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A Hybrid Coordinated Decision-Making Method for CAVs at Unsignalized Intersection

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Abstract— **Aiming at the Connected Autonomous Vehicles (CAVs) crossing the unsignalized intersection problem, a hybrid coordinated optimization method is studied in this paper. The proposed approach consists of a Multi-Risk Management of Cooperative Optimization approach based on the Predicted Inter-Distance Profile (MRMCO-PIDP), and Epsilon Probability Collective algorithm (Epsilon-PC) to make CAVs apply cooperative and adaptive velocity planning to navigate safely and quickly in unsignalized intersections. It is the first use of PIDP for multi-risk assessment and management for CAVs. According to the computation of PIDP metric [1] regarding other vehicles with risk of collision and its controlled minimum (mPIDP), CAVs can find the most effective speed profile for collision avoidance in an unsignalized intersection. Several random scenarios are performed in simulation to demonstrate the reliability of the proposed approach.**

I. INTRODUCTION

Urban traffic congestion is a pressing issue in many cities worldwide. It occurs when the demand for transportation exceeds the available capacity of road infrastructure, leading to slower traffic, longer travel times, increased fuel consumption, air pollution, and overall reduced quality of life. Congestion not only wastes time and resources but also poses significant environmental and health risks.

In the past decade, autonomous vehicles have emerged with enormous potential to reduce urban traffic congestion and the occurrence of road traffic accidents. In the current mainstream field, it is believed that traffic congestion at intersections can be coordinated by altering traffic signal patterns [2] and allocating time slots for vehicles [3]. However, traditional traffic signal control methods in urban areas often cannot be directly applied in the mentioned areas because traffic signals may lead to redundant costs and increase congestion at inappropriate intersections and under certain circumstances. Directly controlling vehicles for coordination proves to be more effective in addressing complex intersection traffic scenarios [4], even the simplest platooning can double the throughput capacity at intersections [5]. Authors in [6] used POMDP to formulate the problem, and used the adaptive belief tree algorithm to find the optimal passing order. Authors in [7] proposed a cooperative control algorithm for multi-objective optimization, to transfer the high-dimensional problem into the single-dimensional problem. A fuzzy logic method to optimize the speed trajectories of two CAVs was proposed in [8]. A stochastic method was proposed in [9] to optimize trajectories of multi-vehicles in mixed-traffic.

The current major challenge in unsignalized intersection traffic coordination algorithms lies in avoiding conflict behavior. Several common methods for detecting collision risks include Time-To-Collision (TTC), Extend Time-To-Collision (ETTC) [10], and Predicted Inter-Distance Profile (PIDP) [11]. Based on these collision-free coordination methods at intersections, the authors in [12] applied the Probability Collective Algorithm (PC) [13] to traffic management at signal-less intersections. This is a probabilistic collective-based vehicle coordination method for shared space research. It was extended to Epsilon-PC in [14] to obtain a better fusion strategy with considering both efficiency and safety. PC-based methods outperform traditional genetic algorithms (GA) in terms of convergence speed and avoiding local minimum. The core of this method is continuous random exploration based on Monte Carlo methods, resulting in a considerable amount of inefficient exploration and computation processes. This leads to relatively long computation times, making it ineffective for optimizing vehicles passing through intersections quickly and interacting/cooperating with the other vehicles in real-time.

This paper proposes a Multi-Risk Management Cooperative Optimization algorithm based on PIDP (MRMCO-PIDP), which can effectively and rapidly find the closest optimization solution under current conditions. Its significant features include low computation cost, speed, and outstanding capability to handle complex intersection scenarios. However, its disadvantage is, this is a local search optimal algorithm, its output is a locally optimal solution, influenced by initial velocities of vehicles and may not be the global optimal solution. As a stochastic algorithm, the PC algorithm excels in finding sub-optimal solution. Considering the practical communication and negotiation among CAVs, we present a hybrid multi-vehicle risk coordination framework. This framework allows CAVs to use the MRMCO-PIDP method to find a feasible solution quickly and, with the remaining negotiation time, find a potential solution better than the solution given by the MRMCO-PIDP.

The remainder of this paper is organized as follows: the methodology of the MRMCO-PIDP is introduced in Section II. The hybrid coordination optimization architecture is proposed in Section III. Simulations and results analysis are given in Section IV. At last, conclusions and some prospects are given in Section V.

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II. PROPOSED INTERSECTION COOPERATIVE ALGORITHM

In this section, the Multi-Risk Management Cooperative Optimization approach based on the Predicted Inter-Distance Profile (MRMCO-PIDP) is introduced, which is extended from PC algorithm and PIDP method to find a feasible solution, where $ePIDP$ is used to find the quickest direction of the feasible solution like the gradient in the gradient descent algorithm. The definition of $ePIDP$ is given in Section II-B.

The overview of the multi-vehicle passing at the unsignalized intersection scenario is depicted in Figure 1. In this study, only CAVs equipped with embedded systems are considered. The path of each CAV is fixed and depends solely on the vehicle's starting position and destination direction. Within the intersection, there is a facility known as the local monitoring station, responsible for gathering information about the relative positions of CAVs in the vicinity of the intersection and facilitating communication between CAVs.

