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Published in:
2023 IEEE International Intelligent Transportation Systems Conference (ITSC)

DOI:
10.1109/ITSC57777.2023.10421986

2024

Document Version:
Peer reviewed version (aka post-print)

Link to publication

Citation for published version (APA):
Chamideh, S., Tärneberg, W., & Kihl, M. (2024). Impact of Positioning Uncertainty on Autonomous Intersection Management System. In *2023 IEEE International Intelligent Transportation Systems Conference (ITSC)* (pp. 1912-1919). IEEE - Institute of Electrical and Electronics Engineers Inc.. https://doi.org/10.1109/ITSC57777.2023.10421986

Total number of authors:
3

Impact of Positioning Uncertainty on Autonomous Intersection Management System

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Abstract— **Connected Autonomous Vehicles (AVs) have the potential to revolutionize Intelligent Transportation Systems (ITS) by addressing urban transport challenges, such as Autonomous Intersection Management (AIM). However, the assumption of highly accurate positioning in most ITS applications does not align with real-life situations. While extensive research has been conducted to improve positioning accuracy, few studies have evaluated the impact of position accuracy on AV systems. This paper investigates the level of positioning errors that our state-of-the-art AIM system, which outperforms conventional intersection management systems, can tolerate. A comprehensive analysis of positioning accuracy requirements for a collision-free AIM system is conducted. The investigation reveals that our AIM system can safely handle vehicles' movements in the presence of positioning errors up to four meters in a high traffic flow rate. Furthermore, the impact of sensor accuracy and wireless communication uncertainties on control strategies is considered. This research provides valuable insights into the challenges of designing robust autonomous systems that can withstand various uncertainties, including positioning techniques, and demonstrates the potential of AVs in enhancing ITS.**

I. Introduction

Future intelligent transportation systems are anticipated to rely significantly on connected Autonomous Vehicles (AVs). Through cooperative vehicle systems and the elimination of human error, these AVs empower themselves with the capability to autonomously perceive the environment, manage mobility, and make independent decisions [1]. Intelligent transportation System (ITS) further enhance this potential by establishing a control framework that improves the overall driving experience through vehicle-to-vehicle and vehicle-to-infrastructure communication [2]. In this context, Cooperative AVs have garnered significant research attention, particularly in the development and evaluation of ITS applications like Autonomous Intersection Management (AIM) and intelligent road merging. These applications heavily rely on positioning technologies, geographic data, and the real-time navigation capabilities of vehicles to ensure reliable travel for all involved vehicles and other road users [3].

In the context of AIM applications, ensuring accurate positioning is crucial for the effective and safe navigation of vehicles. However, various factors can impact the accuracy of positioning systems, including signal interference, multi-path propagation, and atmospheric effects, leading to the accumulation of errors and ultimately reducing positioning accuracy. While Global Navigation Satellite Systems (GNSS), such as the Global Positioning System (GPS), are commonly used for providing positioning inputs, challenges persist, particularly in urban scenarios. Signal blockage, multi-path propagation, and non-line-of-sight propagation can introduce errors ranging from 10 to 20 meters, compromising the accuracy of vehicle positioning [4].

In addition to GNSS, standalone wireless communication-based techniques, such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, can be employed to determine road users' positions. These techniques rely on the relative positions of connected Autonomous Vehicles (AVs) with respect to fixed infrastructure, providing an alternative means of achieving accurate positioning when GNSS signals are obstructed or unavailable [3]. To address the challenges associated with positioning accuracy, several techniques have been developed. These include the utilization of Kalman filtering algorithms and the combination of multiple positioning technologies to improve accuracy [5], [6].

One approach involves combining a reference position obtained through GNSS with information from wireless communication-based positioning. This hybrid technique has demonstrated the capability to estimate the absolute position of road users with an error of less than 1 meter [7], [8]. However, it is important to acknowledge certain drawbacks of this hybrid approach, such as the requirement for additional hardware, which can increase system complexity and cost [9].

Despite numerous research efforts focusing on positioning accuracy, there is a notable lack of investigation into the impacts of position uncertainties onITS applications. Many of these applications are designed with the assumption of flawless position data [10]. While some studies have touched upon related aspects, such as evaluating maximum position errors for AVs in real-world scenarios and comparing the performance of standalone GNSS positioning with hybrid positioning utilizing GNSS and 5G signals [7], there is still a need for comprehensive research in this area. For instance,

*This work was partially supported by the Excellence Center at Linköping-Lund on Information Technology (ELLIIT). Maria Kihl and William Tärneberg are also partially supported by the SEC4FACTORY project, funded by the Swedish Foundation for Strategic Research (SSF), the 5G PERFECTA Celtic Next project funded by Sweden's Innovation Agency (VINNOVA), and the Wallenberg AI, Autonomous Systems and Software Program (WASP) funded by the Knut and Alice Wallenberg Foundation. Also, the authors are part of the Nordic University Hub on Industrial IoT (HI2OT) funded by NordForsk.

