_{k \in M} st_k$ increases by 1 with each transition, it ensures that the transition can only occur from stage h to stage $h + 1$, thereby guaranteeing a finite path length in the state transition network. Finally, we define the initial state ST_{start} as $\mathbf{st}_{start} = [0, 0, 0, 0, 0]$, which is connected to the states in stage 1 through corresponding transitions. Similarly, we introduce the final state ST_{end} as $\mathbf{st}_{end} = [n_1, n_2, n_3, n_4, 0]$, connecting the states in stage n . Figure 6 illustrates an example of a state transition network in the intersection area with two organizing segments, each containing two CAVs.

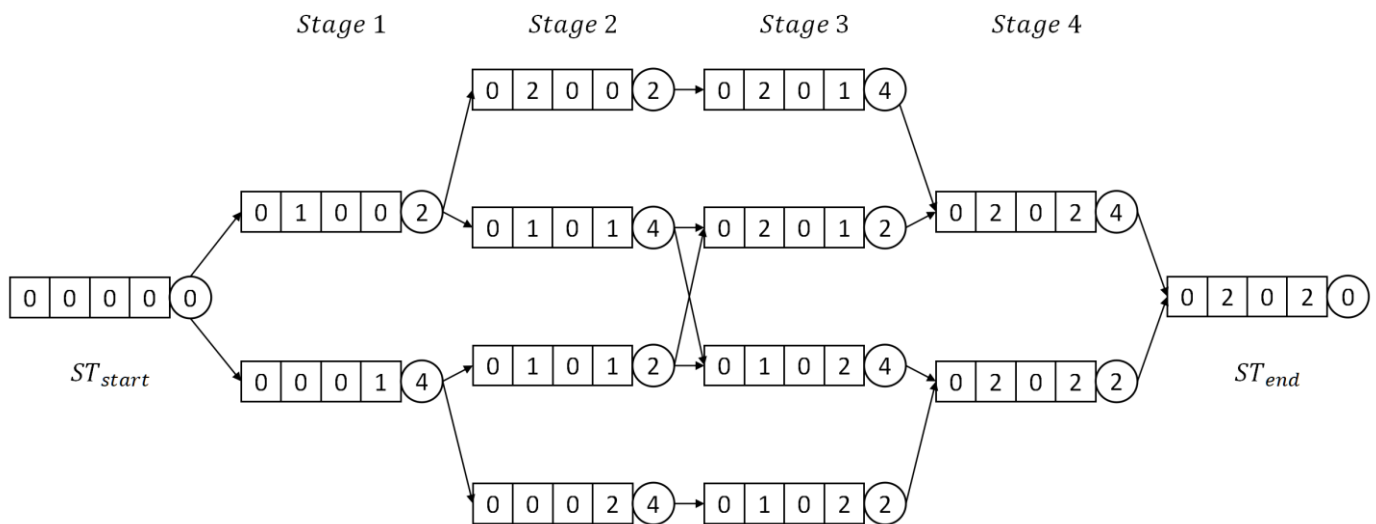


Figure 6. State transition network of CSP.

The path from the initial state ST_{start} to the final state ST_{end} in the state transition network represents a feasible sorting arrangement for CAVs. This arrangement involves a systematic sorting process of CAVs on 4 organizing segments, facilitated through a series of state transitions. Throughout the state transition process, each transition is associated with a specific transition cost. Consequently, the global optimal solution of the CSP corresponds to the path from ST_{start} to ST_{end} that results in the minimum total transition cost.

In Algorithm 1, $cost(end)$ represents the minimum transition cost in the state transition network, and $route(end)$ denotes the shortest path containing n states, where n represents the total number of CAVs on four organizing segments. The sorting vector $\mathbf{sq}_i$ comprises two elements: sq_i records the identification of the CAV entering MZ in the i -th sorted order, and os_i is used to denote the identification of the segment in which the CAV is located. The obtained set $SQ = \{\mathbf{sq}_1, \dots, \mathbf{sq}_n\}$ represents a crossing sequence of CAVs, achieving the minimization of the total collision avoidance cost, thereby constituting the

global optimal solution of the CSP. Additionally, SQ also contains information about the organizing segments where each CAV is situated, which is crucial for subsequent platoon forming algorithms.

Algorithm 1 Resequencing Algorithm based on State Transition Network

1. **Input:** The count of CAVs on each organizing segment k , denoted as n_k , the collision avoidance cost $C_{i,j}$ between any two CAVs i and j , and the organizing segment counter m initialized to zero.
 2. **For** k in range (1, 4) **do**
 If $n_k \neq 0$ **then**
 $m++$.
 End if
 End for
 3. Constructing a state transition network using m and n_k , each state ST possesses a state vector $\mathbf{st} = [st_1, st_2, st_3, st_4, k_{st}]$. The transition cost $C(ST', ST)$ from state ST' to state ST is equivalent to the collision avoidance cost between the CAV identified as $\sum_{i=1}^{k_{st}'-1} n_i + st'_{k_{st}'}$ and the CAV identified as $\sum_{i=1}^{k_{st}-1} n_i + st_{k_{st}}$.
 4. Group each state ST according to $\sum_{k \in M} st_k$ into the stage h .
 5. **Foreach** stage h in $\{1, 2, \dots, n\}$ **do**
 Foreach state ST in stage h **do**
 $cost(ST) = \min_{ST': \exists ST' \rightarrow ST} (cost(ST') + C(ST', ST))$.
 $route(ST) = \min_{ST': \exists ST' \rightarrow ST} route(ST)$ add ST' .
 End
 End
 6. $cost(end) = \min_{ST: \exists ST \text{ in stage } n} (cost(ST))$.
 $route(end) = \min_{ST: \exists ST \text{ in stage } n} (route(ST))$.
 7. **Foreach** state ST in $route(end)$ **do**
 generate the $\mathbf{sq}_i = [sq_i, os_i]$, i depends on the position of ST in $route(end)$.
 $sq_i = \sum_{i=1}^{k_{st}-1} n_i + st_{k_{st}}$, $os_i = k_{st}$, add $\mathbf{sq}_i$ to SQ .
 End
 8. **Output:** $SQ = \{\mathbf{sq}_1, \dots, \mathbf{sq}_n\}$.
-

