Enhancing Road Safety: A Comparative Study between UAV-Assisted and Autonomous Vehicles

Sana Bouassida, Lydie Nouveliere, Najett Neji, Jamel Neji

Enhancing Road Safety: A Comparative Study between UAV-Assisted and Autonomous Vehicles

Sana Bouassida[1,2], Lydie Nouveliere[1], Najett Neji[1], Jamel Neji[2]

***Abstract*— The integration of connected autonomous vehicles (CAV) on open roads has gained significant progress in addressing road safety. These vehicles use advanced sensor technology to perceive and react to the road environment, reducing accident risks. Despite these advancements, limitations persist in their perception capabilities. To overcome these limitations, interest is growing in using Unmanned Aerial Vehicles (UAVs) for traffic surveillance, offering extensive coverage and enhanced responsiveness over fixed sensors. In this article, by tackling an optimization problem in road safety using Particle Swarm Optimization (PSO), we particularly focus on a situation where a random flow of vehicles aims to navigate an intersection safely. We compare two scenarios with and without the assistance of an UAV: one where vehicles autonomously manage their speed, and another one where an UAV improve traffic management. Simulation results underscore the pivotal role of drone-assisted vehicles in enhancing road safety, compared to sensors embedded within CAVs. Towards the end of the article, we explore the efficiency of the drone strategy by addressing the issue of delay in the acceptance and implementation of optimal speed instructions, comparing scenarios with and without this delay.**

***Index Terms*— CAV, UAV, drone to vehicle communication (U2V), optimization, road safety, Acceptability, Multi-Agent system.**

I. Introduction

Ensuring road safety remains a major challenge in transportation. According to the World Health Organization (WHO), road traffic accidents cause around 1.3 million deaths each year [1]. Human error plays a role in approximately 90% of these accidents [2]. The deployment of CAVs at intersections holds great potential for improving road safety through the use of advanced onboard sensors technology [3]. Numerous studies have been described in the literature, highlighting how their integration at intersections significantly enhances road safety by leveraging advanced onboard sensors technology. The research team in [4] worked on radar sensors that detect the speed and distance of objects, which are crucial for collision avoidance. Cameras provide visual information for object recognition and lane detection, as highlighted in their research. GPS and Inertial Measurement Units (IMUs) ensure precise localization and vehicle state estimation, providing accurate positioning and movement tracking. These sensors allow CAVs to predict and react to the road environment, reducing accident risks and enhancing intersection safety [5]. Moreover, CAVs can communicate with other vehicles and infrastructure, facilitating coordinated movements and improved traffic efficiency, thereby minimizing potential collision points at intersections [6].

Despite the advancements of CAVs, their perception capabilities still face limitations. These issues are especially problematic in complex urban environments where visual obstructions like other vehicles or physical barriers can restrict the field of view of onboard sensors. This restriction presents significant challenges to ensuring the robust and safe operation of CAVs [7]. To mitigate these challenges, new technologies have been proposed for traffic regulation and are now being implemented in some cities. One such technology involves the use of aerial monitoring systems, specifically UAVs. UAVs have been utilized since the early 2000s for traffic supervision and monitoring [8]. They offer an effective way to enhance situational awareness and address the limitations of ground-based sensors. They can operate autonomously or be remotely controlled, offering significant advantages in flexibility, cost efficiency, and operational capabilities. [9]. Also, UAVs can cover streets comprehensively and provide multiple perspectives on road conditions, unaffected by terrain [10]. As for examples, the research team in [11] worked on developing an autonomous recognition system using a swarm of UAVs to navigate complex urban environments. They formulated algorithms deploying waypoints for efficient monitoring and route planning. Besides, authors in [12] proposed using UAVs for aerial surveillance through a decentralized navigation scheme. This scheme allows UAVs to detect obstructions and subsequently converge on the obstructed area to obtain improved views of ground vehicles. The research team in [13] developed a method for automatic car detection in high-resolution UAV images of urban areas. Their approach includes identifying asphalted areas, extracting histogram-of-gradient features, and applying similarity measures to detect and determine the orientation of cars. In addition to all these capabilities, UAVs have the ability to detect even the smallest objects. In [14], authors propose a novel real-time small object detection algorithm implemented in the drone, which improves the detection accuracy of small objects.

