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Multi-Priority-Based Strategy for Risk Assessment and Management in the Presence of Multiple Personal Light Electric Vehicles

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Abstract

Navigating safely in environments populated by dynamic and multi-modal agents poses significant challenges to risk assessment and management for Autonomous Vehicles (AV). In particular, we consider urban scenarios involving Personal Light Electric Vehicles (PLEVs) that are known to exhibit varying maneuvers and velocity profiles. We propose a Fusion of Predictive Inter-Distance Profile (F-PIDP) to predict the inter-distances and capture the uncertainties in the motion of the AV and the PLEV's multiple trajectories. Building upon this, a multi-priority-based trajectory sampling algorithm is developed for collision avoidance. This strategy is generalized to assess and prioritize multiple agents with varying motion across several driving lanes, enabling the system to identify and respond to the most dangerous agents. The proposed method is then integrated into a Model Predictive Control (MPC) trajectory tracking framework to perform risk management for safe and adaptive control of the AV's motion. The proposed method is validated through a series of simulations with critical driving scenarios.

Keywords: Autonomous Vehicles, Autonomous driving, Predictive Navigation, Risk Assessment and Risk Management, PLEVs, Multi-modal prediction, Multi-Risk

1 Introduction

Autonomous navigation around diverse road users is a critical challenge for Autonomous Vehicles (AV) operating in real-world environments. While prior studies have predominantly addressed interactions with pedestrians, we consider Personal Light Electric Vehicles (PLEVs), such as electric scooters and bikes, that have received considerably less attention despite their growing presence. To plan safe paths, AVs rely on motion prediction of nearby agents. Traditional trajectory prediction models typically estimate a single most likely future trajectory [1], [2]. However, this approach may not adequately reflect the behavior of PLEVs, which can vary significantly in speed, sometimes reaching velocities up to five times those of pedestrians, leading to multiple possible motion patterns.

To account for this variability, researchers have introduced multi-modal prediction methods that generate several possible future trajectories. For example, [3] and [4] propose multi-model tracking algorithms designed to capture the range of possible behaviors exhibited by dynamic agents like PLEVs.

After predicting the future trajectories of traffic participants including PLEVs, the AV must generate a safe and feasible trajectory toward its intended destination. Model Predictive Control (MPC) has proven to be a robust and effective approach for motion planning and control optimization in autonomous driving systems [5], [6]. Unlike conventional control methods, MPC leverages a system’s dynamic model to forecast future states and optimize control inputs over a finite time horizon. This predictive capability allows it to enforce constraints, such as speed limits, control bounds, and safety margins, while maintaining system performance and safety. However, when multiple potential trajectories exist for a single agent, the complexity of planning a risk-free path increases significantly. Handling such uncertainty poses a major challenge for AVs, particularly in dynamic environments with diverse agent behaviors.

In this paper, we propose a risk assessment approach based on the Fusion of Predictive Inter-Distance Profiles (F-PIDP) [7, 8], which consolidates multiple PIDP [9, 10] values into a single representative prediction. This fusion simplifies the risk representation while preserving critical safety information. Multi-risk management is then performed using a hybrid trajectory planning framework that employs a multi-priority-based trajectory sampling method for collision avoidance and an MPC optimization method for trajectory tracking. Unlike the conservative MPC method that considers all the trajectories for collision avoidance, the proposed method uses the F-PIDP as a less conservative safety reference.

Our contributions are as follows:

- We extend the method introduced in [8], which addresses uncertainty in the trajectory prediction of a single priority agent, to more complex scenarios involving multiple priority agents.
- A multi-priority-based collision avoidance strategy is proposed to effectively incorporate the interaction between the AV and several dynamic agents, each with potentially diverse motion profiles.
- The proposed method integrates the Fusion of PIDPs (F-PIDP) for risk assessment with multi-priority-based trajectory sampling and MPC-based trajectory tracking

for risk management, offering a less conservative alternative to traditional MPC approaches.

2 Related Works

Assessing risk in traffic environments often relies on metrics that identify moments or regions where safety is compromised. Metrics like Time to Collision (TTC) [11] and Time to React (TTR) [12] quantify either the expected time to a collision or the time window remaining for evasive maneuvers to prevent a collision for a linear motion. In contrast, the Predictive Inter-Distance Profile (PIDP) [10, 13] and its extension, the Fusion of PIDPs [7, 8], take a spatio-temporal approach by calculating future inter-agent distances over time. These methods provide a better representation of interaction dynamics between multiple agents and have been found to possess many features that can be harnessed to assess the risk of multiple agents (cf. Section 3.3). One of the notable strengths of these distance-based approaches is their computational efficiency, making them well-suited for real-time applications. However, their performance can degrade in situations involving significant behavioral uncertainty, such as unpredictable maneuvers by surrounding agents, highlighting the need for more robust multi-modal reasoning in risk assessment.

To tackle the challenges posed by uncertain agent behavior, probability-based risk assessment and management approaches have been introduced. These methods model the uncertainty in agents' future motions using probabilistic distributions, enabling more robust decision-making under uncertainty. Frameworks such as Hidden Markov Models (HMMs) [14] and Dynamic Bayesian Networks (DBNs) [15, 16] have been employed to facilitate risk-aware navigation, allowing autonomous vehicles to anticipate and respond to a range of potential behaviors in uncertain environments.

In the domain of autonomous vehicle control, optimization-based methods have been widely adopted to ensure safe and efficient control actions while adhering to both vehicle-specific and environmental constraints. Among these, Model Predictive Control (MPC) [17] stands out as a leading technique, particularly valued for its predictive capabilities and ability to adapt control actions in real time. As demonstrated across various engineering applications [18], MPC excels in scenarios where compliance with physical limitations such as actuator saturation, steering bounds, and acceleration limits are critical. This makes it especially well-suited for autonomous driving, outperforming more traditional methods like PID and sliding mode controllers [19], which often lack explicit constraint-handling mechanisms. MPC can be employed for both risk assessment and management. In this formulation, risk assessment is integrated as collision-avoidance constraints, while risk management is addressed through the optimization of control inputs within the MPC framework, as demonstrated in [20–23]. However, simply accounting for collision risk is often insufficient for ensuring safe navigation in complex, real-world traffic environments. Urban settings, in particular, present significant challenges due to high uncertainty in agent behavior, especially with PLEVs capable of executing a variety of multi-modal motion [24]. Therefore, effective navigation requires more than collision checks, it demands a framework that can reason under uncertainty and adapt to multi-modal agent behaviors.