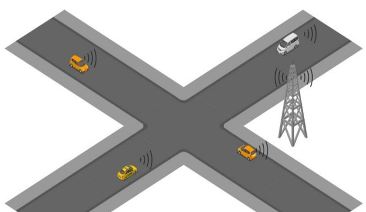


Fig. 1: An unsignalized intersection with 4 CAVs

A. Formulation of Searching Space

Since the paths of vehicles passing through the intersection are solely determined by their starting positions and destination directions, the only available control parameter is the navigation speed. CAVs should make their decisions within a limited time interval (in our approach, this decision relates to the CAV adopted speed) and coordinate the navigation actions of all CAVs.

In the speed profiles generation part, we adopt a method similar to [12]. We generate a set of possible speed profiles (the number of speed profile generated for each vehicle is same, marked as N_s) based on each vehicle's initial speed, the legal maximum speed at the intersection, and dynamic constraints such as the vehicle's maximum acceleration and deceleration (cf. Figure 2). Each speed profile is called a strategy of that vehicle. After a stable solution has been found in the initial planning, secondary speed planning is conducted to seek a more optimal solution with the same method based on the stable solution from the first optimization.

However, what sets this method apart from the speed generation method in [12] is that the proposed approach employs spline curves for speed generation. The speed curves generated using this method are smoother from a kinematic perspective.

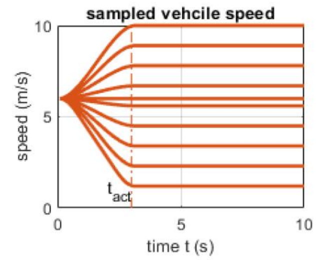


Fig. 2: Speed profiles in searching space [14]

B. Elementary of PIDP-Based Risk Management

The Predicted Inter-Distance Profile (PIDP) is used in [15][16][17][11] for the evaluation and execution of overtaking maneuvers on highways or roundabouts, depicts how the distance between two vehicles or a vehicle and an obstacle will change over a future time frame. If the information of both vehicles' paths and speed profiles is known by each other, and assuming these factors remain constant during a certain time horizon of prediction, it becomes feasible to project the evolution of the inter-vehicle distance between them. The PIDP will be recalculated at the beginning of each optimization iteration.

As shown in Figure 3, the safety distance d_{safety} is the minimum distance between two vehicles without collision:

$$d_{safety} = r_i + r_j + Margin \tag{1}$$

Where r_i is the safety radius of vehicle i, $Margin$ is a certain distance to guarantee to take into account the different uncertainties linked to the system as well as the capacity of maximum braking of the vehicles.

$mPIDP$ is the minimum value of the PIDP curve, which represents the shortest distance between the two vehicles in the future. If $mPIDP$ is smaller than the safety distance d_{safety}, it means that if neither speed changes, the two vehicles will collide. For convenience, we define $ePIDP$ as the difference between mPIDP and d_{safety}:

$$ePIDP = mPIDP - d_{safety} \tag{2}$$

If $ePIDP$ is positive, it indicates no collision risk, and if it is negative, it signifies the presence of collision risk. From Figure 3, the $mPIDP$ between vehicle 1 and vehicle 3 is less than the safe distance, but it is not the case between vehicle 1 and vehicle 2. Therefore, under the current velocity profile case, it can be concluded that there is a collision risk between Vehicle 1 and Vehicle 3, but there is currently no collision risk between Vehicle 1 and Vehicle 2.

The core of the proposed algorithm is to select the acceleration or deceleration behavior of the vehicles based on PIDP curve features. When the current $ePIDP$ with another vehicle is negative, it means that the current solution is not feasible.

Unlike on highways or merging areas, in cases where the collision type is not a rear-end collision in the intersection, both accelerating to pass the intersection quickly and decel-

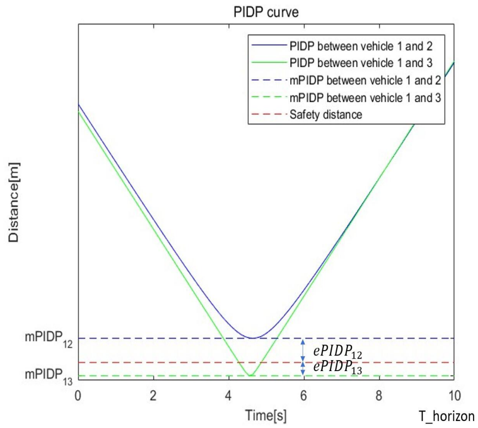
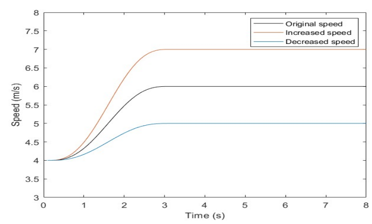
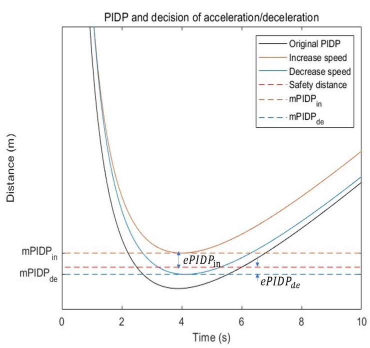


Fig. 3: PIDP curves and the corresponding $mPIDP$ and $ePIDP$



(a) Speed



(b) PIDP

Fig. 4: PIDP-based decision-making

erating to allow another vehicle to pass the intersection are viable solutions. However, the goal is to find the optimal solution while avoiding the collision. Therefore, it is necessary to assess the current state to determine whether accelerating or decelerating for each vehicle is the most suitable to cross the intersection.