In our previous works, we have addressed the impact of drone signaling in a crosswalk [15] and when approaching a crossroad [16] for road safety improvement. In the same context, we address the impact of drone decision-making on traffic safety management throughout this study. Compared to [16], this work highlights the role of drone in enhancing road safety by sending decisions to manually driven vehicles

[1]Authors are affiliated with IBISC Laboratory, Université d'Évry-Val-d'Essonne, Université Paris-Saclay, 36 Rue du Pelvoux, CE 1455 Courcouronnes 91020 Évry Cédex, France

[2]Authors are affiliated with LAMOED Laboratory, ENIT Universit´ de Ťunis El Manar, Rue Béchir Salem Belkhiria Campus Universitaire 1002, Tunis, Tunisie sana.bouassida@univ-evry.fr

and comparing it to sensors of autonomous vehicles, where the work in [16] only presents a proof of concept on the possibility of having UAVs at crossroads to save lives.

In this paper, we present a novel approach that incorporates an aerial component, the drone, which is unbounded by spatial or temporal constraints. The drone possesses a designated level of intelligence, enabling it to make decisions regarding the vehicle's speed and to send corresponding instructions. Hence, while the previous work aimed at improving road safety without optimization, this study focuses on optimizing road safety by utilizing the drone's decision-making capabilities. To this end, this article is structured as follows, In Section II, we present the problem statement and the studied scenarios. In Section III, we outline our proposed strategy adopted by the drone for safety management along with the underlying hypotheses. In Section IV, we present the optimization method as well as our algorithms. In Section V, we detail the results and discuss the main findings. Section VI is, lastly, dedicated to summarize the main conclusions and further work.

II. Problem Statement

In this paper, we examine a scenario that is likely to occur in cities where automated and non-automated vehicles are in circulation. We focus on a randomly distributed flow of N vehicles navigating a straight lane approaching a signalized intersection. The vehicles aim to ensure safe navigation of a lane without any collisions. In other words, they intend to ensure a safe passage in this urban area as they approach the intersection. All parameters and their associated notations employed in this study are comprehensively listed in Table

TABLE I: Parameters used in this work

Notation	Parameter	Value
Constant Parameters		
N	Number of vehicles	10
g	Gravitational acceleration	9.8067 $m.s^{-2}$
$v_{\max}$, $v_{\min}$	Maximum, Minimum speed limit	130, 1 km.h^{-1}
$a_{\max}$, $a_{\min}$	Maximum, Minimum acceleration	0.7 g, -1 g
h	Inter-vehicle time	2 s
l	Desired minimum residual distance at a stop	8 m
δ_t	Step of time	1 s

Variable Parameters	
Notation	**Parameter**
$SM(t)$	Safety margin
$\delta D_i(t)$	Actual distance between two consecutive vehicles
$\delta D_{s,i}(t)$	Desired Safety Distance
speeds$_{v0}$	Speed profile of the lead vehicle
N_{steps}	Number of time steps
$x_{\text{init},i}$, $v_{\text{init},i}$	Initial position, speed of vehicle i
$v_{\text{opt},i}$	Optimized speed of vehicle i
V_{opt}	Matrix containing the optimized speed profiles for all vehicles

Each vehicle aims to optimize its behavior to reach the road intersection safely. This flow of vehicles is led by a vehicle V0 , whose behavior is pre-established and can vary depending on encountered obstacles. Thus, the objective of each vehicle Vi is to determine the velocities $v_i(t)$ over time that optimize its behavior, allowing for a safe passage on the lane. This behavior involves finding the values of $v_i(t)$ that enables:

- To ensure compliance with speed limits: From the viewpoint of creating a system that is both environmentally friendly and safe, the maximum speed limit will be set based on the most restrictive speed regulation among the various guidelines encountered, such as legal speed limits, speed reductions for curves, and speed limits due to roadwork. The minimum constraint is the minimum speed that must be maintained on the road.
- To respect acceleration and deceleration limits. The acceleration must remain within the specified minimum and maximum limits.
- To maintain a safe inter-vehicle distance from the preceding vehicle. The safety margin $SM(t)$ must be non-negative at all times to avoid collisions.
- Maintaining a minimum inter-vehicle distance: $\delta D_i(t)$ must be greater than or equal to the distance l at all times to avoid collisions.

To summarize, the problem formulation is donated in (1).