Due to the nonlinear nature of most dynamical systems, direct optimization methods often yield only locally optimal solutions [25]. This limitation can hinder their effectiveness in complex, high-dimensional environments. In contrast, sampling-based methods offer a more flexible alternative, as they are better suited to explore non-convex spaces and avoid local minima. For instance, the Risk-based Rapidly-exploring Random Tree (Risk-RRT) introduced in [26] is designed to identify safe trajectories within constrained environments. Similarly, [27] proposed a sampling-based optimization approach that generates a diverse set of collision-free trajectories for autonomous vehicles. To enhance computational efficiency and reduce planning time, these methods typically relax strict adherence to agent dynamics, relying instead on approximations that maintain feasibility without fully modeling the system’s physical constraints.

Learning-based approaches have also emerged as powerful tools for computing safe trajectories in autonomous systems. Techniques such as neural networks have been employed to learn driving behaviors directly from real-world data, as demonstrated in [28, 29]. Additionally, [30] introduced a Deep Reinforcement Learning (DRL)-based decision-making framework that enables automated exploration and adaptation in complex environments. While these methods excel at implicitly handling uncertainties and capturing complex patterns in agent behavior, they typically require large-scale datasets and extensive training to achieve reliable generalization across diverse driving scenarios.

Our approach leverages the strengths of PIDP risk assessment to effectively prioritize multiple risk agents based on their probability and impact. By integrating a sampling-based safe trajectory search with MPC-based trajectory tracking, we achieve a balanced strategy that explores diverse, safe trajectories while ensuring precise, real-time trajectory optimization to navigate around multi-modal agents like PLEVs.

3 Problem Formulation

This section gives an overview of the motion prediction methods for the future state of the AV and the other traffic agents. It also highlights the challenges introduced by multi-modal trajectory predictions, where agents may follow multiple motion patterns.

3.1 AV Motion Model

We predict the 2D position of the AV using the bicycle kinematic model, such that the future position and orientation of the AV at each time step t is defined as:

$$\dot{\mathbf{x}}^{AV}(t) = f(\mathbf{x}^{AV}(t), \mathbf{u}^{AV}(t)) \tag{1}$$

where $\mathbf{x}^{AV}(t) = [x^{AV}(t), y^{AV}(t), \theta^{AV}(t)]^T \in \mathbb{R}^{n_x}$ represents the current state of the AV, $\mathbf{u}^{AV}(t) \in \mathbb{R}^{n_u}$ represents its control inputs, and the vehicle’s dynamic model is $f : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \rightarrow \mathbb{R}^{n_x}$. Given that the AV’s control inputs $\mathbf{u}^{AV}(t) = [v, \delta]$ are the velocity v and steering angle δ .

3.2 PLEVs Multi-modal Motion Model

Unlike the ego-vehicle, dynamic agents, such as PLEVs, can have their future trajectories predicted using one or more multi-modal motion prediction algorithms. Therefore, each PLEV can have multiple possible trajectories $j \in \{1, 2, \dots, N_{traj}\}$ with a corresponding probability $Pr(j)$ (cf. Figure 1). The future state of the PLEV along each trajectory follows a linearized unicycle-based dynamic model:

$$\dot{\mathbf{x}}_j^{PV}(t) = A\mathbf{x}_j^{PV}(t) + B\mathbf{u}_j^{PV}(t) \quad (2)$$

where $\mathbf{x}^{PV}(t) = [x^{PV}(t), y^{PV}(t), \theta^{PV}(t)]^T$ represents the longitudinal position, lateral position and orientation of the PLEV's j -th trajectory, while the control input $\mathbf{u}^{PV}(t) = [v, w]$ includes its linear and angular velocities. Matrices A and B are the linearized dynamics and control matrices.

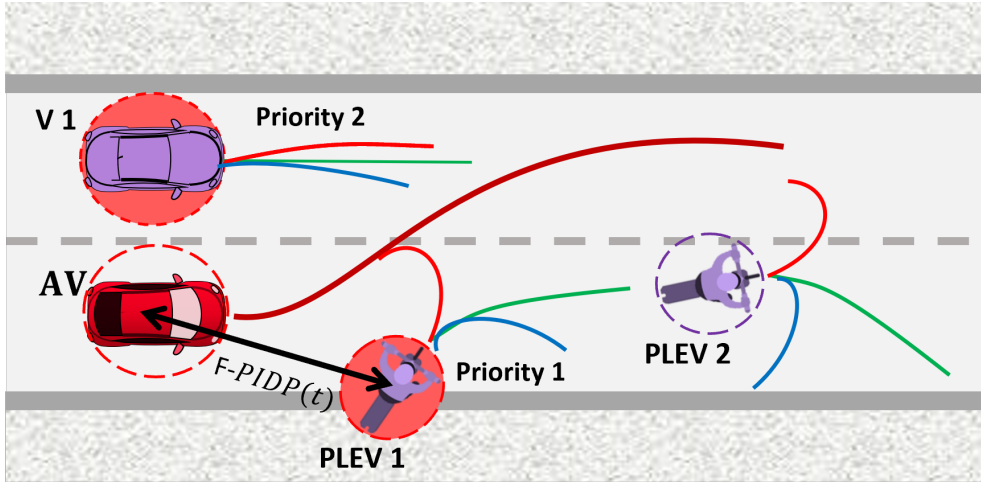


Fig. 1 Urban traffic scenario with AV (in red) and multiple agents including PLEVs (in purple): with multiple possible trajectories and the multiple priority agents to be avoided.

3.3 Risk Assessment using Predictive Inter-Distance Profile (PIDP)

The Predictive Inter-Distance Profile (PIDP) is a collision risk metric designed for traffic environments. It quantifies the likelihood of collision by analyzing the predicted separation between traffic participants, such as an autonomous vehicle and surrounding agents, across a defined time horizon. PIDP does not depend on the geometric form of future trajectories of the interacting agents, which makes it adaptable to diverse traffic scenarios as compared to the conventional risk assessment method. PIDP serves as a dual metric that captures both spatial and temporal dimensions of risk. From a spatial perspective, it evaluates the inter-agent distance, which is critical for assessing proximity among vehicles, pedestrians, and other road users. For instance, given

the radii of two interacting agents, denoted by R and r , and a desired safety margin d_{margin} , the safety distance is expressed as:

$$d_{safe} = R + r + d_{margin} \quad (3)$$

The minimum value of the PIDP is expected to be greater than d_{safe} , which implies that a collision may occur when the minimum Euclidean distance between the agents falls below the safety distance ($minPIDP < d_{safe}$).

From a temporal perspective, PIDP considers how long it will take for the agents to reach a critical distance where a collision might occur. That is, PIDP provides insights into the urgency of potential collision scenarios. For instance, the time when safety is not respected (t_{SNR}) is the point when the safety distance is first violated, which can give an idea of the criticality of the situation as presented in [8] (cf. Figure 2).

However, PIDP assumes a single trajectory is predicted for each agent, which limits its application to traffic scenarios with multi-modal agents like PLEVs. To overcome this limitation, this paper introduces the Fusion of PIDPs (F-PIDP), a novel extension that incorporates multiple possible motion modes to better reflect the behavior of such agents.