The proposed approach to avoid collisions between vehicles is illustrated in Figure 4. Based on the current speed profile, select the increased speed profile and the decreased speed profile, and calculate the PIDP curve according to the conflicted vehicle. The decision to accelerate or decelerate is determined based on the numerical values of both obtained $ePIDP$ (cf. Figure 3):

1) If $ePIDP^{in} > 0 > ePIDP^{de}$ it means the increased speed profile doesn't have collision but the decreased still has the collision, so, select the increased one is better.
2) If $ePIDP^{de} > 0 > ePIDP^{in}$, the decreased speed profile is a better choice.
3) If both of them are positive, it is selected the speed with a smaller absolute value of $ePIDP$ because it has lower cost in terms of modification of the initial vehicle state.
4) If both of them are negative, we select the speed profile with a smaller absolute value of $ePIDP$ too, because it has the larger minimum distance between other conflicted vehicles, even if it doesn't avoid the collision yet.
5) If they have the same value, select the decreased speed profile to prevent unknown risks.

In the Figure 4(a), examples of the original speed profile, the increased speed profile, and the decreased speed profile are shown, with their corresponding PIDP curves are shown in Figure 4(b). In this case, the $ePIDP$ of the increased speed profile is positive but the decreased one is negative, which means the increased speed profile is a feasible solution for this case but the decreased one is not.

C. Multi-Risk Management

In Section II-B, we only consider the simplest scenario. However, the actual situation is usually more complicated. Let us consider a scenario that most of vehicles around the intersection are at risk of collision with multiple vehicles. In such cases, we encounter a special situation: the output of PIDP-based risk management between a CAV and the first collision vehicle is to accelerate, but the output of the second collision vehicle is to decelerate.

In order to deal with this problem, the PIDP-based risk management is extended to multi-risk management method. The final decision of vehicle i is represented as $Decision_i$:

$$Decision_i = \sum_{j \in C_i} (|ePIDP_{ij}^{opt}| * s_{ij}) \tag{3}$$

C_i is the set of vehicles at risk of collision with vehicle i. If $Decision_i$ is positive, the increased speed profile will be selected as the current favorite strategy, otherwise the decreased speed profile will be selected as the current favorite strategy. $ePIDP_{ij}^{opt}$ is the optimized $ePIDP$ between vehicle i and vehicle j through the method shown in Section II-B. s_{ij} indicates the motion of $ePIDP_{ij}^{opt}$, if the optimized speed profile is the increased speed, $s_{ij} = 1$, otherwise $s_{ij} = -1$:

$$s_{ij} = \begin{cases} 1 & \text{if } ePIDP_{ij}^{opt} = ePIDP_{ij}^{in} \\ -1 & \text{if } ePIDP_{ij}^{opt} = ePIDP_{ij}^{de} \end{cases} \tag{4}$$

D. Objective Function

In this paper, the objective is to enable CAVs to reach an optimal collision-free route through the intersection and minimize CAVs speed changes as much as possible during MRMCO-PIDP. Therefore, the objective function is written as:

$$\begin{aligned} f(\mathbf{S}) =& W_{safety}\sum_{i=1}^{N_v}\sum_{j\neq i}^{C} c_{ij} ePIDP_{ij}^{nc} + \\ & W_{cross}\sum_{i=1}^{N_v}\sum_{t=0}^{t_{max}} (v_{max} - v_i(t)) + \\ & W_{penalty}\sum_{i=1}^{N_v}\sum_{j\neq i}^{C} c_{ij} |ePIDP_{ij}^{wc}| \end{aligned} \tag{5}$$

where $\mathbf{S}$ is a joint strategy of all the CAVs, it is a strategy set consisting of one strategy for each vehicle. $W_{safety}, W_{cross}, W_{penalty}$ are weights, and all of them are positive real values. In the first part, $ePIDP$ is used to describes the speed changes of CAVs, nc is "no collision". In the second part, it is used to encourage CAVs to select the faster speed to cross the intersection quickly. The last part is a penalty function, if a collision happens, the penalty function will output a very large cost to make this combined strategy will not be accepted. wc is "with collision". $ePIDP_{ij}^{nc}$ and $ePIDP_{ij}^{wc}$ are given by:

$$ePIDP_{ij}^{nc} = \begin{cases} ePIDP_{ij}^{opt} & \text{if } ePIDP_{ij}^{opt} > 0 \\ 0 & \text{if } ePIDP_{ij}^{opt} \leq 0 \end{cases} \tag{6}$$

$$ePIDP_{ij}^{wc} = \begin{cases} 0 & \text{if } ePIDP_{ij}^{opt} > 0 \\ ePIDP_{ij}^{opt} & \text{if } ePIDP_{ij}^{opt} \leq 0 \end{cases} \tag{7}$$

E. Optimization Process

The optimization process is similar to the PC algorithm proposed in [12]. Each simulation iteration can be split into two parts: Optimization and negotiation.

