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Energy Efficiency of CAVs in Unsignalized Intersections based on Cooperative Risk-Assessment Strategy

Shan He¹ and Lounis Adouane¹

¹Université de technologie de Compiègne, CNRS, Heudiasyc, Compiègne, France

Abstract - *The application of Connected and Automated Vehicles (CAVs) can significantly enhance traffic efficiency and reduce both traffic congestion and fuel consumption. Most existing studies on connected and automated vehicles focus on improving traffic efficiency rather than fuel consumption. This paper investigates the impact of different speed strategies adopted by CAVs on fuel consumption. Initially, a cooperative decision-making method for CAVs at unsignalized intersections based on the Predicted Inter-Distance Profile (PIDP) is introduced. Subsequently, a vehicle fuel consumption model is proposed based on this method. The model compares vehicles' speed-priority and fuel-priority strategies, demonstrating that the approach can effectively alleviate urban traffic congestion and substantially reduce fuel consumption. Several random scenarios were executed in the simulation to demonstrate the reliability and energy efficiency of the proposed method.*

Keywords: *Connected Autonomous Vehicles, Energy Efficiency*

I. INTRODUCTION

Over the past few decades, there has been a growing awareness of the importance of environmental issues. Reducing the consumption of fossil fuels is equally important as developing new renewable energy sources. As a critical infrastructure closely related to the economy and daily life, transportation leads to substantial fuel consumption and emissions [1,2]. Traffic congestion within the transportation system causes a significant amount of unnecessary fuel consumption, transportation emissions and time consumption, placing a severe burden on our environment and an unpleasant travel experience to travelers [3-5]. Therefore, reducing fuel consumption and emissions and traffic congestion in the transportation system is a highly meaningful and necessary area of research.

In recent years, CAVs have emerged as a significant research topic in the fields of autonomous driving and intelligent transportation. An increasing number of studies are focusing on

how to utilize CAVs to enhance safety, stability, and efficiency in traffic. The widespread adoption of CAVs will effectively reduce the response delay of vehicles to changes in surrounding traffic conditions, and shorten the following distance between vehicles [9]. Consequently, CAVs have the potential to improve the inherent characteristics of traffic flow, leading to comprehensive breakthroughs in alleviating traffic congestion, saving energy, and reducing traffic emissions.

Considering the initial queue length at intersections, [6] developed a multi-stage optimal speed control model for vehicles to reduce fuel consumption and greenhouse gas emissions. Numerical results indicate that the proposed method is highly efficient. To optimize the trajectories of multiple vehicles collectively, a dynamic programming model and integer programming based on a space-time lattice were proposed in [7]. This method offers a novel approach for forming compact and adaptive vehicle formations at capacity bottlenecks.

A collision-free decision-making method for CAVs at unsignalized intersections, based on the Predicted Inter-Distance Profile (PIDP) is introduced in section II A. Additionally, we have developed a fuel consumption model for vehicles and on the foundation of this model, the proposed algorithm is extended to a "Fuel-Saving Priority mode", which is introduced in Section II B. Through a series of random scenario simulations, we have demonstrated the reliability and efficiency of the proposed approach to the performance of this method in reducing vehicle fuel consumption.

II. METHODOLOGY

A. Principle of the algorithm

1) Predicted Inter-Distance Profile (PIDP)

The Predicted Inter-Distance Profile (PIDP) is used in [8] for the evaluation and execution of overtaking maneuvers on

highways or roundabouts, depicts how the distance between two vehicles or a vehicle and a dynamic 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 1, the safety distance d_{safety} is the minimum distance between two vehicles without collision:

$$d_{safety} = r_i + r_j + Margin$$

Where r_i is the safety radius of vehicle i , Margin is a certain distance guaranteed to account for various 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} (cf. Figure 1):

$$ePIDP = mPIDP - d_{safety}$$

If ePIDP is positive, it indicates no collision risk, and if it is negative, it signifies the presence of collision risk.