Find $v_i(t)$ for each vehicle i, where:

$$\begin{cases} v_{\min} \leq v_i(t) \leq v_{\max}, & \text{for all } t, \\ a_{\min} \leq \frac{dv_i(t)}{dt} \leq a_{\max}, & \text{for all } t, \\ SM_i(t) = \delta D_i(t) - \delta D_{s,i}(t) \geq 0, & \text{for all } t, \\ \text{with: } \delta D_{s,i}(t) = h \cdot v_i(t) + l, & \\ \delta D_i(t) \geq l, & \text{for all } t, \\ x_i(0) = x_{\text{init},i}, & \text{Initial position,} \\ v_i(0) = v_{\text{init},i}, & \text{Initial speed} \end{cases} \tag{1}$$

In the rest of the paper, we will investigate two cases: In the first case, vehicles are autonomous, and there is no drone above the scene, which will be considered our reference scenario. In the second case, we will introduce a drone above the scene where manually driven vehicles are navigating.

A. Safety Management by autonomous vehicles

The first scenario involves autonomous vehicles navigating the lane without the presence of a drone overhead. Each vehicle autonomously resolves a safety optimization problem through onboard computations. In this context, the vehicles are automated and equipped with sensors to detect preceding vehicles, thereby adjusting their behavior to fulfill optimization objectives. The optimization algorithm is embedded within the automated vehicle's system architecture as demonstrated in Fig. 1a).

B. Safety Management by an UAV

In the second scenario, we add a drone, positioned strategically hovering above the intersection approach. This drone is equipped with a sufficient level of intelligence to make decisions. The drone acquires information about the behavior of the N vehicles within its field of vision and continuously calculates the decision speed $v_{opt,i}(t)$ that each vehicle i should adopt at each time step t (see Fig. 1b). It then

communicates this speed to the vehicle so that it adopts it at each time step. In this second approach, the optimization algorithm is executed at the drone level.

(a) Structure for a safety management by the autonomous vehicle

(b) Structure for a safety management assisted by an UAV

Fig. 1: Safety Management approaches

In the following sections, we detail more the strategy adopted in our approach of safety management by the drone.

III. Adopted Strategy for Safety Management by Drone-Assisted Vehicles on the Road

A. Traffic zone division strategy

In this section, we recall the global strategy adopted in our previous work [16]. Our proposed approach divides the vicinity of the intersection into three distinct areas, with two drones flying over the intersection. This method ensures both spatial continuity (transitioning from Zone 3 to Zone 1) and temporal continuity, as the information provided by the drones is continuous. Zone 3 (Z3) is the farthest from the intersection, where the high altitude (HA) drone collects information about each vehicle's behavior. For further details, see [16]. Zone 2 (Z2) is closer to the intersection, where the low altitude (LA) drone makes decisions to ensure the safe passage of vehicles based on their levels of automation. Zone 1 (Z1) is the final braking zone, nearest to the intersection. The top view of the intersection approach can be seen in Fig. 2a.

In this article, our focus is only on Z2, We assume that the HA drone has gathered sufficient information within Z3 regarding vehicle behaviors and communicated it to the LA drone. Within Z2, the LA drone will address an optimization problem within its database and will communicate optimal speeds to each vehicle over time. To streamline our study, we focus exclusively on LA drone operating within Z2. All subsequent discussions and analyses in this article will pertain only to LA drone.

B. The drone field of view and parameters

The drone strategy involves using a supervising drone equipped with a wide-angle camera to monitor a significant stretch of the road which is Z2 in our context (See Fig. 2b). The main parameters of this system include:

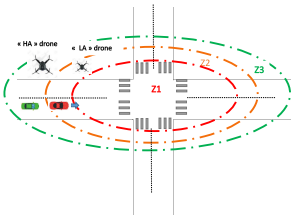
- **Camera Field of View (θ):** The camera's field of view is crucial for defining the drone's visual range. The angle is chosen to ensure extensive coverage of the monitored area without requiring drone movements.
- **Drone Altitude (H_{drone}):** The drone operates at an altitude denoted by H_{drone}, enabling effective surveillance while maintaining adequate image resolution for traffic analysis.
- **Coverage Length:** The length of the area covered by the drone is calculated in (2).

$$\text{Coverage\_Length} = 2H_{\text{drone}} \tan\left(\frac{\theta}{2}\right) \tag{2}$$

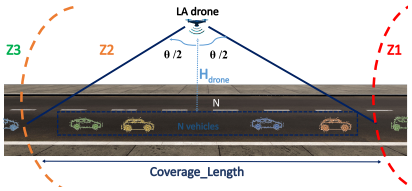
providing an estimate of the maximum distance covered by the camera from its central position. This coverage length presents the length of Z2.
- **The maximum view** The maximum number of vehicles that can fit within the drone's coverage length when stationary is calculated in (3):

$$N\_vehicles\_max = \text{floor}\left(\frac{\text{coverage\_length}}{L_{\text{VEH}} + l}\right) \tag{3}$$

where L_{VEH} is the length of a vehicle.