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limited research has been conducted on the effect of position uncertainties on intelligent signalized intersections controlled by traffic lights [11] . In a subsequent study, authors have mathematically modeled position uncertainty and proposed a robust algorithm for controlling vehicles' movements in a road merging application [12] . However, the broader impact of position uncertainties on autonomous intersection management remains largely unexplored. Therefore, it is essential to investigate the specific influence of position uncertainties on the performance and efficiency of autonomous intersection management systems. This leads us to the research question: How do position uncertainties affect the effectiveness and reliability of autonomous intersection management?

In order to investigate the impact of positioning uncertainties on the performance of AIM systems as the main objective of this study, we conducted our study using our previously proposed state-of-the-art autonomous intersection management system, known as Hierarchical Model Predictive Control (HMPC) [13]. The selection of HMPC as our study case was based on our previous research where we demonstrated its superiority over other AIM strategies. The results of our simulations clearly demonstrate the effectiveness of HMPC in handling positioning uncertainties. HMPC exhibited safety, scalability, and robustness against packet loss and delays caused by wireless communication systems. Therefore, we believe that an AIM system based on HMPC is an ideal choice for evaluating the impact of positioning uncertainties on AIM system performance. Our simulation experiments were performed in the realistic simulation environment SUMO, specifically focusing on an urban scenario with varying levels of positioning uncertainties.

Throughout our investigation, we aimed to gain a deeper understanding of the influence of positioning uncertainties on the AIM system and provide valuable insights to enhance its overall performance. Our findings indicate that HMPC can safely handle vehicle movements even in the presence of positioning errors of 10 meters. However, as the traffic flow rate exceeds 500 vehicles per hour, the control algorithm requires more accurate positioning information to ensure safe operations.

Furthermore, our simulation results demonstrate that more accurate positioning not only contributes to collision-free operations at lower traffic flow rates but also facilitates smoother movement, reduces fuel consumption, and promotes a sustainable system. Therefore, understanding and mitigating the impact of positioning uncertainties on the AIM system can significantly enhance its efficiency, safety, and environmental performance.

II. TARGETED SYSTEM

The objective of this paper is to analyze the effects of positioning uncertainties on the complex issue of the AIM system. Specifically, our study focuses on a network of three intersections, as illustrated in Figure 1. These intersections are designed without the reliance on traditional traffic lights, posing unique challenges for traffic management. To ensure the safe crossing of vehicles in this scenario, a comprehensive examination of the behavior of autonomous vehicles is necessary. By analyzing the effects of positioning uncertainties in this context, we aim to provide valuable insights and strategies to enhance the performance and safety of the AIM system.

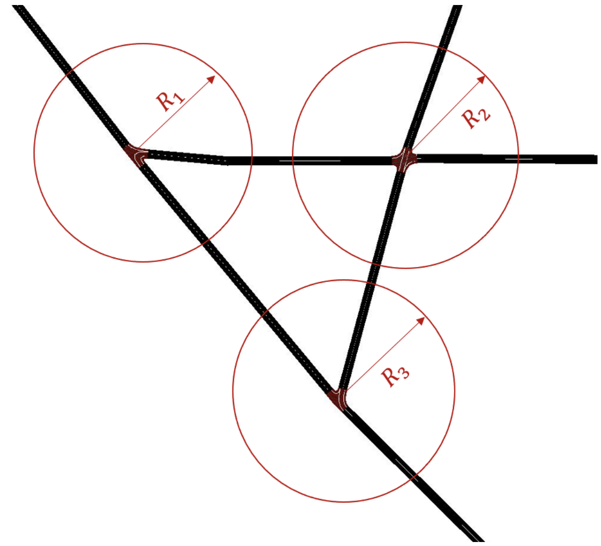

Fig. 1: Targeted System and Intersections layout

Each intersection is equipped with an Intersection Coordination Unit (ICU), which serves as a control unit and has a designated *coverage area*. The ICU is capable of covering and coordinating the traffic within its coverage area. The ICU is called the *corresponding ICU* for the vehicles in its coverage area. Vehicles are equipped with an On-Board Unit (OBU) that integrates various sensors such as LiDAR, RADAR, and cameras. Additionally, each vehicle also has a local computing node connected to the OBU, which can utilize optimization algorithms to prevent dangerous situations. This robust system enables efficient management of traffic flow and enhances safety for autonomous vehicles navigating the intersections.

Each vehicle periodically sends its status message to its corresponding ICU. Wireless network communication is enabled through V2I links, but packet losses and delays are expected. Modern vehicles with advanced collision avoidance functions are capable of perceiving their surroundings. For instance, vehicles use cameras or radar sensors to detect other vehicles in front of them and take necessary actions to avoid collisions. However, several factors can affect perception accuracy, which can, therefore, affect the AIM system performance [14]. In this research, we will consider sensors' accuracy and uncertainties in wireless communication as additional uncertainties that will pose significant challenges when designing control strategies.

By utilizing aggregated data from vehicles, the ICU is able to predict and prevent potentially dangerous situations that may not be anticipated by an individual vehicle's OBU. This is particularly crucial in scenarios where line-of-sight is obstructed between vehicles approaching from different directions. To achieve this, the ICU employs a Model Predictive Control (MPC) algorithm, which is a control strategy that uses a predictive model of a system to optimize future actions based on current and predicted states, that incorporates data from all vehicles within the intersection. The primary objective of the MPC algorithm is to determine optimal speeds for each vehicle, ensuring smooth traffic flow and minimizing the risk of accidents or collisions.