In the optimization part, the method shown in Section II-C will be run by each CAV. In the negotiation part, each CAV proposes their current favorite joint strategy. The best one will be selected to compare with the current best joint strategy, the best one will be accepted as the new current best joint strategy and proposed to all the CAVs.

More details can be found in Algorithm 1. Results of simulation are given in Section IV-A.

Algorithm 1 MRMCO-PIDP Algorithm

Generate speed profile $\mathbf{X^i}$for each vehicle
Generate best combined strategy $\mathbf{S}_{best}$
Initialize current strategy $X^i_{current}$ to the the initial speed
while $\mathbf{S}_{best}$ is not convergence **do**
  for Each vehicle i **do**
    Get strategies $X^{(i)}$ from $\mathbf{S}^i$
    if Collision **then**
      for Vehicle $j \in$ collision list CL_i **do**
        Calculate $ePIDP_{ij}^{opt}$
        if $ePIDP_{ij}^{opt}$ == $ePIDP_{ij}^{in}$ **then**
          $s_j = 1$
        else
          $s_j = -1$
        end if
      end for
      $decision_i$ = $\sum_{j\in CL_i} |ePIDP_{ij}^{opt}| * s_j$
    else
      $decision_i$ = 1;
    end if
    if $decision_i > 0$ **then**
      $X^i_{current} \leftarrow X^i_{current+1}$
    else
      $X^i_{current} \leftarrow X^i_{current-1}$
    end if
    Form new combine strategy set $\mathbf{S}^i$ with the updated $X^i_{current}$
  end for
  Find $\mathbf{S^i}$ minimizing $f(\mathbf{S}^i)$
  if $f(\mathbf{S}^i) < f(\mathbf{S}_{best})$ **then**
    $\mathbf{S}_{best} \leftarrow \mathbf{S}^i$
    for all vehicle i **do**
      $\mathbf{S}^i \leftarrow \mathbf{S}_{best}$, $X^i_{current} \leftarrow X^i \in \mathbf{S}^i$
    end for
  end if
end while

III. PROPOSED HYBRID COORDINATION OPTIMIZATION ARCHITECTURE

The proposed hybrid approach consists of two parts: the Multi-Risk Management Cooperative Optimization approach based on the Predicted Inter-Distance Profile (MRMCO-PIDP), and the Epsilon Probability Collective algorithm (Epsilon-PC) [14]. The methodology of MRMCO-PIDP is detailed in Section II. Epsilon-PC algorithm is extended from PC algorithm by adding TTC as a collision detection constraint. The advantages and disadvantages analysis is presented in Section IV-A. In summary, MRMCO-PIDP has a short processing time and fast iteration speed, making it advantageous in high-frequency intersection management systems, allowing it to rapidly produce an optimized solution. However, this solution may not be a global optimum. On the other hand, Epsilon-PC takes slightly more time to execute and is more advantageous in low-frequency intersection management systems. It also has a probability of finding a better solution than MRMCO-PIDP.

A. Intersection Management System

A general intersection management is shown in Figure 5. The gray area is the buffer area, which is used to connect CAVs and the intersection management system. The green area is the decision-making area, which is used to do the optimization and negotiation. The blue area is the action area, vehicles in this area will not change their decisions again. The red area is the core area, which is the shared space with other CAVs, generally it's the intersection zone. Before a CAV enters the action area, all its optimization and negotiation should be completed.

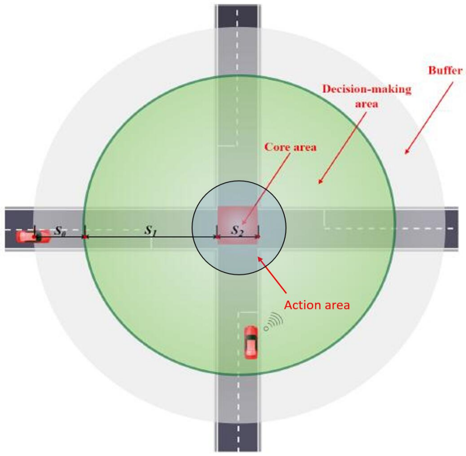


Fig. 5: General intersection management with CAVs [18]

B. Time-Slot-Based Negotiation System

Time-slot-based (TSB) is a negotiation mechanism proposed in [14], which is shown in Figure 6. It is used to define the negotiation mechanism between CAVs. t_{max} is the maximum time for decision-making process, Δt_{sol} is the processing time of each iteration.