(a) Top view of the road



(b) Longitudinal view of the road

Fig. 2: Adopted strategy

The drone can simultaneously detect multiple vehicles, thus optimizing real-time speed management. The optimization algorithm, executed by the drone, adjusts vehicle routes to maximize security while minimizing the risk of accidents.

In a second phase, to evaluate the effectiveness of this approach, we will also consider that the adaptation of the optimal speed instruction is associated with the driver's acceptance delay δ_{delay}. In this work, this delay is assumed to be constant for a specific vehicle. We will then assess whether this delay impacts the drone safety management strategy or not.

C. Assumptions

In this work, we assume that all vehicles are cooperative, receiving and immediately adopting the prescribed speeds.

Thus, we consider perfect communication with no transmission delay between the drone and vehicles. This allows us to focus on the fundamental capabilities of the centralized strategy. Later, we will test the impact of a delay related to the driver's acceptability rate, including response and interpretation time.

IV. Method and Algorithms

A. Particle Swarm Optimization

In this research, we employed the PSO to optimize the speed profiles in both scenarios described below: firstly, for CAVs managing their speed autonomously, and secondly, for manually driven vehicles receiving speed decisions and thus instructions from an UAV. PSO is a computational method inspired by the social behavior of birds flocking or fish schooling, which is widely used for solving complex optimization problems. By simulating the movement and intelligence of swarms, PSO efficiently searches for optimal solutions by iteratively improving a candidate solution with regard to a given measure of quality [17]. This technique was particularly effective in our study for optimizing the speed instructions communicated by a drone to vehicles, ensuring enhanced traffic flow and safety.

B. Algorithm of Safety Management by each autonomous vehicle

Algorithm SSO-NDA illustrates the road safety optimization by a CAV.

Algorithm SSO-NDA Sequential Speed Optimization Without any Drone Assistance

Require: N, speeds_{v0}, l, h, δ_t, $v_{\min}$, $v_{\max}$, $a_{\min}$, $a_{\max}$
Ensure: $V_{\text{opt}}[N-1][N_{steps}]$
  $N_{steps} \leftarrow \text{length}(\text{speeds}_{v0})$
  Initialize $v_{\text{init}}[N-1]$, $x_{\text{init}}[N-1]$
  Define the bounds lb, ub for the optimization
  Configure the PSO optimization options (swarm size, maximum iterations, inertia range, hybrid function, display settings)
  for each vehicle i from 2 to N **do** ▷ Sequential optimization for each vehicle
    Define the objective function for vehicle i based on its initial parameters and constraints, considering the preceding vehicle
    Execute the PSO individually for vehicle i to obtain v^i_{opt}
    Store the optimized speeds for vehicle i: $V_{\text{opt}}[i-1] = [v^i_{\text{init}}; v^i_{\text{opt}}]$
    Calculate the cumulative positions for vehicle i:

$$x_i(t+1) = x_i(t) + V_{\text{opt}}[i-1][t] \cdot \delta_t$$

  end for
  return V_{opt}

This algorithm outlines the process by which each CAV optimizes its speed sequentially in the absence of a drone. When vehicle i enters the optimization phases, it uses the position and speed of the preceding vehicle, which has already optimized its speed. Vehicle i then defines its objective function and constraints based on its initial parameters and the behavior of the preceding vehicle. Using PSO, it determines its optimal speed. After obtaining the optimal speed, vehicle i updates its speed and calculates its new position for the next time step. In this approach, each vehicle acts independently based on its onboard sensors and the information from the preceding vehicle. There is no central coordination; the optimization is decentralized, with each vehicle optimizing its behavior sequentially.