Through the analysis of aggregated data from multiple vehicles, the ICU plays a vital role in identifying and addressing potential hazards. Unlike a single vehicle's sensors, the ICU considers factors beyond the scope of individual vehicles, including the movements of vehicles that may not be directly visible due to obstructed line-of-sight. By orchestrating the movement of AV within its coverage area and assigning reference speeds, the ICU optimizes traffic flow and enhances safety on the road. This comprehensive approach to traffic management, leveraging aggregated data and precise control, reduces the likelihood of accidents and promotes efficient and safe transportation. In our study, the ICU, along with the control algorithm executed within it, is referred to Global Centralized Layer (GCL) [13].

The OBUs receive reference speeds from their corresponding ICU, which are then utilized by a local MPC optimization algorithm. This algorithm empowers the vehicle to precisely govern its movements, maintaining the reference speed and effectively avoiding collisions with leading vehicles. In our study, we refer to this vehicle-centric control algorithm as the Local Decentralized Layer (LDL). As the local MPC algorithm primarily focuses on the vehicle's immediate surroundings and its leader, it operates at a significantly faster pace than the GCL. Importantly, the OBU is designed to perform this optimization autonomously, independent of the ICU. This autonomy mitigates potential collision risks stemming from lost, inaccurate, infeasible solution, or delayed messages from the ICU. By incorporating this additional layer of safety, the system ensures that the vehicle consistently makes the safest and most optimal decisions while navigating the road.

III. System Model

This section presents an overview of the system model utilized in this research, which serves as the foundation for defining metrics and conducting experiments. Additionally, to enable the utilization of our Hierarchical Model Predictive Control (HMPC) algorithm in a network of intersections, while considering positioning errors, we propose modifications not only to the control algorithm but also to the system model.

A. Intersection Model

In the system, there exists a set of $\mathcal{K} = \{1, 2, \ldots, K\}$ ICUs which is located at K intersections. The coverage area of an ICU is determined by the geometry and layout of the intersections. It is designed to encompass the region where vehicle-ICU interactions occur, enabling effective monitoring and coordination of traffic within that area. The size and shape of the coverage area can vary based on factors such as lane count, proximity of neighboring intersections. For the sake of simplicity, we simplify the representation of each ICU's coverage area by using a circular shape with a specific radius, denoted as R_k. When a vehicle enters the coverage area of two ICUs, it will select the ICU associated with the nearest upcoming intersection as the corresponding ICU for communication.

An ICU covers a set of $\mathcal{N}_t^k$ AVs at time t and it is called the corresponding ICU for the vehicle $i \in \mathcal{N}_t^k$. A *vehicle* that enters the intersection will follow a *path*. Since the coverage area is modeled as a circle, all different paths have almost the same length. We describe all possible paths in the critical zone with the set Γ^k. Two different paths may intersect inside the *critical zone* where the vehicles on these paths have a potential risk of side collision in this specific intersect point, called the *conflict point (CP)* of the corresponding paths.

B. Vehicle model

A set of $\mathcal{N}_t = \{1, 2, \ldots, N_t\}$ AVs exist in the system described in Section II at time t where $\mathcal{N}_t^k \subset \mathcal{N}_t$ are in the coverage area of ICU $k \in \mathcal{K}$. If a vehicle $i \in \mathcal{N}_t$ does not exist in the coverage area of any ICU, i.e, $i \notin \forall \mathcal{N}_t^k$, the vehicle can continue with its local controller.

Each vehicle $i \in \mathcal{N}_t^k$ has a predetermined path $\gamma_i^k \in \Gamma^k$ and the path is perfectly followed. A vehicle will not change its path while crossing the intersection. The position of the vehicle at ICU, centralized controller, corresponds to the remaining distance from the center of its corresponding path. However, in the local controller, only the relative distance to the vehicle ahead is taken into account, not the absolute position. In other words, the local controller ensures that the vehicle maintains a safe distance from the vehicle in front of it on the same path, without regard to the vehicle's position with respect to the intersection as a whole.

The system imposes certain limitations on vehicle dynamics, including the maximum deceleration (represented as u_{min}) and maximum acceleration (represented as u_{max}). Furthermore, in accordance with common traffic regulations observed in many jurisdictions, vehicles are not permitted to make U-turns within the intersection area. This restriction aims to promote the smooth flow of traffic and mitigate the potential risks of accidents, particularly in busy intersections. Consequently, the assumption that U-turns are prohibited ensures that the minimum speed along a vehicle's trajectory is always positive. Additionally, a speed limit, denoted as v_{max}, is enforced within the intersection.