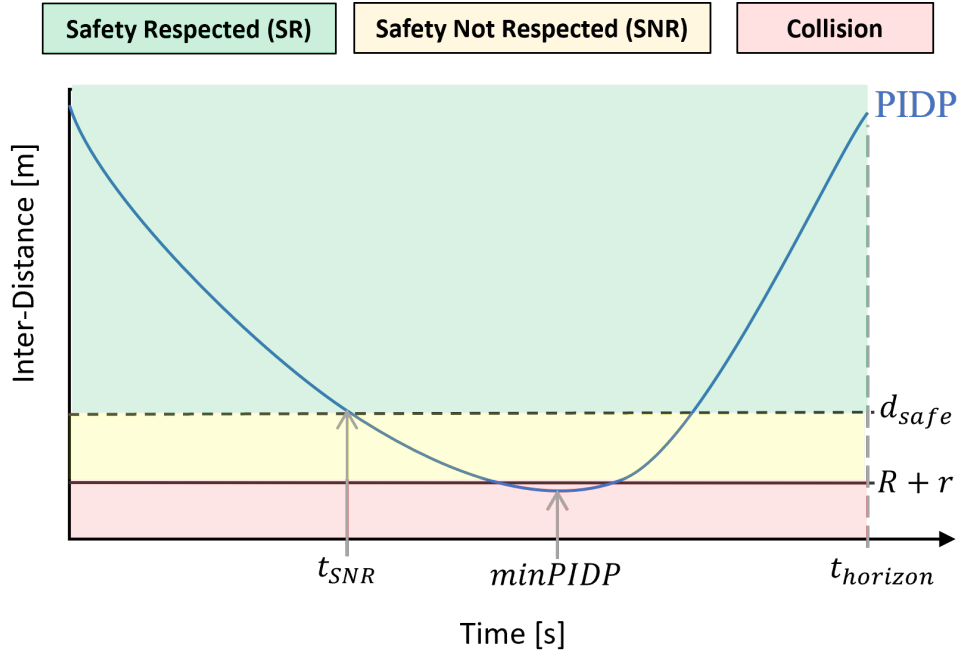


Fig. 2 Predictive Inter-distance Profile (PIDP): showing the time when safety is not respected t_{SNR} , the minimum PIDP ($minPIDP$) and safety distance d_{safe} , presented in [8].

3.4 Dimensionality Problem in Model Predictive Control

A control algorithm is generally required to ensure a safe motion between the AV and the surrounding vehicle. Advanced control strategies such as MPC use a predictive model of the system to determine optimal control actions. MPC predicts the system's future states over a finite prediction horizon by solving an optimization problem. The objective is to minimize a predefined cost function, typically a combination of tracking error and control effort, while ensuring the system respects physical and operational constraints (e.g., limits on velocity, acceleration, or steering angles). The optimization problem solved by MPC can be formulated as:

$$\min_U \sum_{t=0}^{N-1} \left(\|\Delta \mathbf{x}^{AV}(t)\|_Q^2 + \|\mathbf{u}^{AV}(t)\|_R^2 \right) + \|\Delta \mathbf{x}^{AV}(N)\|_S^2 \quad (4)$$

such that:

$$\mathbf{x}^{AV}(t+1) = f(\mathbf{x}^{AV}(t), \mathbf{u}^{AV}(t)), \quad t \in [0, N] \quad (5)$$

$$\mathbf{x}^{PV}(t+1) = f(\mathbf{x}^{PV}(t), \mathbf{u}^{PV}(t)), \quad t \in [0, N] \quad (6)$$

$$\mathbf{u}^{AV}(t) \in \mathcal{U}, \quad t \in [0, N] \quad (7)$$

$$\mathbf{x}_{p,j}^{PV}(t) \in \Xi_{safe}, \quad p \in \mathbb{N}^{N_p} \times j \in \mathbb{N}^{N_{traj}} \times t \in [0, N] \quad (8)$$

the AV's control input sequence is represented by $U = (\mathbf{u}(0), \dots, \mathbf{u}(N-1))^T$. The objective is to minimize the deviation from the reference state, defined as $\Delta \mathbf{x}^{AV}(t) = \mathbf{x}^{AV}(t) - \mathbf{x}_{ref}^{AV}(t)$, using weighting matrices $Q, S \in \mathbb{R}^{3 \times 3}$ for the state and $R \in \mathbb{R}^{2 \times 2}$ for the control input. The norm $\|\mathbf{x}\|_M^2 = \mathbf{x}^T M \mathbf{x}$ represents a quadratic cost with respect to matrix M . The constraints on the prediction model of the AV and the PLEVs are represented by $f(\mathbf{x}^{AV}(t), \mathbf{u}^{AV}(t))$ and $f(\mathbf{x}^{PV}(t), \mathbf{u}^{PV}(t))$, respectively. \mathcal{U} represents the limits on the AV's control, while Ξ_{safe} is the collision avoidance constraint. It is important to note that the dimensionality of the collision avoidance constraint (8) grows exponentially with the number of surrounding agents N_p , the number of agents' predicted trajectories N_{traj} , and the prediction horizon N . This rapid growth in constraint size leads to overly conservative behavior, often making the optimization problem infeasible and preventing the algorithm from identifying a valid, collision-free solution.

4 Multi-Risk Assessment using Fusion of PIDPs (F-PIDP)

As detailed in Section 3.3, the standard PIDP framework is not inherently designed to accommodate multi-modal motion predictions. When multiple future trajectories are predicted for a single agent, it becomes ambiguous which PIDP should be used for effective collision avoidance (cf. Figure 1 & 3). A naive approach would be to treat all possible trajectories as constraints to be avoided. However, this often results in overly

conservative behavior, causing the AV to decelerate excessively or execute abrupt, unsafe maneuvers. To address this, we adopt the Fusion of PIDPs (F-PIDP), as proposed in [7, 8], which integrates multiple PIDPs based on the probability distribution over the agent’s predicted trajectories.

4.1 Multi-modal PIDP

To assess potential collision risks, the inter-distance is computed between the predicted trajectory of the AV and each possible future trajectory $j \in \mathcal{P}$ of the PLEV. At any given time step t , let the AV’s position be represented by (x^{AV}, y^{AV}) while the position of the PLEV along trajectory j is represented by (x^j, y^j) . Then, the predictive inter-distance $PIDP_j$ associated with the j -th trajectory is:

$$PIDP_j(t) = \{d_j(t) | j \in \mathcal{P}, 0 \leq t \leq t_{horizon}\} \quad (9)$$

$$d_j(t) = \sqrt{(x^{AV}(t) - x^j(t))^2 + (y^{AV}(t) - y^j(t))^2} \quad (10)$$

4.2 Extraction and Fusion of PIDP features

Each predicted trajectory of a PLEV contributes key information that is critical for risk assessment. Specifically, as presented in [8], three representative points are extracted from every PIDP: (1) the initial value at the start of the prediction horizon $PIDP(t_0)$, (2) the minimum value along the trajectory $PIDP(t_{min})$, and (3) the final value at the end of the trajectory $PIDP(t_{horizon})$. Rather than treating each PIDP independently, a unified representation is constructed by performing a weighted fusion of these features. This is accomplished using the probabilistic center of mass (pCOM), which aggregates the values of each feature across all trajectories based on their likelihood. Formally, the pCOM at any key point $t \in \{t_0, t_{min}, t_{horizon}\}$:

$$pCOM(t) = \sum_{j=1}^{N_{traj}} Pr(j) \times PIDP_j(t) \quad (11)$$

here $Pr(j)$ represents the probability of trajectory j , and $N_{traj} \in \mathbb{N}$ is the total number of predicted trajectories. This fusion yields three parameters that summarize the overall risk across all predicted trajectories.