3.2. Platoon Forming Algorithm

In the framework of the DRP strategy, the crossing sequence of CAVs within the OZ undergoes reassessment every 2 s to ensure the timely sorting of newly entering CAVs. However, this mechanism may introduce challenges in certain scenarios. Figure 7 depicts a scenario where CAV 1, potentially colliding with CAV 2, exits the OZ. Subsequently, the updated crossing sequence may allow CAV 2 to enter the MZ before CAV 3, which shares the same organizing segment as CAV 1. These unnecessary updates could result in additional collision avoidance costs, leading to increased travel delays and impacting the overall efficiency of traffic flow.

To mitigate this challenge, we have developed a PFA. This algorithm's essence lies in facilitating CAVs entering the MZ one after another within a single organizing segment to organize and sustain an orderly platoon. With this approach, even after the leading vehicle exits the OZ, the succeeding vehicles within the platoon can proceed into the MZ in a predetermined sequence, effectively minimizing the need for unnecessary updates to the crossing sequence. This strategic measure averts superfluous collision avoidance costs, resulting in a significant reduction in travel delays experienced by CAVs.

Specifically, if the organizing segment identifier os_i in $\mathbf{sq}_i$ is the same as the organizing segment identifier os_{i-1} in $\mathbf{sq}_{i-1}$, then CAV sq_i will join the platoon P_j where CAV sq_{i-1} is located, forming the platoon vector $\mathbf{p}_j = [sq_i, sq_{i-1}, os_i]$. A platoon can accommodate multiple CAVs. If the organizing segment identifier os_{i+1} in $\mathbf{sq}_{i+1}$ is different from the organizing segment identifier os_i in $\mathbf{sq}_i$, then CAV sq_{i+1} will be unable to join platoon P_j and will instead form a new platoon P_{j+1} .

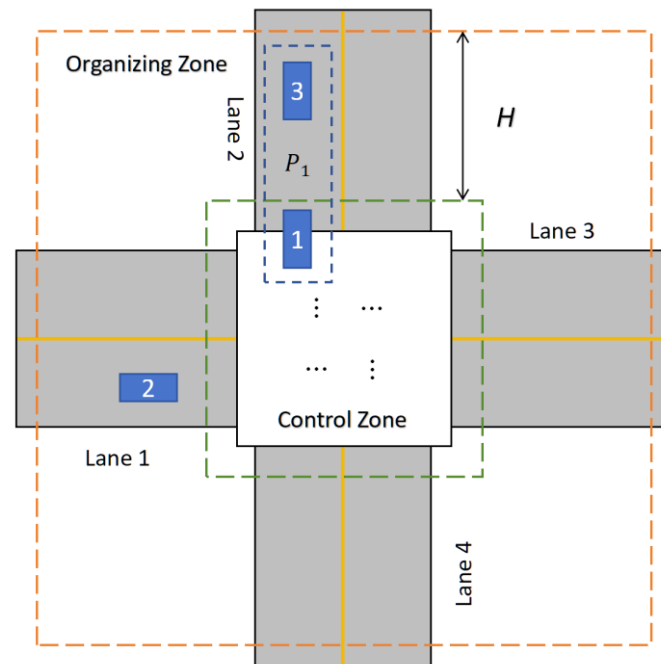


Figure 7. Scenario where unnecessary updates may occur.

In Algorithm 2, m is the number of platoon vectors, and $m \leq n$. The obtained set $PQ = \{\mathbf{p}_1, \dots, \mathbf{p}_m\}$ constitutes a crossing sequence of CAV platoons, achieving minimization of travel delays for CAVs. When the lead vehicle in platoon P_j exits the OZ, all CAVs in platoon P_j are removed from SQ and no longer participate in the PFA.

Algorithm 2 Platoon Forming Algorithm

1. **Input:** $SQ = \{\mathbf{sq}_i, \dots, \mathbf{sq}_n\}$.
 2. Generate the initial platoon P_1 , where the initial platoon vector $\mathbf{p}_1 = [sq_1]$, and the initial platoon label $j = 1$.
 3. **For** i in range $(2, n)$ **do**
 - If** the identifier os_i in $\mathbf{sq}_i$ is the same as the identifier os_{i-1} in $\mathbf{sq}_{i-1}$ **then**
 - add sq_i to platoon vector $\mathbf{p}_j$.
 - Else**
 - add os_{i-1} to platoon vector $\mathbf{p}_j$.
 - add platoon vector $\mathbf{p}_j$ to PQ .
 - $j++$, generate platoon P_j , add sq_i to platoon vector $\mathbf{p}_j$.
 - End if**
 - End for**
 4. $m = j$.
 5. **Output:** $PQ = \{\mathbf{p}_1, \dots, \mathbf{p}_m\}$, $m \leq n$.
-

4. Decentralized Energy-Optimal Control Framework for Solving TOP

In this section, we persist in employing the decentralized energy-optimal control framework [9] and enhance the current recursive algorithm for the MZ arrival time to accommodate the requirement for CAV platoons. This endeavor is geared toward establishing the requisite temporal constraints for the energy-optimal control problem (13) transformed from the TOP. Following this, through the application of Hamiltonian functions [19] to address (13), we derive the optimal control input $u_i^*(t)$ within the interval $[t_i^0, t_i^x]$, thus effectively tackling the TOP.