C. Space state model

The main objective of the HMPC is to ensure a safe intersection with a smooth and comfortable flow of all vehicles. The optimization process occurs at every sampling intervals, denoted by τ, for a predefined time horizon of T. The specific values of τ and T depend on the layer of the HMPC in optimization problem. For instance, the control system in LDL and GCL updates at discrete sampling intervals of τ_d and τ_c, respectively. In each interval, the state of a given vehicle i in the discrete space model is defined by the equation (1) at time n.

$$x_{i,n+1} = \begin{bmatrix} 1 & -\tau \\ 0 & 1 \end{bmatrix} x_{i,n} + \begin{bmatrix} -\frac{1}{2}\tau^2 \\ \tau_c \end{bmatrix} u_{i,n} \qquad 0 \le n \le T \quad (1)$$

Equation (1) is derived using a displacement formula that represents the distance vector an object travels, i.e. its displacement, based on its initial velocity, acceleration, and travel time. The initial value, $x_{i,0}$, used to initiate the algorithm. In GCL, it is obtained from the latest information status collected from vehicle i, while in LDL, it is derived from the vehicle's current position.

D. Uncertainties model

To develop and test the impact of realistic position uncertainty on our AIM system, HMPC, we need to model positioning errors based on real-world data. In this section, we describe how we mathematically modeled positioning errors at the GCL and LDL layers.

In LDL, we assume that vehicles are aware of leader vehicle and obstacles, with the help of on-board sensors such as IMU and LiDAR. The sensors can measure the relative position of detected objects with a maximum bound for positioning error. The maximum possible positioning error from on-board perception is represented by e_{max}. We model the relative positioning error in LDL level as a normal distribution where $\sigma_l = 0.5e_{max}$. This means that there is a 60% probability that the position error falls within $0.25e_{max}$ and e_{max}.

$$\hat{p}_{i,t} = p_{i,t} + \mathcal{N}(0, 0.5e_{max}) \quad (2)$$

In Equation (2), the variable $p_{i,t}$ denotes the actual position of vehicle i at time t, whereas the estimated position of vehicle i, denoted by $\hat{p}_{i,t}$, corresponds to the position detected by the following car. It is worth noting that $\hat{p}_{i,t}$ is utilized in the LDL of the following vehicle that is behind vehicle i.

In GCL, an positioning uncertainty model was utilized, which was proposed in [12]. Through a real-world experiment, it was observed that the position error could be characterized by a zero-mean normal distribution with variance σ_g. Meanwhile, the rate of change of the position error was found to conform to a logistic distribution $L(0, s)$, where s is a scale parameter determines the rate at which the distribution's density function changes. As a result, the values of the position error at time t can be determined by combining the previous error value at time $t-1$ and an error drift that is modeled using a logistic distribution as described in Equation (3).

$$e_{i,t} = e_{i,t-1} + L(0, s) \quad (3)$$

Therefore, the estimated position of vehicle i at the GCL, denoted by $\tilde{p}_{i,t}$ can be expressed as an equation based on its actual position, which is as Equation (4).

$$\tilde{p}_{i,t} = p_{i,t} + e_{i,t} \quad (4)$$

Upon a vehicle's entry into the simulation network, its initial longitudinal position error e_0 is derived from a normal distribution. The mean and variance of the distribution depends on the vehicle's location and surrounding environment.

IV. Optimization Algorithms Across Different Layers

In this section, we will comprehensively describe our optimization algorithms across various layers.

A. System cost and optimization

In the context of MPC, a system cost function is required to minimize. In our study, we have formulated the system cost as a function of vehicle speed and fuel consumption. However, alternative metrics can also be employed to optimize the control objectives.

The first objective of the control system is to maximize vehicle speed. To this end, a target speed is utilized as the reference value for the optimization algorithm. The target speed must not exceed the maximum speed limit. In GCL, the target speed is dependent on the traffic situation around the ICUs. However, the strategy for determining the target speed is beyond the scope of this paper. In LDL, the target speed for the optimization problem is the vehicle's reference speed which obtained from its corresponding ICU. In instances where a vehicle is not within the coverage area of any ICU, the current velocity of the vehicle is set as the target speed for the optimization problem.

The second objective of the control system is to ensure a smooth flow of vehicles, which entails promoting gradual and seamless changes in speed. This means that vehicles should adjust their speed in a controlled manner, avoiding sudden or abrupt accelerations or decelerations. Additionally, studies conducted by the Environmental Protection Agency (EPA) have demonstrated that minimizing accelerations and acceleration rates can contribute to a reduction in fuel consumption. Therefore, in addition to improving traffic flow, the control system also plays a role in reducing the environmental impact of vehicles on the road.

