Communication-free Distributed Model Predictive Control for Autonomous Vehicles at Lane-free and Signal-free Intersections

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1 INTRODUCTION

The rapid advance of autonomous vehicle (AV) technology has set the stage for innovative traffic management approaches that can significantly reduce congestion and enhance road safety. One promising approach is the operation of AVs in lane-free environments (Sekeran *et al.*, 2022), particularly at intersections, which are major bottlenecks in urban traffic systems. These configurations aim to increase throughput, reduce delays, and improve overall traffic efficiency by eliminating dependencies on traffic signals and lane-based navigation.

Signal-free intersections, where connected and automated vehicles (CAVs) operate without traffic signals, can improve traffic flow and reduce fuel consumption by enabling vehicles to move freely over a two-dimensional surface. This approach aligns with the "TrafficFluid" paradigm (Papageorgiou *et al.*, 2021), which combines lane-free driving with "vehicle nudging" (Yanumula *et al.*, 2023) to enhance traffic stability and capacity.

While centralized control methods have been studied for such systems (Naderi *et al.*, 2024), they often face scalability and computational feasibility challenges, particularly when managing a large number of vehicles. To address these issues, decentralized or distributed control methods are being increasingly explored (Naderi *et al.*, 2023). Each vehicle makes independent decisions in these approaches, balancing collision avoidance and optimal navigation without centralized coordination.

Distributed model predictive control (MPC) has been shown to be an effective tool for managing AV dynamics in a distributed manner in simulation (Bemporad *et al.*, 2010). MPC optimizes vehicle trajectories over a predictive horizon, ensuring smooth, efficient, and collision-free navigation. Prior studies have tested its effectiveness in controlling vehicle dynamics for lane-free roads, urban roundabouts, and intersections (Yanumula *et al.*, 2021). However, most implementations depend on inter-vehicle communication to exchange real-time information, which can be impractical due to communication lags, unreliability, or infrastructure constraints.

We propose a novel distributed MPC framework for AVs at lane-free, signal-free intersections that operate without communication, relying only on onboard sensors. This approach allows each AV to detect positions and speeds of nearby AVs, making autonomous decisions that enhance robustness and reduce infrastructure dependence. By adopting a lane-free paradigm, AVs dynamically adjust their trajectories for optimal space use, achieving real-time collision avoidance.

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Each AV manages its own MPC independently, enabling faster, scalable performance without the computational burden of centralized control.

2 METHODOLOGY

This section outlines the vehicle modeling, dynamic constraints, and the distributed MPC formulation for AVs navigating lane-free, signal-free intersections.

2.1 Vehicle modeling and dynamic constraints

The vehicle dynamics are represented by a simplified kinematic bicycle model, where each vehicle's state is defined by its position (x, y), heading angle (θ), and speed (v). The control inputs include acceleration (a) and steering angle (δ), directly influencing the vehicle's motion and heading.

Physical limits, including maximum acceleration, steering angle, speed, and road boundaries, constrain the optimization problem for each AV. The AV state is updated iteratively over discrete time steps:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta t \cdot f(\mathbf{x}_k, \mathbf{u}_k), \quad k = 0, \ldots, N-1, \tag{1}$$

where $\mathbf{x}_k = [x_k, y_k, \theta_k, v_k]$ is the state vector, $\mathbf{u}_k = [a_k, \delta_k]$ is the control vector at time step k, and $f(\mathbf{x}_k, \mathbf{u}_k)$ represents the state transition function based on the kinematic bicycle model. N, represents the duration of the decision-making process.