- $F_PIDP(t_0)$:= $pCOM(t_0)$, the fused start points of each trajectory $PIDP_j(t_0)$
- $F_PIDP(t_{min})$:= $pCOM(t_{min})$ the fused minimum points $PIDP_j(t_{min})$ of each trajectory
- $F_PIDP(t_{horizon})$:= $pCOM(t_{end})$ fusion of all the end points $PIDP_j(t_{horizon})$

4.3 Fusion of PIDP (F-PIDP) curve

The goal of fusing PIDPs is to generate a single representative curve—an F-PIDP—that encapsulates the inter-distance information from all predicted trajectories, weighted by their likelihoods. Since the curve is constructed based on the Euclidean distance between the AV and the predicted positions of the PLEV, the fused inter-distance profile can be effectively approximated using a quadratic polynomial. To model the F-PIDP as described in our previous work [7, 8], the features outlined previously ($F_PIDP(t_0)$, $F_PIDP(t_{min})$, and $F_PIDP(t_{horizon})$) are used to determine the coefficients $[q_0, q_1, q_2]$ of the quadratic curve. These coefficients are computed by solving a linear system, as defined in Equation (12), using the matrix (or pseudo) inverse evaluated at time points $t \in [t_0, t_{min}, t_{horizon}]$. The resulting F-PIDP curve consolidates information from all PIDPs, as illustrated in Figure 3.

$$\begin{bmatrix} F_PIDP(t_0) \\ \vdots \\ F_PIDP(t_{horizon}) \end{bmatrix} = \begin{bmatrix} 1 & t_0 & t_0^2 \\ \vdots & \vdots & \vdots \\ 1 & t_{horizon} & t_{horizon}^2 \end{bmatrix} \cdot \begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix} \quad (12)$$

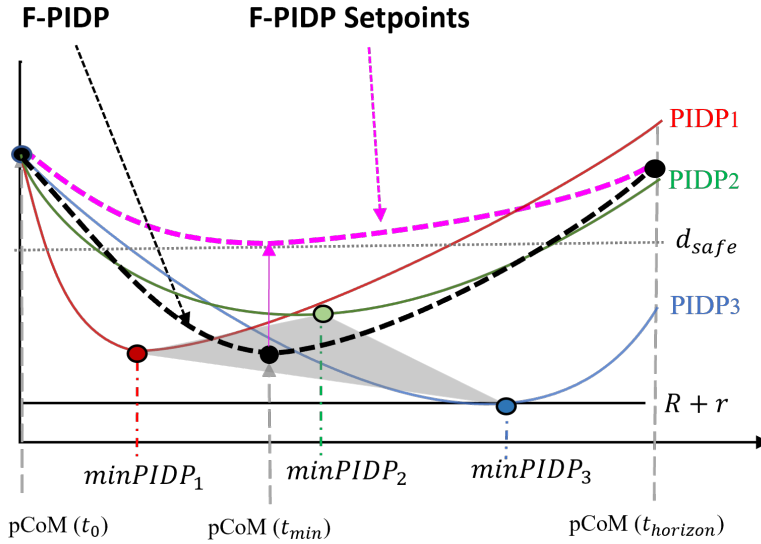


Fig. 3 Fusion of PIDPs (F-PIDP) of an AV and a PLEV with three (3) possible multi-modal trajectories from [8].

4.4 F-PIDP Setpoint for ensuring safety

To guarantee safety, the risk management algorithm requires a well-defined F-PIDP and a consistent setpoint. However, some PIDPs may fall below the safety distance, potentially entering the collision zone (see Figures 2 and 3), and this can influence

the shape of the F-PIDP curve based on their probability. To address this, a setpoint interpolation step is introduced to ensure the F-PIDP curve remains above the safety distance, d_{safe} . This interpolation adjusts the minimum of the F-PIDP curve to satisfy:

$$F_PIDP(t_{min}) \triangleq \max\{F_PIDP(t_{min}), d_{safe}\} \quad (13)$$

$$d_{safe} \triangleq R + r + v \times ETTC(1sec) \quad (14)$$

where R and r are the radii of the interacting agents, v is the ego-vehicle's current linear velocity, and $ETTC$ is the extended time to collision, set to 1 second [13]. The adjusted curve, termed the F-PIDP setpoint (see Figure 3), can be provided to the risk management algorithm as a reference. This interpolation step is critical for proactively mitigating collision risks.

5 Multi Risk Management with Safety Guarantee using F-PIDP + MPC

5.1 Priority-based Collision Avoidance Strategy

Computing a safe trajectory for the AV using classical algorithms like MPC can be overly conservative due to the restrictive size of the road boundary. In [8], we proposed to solve this problem by selecting the most dangerous agent using a priority-based strategy, assuming a lane change maneuver is possible. Algorithm 1 summarizes the single priority target selection steps.

- **Step 1:** Compute the F-PIDP of all the agents,
- **Step 2:** Find P_{dmin} : the PLEV with the minimum inter-distance to the AV, and P_{tSNR} : the PLEV with the minimum t_{SNR} ,
- **Step 3:** If $P_{dmin} < d_{safe}$, then set the priority target PLEV P_T , to avoid collision with P_{dmin} , else set the priority target PLEV P_T as P_{tSNR} . P_T is considered to be the most dangerous agent.
- **Step 4:** Find collision-free trajectory between target PLEV and AV, goto **Step 1**.