The system cost, J^k, in GCL, which operates on the ICU $k \in \mathcal{K}$, is defined as in Equation (5). where $v_{i,n}$ (the speed of vehicle i at time interval n) and v_d^t (the target speed at time t) are the MPC control and reference variables, respectively, and $u_{i,n}$ (the acceleration of vehicle i at time interval n) is the manipulated variable.

$$\begin{aligned} J^k = & \sum_{n=0}^{T_c} \sum_{i=1}^{N_t^k} (w_{v_i}(v_{i,n+1} - v_d^t)^2 + w_{u_i}(u_{i,n})^2) \\ & + \sum_{n=0}^{T_c-1} \sum_{i=1}^{N_t^k} w'_{u_i}(u_{i,n+1} - u_{i,n})^2 \qquad i \in \mathcal{N}_t^k,\ k \in \mathcal{K} \end{aligned} \quad (5)$$

In LDL, which operates on the vehicle $i \in \mathcal{N}_t$, the system cost, J_i, is defined in Equation (6). The algorithm's target speed, $\hat{v}_i^t$, at time t is obtained from the most recent optimization results of corresponding ICU.

$$J_i = \sum_{n=0}^{T_d} (w_{v_i} \delta_i (v_{i,n+1} - \hat{v}_i^t)^2 + w_{u_i} (u_{i,n})^2) + \sum_{n=0}^{T_d-1} w'_{u_i} (u_{i,n+1} - u_{i,n})^2 \qquad i \in \mathcal{N}_t \tag{6}$$

In Equations (5) and (6), w_{v_i} ,w_{u_i} and w'_{u_i} are weight coefficients.

B. Constraints

The objective of the constraints is to avoid collisions by keeping a safe distance between vehicles. The constraints are a function of vehicles' states, positions and speeds, and the control input, i.e, vehicles' acceleration.

At ICU k to avoid rear-end collisions between all vehicles in coverage area, a minimum separation distance between two vehicles on the same lane, d_{min}, is considered. The following constraint in Equation (7) is defined to prevent rear-end collisions between vehicle i and its *leading vehicle (LV)* j, where $j \in \mathcal{N}_t^k$, at step n=0.

$$\tilde{p}_{i,n} - \tilde{p}_{j,n} \geq d_{min} \qquad \forall i \in \mathcal{N}_t^k, j = LV(i) \tag{7}$$

To ensure that no side collisions occur between vehicle i and vehicle j within the intersection only one vehicle must enters a conflict point $CP(\gamma_i, \gamma_j)$ at a specific time, a linear inequality constraint is defined as in equation (8) below.

$$|\tilde{p}_{i,n} - \tilde{p}_{j,n}| \geq R_{min} \quad i, j \in \mathcal{N}_t^k, \gamma_i, \gamma_j \in \Gamma^k, \gamma_j \in \Gamma_i^k \tag{8}$$

$\Gamma_i^k \subset \Gamma^k$ is a sub set of all possible paths in the intersection k where vehicle j from path $\gamma_j \in \Gamma_i^k$, have the potential to collide with vehicle i from path γ_i inside the critical zone.

The GCL control algorithm is responsible for computing a reference speed that guarantees each vehicle has exclusive access to every conflict point on its path. However, to ensure resilience and robustness, the LDL will not blindly follow the reference speed provided by the GCL. The primary goal of the constraints incorporated into the LDL is to continuously maintain a safe distance from adjacent vehicles, as detected by on-board sensors, and thereby prevent any unanticipated collisions. To achieve this objective, the constraint specified in Equation (9) is defined as follows:

$$p_{i,n} - \hat{p}_{j,n} \geq d_{min} \qquad i \in \mathcal{N}_t, j = \mathcal{O}(i), 1 \leq n \leq T_d + 1 \tag{9}$$

where d_{min} is the minimum separation distance between two vehicles and $\mathcal{O}(i)$ is the obstacle or vehicle ahead detected by vehicle i.

V. EVALUATION

In this section, we will describe our simulation environment with the primary goal of assessing the effect of uncertain positioning on an intersection managed by HMPC. The main focus is to evaluate the system's safety and environmental efficiency performance. Through our experiments, we will investigate the impact of positioning uncertainty on these metrics.

A. Simulation Environment

We have used our simulation environment that has been developed based on SUMO [15] in our previous works [13]. We made modifications to SUMO to enable our control strategy to manipulate the speed of each vehicle, rather than relying on the default microscopic flow algorithms. The precise positions of the vehicles obtained from the SUMO simulator are manipulated using Equations (2) and (4) in our LDL and GCL control layers, respectively. These equations allow us to evaluate the effect of position uncertainties on HMPC.

B. Experiments

In this paper, we examine a network of three intersections that operate without traffic lights. Each lane in the system is 3.5 meters wide, and the maximum speed limit is 72 km/h (v_{max} = 20 m/s). We assume that vehicles enter the system with an initial speed slightly lower than the maximum speed limit. In our simulations, we assume similar traffic flow rates for all system entries. We used a fixed target speed of 45 km/h for all three intersections. The GCL algorithm is performed every 1 second at each ICU. We modeled each intersection area as a circle with a radius of 90m. Therefore, each vehicle will stay within the coverage area of one intersection for at least four ICU simulation intervals.

We assumed that the ICU has access to vehicles' status messages via V2I communication and the wireless links have a reliability of 98% (i.e. a packet loss probability of 2%).

In our study, we examined three different scenarios:

- AVs that are exposed to line-of-sight GNSS signal, and a standalone GNSS-based positioning is utilized.
- A hybrid 5G-GNSS positioning technique is used and it is assumed that at least one 5G base station (gNBs) and one satellite are accessible.
- Vehicles with hybrid 5G-GNSS positioning have access to at least two 5G base stations (gNBs) and one satellite.