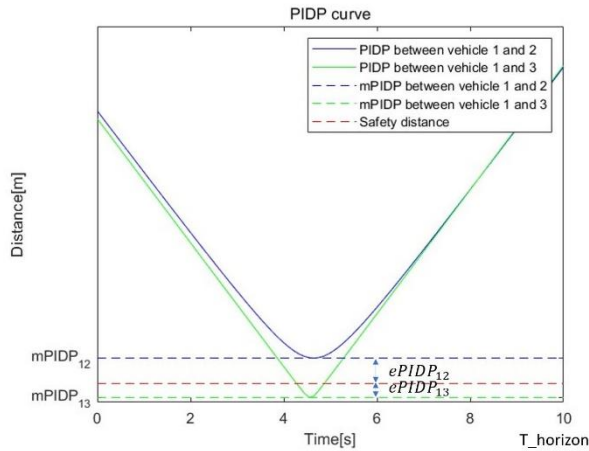


Figure 1. PIDP curves and the corresponding mPIDP and ePIDP

2) Multi-Risk Management Cooperative Optimization (MRMCO)

The core of the MRMCO 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, which means that the current solution is not feasible (a collision will happen if no new action is performed). If the collision type is not a rear-end collision in the intersection, both accelerating to pass the intersection quickly and decelerating 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.

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. An example is shown in the Figure 2.

We always select the strategy with a positive value of ePIDP. If both are positive or negative, the strategy with the ePIDP close to zero will be selected as the current best strategy because they have less action to do to change their strategies.

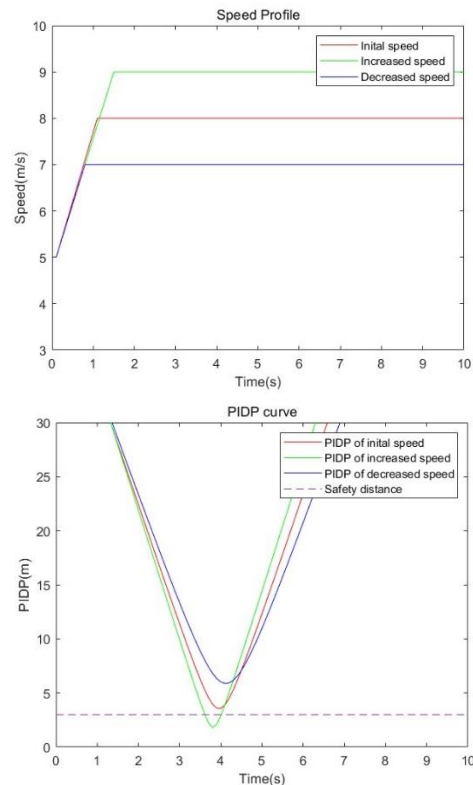


Figure 2 PIDP-based decision-making

Let us consider a scenario that most of vehicles around the intersection are at risk of collision with more than one other vehicle, we may face to the following 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 $Decision_i$:

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

Where C_i is the set of vehicles who can collide 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. $PIDP_{ij}^{opt}$ is the optimized $ePIDP$ between vehicle i and vehicle j . s_{ij} indicates the motion of $ePIDP_{ij}^{opt}$, if the optimized speed profile is the increased speed, $s_{ij} = 1$, otherwise $s_{ij} = -1$.

3) Objective function and optimization process

In the initial approach, the Multi-Risk Management of Cooperative Optimization (MRMCO) was employed to find the solution that minimizes the travel time for CAVs passing through unsignalized intersections without any hindrance. To achieve this objective, we constructed an objective function consisting of three components: safety consumption, speed consumption, and a penalty function. The first two components were used to find the fastest method to pass through the intersection, while the penalty function ensured that this method was collision-free. Therefore, the objective function is written as:

$$J(S) = \sum_i^{N_v} \{W_{safety} \sum_{j \neq i} c_{ij} * ePIDP_{ij} + W_{cross} \sum_{t=t_0}^{t_{max}} (v_{max} - v(t)) + W_{penalty} \sum_{j \neq i} c_{ij} |ePIDP_{ij}^{ne}|\}$$

Where S is the combined strategy set. c_{ij} is the collision relationship between vehicle i and j , if their paths have no crossing point, c_{ij} is 0, otherwise, c_{ij} is 1. v_{max} is the maximum legal velocity in the designed road near the intersection. $ePIDP_{ij}^{ne}$ is the value of $ePIDP_{ij}$ if and only if it is negative. If $ePIDP_{ij}$ is positive, $PIDP_{ij}^{ne}$ is 0. N_v is the number of CAVs

near the intersection. W_{safety} , W_{cross} and $W_{penalty}$ are weight coefficients and all of them are positive, and $W_{penalty}$ approaches positive infinity.

The main optimization process of MRMCO based on PIDP (MRMCO-PIDP) is shown in Algorithm 1. It will be run by each vehicle in the CAV at each iteration. 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. The convergence criteria are: the already defined number of iterations is reached, or a better solution was not found within the past few iterations.