Algorithm 1 Priority-based Target Selection Algorithm using F-PIDP [8]

Require: $\mathbf{x}^{AV}(t, \dots, N)$, $\mathbf{x}^{PV}(t, \dots, N)$

```

1: while Goal not reached do
2:   Compute F-PIDP of all the PLEVs
3:   Compute  $P_{dmin}$ : the PLEV with the minimum inter-distance to the AV
4:   Compute  $P_{tSNR}$ : the PLEV with the minimum  $t_{SNR}$ 
5:   if  $P_{dmin} < d_{safe}$  then
6:      $P_T := P_{dmin}$ 
7:   else
8:      $P_T := P_{tSNR}$ 
9:   end if
10:   $\mathbf{U}^{AV} \leftarrow \text{F-PIDP+MPC}(P_T)$ 
11: end while

```

5.2 Multi-priority-based Collision Avoidance Strategy

In this work, we also address scenarios where there may be a potential conflict with other vehicles in the adjacent lane. Here, the decision-making and control problem regarding the appropriate maneuver that the AV can execute is divided into two parts:

1. Decision on possible lane maneuver
2. Evaluation of the vehicle control inputs

The decision on a potential lane change maneuver depends on whether the adjacent lane is safe for the AV to move into. Hence, instead of a single priority agent, a set of multiple priority agents are considered based on the level of danger posed to the AV. To be less conservative we consider a priority agent on each lane of the road. Therefore, we modify Algorithm 1 to identify multiple priority agents in the environments as shown in Algorithm 2.

Algorithm 2 Multi-priority-based Target Selection Algorithm using F-PIDP

Require: $\mathbf{x}^{AV}(t, \dots, N)$, $\mathbf{x}^{PV}(t, \dots, N)$

```

1:  $P_{multi} \leftarrow \emptyset$ 
2: while Goal not reached do
3:   Compute F-PIDP of all the PLEVs
4:   for Each Road Lane do
5:     Compute  $P_{dmin}$ : the PLEV with the minimum inter-distance to the AV
6:     Compute  $P_{tSNR}$ : the PLEV with the minimum  $t_{SNR}$ 
7:     if  $P_{dmin} < d_{safe}$  then
8:        $P_{multi} \leftarrow P_{dmin}$  : Add to multi-priority agents list
9:     else
10:       $P_{multi} \leftarrow P_{tSNR}$  : Add to multi-priority agents list
11:    end if
12:  end for
13: end while

```

5.3 Hybrid Trajectory Planning Framework

The presence of multiple priority agents increases the dimensionality of the problem when using MPC to compute a safe trajectory, as discussed in Section 3.4. To address this challenge, we propose a hybrid trajectory planning framework. The core idea is to use a sampling-based planner to first select a safe maneuver from a set of candidate trajectories, which include both lane-keeping and lane-change maneuvers. Subsequently, an MPC-based trajectory tracking optimization is employed to compute the appropriate control inputs required to follow the selected safe trajectory.

5.3.1 Multi-priority-based Trajectory Sampling Method

The sampling-based planner generates trajectory samples around the current state of the vehicle, represented in the road-aligned Frenet frame. Each trajectory sample corresponds to a potential lane-keeping or lane-change maneuver. The optimal trajectory

is selected from this set of candidate trajectories based on an objective function and adherence to safety constraints. The trajectory sampling problem is formally defined as:

$$\min_{\mathbf{x}_{ref}[0:N]} \sum_{t=0}^N \left(\ddot{x}(t) + \ddot{y}(t) + (v(t) - v_{ref}) \right) \quad (15)$$

subjected to:

$$g(\ddot{x}(t), \ddot{y}(t), \dot{x}(t), \dot{y}(t), x(t), y(t)) \leq \mathbf{0} \quad \forall t \in [0, N], \quad (16)$$

$$\mathbf{x}_{traj} \in \Xi_{safe}^{P_{multi}} \quad \forall t \in [0, N], \quad (17)$$

where \mathbf{x}_{ref} is the desired optimal trajectory (cf. Figure 4), (x, y) are the longitudinal and lateral position of the vehicle along a sample trajectory \mathbf{x}_{traj} . The cost function (15) aims to optimize the smoothness of the trajectory and track the reference velocity v_{ref} . The constraint in (16) represents limitations on the vehicles dynamics, while (17) ensures that the motion of the vehicle is safe with respect to other road users.

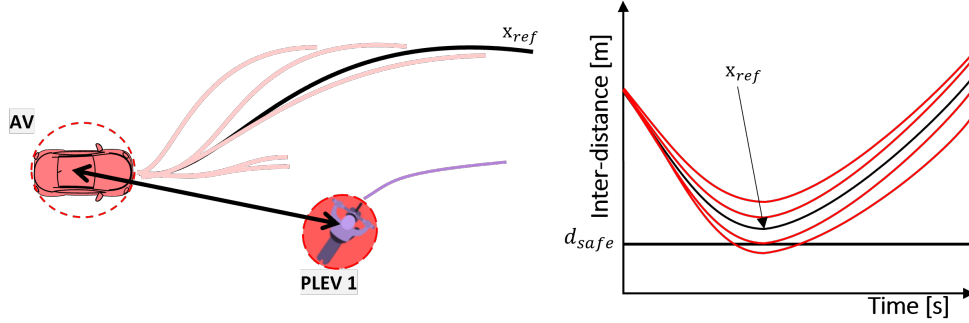


Fig. 4 The candidate trajectories and the corresponding PIDP between an AV and an agent: the multi-priority collision avoidance algorithm selects the optimal reference trajectory \mathbf{x}_{ref} .

5.3.2 Collision Safety Guarantee

The safety constraint in (17) ensures that the vehicle's trajectory remains within the desired set of collision-free positions $\Xi_{safe}^{P_{multi}}$ with respect to the priority agents. In other words, this constraint enforces collision avoidance, and the safe set is defined as:

$$\Xi_{safe}^{P_{multi}} := \left\{ \mathbf{x}_{traj} : \min \text{PIDP} \geq d_{safe} \right\} \quad (18)$$

This implies that a candidate trajectory \mathbf{x}_{traj} is considered safe if its minimum PIDP with regards to all agents in the priority list P_{multi} is greater than d_{safe} .

Therefore, at each time step, we consider collision avoidance with the most dangerous (critical) agents, which is a less conservative approach.

5.3.3 MPC-based Trajectory Tracking

The MPC-based tracking of the optimal trajectory in Section 5.3.1 is formulated as a Quadratic Programming (QP) problem. The objective is to compute control inputs for the ego-vehicle that enable it to follow the selected trajectory \mathbf{x}_{ref} as accurately as possible, while adhering to vehicle control constraints such as acceleration, steering limits, and dynamic feasibility of the vehicle’s motion.