Table I provides a summary of the simulation parameters and specifications utilized in our simulations.

Figure 2 shows the histogram of positioning error for 500 vehicles which cross the system with average speed of 45 km/h in our three different scenarios. As it is clearly shown in Figure 2 Scenario 1 with the probability of 40% the positioning error can be higher than 10 meters. However, In Scenario 2 the maximum position error is 10 meters but still in 40% of situations error is higher than 5 meters. Scenario 3 has the best positioning accuracy with maximum error 2 meters.

Figure 2 depicts a histogram displaying the positioning errors of 500 vehicles traveling through our system at an average speed of 45 km/h in three distinct scenarios. As illustrated in the figure, Scenario 1 exhibits a probability of 40% for positioning errors exceeding 10 meters. Conversely, in Scenario 2, the maximum error is capped at 10 meters, but 40% of the cases still experience errors higher than 5 meters. Finally, in Scenario 3, system has the highest level of positioning accuracy, with a maximum error of only 2 meters.

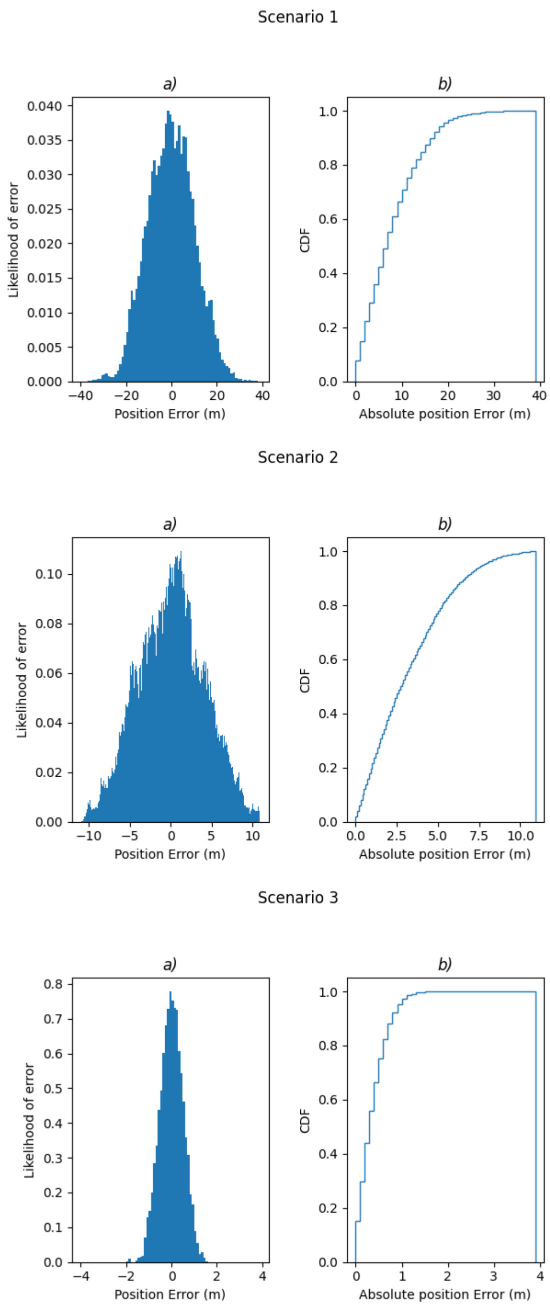

Fig. 2: The distribution of positioning error when 500 random vehicles cross the intersection with average speed of 45 km/h 1) Scenario 1 standalone GNSS positioning 2) Scenario 2 hybrid method based on GNSS and one gNB availability 3) Scenario 3 hybrid method based on GNSS and two gNBs availability.

C. Performance Metrics

In this work, we investigate how inaccurate position data affects the safety and efficiency of AIM system. The system performs well when vehicles can pass the intersection with a high speed which results in reduced waiting times and lower congestion levels. Therefore, we have evaluated the *average speed* of all vehicles in the system for different scenarios described in Section V-A. The simulations were carried out for a traffic flow rate of 600 vehicles per hour per entry over a 50-minute period, starting 30 minutes after the simulation began to ensure a steady-state situation. Each vehicle may choose a random route to one of the exits. All three scenarios were subjected to the same traffic demand profile.

TABLE I: Simulation Parameters

Intersection parameters				
u_{max}	$5\ m/s^2$	Maximum allowed acceleration		
u_{min}	-6 m/s^2	Maximum allowed deceleration		
v_{max}	$20\ m/s$	Maximum allowed speed		
v_{min}	$0\ m/s$	Minimum allowed speed		
Control Parameters				
v_d^t	$45\ km/h$	Target speed at intersection $\forall t$		
R_{min}	$7\ m$	Minimum separation distance between the center of two vehicles from different approaching lanes		
d_{min}	$6\ m$	Minimum separation distance between the center of two vehicles in the same lane		
w_{v_i}	1	Weighting coefficient $\forall i$		
w_{u_i}	0.1	Weighting coefficient $\forall i$		
w'_{u_i}	0.5	Weighting coefficient $\forall i$		
GCL		LDL		
T_c	$10\ s$	T_d	$2\ s$	MPC prediction horizon
τ_c	$1\ s$	τ_d	$0.1\ s$	MPC sampling interval
Uncertainly Parameters				
Reliability	98%	V2I links are reliable in 98% of cases		
Scenario 1				
σ_g	$5\ m/s$	Standard deviation for position error		
s	$0.3\ m/s$	Rate of change of the position error		
Scenario 2				
σ_g	$1\ m/s$	Standard deviation for position error		
s	$0.1\ m/s$	Rate of change of the position error		
Scenario 3				
σ_g	$0.1\ m/s$	Standard deviation for position error		
s	$0.01\ m/s$	Rate of change of the position error		
LDL level position error parameters				
σ_l	$0.3\ m/s$	Standard deviation for position error		