Algorithm 1 MRMC-PIDP Algorithm

```

1: Input vehicle information
2: while  $S_{best}$  is not convergence do
3:   for Each vehicle  $i$  do
4:     Get strategies  $X^{(i)}$  from  $S^i$ 
5:     if Collision then
6:       for Vehicle  $j \in$  collision list  $CL_i$  do
7:          $ePIDP_{ij} = \max(ePIDP_{ij}^{in}, ePIDP_{ij}^{de})$ 
8:         if  $ePIDP_{ij} = ePIDP_{ij}^{in}$  then
9:            $s_j = 1$ 
10:        else
11:           $s_j = -1$ 
12:        end if
13:      end for
14:       $decision_i = \sum_{j \in CL_i} |ePIDP_{ij}| * s_j$ 
15:      else
16:         $decision_i = 1$ ;
17:      end if
18:      if  $decision_i > 0$  then
19:         $X_{current}^i \leftarrow X_{current+1}^i$ 
20:      else
21:         $X_{current}^i \leftarrow X_{current-1}^i$ 
22:      end if
23:      Form new combine strategy set  $S^i$  with the updated  $X_{current}^i$ 
24:    end for
25:    Find  $S^i$  minimizing  $f(S^i)$ 
26:    if  $f(S^i) < f(S_{best})$  then
27:       $S_{best} \leftarrow S^i$ 
28:      for all vehicle  $i$  do
29:         $S^i \leftarrow S_{best}$ 
30:         $X_{current}^i \leftarrow X^i \in S^i$ 
31:      end for
32:    end if
33:  end while

```

B. Model of fuel consumption

Currently, mainstream vehicle emission models include MOBILE5a, MOBILE6, and the Virginia Tech microscopic energy and emission model (VT-Micro). They provide comprehensive models for fuel consumption and emissions of vehicles in motion. However, these models are quite complex, and for the purpose of our study, which focuses solely on the energy efficiency of vehicles, such complexity is not necessary.

Therefore, building upon these existing models, we have abstracted the primary factors of fuel consumption in vehicles into two parts: 1. Fuel loss related to speed, including factors like air resistance; 2. Fuel loss related to acceleration, including acceleration or deceleration. The magnitude of air resistance is directly proportional to the square of the vehicle's speed, and the resistance coefficients vary between different vehicle models. However, when considering the relationship between driving speed and fuel consumption, it is essential to account for a concept known as the "economical speed". This concept suggests that each vehicle, based on its physical parameters, has an optimal speed at which the average fuel consumption is minimized, it is marked below as v_{eco} . Therefore, the model of fuel consumption we proposed is:

$$F = W_{spd} \int_{t_0}^{t_{end}} ((v(t) - v_{eco})^2 + c_v) dt + W_{acc} \int_{t_0}^{t_{end}} |a(t)| dt$$

F is the fuel consumption of vehicle, $v(t)$ and $a(t)$ denote the velocity function and the acceleration function. W_{spd} , W_{acc} and c_v are positive coefficients, related to the vehicle model.

Given that our optimization method is based on the optimization of an objective function, we established a new objective function on the foundation of our fuel consumption model. This objective function is designed to describe the fuel consumption scenario of CAVs' strategies. Considering that collision avoidance is a mandatory component of our speed planning algorithm, we retained the penalty function for collision detection in our originally "Time-Saving Priority" objective function, while altering other parts to accommodate the fuel consumption model. The new objective function is formulated as follows:

$$J(S) = \sum_i^{N_v} (W_{spd} \int ((v(t) - v_{eco})^2 + c_v) dt + W_{acc} \int |a(t)| dt + W_{penalty} \sum_{j \neq i} c_{ij} |ePIDP_{ij}^{ne}|)$$

III. SIMULATION RESULTS

All the experiments were run by a program developed in MATLAB with a computer of Core i7-12700H, 2.30GHz and 16GB RAM. All the scenarios are generated by random scenarios generator, which includes: initial position, initial speed, final direction. For each scenario, it will be run by "Fuel-Saving Priority" model and "Time-Saving Priority" mode. Parameters of the simulation are given in Table 1.