$$\min_{\mathbf{U}} \sum_{t=0}^N \left[\left(\mathbf{u}(t) - \mathbf{u}_{ref}(t) \right)^T \cdot R \cdot \left(\mathbf{u}(t) - \mathbf{u}_{ref}(t) \right) + Q \cdot \delta^2(t) \right] \quad (19)$$

subjected to:

$$\mathbf{x}^{AV}(t+1) = f(\mathbf{x}^{AV}(t), \mathbf{u}(t)) \quad \forall t \in [0, N], \quad (20)$$

$$\delta(t) \geq \|\mathbf{x}^{AV}(t) - \mathbf{x}_{ref}(t)\| \quad \forall t \in [0, N], \quad (21)$$

$$\mathbf{u}(t) \in \mathcal{U} \quad \forall t \in [0, N], \quad (22)$$

$$\mathbf{x}^{AV}(t) \in \mathcal{X} \quad \forall t \in [0, N], \quad (23)$$

the aim of the QP problem is to minimize the error between the predicted trajectory $\mathbf{x}^{AV}(t)$ and the reference trajectory \mathbf{x}_{ref} while driving the control inputs of the vehicle \mathbf{u} towards the desired control inputs \mathbf{u}_{ref} . R and Q are weights for tracking the reference trajectory and control, respectively. The constraints in (20) enforce that the control inputs must produce a physically valid trajectory according to the vehicle’s dynamics. It ensures the trajectory tracking is not only optimal with respect to the cost function but also feasible in practice. The constraint (21) is related to the trajectory tracking cost, while (22) and (23) are limits on the vehicle’s control inputs and states. This approach is less conservative because the state-level collision avoidance problem is already addressed through the multi-priority-based trajectory sampling method, in contrast to Equation (8), which employs classical MPC for collision avoidance.

6 Simulation Results

The proposed risk assessment and management framework was implemented and evaluated in a MATLAB-based simulation environment. The setup features an AV navigating alongside multiple Personal Light Electric Vehicles (PLEVs) within a dual-lane traffic scenario. A series of challenging and dynamic situations were evaluated to test the system’s robustness (cf. Figure 5 & 10). These scenarios introduce two primary challenges:

- the uncertainty in the actual trajectory that each agent will follow, and

- the potential for sudden behavioral changes, particularly in terms of speed, by agents such as PLEVs.

Using similar agents' parameters as [8] (cf. Table 1), PLEV 1, for instance, may accelerate significantly from an initial speed of 2 m/s up to 10 m/s, adding to the unpredictability of the environment. To simplify collision-checking and minimize computational overhead, each agent is modeled using a single enclosing circle. While this approximation introduces some conservatism, it provides a practical balance between accuracy and efficiency. However, a less conservative approach could involve modeling agents with multiple circumcircles, as proposed in [10], to better capture their shape.

Table 1 Agents Parameters and initial states [8]

AV Parameters	Value	Unit
radius	2	m
initial position	[0, -6]	m
initial velocity	[8, 0]	m/s
\mathbf{u}_{max}^{AV}	[8, 35]	[m/s, °]
\mathbf{u}_{min}^{AV}	[0, -35]	[m/s, °]
PLEV 1 Parameters	Value	Unit
radius	0.5	m
initial position	[10, -9]	m
initial velocity	[2, 0]	m/s
v_{max}	10	m/s
PLEV 2 Parameters	Value	Unit
radius	0.5	m
initial position	[16, -6]	m
initial velocity	[2, 0]	m/s
v_{max}	2	m/s

6.1 Scenario with a Single Priority Agent

In this simulation setup, PLEV 1 accelerates its speed after approximately 1 second. A range of five speed levels is considered: $v \in \{2, 4, 6, 8, 10\}m/s$. The first level represents a constant-speed case, where PLEV 1 maintains its initial velocity of 2 m/s throughout the trajectory. The remaining speed levels correspond to cases of sudden acceleration, introducing variability in agent behavior. The total simulation duration is set to 7.5 seconds, with a time step of $\Delta t = 0.05$ seconds. A prediction horizon of $t_{horizon} = \Delta t \times N = 2s$ is used at each step to predict future agent positions.

6.1.1 Result using Standard MPC formulation

We first evaluate the simulation results using standard MPC. At the initial speed levels of 2 m/s and 4 m/s, the MPC effectively manages these small variations in agent speeds without violating collision constraints, as illustrated in Figure 5. The PIDP

remains above the safe distance threshold, d_{safe} , indicating safe navigation throughout the prediction horizon. This can be observed in the inter-distance plot between the AV and the two PLEVs at time $t \leq 1s$ (cf. Figure 6 (a) & (c)).

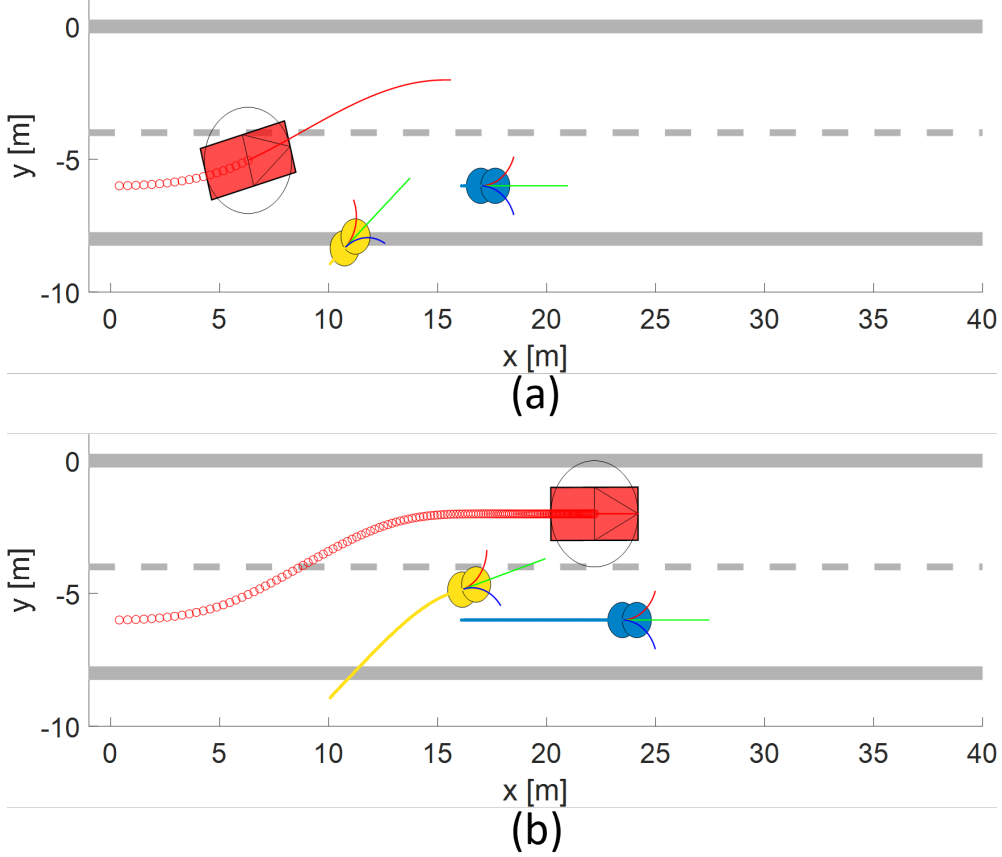


Fig. 5 A scenario using MPC showing an AV (in red) and multi-modal PLEVs (1 in Yellow & 2 in Blue): (a) At $t = 1$ s, the actual speed of both PLEVs is 2 m/s, (b) At $t = 7.5$ s, AV overtakes PLEV 1 but stays beside PLEV 2 to avoid a possible collision with a possible Left turn trajectory of PLEV 2, reproduced from [8].