4.1. Arrival Time Recursion Algorithm for CAV Platoons

Since CAV sq_{i-1} and CAV sq_i inevitably enter the MZ consecutively, $t_{sq_i}^m$ is always determined recursively through $t_{sq_{i-1}}^m$ and $C_{sq_i, sq_{i-1}}$ [8]. Therefore, obtaining $t_{sq_1}^m$ is crucial for deducing the arrival time of subsequent CAVs at the MZ. For the CAV sq_1 that enters the MZ first, it is evident that the optimal solution to problem (13) is $u_{sq_1}^*(t) = 0$ because CAV sq_1 does not need to evade any other CAVs. To address the new demand for CAV platoons, we have made corresponding improvements to the algorithm. Since the CAVs in platoon P_1 travel on the same lane, once the arrival time $t_{sq_1}^m$ of the lead vehicle CAV sq_1 in P_1 is determined, the entry times $t_{sq_i}^m$ of the other CAVs sq_i in P_1 can be easily obtained by shifting them on the time scale $t_{sq_i}^0 - t_{sq_1}^0$. Similarly, for adjacent platoon P_j and P_{j+1} , only the collision avoidance cost between the lead vehicle of P_{j+1} and the trailing vehicle of P_j needs to be considered. Ultimately, through the Algorithm 3, we can obtain the controllable arrival times at the MZ for all CAVs.

Algorithm 3 Arrival Time Recursion Algorithm for CAV Platoons

1. **Input:** $PQ = \{p_1, \dots, p_m\}$, the number of CAVs within each platoon vector p_j , denoted as np_j , along with the collision avoidance cost $C_{sq_i, sq_{i-1}}$ between any two CAV sq_i and sq_{i-1} .
 2. **For** i in range $(1, np_1)$ **do**
 - If** $i = 1$ **then**

$$t_{sq_1}^m = t_{sq_1}^0 + \frac{v_0}{L}.$$

arrival time of the lead vehicle in p_1 at the MZ $t_{p_1}^m = t_{sq_1}^m$.

arrival time of the lead vehicle in p_1 at the CZ $t_{p_1}^0 = t_{sq_1}^0$.
 - Else**

$$t_{sq_i}^m = t_{p_1}^m + t_{sq_i}^0 - t_{p_1}^0.$$
 - End if**
 - End for**
 3. arrival time of the trailing vehicle in p_1 at the MZ $t_{p_1b}^m = t_{sq_i}^m$.
 4. **For** j in range $(2, m)$ **do**
 - For** i in range $(\sum_{a=1}^{j-1} np_a + 1, \sum_{a=1}^j np_a)$ **do**
 - If** $i = \sum_{a=1}^{j-1} np_a + 1$ **then**

$$t_{sq_i}^m = t_{p_{j-1}b}^m + C_{sq_i, sq_{i-1}}.$$

arrival time of the lead vehicle in p_j at the MZ $t_{p_j}^m = t_{sq_i}^m$.

arrival time of the lead vehicle in p_j at the CZ $t_{p_j}^0 = t_{sq_i}^0$.
 - Else**

$$t_{sq_i}^m = t_{p_j}^m + t_{sq_i}^0 - t_{p_j}^0.$$
 - End if**
 - End for**
 - arrival time of the trailing vehicle in p_j at the MZ $t_{p_jb}^m = t_{sq_i}^m$.
 - End for**
 5. **Output:** The arrival time of all CAVs at the MZ.
-

4.2. Solution for Energy-Optimal Control Problem

The integration of the energy-optimal control problem (13) with the vehicle dynamic constraint (10) and the velocity and control input constraint (11) facilitates the derivation of Hamiltonian functions for each CAV [19]:

$$H_i(t, p_i(t), v_i(t), u_i(t)) = \frac{1}{2}u_i^2(t) + \lambda_i^p(t) \cdot v_i(t) + \lambda_i^v(t) \cdot u_i(t) + \mu_i^a \cdot (u_i(t) - u_{\max}) + \mu_i^b \cdot (u_{\min} - u_i(t)) + \mu_i^c \cdot (v_i(t) - v_{\max}) + \mu_i^d \cdot (v_{\min} - v_i(t)) \quad (15)$$

where $\lambda_i^p(t)$ and $\lambda_i^v(t)$ denote the costates, and μ_i^a , μ_i^b , μ_i^c , and μ_i^d are the Lagrange multipliers. The Hamiltonian functions are divided into seven cases depending on whether different control inputs $u_i(t)$ and velocities $v_i(t)$ satisfy the boundary conditions (i.e., whether they attain $u_{\max}$, $u_{\min}$, $v_{\max}$, $v_{\min}$). More specifically, the seven cases are as follows [9]:

1. Control and State Constraints not Active, $u_i(t) \neq u_{max}$, $u_i(t) \neq u_{min}$, $v_i(t) \neq v_{max}$, $v_i(t) \neq v_{min}$.
2. Control Constraints Active, $u_i(t) = u_{max}$.
3. Control and State Constraints Active, $u_i(t) = u_{max}$, $v_i(t) = v_{max}$.
4. Control Constraints Active, $u_i(t) = u_{min}$.
5. Control and State Constraints Active, $u_i(t) = u_{min}$, $v_i(t) = v_{min}$.
6. State Constraints Active, $v_i(t) = v_{max}$.
7. State Constraints Active, $v_i(t) = v_{min}$.