Furthermore, both layers of our AIM method have optimization objectives that aim to facilitate smooth and comfortable vehicle movements [13]. Therefore, vehicles will avoid high acceleration and deceleration, resulting in lower fuel consumption and smoother movement of vehicles in the system [16]. In our previous study [13], we demonstrated the effectiveness of HMPC in minimizing acceleration and acceleration rate, outperforming conventional intersection management methods. However, in this study, we investigate the impact of uncertainties on the performance of the system. To accomplish this, we compared the normalized histograms of acceleration of vehicles that passed through the system during four hours. The vehicles will enter the system at a traffic flow rate of 600 vehicles/hour/entry.

The AIM system is designed to be completely safe, without any collisions. To assess the system's safety, we utilize the average number of collisions per hour as the primary performance metric for traffic safety. To ensure the reliability of our results, we conduct simulations multiple times, employing different random seeds for each traffic flow

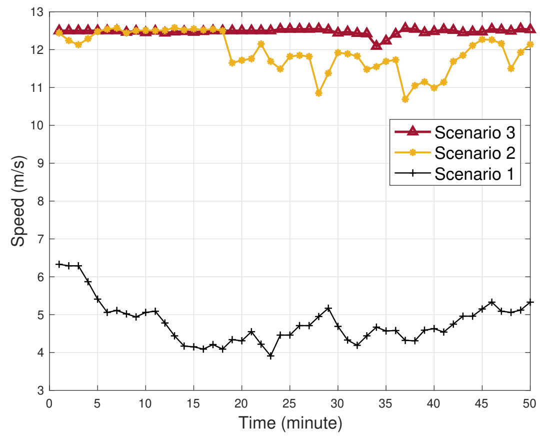

Fig. 3: Comparison of average vehicle speeds over a 50-minute period for three different scenarios with a consistent traffic demand of 600 vehicles per hour. The figure illustrates the influence of varying levels of positioning uncertainties on vehicle speeds within the AIM system. Scenario 1 represents the highest level of uncertainties, with a maximum positioning error exceeding 20 meters. Scenario 2 demonstrates a medium level of positioning accuracy, with a maximum error of 10 meters. Conversely, Scenario 3 exhibits the best positioning accuracy, with a maximum error of 4 meters.

rate, which represents various traffic demand profiles. During each simulation run, we record the number of collisions detected by the SUMO simulator and then calculate the average number of detected collisions per hour. Additionally, to gain insight into the average number of hazardous situations, we also perform simulations without control strategies and calculate the average number of collisions to quantify the efficacy of our control strategies in preventing collisions. This scenario is labelled as *Without Control* in our results figure, and it enables us to assess the effectiveness of our control strategies in ensuring the safety of the AIM system.

VI. RESULTS AND DISCUSSION

In Figure 3, we present the average vehicle speeds over a 50-minute period starting 30 minutes into the simulation run for a traffic flow rate of 600 vehicles per hour. This flow rate was chosen to generate sufficient dangerous situations for evaluating the impact of uncertainties. Notably, scenario 3 with accurate positioning information available to the ICUs demonstrated the best performance, with resulting average speeds similar to or slightly below the target speed. However, in scenarios 1 and 2, the GCL results may not be safe enough in certain situations due to the lack of accurate positioning, resulting in the need for LDL to react faster to avoid unpredictable dangerous situations. This could result in sudden braking or local speed reductions. As shown in Figure 3, scenario 1 demonstrated the worst system performance. This suggests that positioning uncertainties have a significant influence on the behavior and performance of vehicles within the AIM system. The observed trend indicates that increased inaccuracies require vehicles to constantly adapt their speeds to compensate for the lack of precise positioning information.