2.2 Distributed MPC formulation

The distributed MPC framework enables each AV to optimize its trajectory within a prediction horizon independently, facilitating rapid decision-making and effective responses to dynamic intersection conditions. In the distributed MPC framework, onboard sensors provide real-time data on nearby AVs positions and speeds, enabling AVs to autonomously adjust their trajectories without relying on external communication. The cost function (J) for MPC optimization is designed to achieve multiple objectives simultaneously. It is defined as:

$$J = \sum_{k=0}^{N_\mathbf{p}-1} \left(\frac{\omega_1 a_k^2}{a_{\max}^2} + \frac{\omega_2 (\delta_k - \delta_{\text{des}})^2}{\delta_{\max}^2} + \frac{\omega_3 (v_k - v_{\max})^2}{v_{\max}^2} + \sum_{i=1}^{M} \frac{\omega_4}{d_{k,i}} + \omega_5 n_{\text{conflicts}} + \frac{\omega_6 t_{\text{remaining}}}{t_{\min}} \right), \tag{2}$$

where $N_\mathbf{p}$ is prediction horizon, M is the number of surrounding vehicles, a_k is the acceleration, δ_k is the steering angle, δ_{des} is the desired steering angle, v_k is the speed, $d_{k,i}$ is the distance to nearby vehicle i, $n_{\text{conflicts}}$ is the number of potential conflicts, and $t_{\text{remaining}}$ is the remaining travel time to exit the intersection. The term $t_{\min}$ represents the minimum possible travel time for a vehicle to clear the intersection.

The cost function components address different aspects of the AV's behaviour. The first term minimizes acceleration to improve energy efficiency and comfort, while the second term reduces deviations from the desired steering angle, contributing to smoother turnings. The third term aims to maintain a target speed, enhancing traffic flow efficiency. The fourth term enforces safe distances from adjacent vehicles, while the fifth term estimates potential conflicts by predicting where and when nearby vehicles may intersect the AV's path, assuming other vehicles maintain their current speeds and nominal paths. This term helps the MPC anticipate and mitigate collision risks despite a short prediction horizon. The final term minimizes travel time to the intersection exit, guiding AVs toward more time-efficient paths.

The first three terms are normalized by dividing by the square of their respective maximum values ($a_{\max}$, $\delta_{\max}$, $v_{\max}$), ensuring that each term contributes proportionally to the overall optimization. The weights ω_i control the relative influence of each objective and are crucial for tuning the MPC's performance, allowing adaptation to different traffic scenarios and operational goals. Constraints are applied to maintain realistic behavior:

$$a_{\min} \leq a_k \leq a_{\max}, \tag{3}$$

$$\delta_{\min} \leq \delta_k \leq \delta_{\max}, \tag{4}$$

$$0 \leq v_k \leq v_{\max}, \tag{5}$$

$$x_{\min} \leq x_k \leq x_{\max}, \quad y_{\min} \leq y_k \leq y_{\max}. \tag{6}$$

The distributed nature of this MPC approach allows each AV to function independently, enhancing scalability and reducing computational burden. The system remains robust without communication requirements, delivering consistent performance even in environments with unreliable connectivity. In our predictions, we assume that all other detected vehicles maintain their current speed, and their paths toward the intersection exit follow nominal trajectories assigned based on their current positions. This nominal path represents the most likely route each vehicle would take, disregarding any adjustments made for conflict resolution.

3 RESULTS

The proposed distributed MPC framework was tested in a simulated environment with two orthogonal traffic flows and potential conflict zones at the intersection. The simulation included 108 AVs over 160 seconds, with 12 AVs using distributed MPC in a lane-free manner and 96 AVs following a lane-based, first-come, first-served rule. The MPC-controlled AVs autonomously optimized their trajectories, navigating independently of other vehicles' behaviours. The intersection was modelled as a 400 m^2 square, with AVs measuring 4 m in length and 1.5 m in width. All AVs started at 15 m/s, with maximum speeds between 13 and 17 m/s, a maximum steering angle of $\pi/12$, and a maximum acceleration/deceleration value of 4 m/s^2.

The cost function weights for the distributed MPC were set as $\omega_i = [0.02, 0.01, 10, 2, 100, 100]$, corresponding to acceleration, steering, speed deviation, proximity to other vehicles, potential conflicts, and remaining travel time. The prediction horizon was 3 seconds, with a control horizon of 1 second. Lane-based AVs followed a coordinated car-following pattern, while MPC-controlled AVs dynamically adjusted their trajectories. The high vehicle density led to frequent conflicts, especially for the 12 MPC-controlled AVs, which resolved these interactions autonomously, demonstrating the framework's robustness and adaptability.