Based on the statistical data presented in reference [9], the case in which neither control constraints nor state constraints are active exerts a significant influence on the driving process of the CAVs, rendering them pivotal for investigating the control input functions. In such a case, $\mu_i^a = \mu_i^b = \mu_i^c = \mu_i^d = 0$, and the Hamiltonian functions are transformed into the following [9]:

$$H_i(t, p_i(t), v_i(t), u_i(t)) = \frac{1}{2}u_i^2(t) + \lambda_i^p(t) \cdot v_i(t) + \lambda_i^v(t) \cdot u_i(t) \quad (16)$$

The costates transform into the following [9]:

$$\dot{\lambda}_i^p = -\frac{\partial H_i}{\partial p_i} = 0, \quad \dot{\lambda}_i^v = -\frac{\partial H_i}{\partial v_i} = -\lambda_i^p(t) \quad (17)$$

The extremum condition is as follows [9]:

$$\frac{\partial H_i}{\partial u_i} = u_i(t) + \lambda_i^v(t) = 0 \quad (18)$$

By Equation (17), it can be readily inferred that $\lambda_i^p(t) = a_i$ and $\lambda_i^v(t) = -(a_i t + b_i)$, where a_i and b_i are integral constants. Thus, the optimal control input $u_i^*(t)$ is as follows [9]:

$$u_i^*(t) = a_i t + b_i \quad (19)$$

According to the second-order vehicle dynamics (10) relationship, we can derive the following [9]:

$$v_i^*(t) = \frac{1}{2}a_i t^2 + b_i t + c_i \quad (20)$$

$$p_i^*(t) = \frac{1}{6}a_i t^3 + \frac{1}{2}b_i t^2 + c_i t + d_i \quad (21)$$

In our strategy, CAV i will maintain a constant speed v_i^m while traversing MZ after entering. Therefore, the boundary conditions of the costates are: $\lambda_i^v(t_i^m) = -u_i^*(t_i^m) = 0$. Then, the three equations derived from substituting the provided initial and final state constraints (14) into (20) and (21) are: $p_i^*(t_i^0) = \frac{1}{6}a_i(t_i^0)^3 + \frac{1}{2}b_i(t_i^0)^2 + c_i t_i^0 + d_i = 0$, $p_i^*(t_i^m) = \frac{1}{6}a_i(t_i^m)^3 + \frac{1}{2}b_i(t_i^m)^2 + c_i t_i^m + d_i = L$, $v_i^*(t_i^0) = \frac{1}{2}a_i(t_i^0)^2 + b_i t_i^0 + c_i = v_0$, where L is the distance from the entrance of the CZ to the entrance of the MZ. The simultaneous representation of these four equations in matrix form is as follows [9]:

$$\begin{bmatrix} \frac{1}{6}(t_i^0)^3 & \frac{1}{2}(t_i^0)^2 & t_i^0 & 1 \\ \frac{1}{6}(t_i^m)^3 & \frac{1}{2}(t_i^m)^2 & t_i^m & 1 \\ \frac{1}{2}(t_i^0)^2 & t_i^0 & 1 & 0 \\ -t_i^m & -1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} a_i \\ b_i \\ c_i \\ d_i \end{bmatrix} = \begin{bmatrix} 0 \\ L \\ v_0 \\ 0 \end{bmatrix} \quad (22)$$

Solving (22) will provide the values of a_i , b_i , c_i , and d_i .

5. Results and Discussion

The research utilized the Python language and the Traci toolkit to conduct simulation experiments on intersection traffic scenarios, interfacing with the traffic simulator SUMO, creating models for both a conventional signalized intersection and signal-free intersection. In the conventional signalized intersection model, the duration of the green light was set to 62 s, while the yellow light lasted for 3 s. For the simulation of the signal-free intersection, the FIFO strategy, LDR strategy, and our newly devised DRP strategy were employed. Moreover, the study employed the 2010 Toyota Prius CAV model, which encompasses an Internal Combustion Engine (ICE), two electric Motors/Generators (MG1 and MG2), a Planetary Gear Train (PGT), and a battery [25]. To emulate real traffic conditions, vehicle arrivals were assumed to follow a Poisson process, with four different arrival rates established to simulate various traffic demands. By comparing the driving performance and fairness of CAVs under different strategies, the merits and drawbacks of each strategy were scrutinized. To mitigate the influence of stochastic factors, each scenario underwent simulation for a duration of 15 min.

Performance metric 1, denoted as the travel delay dl_i of CAV i , reflects the performance of the strategy in terms of traffic efficiency. It is defined as follows:

$$dl_i = t_i^m - t_i^{min} \quad (23)$$

The term t_i^{min} denotes the minimum time required for CAV i to reach the MZ while traveling at u_{max} and v_{max} within the CZ.

Performance metric 2, referred to as fuel consumption FC_i of CAV i , elucidates the strategy's efficacy concerning energy efficiency. It is derived by computing the definite integral of the fuel consumption rate function $fc_i(t)$ over the interval $[t_i^0, t_i^m]$. It is pertinent to acknowledge that the fuel consumption of HEVs encompasses not solely the fuel consumption of the internal combustion engine but also the commensurate fuel consumption of the electric motors:

$$FC_i = \int_{t_i^0}^{t_i^m} fc_i(t) dt \quad (24)$$

The fuel consumption rate is contingent upon the velocity and power of the vehicle, and is defined as follows [25]:

$$fc_i(t) = \begin{cases} fc_{ev} & \text{for } \begin{cases} P_i(t) \leq 0 \\ P_i(t) < P_{ev} \text{ and } v_i(t) < v_{ev} \end{cases} \\ e_1 + e_2 * v_i(t) + e_3 * P_i(t) + e_4 * P_i^2(t) & \text{for } \begin{cases} P_i(t) > 0 \text{ and } v_i(t) \geq v_{ev} \\ P_i(t) \geq P_{ev} \text{ and } v_i(t) < v_{ev} \end{cases} \end{cases} \quad (25)$$