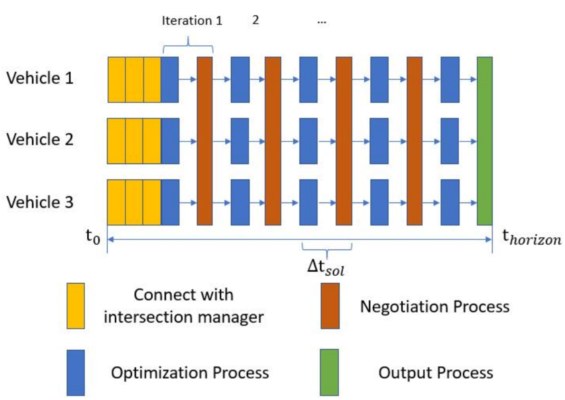


Fig. 6: Time-slot-based negotiation mechanism

C. Hybrid Coordination Optimization Architecture

As introduced in Section III-A, if the optimization approach is used in that scenario, the most important is whether the approach can find a sub-optimal solution or a feasible solution before leaving the decision-making area. However, the disadvantage of the Epsilon-PC is its processing time which is too long, which means $\Delta t_{sol}^{EpsilonPC}$ is large. Given that the simulation's horizon time is fixed, longer iteration times mean fewer available iterations. This is the primary challenge hindering the practical application of the Epsilon-PC algorithm: an algorithm that cannot quickly find a feasible solution is not acceptable, even if its output of the stable solution is an optimal or sub-optimal solution. Its advantages and disadvantages are complementary to MRMCO-PIDP: MRMCO-PIDP can provide an optimized solution very quickly, but this solution may not be optimal.

Based on the respective advantages and disadvantages of the two algorithms, we propose a hybrid coordination optimization architecture: at the beginning of the optimization process, the MRMCO-PIDP algorithm is prioritized to rapidly output a feasible solution, which is set as the current preferred solution. During the subsequent decision-making process before entering the intersection, the Epsilon-PC algorithm is employed to search for a better solution than the current preferred one. If a better solution is found, it is used to update the CAVs' preferred solution. If not, at least MRMCO-PIDP ensures that CAVs have a collision-free feasible solution before entering the intersection. More details can be found in Figure 7.

Due to the significant difference in processing time between the two algorithms (cf. Table II and III), we will use different iteration time intervals at different stages. For MRMCO-PIDP, with each iteration taking less than 0.02 seconds, the negotiation frequency can be set to 10Hz or even faster (i.e., the iteration time interval $\Delta t_{sol}^{MRMCO} < 0.1$ seconds). For Epsilon-PC, with an average processing time per iteration of up to 0.6 seconds, assuming its processing time can be reduced to less than 0.5 seconds with code optimization, its negotiation frequency should not exceed 2Hz (i.e., the iteration time interval $\Delta t_{sol}^{EpsilonPC} > 0.5$s).

IV. SIMULATION RESULTS

All experiments were conducted using a program developed in MATLAB on a computer equipped with Core i7-12700H, 2.30GHz and 16GB RAM. All scenarios are generated by a random scenarios generator, which includes: initial position, initial speed, final direction. Given that Epsilon-PC is a probabilistic algorithm, the solutions it provides often vary after each simulation run. Therefore, in the simulations involving this method, each scenario is repeated 10 times. For each repetition, the average of the optimized solutions is considered to comparison with the corresponding optimized solution by MRMCO-PIDP. In the case of MRMCO-PIDP, as a local search algorithm, the output remains consistent when the initial conditions (initial position, initial speed, final direction) are kept the same, so there is no need to conduct multiple tests for the same scenario. Some examples of the simulation can be found `https://youtu.be/5vUSt66qYmU`

A. Simulation Results of MRMCO-PIDP

One hundred different scenarios were randomly generated for the passage of 3, 4, and 5 vehicles through the unsignalized intersection. These scenarios were separately optimized using the MRMCO-PIDP and Epsilon-PC algorithms. A comparison was made by analyzing the distributions of the average vehicle crossing times and the overall optimization times for random scenarios to illustrate the advantages of the MRMCO-PIDP method. Main parameters considered in the simulation are summarized in Table I.