The MPC approach, however, adopts an overly conservative strategy, nearly halting the motion of the AV to avoid a potential collision with PLEV 2. This caution stems from the PIDP indicating a risk of collision due to a possible left-turn trajectory by PLEV 2 (cf. Figure 6 (d), in red). To mitigate this risk, the MPC algorithm prioritizes maintaining a safe distance behind PLEV 2 rather than attempting to overtake it. Consequently, even at the end of the simulation, $t = 7.5$, the AV remains at a significant distance from the final goal position $\mathbf{x}_{goal} = [-2, 60]m$ (cf. Figure 5 (b)).

At higher speeds of 6 m/s and above, the MPC algorithm struggles to identify a solution that satisfies all safety constraints. Notably, as shown in Figure 7, the AV

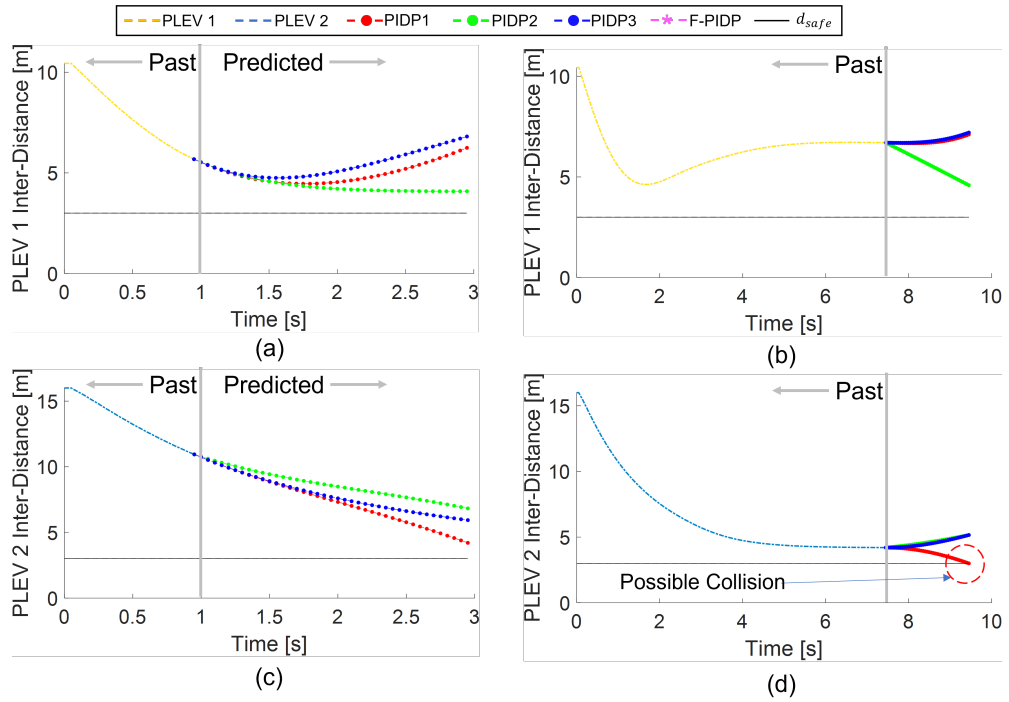


Fig. 6 Inter-Distance plot between the AV and the PLEVs using MPC: (a) & (c) At $t = 1$ s, all PIDPs (red, blue, green) of PLEV 1 & 2 are above safety distance d_{safe} , (b) & (d) At $t = 7.5$ s, the PIDPs of PLEV 1 are above d_{safe} while a PIDP of PLEV 2 may lead to collision, reproduced from [8].

violates the road boundary constraint in an attempt to avoid a collision with other agents following the sudden acceleration of the PLEV.

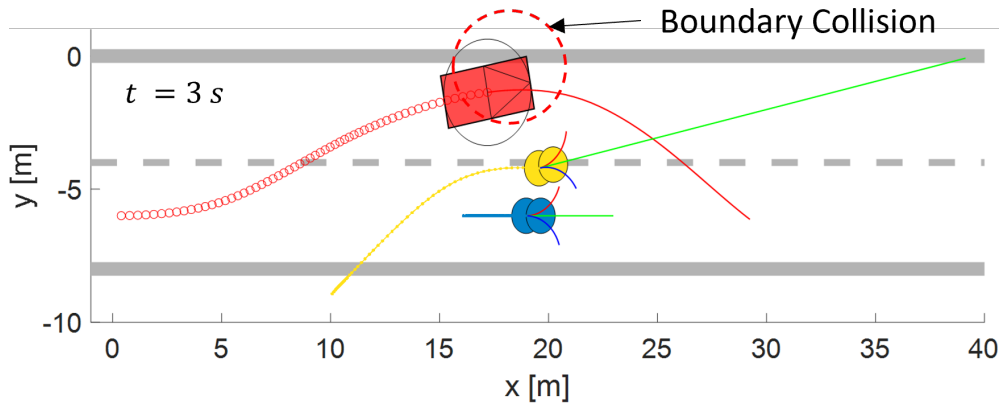


Fig. 7 At $t = 3$ s, MPC violates the boundary constraint due to the sudden change in speed of PLEV, as presented in [8].

6.1.2 Result using Priority-based F-PIDP+MPC

The approach proposed in [8], which integrates F-PIDP+MPC, outperforms standard MPC across all speed variations, provided the alternative lane remains collision-free. By utilizing F-PIDP as a risk metric and prioritizing the target PLEV identified as the most dangerous, the AV can compute a less conservative trajectory that effectively meets all safety constraints.

For example, at $t = 1s$, PLEV 1 is identified as the priority target P_T , as shown in Figure 8 (a). After the fusion of the PIDPs, the F-PIDP setpoint indicates that the AV should increase its distance from PLEV 1 to prevent a potential collision, as depicted in Figure 9 (a). By focusing solely on the priority target, PLEV 1, the F-PIDP+MPC algorithm finds a solution that enables the AV to safely overtake PLEV 1. Subsequently, at $t = 5s$, PLEV 2 becomes the new priority target, which the AV overtakes after passing PLEV 1 (cf. Figure 8 (b)).