The equivalent fuel consumption rate of the 2010 Toyota Prius in EV mode, denoted as fc_{ev} , represents a key parameter. Here, $P_i(t)$ signifies the instantaneous power of CAV i , while P_{ev} denotes the maximum power achievable in EV mode, and v_{ev} stands for the maximum velocity attainable in EV mode. When $P_i(t)$ is negative or $v_i(t)$ falls below v_{ev} with power lower than P_{ev} , the HEV transitions to EV mode. We adopted the parameters summarized from the experiments conducted by researchers, as documented in reference [25], where the specific values for v_{ev} and P_{ev} of the 2010 Toyota Prius are 32 km/h and 10 kW, respectively, with fc_{ev} set at 0.006. Additionally, the coefficients e_1 , e_2 , e_3 , and e_4 were determined to be 0.006, 0.003998, 0.077092, and -9.155×10^{-5} . Researchers have elucidated the relationship between $P_i(t)$, $v_i(t)$, and $u_i(t)$ in reference [26]:

$$P_i(t) = \left(mu_i(t) + mg \cdot \cos(\theta) \cdot \frac{C_r}{1000} (C_c v_i(t) + C_t) + \frac{1}{2} \rho_{Air} A_f C_D v_i^2(t) + mg \cdot \sin(\theta) \right) \cdot v_i(t) \quad (26)$$

We designated the mass of the Toyota Prius as $m = 1521$ kg, the gravitational acceleration g as 9.8066 m/s², and the road slope θ as 0. The parameters for rolling resistance, denoted as C_r , C_c , and C_t , are assigned values of 1.75, 0.0328, and 4.575, respectively, and

are subject to variation based on factors such as road surface type, road conditions, and vehicle tire type. The air mass density, represented as ρ_{Air} , is 1.2256 kg/m³, while the frontal projection area of the Prius, identified as A_f , measures 2.3316 m². Additionally, the aerodynamic drag coefficient C_D is determined to be 0.28 [26].

As a result of the resequencing strategy modifying the sequence of CAVs entering the MZ, the trip duration of CAVs is prolonged. Recognizing the potential for this alteration to raise fairness concerns among drivers, we will also assess the fairness of each strategy. The fairness metric, symbolized as ρ , is delineated as follows:

$$\rho = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i^m - \bar{t}^m)^2} \quad (27)$$

$$\bar{t}^m = \frac{1}{N} \sum_{i=1}^N t_i^m \quad (28)$$

N symbolizes the aggregate count of CAVs during 15 min, while $\bar{t}^m$ signifies the mean trip duration of all CAVs. A heightened ρ value suggests diminished fairness.

5.1. Comparison of Driving Performance

In this experimental setup, we standardized the length of the OZ at 80 m and the CZ at 170 m, maintaining uniform arrival rates across all four lane entrances. To evaluate the efficacy of the four strategies across varying traffic demands, we systematically escalated the arrival rate from 160 veh/h/lane to 800 veh/h/lane, leveraging the arrival rate values outlined in reference [11]. In our scenario of high traffic demand, where the arrival rate exceeds that of reference [11], it provides a better indication of the performance of cooperative driving strategies, particularly under extreme circumstances. When contrasting with the traffic light strategy, we categorize the FIFO, LDR, and DRP strategies collectively as cooperative driving strategies. Following a 15 min simulation period, we meticulously collected and organized data on the average travel delay and fuel consumption for all CAVs across the four strategies. These findings are detailed in Table 1 and visually depicted in Figure 8.

Table 1. Data on the average travel delay and average fuel consumption of different driving strategies under different arrival rates.

Arrival Rates (veh/h/lane)	Driving Strategies	Average Travel Delay (s)	Average Fuel Consumption (mL)	Emergency Braking (Times/Minute)
160	Traffic light	17.7638	7.3590	3
	FIFO	5.5709	5.9439	0
	LDR	4.1391	6.3117	0.3
	DRP	3.3987	5.6261	0
320	Traffic light	19.4790	7.5354	6.6
	FIFO	5.8475	6.2172	0
	LDR	4.365	6.6804	0.6
	DRP	3.5226	6.0689	0
480	Traffic light	20.9306	7.7357	9.6
	FIFO	6.3904	6.9200	0.6
	LDR	4.732	7.313	1.8
	DRP	3.7720	6.4463	0.3
640	Traffic light	23.3576	7.9991	13.8
	FIFO	17.1052	7.8918	6.3
	LDR	14.5286	7.4562	9.5
	DRP	13.5747	6.7870	3.3
800	Traffic light	26.6526	8.3024	18.6
	FIFO	31.8643	8.6395	11.4
	LDR	24.9121	8.2642	12.3
	DRP	22.7679	7.4544	7.8