C. Algorithm of Safety Management by an UAV

Algorithm CSO-WDA illustrates the road safety optimization for manual vehicles by an UAV. This algorithm details how a drone manages the speed optimization of manual vehicles within its coverage area. At each time step t, the drone calculates the optimal speeds for all vehicles in its field of view, considering their interactions and constraints. The maximum number of vehicles that can be covered by the drone is determined by the coverage length, and the algorithm ensures that the number of vehicles N is within this maximum limit. Upon a vehicle entering Z2, the drone receives the latest speeds and positions of each vehicle from the HA drone, based on their behavior in Z3. Using this information, the drone initializes the positions and speeds of the vehicles. It then defines a centralized objective function

Algorithm CSO-WDA Centralized Speed Optimization with Drone Assistance

Require: N, N_{steps}, speeds_{v0}, l, h, δ_t, $v_{\min}$, $v_{\max}$, θ, H_{drone}, L_{VEH}
Ensure: $V_{\text{opt}}[(N-1) \times N_{\text{steps}}]$
  $N_{\text{steps}} \leftarrow \text{length}(\text{speeds}_{v0})$
  Calculate $\text{Coverage\_Length} = 2H_{\text{drone}} \tan\left(\frac{\theta}{2}\right)$
  Calculate $N\_vehicles\_max = \text{floor}\left(\frac{\text{Coverage\_Length}}{L_{\text{VEH}}+l}\right)$
  $N \leftarrow \min(N, N\_vehicles\_max)$ ▷ Ensure N is within the drone's coverage capacity
  Initialize $x_{\text{init}}[N]$ and $v_{\text{init}}[N]$
  Define the global bounds lb and ub for PSO optimization
  Configure the PSO optimization options
  Define a centralized objective function J that accounts for all vehicles and their interactions
  Execute the PSO to obtain V_{opt} for vehicles 1 to $N-1$
  for $t = 1$ to N_{steps} **do**
    Store: $V_{\text{opt}}[:,t] = v_{\text{opt}}[:,t]$
    The drone communicates $v_{\text{opt}}[:,t]$ to each vehicle within Z2
    for each vehicle i from 2 to N **do**

$$v_i(t+1) = V_{\text{opt}}[i-1,t], \quad x_i(t+1) = x_i(t) + V_{\text{opt}}[i-1,t] \cdot \delta_t$$

    end for
  end for
  return V_{opt}

that incorporates the interactions between the vehicles and employs PSO to determine the optimal speeds.

Once the optimal speeds are identified, the drone communicates these speed decisions to the vehicles, which then update their speeds and positions accordingly. This centralized approach ensures coordinated optimization, with the drone overseeing the overall traffic scenario and optimizing the speeds of all vehicles within its field of view.

V. Simulation and Results

A. Parameters

We evaluate these algorithms in a MATLAB environment simulation, considering our traffic scenario described below with $N = 10$ vehicles approaching an intersection led by the vehicle V0. Hence, we consider that only N vehicles are in the field of view of the UAV including V0. Each vehicle maintains a safety distance from the preceding vehicle at the start, with initial positions given by $x_{\text{init i}} = -i \cdot (l + h \cdot v_{\text{init 0}})$, where i is the vehicle index. The values of further parameters are provided in Table I. The simulation evaluates the performance of both SSO-NDA and CSO-WDA algorithms under these conditions for the speed. The leader vehicle's random but realistic profile sets the initial conditions for the speed. This setup allows us to observe how each algorithm handles real-time traffic optimization in a controlled environment. The V0 speed profile is illustrated in Fig. 3 with realistic variations.

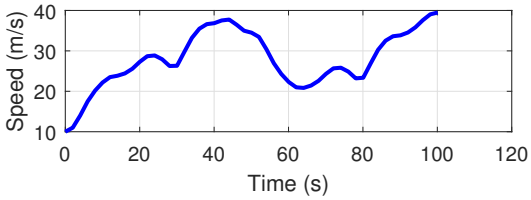
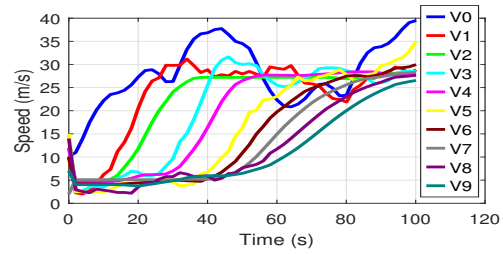


Fig. 3: Speed Profile of V0

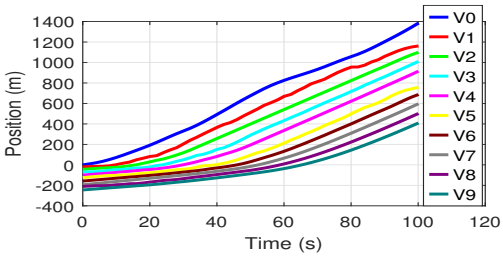
B. Results and Discussion

1) Impact of drone on road Safety Optimization: To conclude the impact of the drone on optimizing road safety by bringing other information to the Vi vehicles than its sensors one, we plot the optimal speed curves over time for the two scenarios: safety management by autonomous vehicles without any drone (see Fig. 4) and safety management assisted by the drone (see Fig. 5) for manually driven vehicles.