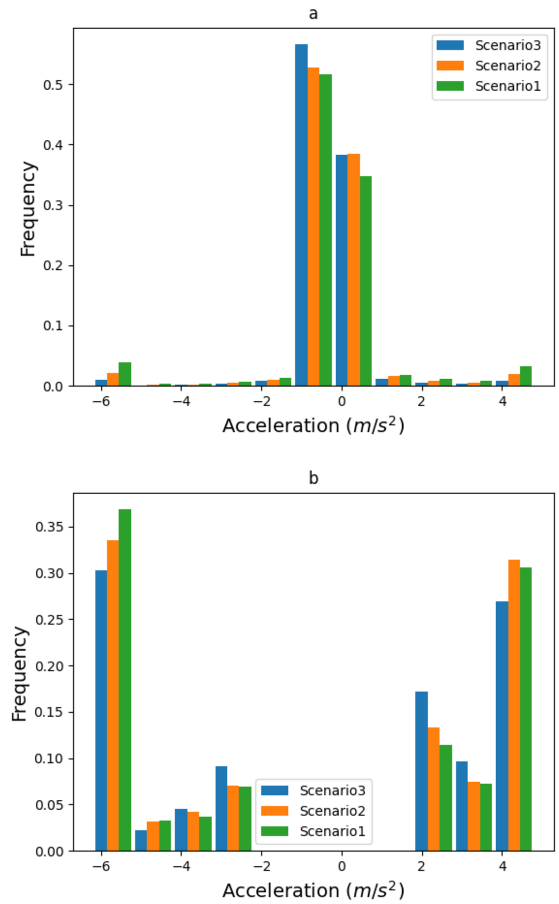

Fig. 4: Comparison of average vehicle accelerations for three different scenarios over a four-hour period within the system. The subfigure (a) shows the average acceleration including both high and low acceleration data, while the subfigure (b) focuses solely on high acceleration data by removing low acceleration data. The results highlight the impact of different scenarios on vehicle acceleration and demonstrate the effectiveness of the AIM system in minimizing high acceleration events.

Figure 4 depicts the histogram of vehicles accelerations within the system, where vehicles enter at a traffic flow rate of 600 vehicles per hour. The findings from this analysis reveal that the control algorithms effectively prevent excessive acceleration or deceleration. This outcome aligns with our system's objectives, as minimizing absolute acceleration is a key priority. However, it is worth noting that at the LDL level, an increased number of non-autonomous and non-cooperative vehicles may lead to the detection of more unpredicated dangerous situations at GCL level. Nonetheless, as demonstrated in Figure 4 , the difference between different scenarios are relatively minor. This indicates that the vehicles' acceleration and deceleration requirements remain moderate. These results further validate the success of our AIM system in effectively managing the movement of vehicles.

In order to implement an AIM in an operational system, it is crucial to evaluate the traffic safety. To this end, we have

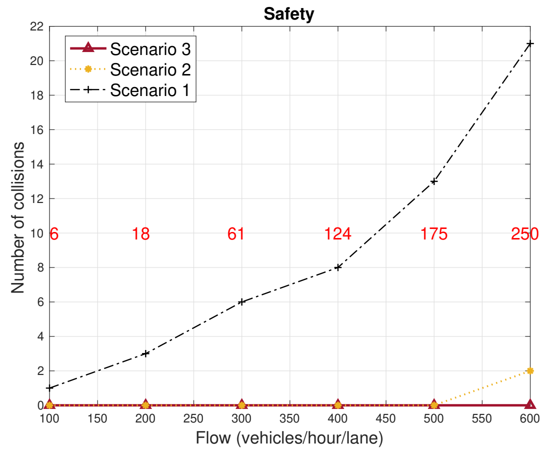

Fig. 5: The average number of collisions per hour at various traffic flow rates. The red text represents the average number of collisions that would be expected in the absence of any control strategies , i.e, *Without Control* scenario. The results highlight the effectiveness of the HMPC system in reducing the number of collisions across varying traffic flow rates.

approximated the average number of collisions per hour, as explained in Section V-C, and assessed this metric for various traffic flow rates. In the simulations presented in this study, we assumed that the wireless communication links would be reliable in 98% of cases. The results of our simulations are displayed in Figure 5. It is important to note that evaluating traffic safety in different level of uncertainties is a critical aspect of deploying AIM methods in real-world applications.

Figure 5 clearly demonstrates that the HMPC system faces significant safety issues in Scenario 1 when the positioning error exceeds 12 meters as shown in Figure 2, which is nearly three times longer than a typical car length. The ICU, GCL, experiences complete randomness in positioning, which limits the vehicle's ability to respond effectively to hazardous situations at the LDL level. However, in comparison with the absence of control strategies, the LDL layer is still able to avoid many collisions. For instance, at flow rates of 500 vehicles per hour, the system can prevent almost 160 collisions, although 16 collisions are still considered high-risk safety concerns.

In contrast, our simulation results show that the HMPC system can safely manage AVs' behavior in Scenario 2 at flow rates below 500 vehicles/hour, even with a maximum position error of 10 meters. In Scenario 3, where the maximum position errors at both the GCL and LDL levels are less than 1 meter, as evident in Figure 5, the system is completely safe, even during high traffic flow rates.

VII. Conclusions

In conclusion, this study presents a comprehensive investigation of the impact of positioning uncertainties on real-time intersection management systems. By applying modification to our previously proposed AIM method and conducting simulations in the SUMO environment, we demonstrated that our system is safe for positioning errors less than 10 meters and traffic flow rates of up to 500 vehicles/hour/lane. However, when traffic flow rates increase, more accurate positioning is necessary to maintain safe and comfortable vehicle movements with lower acceleration. These findings highlight the importance of accurate positioning in the design of real-time intersection management systems, which could ultimately lead to safer and more efficient traffic flow.

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