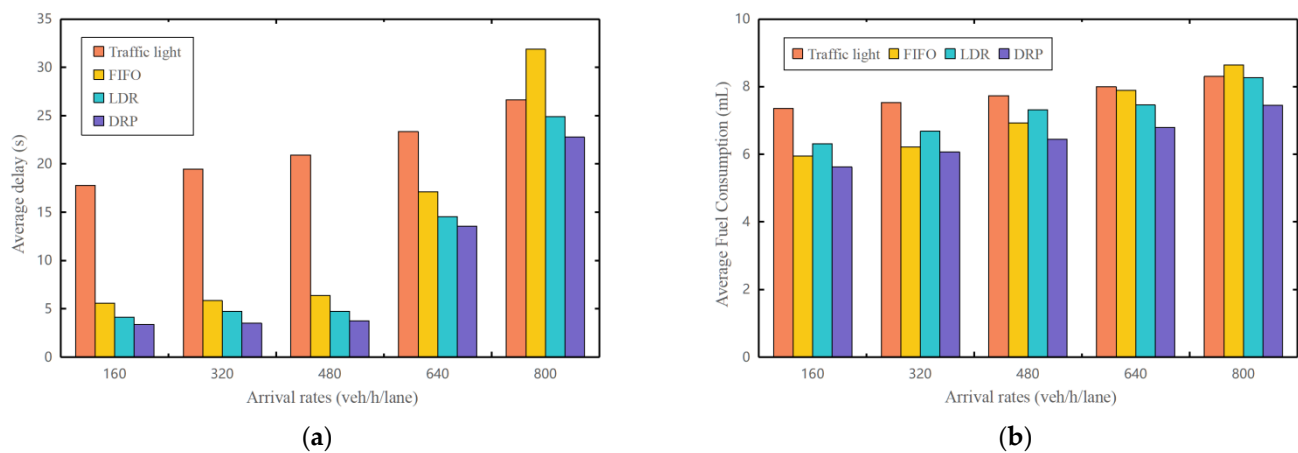


Figure 8. Average travel delay (a) and average fuel consumption (b) of different driving strategies under different arrival rates.

Analysis of the data presented in Table 1 reveals that cooperative driving strategies, when compared to traditional traffic light strategy, can notably diminish average travel delay by up to 82.1% under lower traffic demands, ranging from 160 veh/h/lane to 480 veh/h/lane, thus significantly augmenting traffic efficiency. The conventional traffic light strategy, rooted in fixed time cycles aimed at coordinating conflicting traffic flows, frequently impose unnecessary waiting times on CAVs, even under low-density traffic scenarios, thereby culminating in intersection delays. Furthermore, the average travel delay metrics for the DRP strategy are inferior to those of the LDR and FIFO strategies, thereby substantiating the superior efficacy of the DRP strategy in enhancing traffic efficiency. Moreover, cooperative driving strategies evince a superior energy economy performance relative to the conventional traffic light strategy, resulting in potential savings of approximately 19.84% in average fuel consumption. Nonetheless, it is imperative to note that this efficiency gain is marginally lower compared to the fuel consumption reductions observed when cooperative driving strategies are applied to fuel vehicles, amounting to approximately 46.6%. This discrepancy primarily arises from the continuous operation of fuel vehicle engines during traffic signal stops, leading to additional fuel consumption. In contrast, HEV vehicles incorporate an EV mode where the engine shuts off during traffic signal stops. Thus, despite reducing CAVs' waiting times, fuel consumption reductions are not significant. Figure 9 delineates the acceleration and fuel consumption rate curve of a CAV encountering a red light [27–30]. Detailed scrutiny reveals that CAVs facing red lights necessitate braking to a complete stop and subsequent acceleration to the desired velocity upon the green light's appearance, thereby engendering frequent acceleration and deceleration cycles that elevate fuel consumption. Consequently, the emphasis of cooperative driving strategies on coordinating CAVs to curtail unnecessary acceleration and deceleration elucidates the superior energy economy performance of the DRP strategy compared to the LDR and FIFO strategies. The latter two evince weaker capabilities in coordinating conflicting CAVs, necessitating more frequent modulation of CAVs' velocity changes, thereby amplifying fuel consumption. Finally, we assess the efficiency of the crossing sequence by examining the frequency of emergency braking per minute. Under conditions of lower traffic demands, this metric tends toward zero across all cooperative driving strategies except for the LDR strategy. Analysis indicates that the frequent revision of the crossing sequence by the LDR strategy is the primary driver of this trend. Conversely, the DRP strategy addresses this issue by centralizing enhancements to the CSP and integrating platooning algorithms.

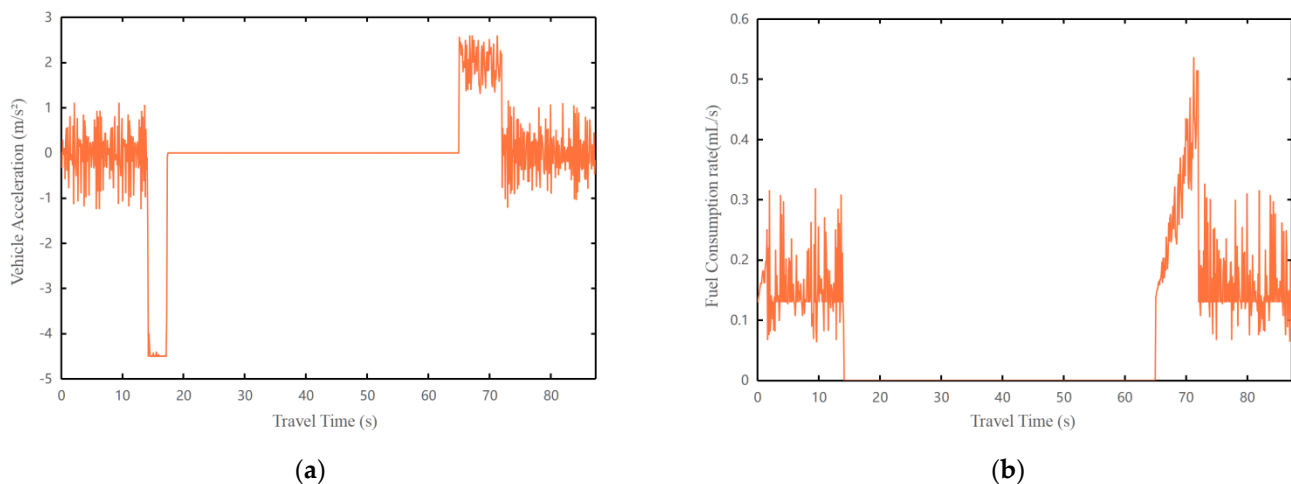


Figure 9. Acceleration (a) and fuel consumption rate (b) for a CAV encountering red lights.