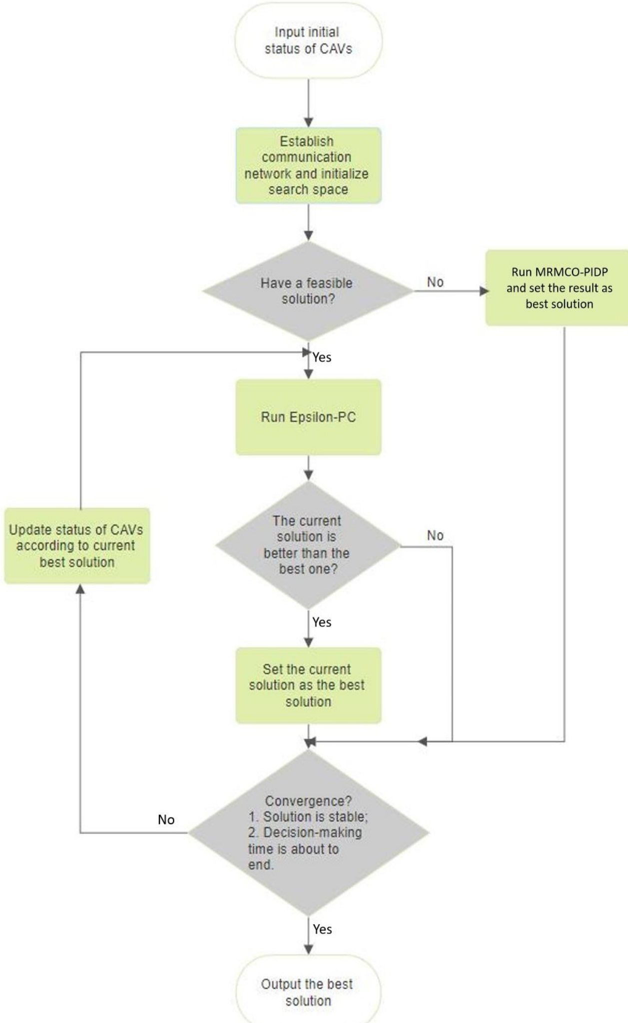


Fig. 7: Flowchart of the proposed hybrid coordination optimization architecture

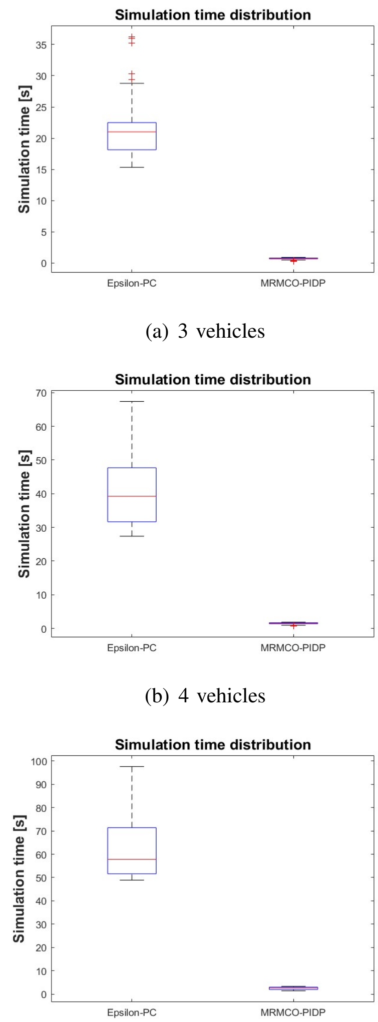
We can observe that the MRMCO-PIDP method exhibits a slight advantage in optimizing the average vehicle crossing time from Figure 8 and Figure 10, . In specific scenarios, MRMCO-PIDP either performs exceptionally well or poorly when compared to the Epsilon-PC algorithm. However, in terms of simulation time, MRMCO-PIDP exhibits a significant advantage. It can achieve an overall solution slightly better than Epsilon-PC in much less processing time, sometimes as low as 4% of the processing time of Epsilon-PC.

Furthermore, these advantages become more pronounced with an increase in the number of vehicles in the simulation. This also demonstrates the excellent performance of MRMCO-PIDP in handling complex intersection scenarios. The results analysis is detailed in Tables II and III.

Additionally, Figure 9 shows the comparison of optimization process of average crossing time for each method. In Figure 9(a), we observe that the average crossing time of Epsilon-PC decreases very quickly in each iteration, and there is a probability of finding a better solution, which

TABLE I: Parameters of vehicles and simulation

Parameters	Value	Parameters	Values
a_{max}	$2[m/s^2]$	W_{Safety}	0.1
$[v_{min}, v_{max}]$	[0,10][m/s]	W_{cross}	0.9
r_{safety}	1.5[m]	$W_{penalty}$	1000
T_{sample}	0.1[s]	N_s	10



(a) 3 vehicles

(b) 4 vehicles

(c) 5 vehicles

Fig. 8: Simulation time with different number of vehicles

reflects to Epsilon-PC's efficiency in achieving a feasible solution with fewer iterations,, as shown in Table II.

However, considering that the time of each optimization iteration in Epsilon-PC is much longer than MRMCO-PIDP, we transfer the x-axis in Figure 9(a) from iteration number to simulation time, the results are given in Figure 9(b) and 9(c). We can see that Epsilon-PC took more time to find a feasible solution, while MRMCO-PIDP's processing time is significantly less than Epsilon-PC.

Here, we can draw conclusions:

1) If CAVs have a high negotiation frequency (greater than

TABLE II: Analysis of Epsilon-PC

Parameters	3 vehicles	4 vehicles	5 vehicles
Average crossing time	3.75s	3.81s	4.35s
Variance crossing time	0.447	1.168	0.668
Average simulation time	21.03s	40.04s	63.05s
Average processing time	0.42s/iter	0.58s/iter	0.74s/iter
Avg iteration number for feasible solution	1.15	1.16	1.18

TABLE III: Analysis of MRMCO-PIDP

Parameters	3 vehicles	4 vehicles	5 vehicles
Average crossing time	3.67s	3.62s	3.93s
Variance crossing time	0.733	0.736	0.411
Average simulation time	0.70s	1.44s	2.48s
Average processing time	0.011s/iter	0.015s/iter	0.020s/iter
Avg iteration number for feasible solution	1.75	2.16	3.58

5Hz), then MRMCO-PIDP has a clear advantage. If the negotiation frequency is low (less than 2Hz), then Epsilon-PC has a relatively larger advantage.