Table 1 Parameters of vehicles and simulation

Parameter	Value	Parameter	Value
a_{max}	2 m/s ²	W_{safety}	0.1
$[v_{min}, v_{max}]$	[0.1, 10]m/s	W_{cross}	0.9
r_{safety}	1.5 m	$W_{penalty}$	1000
c_v	1	W_{acc}	3
v_{eco}	8 m/s	W_{spd}	0.1

An example of the 4 vehicles simulation is given as Figure 3 and 4. All those vehicles cooperate to find a global optimal solution, and the final speed approaches the economical speed v_{eco} . Videos are given in:

<https://youtu.be/GqBHluV2hmU>

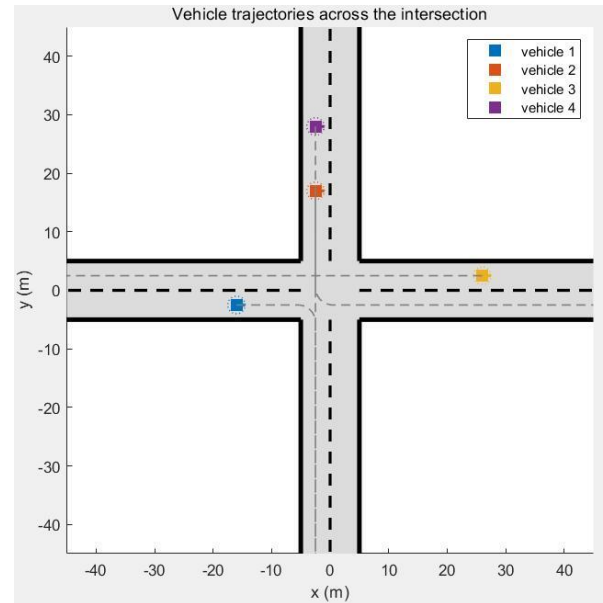


Figure 3 Intersection model

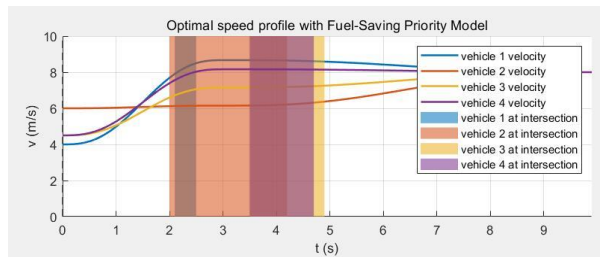


Figure 4 Speed Profiles of CAVs

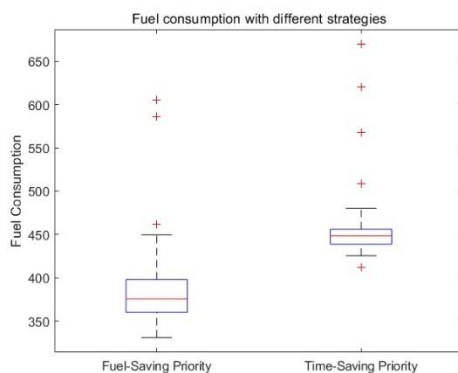


Figure 5 Fuel consumption comparison of 3 vehicles

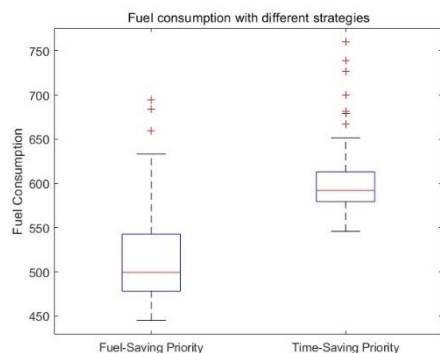


Figure 6 Fuel consumption comparison of 4 vehicles

Figure 5 and 6 are boxplots of 100 times simulation with random scenarios by two modes, we can find that the proposed "Fuel-Saving Priority" mode is more energy efficiency compared to the "Time Saving Priority" mode. The overall energy efficiency is improved by 15-18%. It is important to note that this better energy efficiency is the result of the CAVs adopting fuel efficiency strategies. The improvement in fuel efficiency relative to traditional non-CAVs vehicles is even more significant.

IV. CONCLUSION AND PROSPECTS

This paper proposed a multi-vehicle cooperative method for unsignalized intersections based on PIDP. This method can swiftly find feasible solutions for collision problems at unsignalized intersections. Building upon this algorithm, we further propose an energy-saving mode aimed at conserving fuel. We demonstrate that the fuel-saving mode can further enhance efficiency by 15-18% for CAVs compared to the strategy given in [11].

In our future research, we will extend this method to mixed intersection models that include both CAVs and human-driven vehicles. We aim to explore further methodological expansions based on this foundation.

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