In conditions of moderate traffic demands (640 veh/h/lane), cooperative driving strategies demonstrate a 41.89% decrease in average travel delay compared to the traffic light strategy, indicating a slightly reduced improvement compared to lower traffic demands. This reduction primarily arises from the escalating expense of collision avoidance as the number of CAVs within the intersection area increases. To circumvent collision incidents, CAVs progressively delay their arrival time at the MZ, thereby incurring additional average travel delay. In this context, the average travel delay data for the DRP strategy are lower than those of the LDR and FIFO strategies, signifying the superior performance of the DRP strategy in mitigating collision avoidance costs. Moreover, cooperative driving strategies show a diminished potential for savings in average fuel consumption compared to the traffic light strategy, declining to 15.16%. This phenomenon is ascribed to the necessity for more frequent modulation of CAV velocity changes to avoid collisions, resulting in increased fuel consumption. Moreover, the incidence of emergency braking incidents rises for cooperative driving strategies. Analysis indicates that as the quantity of CAVs within the intersection area increases, the complexity of computing the optimal crossing sequence also escalates. Nonetheless, the DRP strategy consistently registers the lowest number of incidents, underscoring that the crossing sequence derived from this strategy outperforms those of the other two strategies.

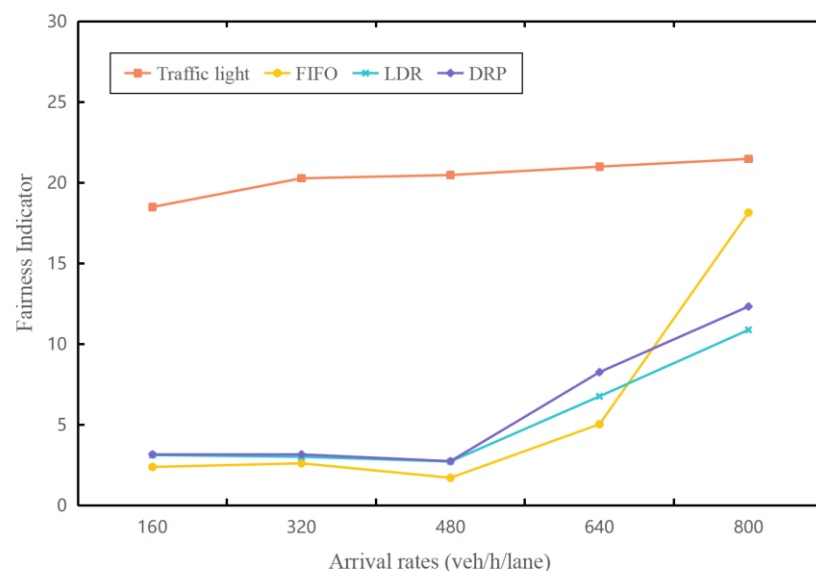
In scenarios characterized by higher traffic demands (800 veh/h/lane), the performance of the FIFO strategy significantly deteriorates, with a 19.55% increase in average travel delay and a 4.06% increase in average fuel consumption. This outcome underscores the capacity constraint of the FIFO strategy, representing a bottleneck to further enhancing traffic efficiency and optimizing energy economy. Conversely, the DRP and LDR strategies persist in reducing average travel delay and lowering average fuel consumption. Particularly notable is the more pronounced effect of the DRP strategy in reducing travel delay and fuel consumption, thereby validating its superiority over the LDR strategy in improving traffic efficiency and optimizing energy economy. Additionally, the order of emergency braking incidents for cooperative driving strategies is similar to that observed under moderate traffic demand, leading to the same conclusion: the crossing sequence obtained from the DRP strategy outperforms those of the other two strategies.

5.2. Comparison of Fairness

During the experimentation outlined in Section 5.1, aside from collating data pertaining to the average travel delay and average fuel consumption of CAVs, we also amassed fairness metrics for the four strategies. These metrics have been delineated in Table 2 and graphically depicted in Figure 10.

Table 2. Data on the fairness indicator of different driving strategies under different arrival rates.

Arrival Rates (veh/h/lane)	Driving Strategies	Fairness Indicator ρ (s)
160	Traffic light	18.50
	FIFO	2.38
	LDR	3.12
	DRP	3.16
320	Traffic light	20.28
	FIFO	2.61
	LDR	3.01
	DRP	3.16
480	Traffic light	20.48
	FIFO	1.71
	LDR	2.72
	DRP	2.74
640	Traffic light	21.00
	FIFO	5.03
	LDR	6.76
	DRP	8.26
800	Traffic light	21.48
	FIFO	18.15
	LDR	10.88
	DRP	12.33