The speed profiles of MPC-controlled AVs (Fig. 1a) show that most AVs maintained steady speeds after an initial acceleration or deceleration phase needed to match their maximum speeds (13–17 m/s). After this adjustment, the distributed MPC ensured smooth trajectories with minimal fluctuations, even amid potential conflicts. Acceleration profiles (Fig. 1b) demonstrate the distributed MPC's ability to resolve conflicts with minor adjustments. Brief acceleration or deceleration bursts occurred during collision management but quickly stabilized, reflecting the MPC's simultaneous optimization of speed and steering. The steering profiles (Fig. 1c) indicate that AVs primarily used gradual steering adjustments to avoid collisions and utilize intersection space efficiently. This approach ensured safer, smoother manoeuvres. The time-to-collision (TTC) analysis in Fig. 1(d) shows that the distributed MPC framework manages potential collisions effectively, with AVs adjusting trajectories to maintain safe TTC values in advance. AVs used controlled acceleration as TTC approached lower values. Importantly, the minimum TTC stayed above 0.5 seconds, confirming no collisions occurred in the system.

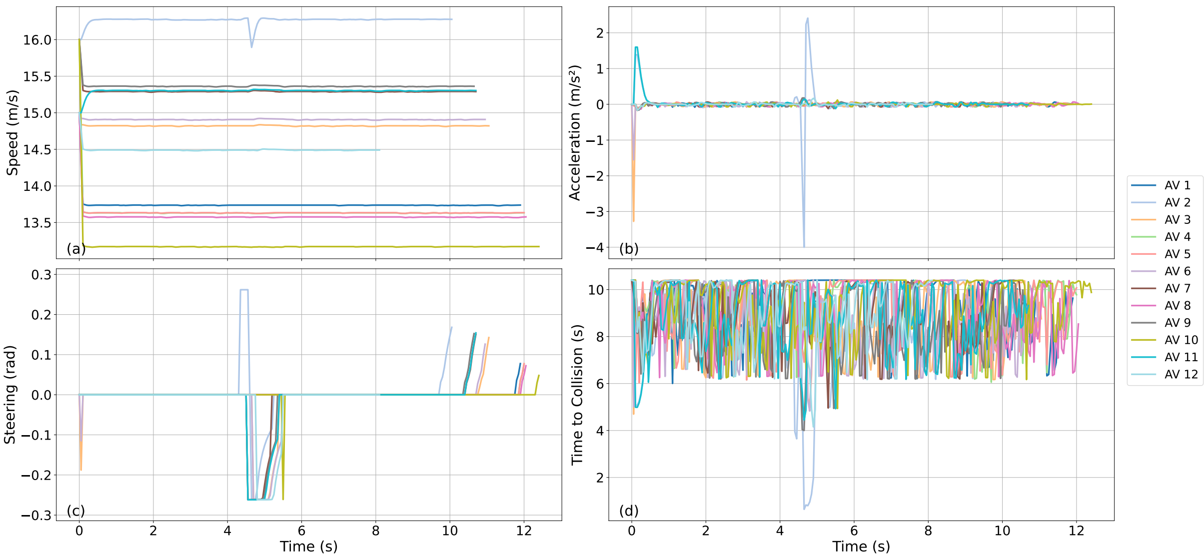

Figure 1 – *Speed (a), acceleration (b), and steering (c) profiles show smooth transitions with minimal fluctuations, indicating efficient handling of manoeuvres. The time-to-collision (d) shows that collisions are prevented by manoeuvres in advance, with a minimum TTC of 0.5 seconds, confirming collision-free operation in the system.*

4 DISCUSSION

The distributed MPC framework effectively managed AV interactions in a complex, lane-free, signal-free environment. Simulations showed that MPC-controlled AVs achieved collision-free navigation with efficient travel times and smooth trajectories. Despite high vehicle density and frequent conflicts, the system remained robust, adapting to other vehicles and maximizing intersection use. The results highlight the scalability and applicability of the MPC framework.Future research could enhance decision-making at higher densities and explore integration with other control strategies to optimize performance.

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