The comparative analysis of the scenarios SSO-NDA and CSO-WDA reveals distinct differences in speed optimization and safety. Without any drone assistance, speed profiles exhibit significant fluctuations and variability, with the leader vehicle (V0) following a pre-established profile. while follower vehicles (V1 to V9) show erratic speed patterns. This lack of coordinated speed optimization leads to abrupt speed changes and varied distances between vehicles, creating challenges in maintaining consistent safety gaps.

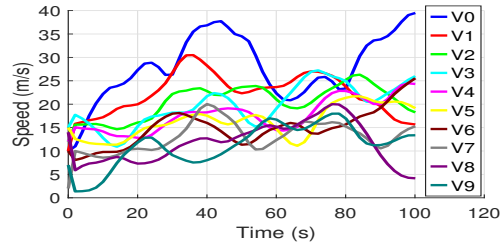


(a) Optimal speeds calculated by CAVs

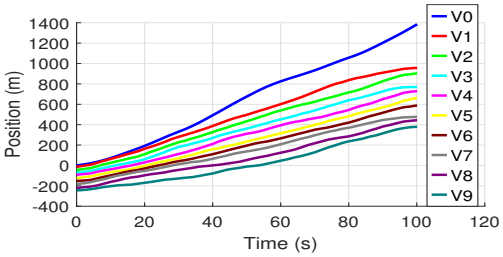


(b) Cumulative Positions Over Time for Each Vehicle

Fig. 4: Sequential speed Optimization



(a) Optimal speeds calculated by the drone



(b) Cumulative Positions Over Time for Each Vehicle

Fig. 5: Centralized speed Optimization

In contrast, CSO-WDA scenario demonstrates more regulated speeds across all vehicles, with smoother transitions and frequent adjustments. The drone facilitates a more dynamic and responsive control strategy, allowing for real-time speed adjustments and a cohesive convoy movement. This dynamic optimization ensures that each vehicle adapts its speed in response to both the leader's pace and the drone's communications, promoting a more flexible and adaptive convoy behavior. The cumulative positions in this scenario show more synchronized increases with V0, ensuring that safety distances are more consistently maintained. The drone's intervention results in better coordination, enhancing overall speed management, efficiency, and safety.

2) Impact of the driver's acceptability delay on the Safety Management by the drone: In this section, we investigate the impact of a δ_{delay} acceptability delay in receiving optimal speed instructions and applying them in real time, focusing on V1 and V4. To analyze this impact on traffic stability and road safety, we plot the standard deviation of vehicle speeds for both scenarios: with and without delay. In the delayed scenario, the delay is applied to V1($\delta_{\text{delay}} = 1s$) and V4($\delta_{\text{delay}} = 3s$). This translates that the V1 and V4 respective drivers have a reduced acceptability compared to the other Vi's drivers. This delay reflects how the driver more or less accepts the UAV's decision supposed to be the best one. This analysis quantifies the speed variability and evaluates the delay's impact on overall traffic flow stability and safety. Fig. 6 illustrates the standard deviation of speeds for each vehicle, comparing both scenarios.

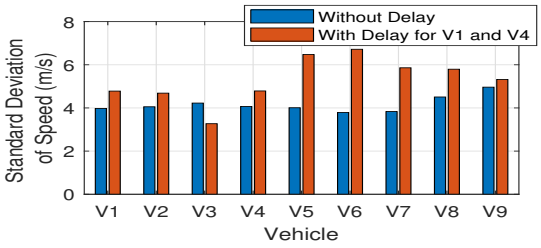


Fig. 6: Comparison of Speed Standard Deviations (Without Delay vs With Delay for V1(1s) and V4(3s))

The results show that the standard deviation of vehicle speeds is consistently higher in scenarios with a delay, indicating greater variability and reduced stability in traffic flow. This increased variability implies that the delay in accepting the drone's recommended speeds affects traffic stability.