**Figure 10.** The fairness indicator of different driving strategies under different arrival rates.

In line with the findings from the analysis of driving performance, under scenarios of moderate to low traffic demands, cooperative driving strategies also demonstrate significant enhancements in fairness compared to the traffic light strategy. However, unlike in the evaluation of driving performance, both the DRP and LDR strategies marginally trail behind the FIFO strategy in terms of fairness. This discrepancy primarily stems from the inclination of resequencing strategies to prioritize non-conflicting CAVs with lower collision avoidance costs for intersection passage. While conflicts among CAVs on the same or opposing lanes remain minor, congestion tends to dissipate more readily but may exacerbate in other lanes. Furthermore, the DRP strategy, through the incorporation of platooning algorithms, exhibits a greater propensity to prioritize CAV passage on the same or opposing lanes. In the assessment of cooperative driving strategies, its fairness performance ranks third. However, it is important to note that across five different traffic

demands, the fairness indicator of the DRP strategy trails the top-ranked strategy by only 0.72 s, 0.49 s, 1.03 s, 3.23 s, and 1.35 s, respectively. In Table 1, under the same five traffic demands, the DRP strategy surpasses these strategies by reducing the time by 2.17 s, 2.32 s, 2.61 s, 3.53 s, and 2.14 s, respectively. This suggests that, when considering both overall driving performance and fairness, the DRP strategy maintains an advantage over other strategies.

It is noteworthy that, under higher traffic demands, the fairness performance of the LDR and DRP strategies surpasses that of the FIFO strategy. To delve deeper into this phenomenon, we conducted a detailed analysis and visualized the comparison of trip durations for 90 CAVs under the FIFO, LDR, and DRP strategies when the arrival rate is 800 veh/h/lane in Figure 11. From the graph, it is evident that, under the FIFO strategy, the trip duration for CAVs after ID 61 exceeds 70 s, with some even reaching up to 100 s. This accumulation occurs due to the substantial buildup of CAVs within the intersection, highlighting the inefficacy of the FIFO strategy in coordinating CAVs' departure from the intersection, resulting in severe traffic congestion. In contrast, the trip durations of CAVs under the LDR and DRP strategies remain within 60 s. This indicates that enhancing the traffic coordination capability of strategies to mitigate traffic congestion may not necessarily conflict with improving fairness, particularly under high traffic demands.

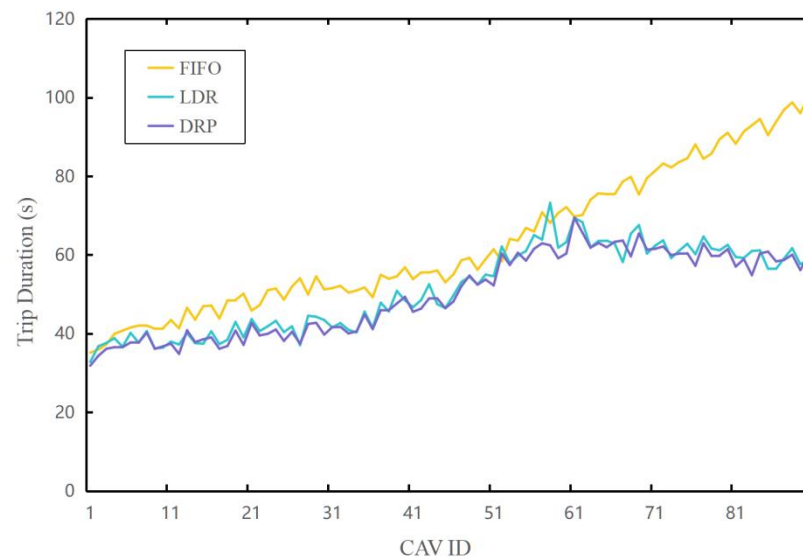


Figure 11. The trip duration of CAVs under different driving strategies at arrival rates of 800 veh/h/lane.

6. Conclusions

This research established a centralized model for the CSP and TOP concerning CAVs. An advanced RA approach grounded on state transition networks was proposed and fused with a PFA to formulate the RPA. The objective was to achieve the global optimal solution of the centralized CSP within a finite time. Additionally, an enhanced controllable arrival time recursive algorithm tailored for CAV platoons was developed to impose time constraints on the energy-optimal control problem, effectively tackling the TOP. Subsequently, these novel algorithms were integrated to introduce an innovative strategy—the DRP strategy. To validate the efficacy of this strategy, we conducted integrated simulations of symmetrical intersections across diverse traffic demands using Python 3.10.7, Traci 1.19.0, and SUMO 1.19.0. The performance and fairness of CAVs under diverse driving strategies were evaluated. Findings indicated that the DRP strategy outperformed others significantly in terms of driving performance, exhibiting reduced travel delay and fuel consumption. However, concerning fairness, the DRP strategy showed a marginally inferior performance. This was ascribed to the influence of frequent adjustments in CAV passing sequences on fairness. Nonetheless, experiments also suggest that, in situations of heightened traffic

demand, strategies endowed with augmented traffic coordination capabilities can alleviate traffic congestion while concurrently upholding fairness from an alternative standpoint. Furthermore, it was noted that cooperative driving strategies were more proficient in enhancing energy efficiency compared to the traffic light strategy. This was chiefly attributed to the mitigation of intense acceleration and deceleration during start–stop scenarios. This observation offers valuable insights for further enhancing the energy efficiency of CAVs.

The primary limitation of this study lies in its focus on the analysis of single-lane, one-way symmetric intersection scenarios. However, the conclusions drawn have the potential to be extended to multi-lane intersections and scenarios involving turning maneuvers by CAVs. Additionally, earlier discussions have revealed that there is still room for improvement in terms of fairness with regard to the DRP strategy. Subsequent research endeavors could explore strategies for striking a balance between driving performance and fairness within the DRP strategy and devise mathematical frameworks to quantitatively assess the equilibrium between these factors. Such endeavors would serve to augment drivers' contentment with traffic control systems and intersection layouts, thus fostering progress in the realm of intelligent transportation systems.

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