2) MRMCO-PIDP is more stable than Epsilon-PC algorithm, similarly, it also loses the ability of Epsilon-PC to potentially find some optimal solutions.

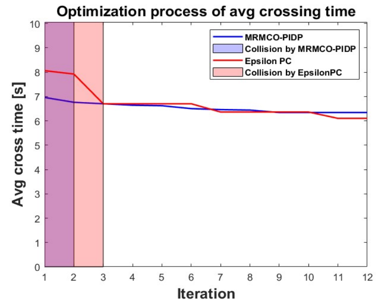
B. Simulation Results of Hybrid Coordination Optimization Architecture

In this section, the results of the hybrid architecture are given to compare with MRMCO-PIDP and Epsilon-PC algorithm in same scenarios. Main parameters considered in the simulation are summarized in Table I and Table IV. Figure 10 shows the boxplot distribution of these algorithms with different numbers of vehicles. Average and variance parameters are detailed in Table V.

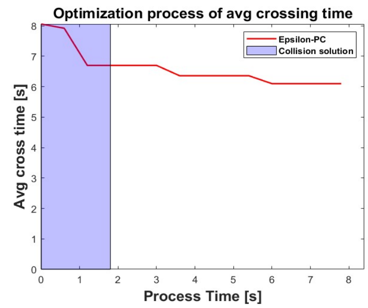
We observe that, in both the simple 3-vehicle simulation and the complex 5-vehicle simulation, the hybrid architecture significantly outperforms MRMCO-PIDP and Epsilon-PC in terms of mean and median crossing times. Additionally,

TABLE IV: Parameters of hybrid optimization architecture

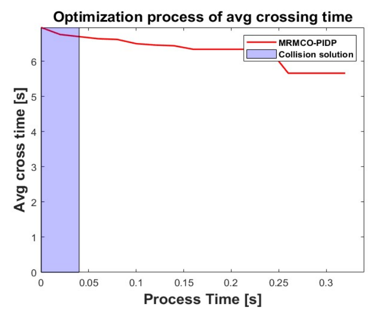
Parameters	Value	Parameters	Values
$N^{EPC}_{opt\_max}$	20	t_{max}	10s
Δt^{MRMCO}_{sol}	0.1s	Δt^{EPC}_{sol}	0.5s



(a) Number of iterations



(b) Processing time of Epsilon-PC



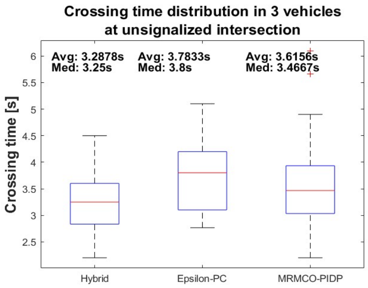
(c) Processing time of MRMCO-PIDP

Fig. 9: Convergence speed comparison between Epsilon-PC and MRMCO-PIDP

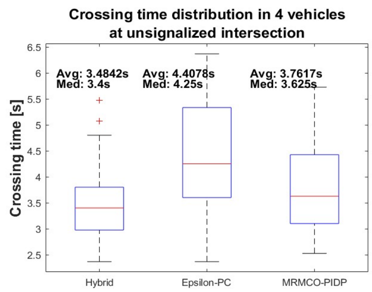
it exhibits lower variance, indicating remarkable stability of the hybrid method when addressing randomly generated scenarios.

V. CONCLUSION AND PROSPECTS

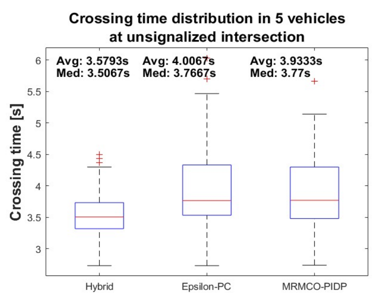
This paper proposed an efficient local search distributed algorithm MRMCO-PIDP for CAVs crossing unsignalized intersection. It also proposed a hybrid coordination optimization architecture consisting of MRMCO-PIDP and Epsilon-PC. MRMCO-PIDP is a fast approach that is used to get a feasible optimized solution. Vehicles at risk of collision can utilize their PIDP curve to identify the quickest collision avoidance strategy, whether by accelerating or decelerating. Simulation results demonstrate its superior performance in multi-vehicle collision problems. This hybrid architecture combines the advantages and disadvantages of Epsilon-PC and MRMCO-PIDP, allowing them to complement each other. It enables Epsilon-PC to be potentially applied in real-world scenarios without significantly increasing its process-



(a) 3 vehicles



(b) 4 vehicles



(c) 5 vehicles

Fig. 10: Crossing time with different number of vehicles

TABLE V: Analysis of Hybrid Architecture

Parameters	3 vehicles	4 vehicles	5 vehicles
Average crossing time	3.67s	3.62s	3.93s
Variance crossing time	0.296	0.615	0.219

ing time. Compared with Epsilon-PC algorithm, the proposed method's optimization efficiency significantly increases as the number of vehicles grows.