VI. Conclusion

In this paper, we introduced a novel centralized strategy for optimizing road safety using drones, using PSO as our optimization method. We demonstrated that the drone strategy is more beneficial compared to onboard sensors in autonomous vehicles, as it enhances road safety through more efficient speed optimization. This approach not only improves road safety but also holds potential for reducing vehicle energy consumption, which will be a focus of our future work. To better implement our approach, we explored the impact of an acceptability delay of optimal speed instructions to a single vehicle and found that this delay affects the behavior of follower vehicles, although the approach remains feasible. Future work will extend this approach by examining variable delays based on the nature of the vehicle and its capacity to receive instructions, and their effects on traffic stability and safety.

References

[1] https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries.

[2] A Haghi, D Ketabi, M Ghanbari, and H Rajabi. Assessment of human errors in driving accidents; analysis of the causes based on aberrant behaviors. *Life Science Journal*, 11(9):414–420, 2014.

[3] Faran Awais Butt, Jawwad Nasar Chattha, Jameel Ahmad, Muhammad Umer Zia, Muhammad Rizwan, and Ijaz Haider Naqvi. On the integration of enabling wireless technologies and sensor fusion for next-generation connected and autonomous vehicles. *IEEE Access*, 10:14643–14668, 2022.

[4] Amirhosein Karbasi and Steve O'Hern. Investigating the impact of connected and automated vehicles on signalized and unsignalized intersections safety in mixed traffic. *Future Transportation*, 2(1):24–40, 2022.

[5] Shen Li, Keqi Shu, Chaoyi Chen, and Dongpu Cao. Planning and decision-making for connected autonomous vehicles at road intersections: A review. *Chinese Journal of Mechanical Engineering*, 34:1–18, 2021.

[6] Vinith Kumar Lakshmanan, Antonio Sciarretta, and Ouafae El Ganaoui-Mourlan. Cooperative control in eco-driving of electric connected and autonomous vehicles in an un-signalized urban intersection. *IFAC-PapersOnLine*, 55(24):64–71, 2022.

[7] Regina Nkemchor Adejo. A qualitative study on expectations of potential users of connected and automated vehicles (cavs), 2022.

[8] Haoran Niu, Nuria Gonzalez-Prelcic, and Robert W Heath. A uav-based traffic monitoring system-invited paper. In *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, pages 1–5. IEEE, 2018.

[9] Jayme Garcia Arnal Barbedo. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. *Drones*, 3(2):40, 2019.

[10] Shuai Liu and Yuebin Bai. Multiple uavs collaborative traffic monitoring with intention-based communication. *Computer Communications*, 210:116–129, 2023.

[11] Petr Stodola, Jan Drozd, Karel Šilinger, Jan Hodický, and Dalibor Procházka. Collective perception using uavs: Autonomous aerial reconnaissance in a complex urban environment. *Sensors*, 20(10), 2020.

[12] Hailong Huang, Andrey V Savkin, and Chao Huang. Decentralized autonomous navigation of a uav network for road traffic monitoring. *IEEE Transactions on Aerospace and Electronic Systems*, 57(4):2558–2564, 2021.

[13] Thomas Moranduzzo and Farid Melgani. Detecting cars in uav images with a catalog-based approach. *IEEE Transactions on Geoscience and Remote Sensing*, 52(10):6356–6367, 2014.

[14] Wei Sun, Liang Dai, Xiaorui Zhang, Pengshuai Chang, and Xiaozheng He. Rsod: Real-time small object detection algorithm in uav-based traffic monitoring. *Applied Intelligence*, pages 1–16, 2022.

[15] Sana Bouassida, Najett Neji, Lydie Nouvelière, and Jamel Neji. Evaluating the impact of drone signaling in crosswalk scenario. *Applied Sciences*, 11(1):157, 2020.

[16] Sana Bouassida, Najett Neji, Lydie Nouveliere, Jallouli Mohamed, and Jamel Neji. System of unmanned aerial vehicles for road safety improvement. In *2023 Integrated Communication, Navigation and Surveillance Conference (ICNS)*, pages 1–8. IEEE, 2023.

[17] Dongshu Wang, Dapei Tan, and Lei Liu. Particle swarm optimization algorithm: an overview. *Soft computing*, 22:387–408, 2018.