In future research, we aim to integrate the PIDP method with dynamic environments, developing a fully reactive algorithm to address uncertainties such as pedestrians, human-driving vehicles, and unexpected accidents.

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References

[1] K. Bellingard, L. Adouane, and F. Peyrin, "Adaptive and reliable multi-risk assessment and management control strategy for autonomous navigation in dense roundabouts," in *IFAC World Congress, Yokohama, Japan*, 2023.

[2] H. Suzuki and Y. Marumo, "A new approach to green light optimal speed advisory (glosa) systems for high-density traffic flowe," in *21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 362–367.

[3] R. Hult, G. R. Campos, P. Falcone, and H. Wymeersch, "An approximate solution to the optimal coordination problem for autonomous vehicles at intersections," in *American Control Conference (ACC)*, 2015, pp. 763–768.

[4] S. Manzinger and M. Althoff, "Tactical decision making for cooperative vehicles using reachable sets," in *21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 444–451.

[5] J. Lioris, R. Pedarsani, F. Y. Tascikaraoglu, and P. Varaiya, "Platoons of connected vehicles can double throughput in urban roads," *Transportation Research Part C: Emerging Technologies*, vol. 77, pp. 292–305, 2017.

[6] C. Hubmann, M. Becker, D. Althoff, D. Lenz, and C. Stiller, "Decision making for autonomous driving considering interaction and uncertain prediction of surrounding vehicles," in *IEEE Intelligent Vehicles Symposium (IV)*, 2017, pp. 1671–1678.

[7] J. Wang, X. Zhao, and G. Yin, "Multi-objective optimal cooperative driving for connected and automated vehicles at non-signalised intersection," *IET Intelligent Transport Systems*, vol. 13, no. 1, pp. 79–89, 2019.

[8] V. Milanes, J. Perez, E. Onieva, and C. Gonzalez, "Controller for urban intersections based on wireless communications and fuzzy logic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 1, pp. 243–248, 2010.

[9] V.-A. Le, B. Chalaki, F. N. Tzortzoglou, and A. A. Malikopoulos, "Stochastic time-optimal trajectory planning for connected and automated vehicles in mixed-traffic merging scenarios," 2023.

[10] M. Minderhoud, M. and P. Bovy, H.L., "Extended time-to-collision measures for road traffic safety assessment," in *Accident Analysis and Prevention*, vol. 33, 2001, pp. 89–97.

[11] D. Iberraken, L. Adouane, and D. Denis, "Reliable risk management for autonomous vehicles based on sequential bayesian decision networks and dynamic inter-vehicular assessment," in *IEEE Intelligent Vehicles Symposium (IV'19)*, Paris-France, 9-12 June 2019.

[12] C. Philippe, L. Adouane, A. Tsourdos, H.-S. Shin, and B. Thuilot, "Probability collectives algorithm applied to decentralized intersection coordination for connected autonomous vehicles," in *IEEE Intelligent Vehicles Symposium (IV'19)*, Paris-France, 9-12 June 2019.

[13] K. Kulkarni, J. and K. Tai, "Probability collectives: A multi-agent approach for solving combinatorial optimization problems," in *Applied Soft Computing*, vol. 10, no. 3, 2010, pp. 759–771.

[14] Z. Zhu, L. Adouane, and A. Quilliot, "Flexible multi-unmanned ground vehicles (mugvs) in intersection coordination based on ϵ-constraint probability collectives algorithm," *International Journal of Intelligent Robotics and Applications*, vol. 5, pp. 156–175, 4 2021.

[15] K. Bellingard, L. Adouane, and F. Peyrin, "Safe and adaptive roundabout insertion for autonomous vehicle based on limit-cycle and predicted inter-distance profiles," in *21st European Control Conference (ECC'23), Bucharest, Romania*, 2023.

[16] D. Iberraken, L. Adouane, and D. Denis, "Safe autonomous overtaking maneuver based on inter-vehicular distance prediction and multi-level bayesian decision-making," in *IEEE International Conference on Intelligent Transportation Systems (ITSC'18)*, Hawaii-USA, 4-7 Novembre 2018.

[17] K. Bellingard, L. Adouane, and F. Peyrin, "Safe overtaking maneuver for autonomous vehicle under risky situations based on adaptive velocity profile," in *IEEE 24th Inter. Conference on Intelligent Transportation Systems (ITSC'21)*, 2021.

[18] Z. Zhu, L. Adouane, and A. Quilliot, "A decentralized multi-criteria optimization algorithm for multi-unmanned ground vehicles (mugvs) navigation at signal-free intersection," *IFAC-PapersOnLine, Special issue, IFAC Control in Transportation Systems*, vol. 54, no. 2, pp. 327–334, 2021.