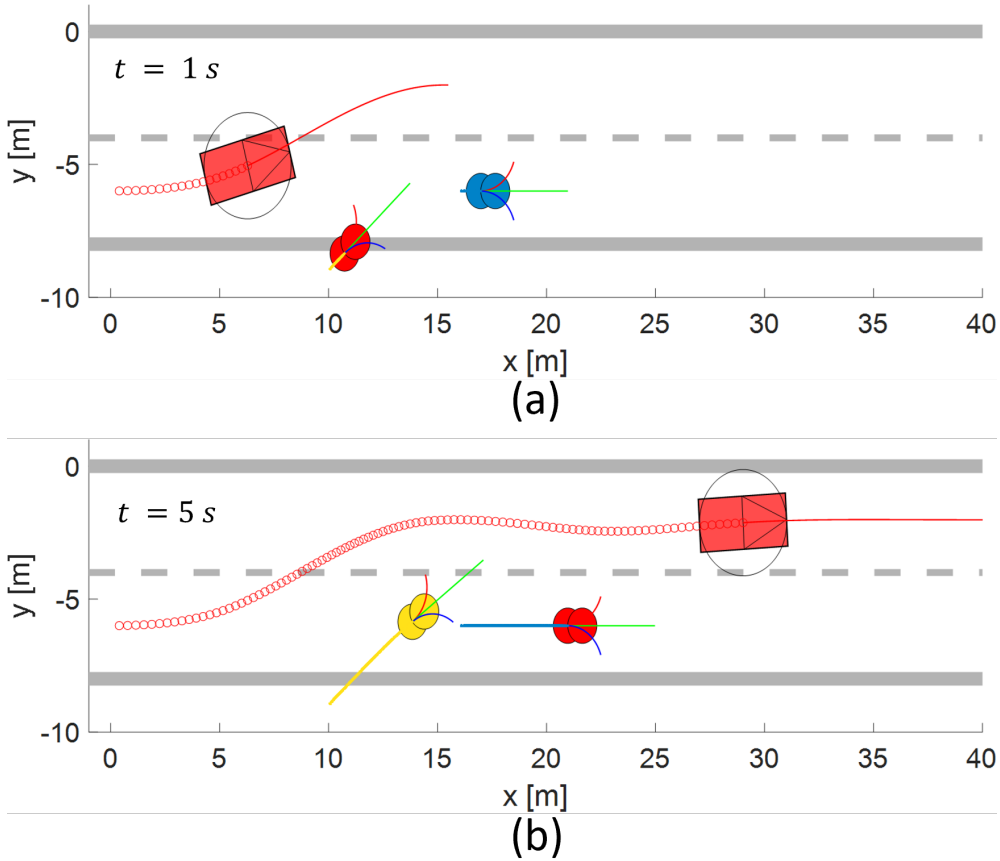


Fig. 8 A scenario using the F-PIDP+MPC reproduced from [8]: (a) At $t = 1s$, AV overtakes the priority target PLEV 1 (in red), (b) then at $t = 5s$, AV overtakes the new priority target PLEV 2 (in red).

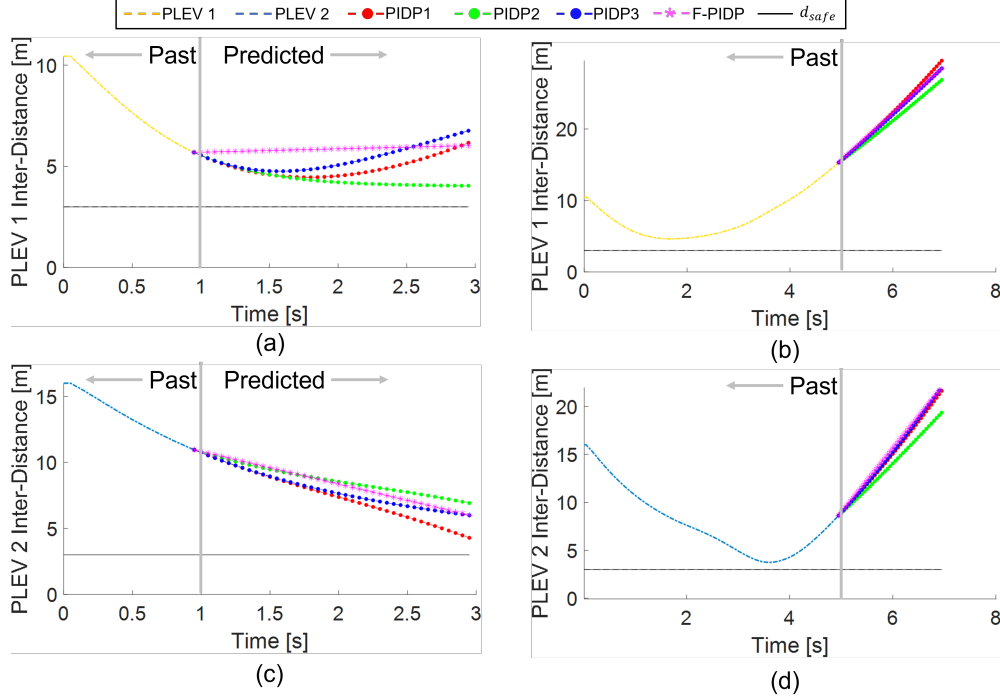


Fig. 9 Inter-Distance plot between the AV and the PLEVs using F-PIDP+MPC: (a) At $t = 1$ s, F-PIDP suggest creating more distance between AV and PLEV 1, (b), (c), & (d) All PIDPs are above d_{safe} as presented in [8]

This priority-based behavior enables the AV to quickly leave the dangerous region by focusing on the most critical agent, rather than simultaneously accounting for all multi-modal agents' motion (using standard MPC), which often results in overly conservative behavior. Consequently, the AV covers greater distances in less time compared to the standard MPC method, which remains alongside PLEV 2 after 7.5 seconds, as shown in Figure 8 (b). Throughout the simulation, the proposed F-PIDP+MPC method ensures that the PIDPs of all agents consistently remain above the safety distance threshold, as illustrated in Figure 9. This strategy is effective for both PLEVs and other road vehicles.

6.2 Scenario with Multiple Priority Agents

In this simulation setup, we incorporate an additional vehicle, V1, moving in the adjacent lane, which influences the feasibility of a lane change maneuver based on V1's motion. This introduces the possibility of multiple priority agents depending on the lane, contrary to the situation in [8] that uses F-PIDP+MPC. To address this, our proposed multi-priority-based trajectory sampling method first evaluates whether a safe lane change is viable. If feasible, the algorithm proceeds with the MPC-based trajectory tracking to follow the reference trajectory.

We evaluate three speed levels for vehicle V1: $v \in \{2, 4, 6\}m/s$. At $t = 0s$, when V1 operates at lower speeds of 2 m/s or 4 m/s, the algorithm identifies two priority targets: PLEV 1 (on the same lane as AV) and V1 (on the adjacent lane). The sampling-based planner then generates a safe lane change maneuver \mathbf{x}_{ref} to avoid collision with both priority agents (cf. Figure 10 (a), black dotted lines). By $t = 4.0s$, the AV successfully tracks the reference lane change trajectory (cf. Figure 10 (b)). Subsequently, the priority target shifts from PLEV 1 to PLEV 2, and the reference trajectory transitions to a lane-keeping motion.

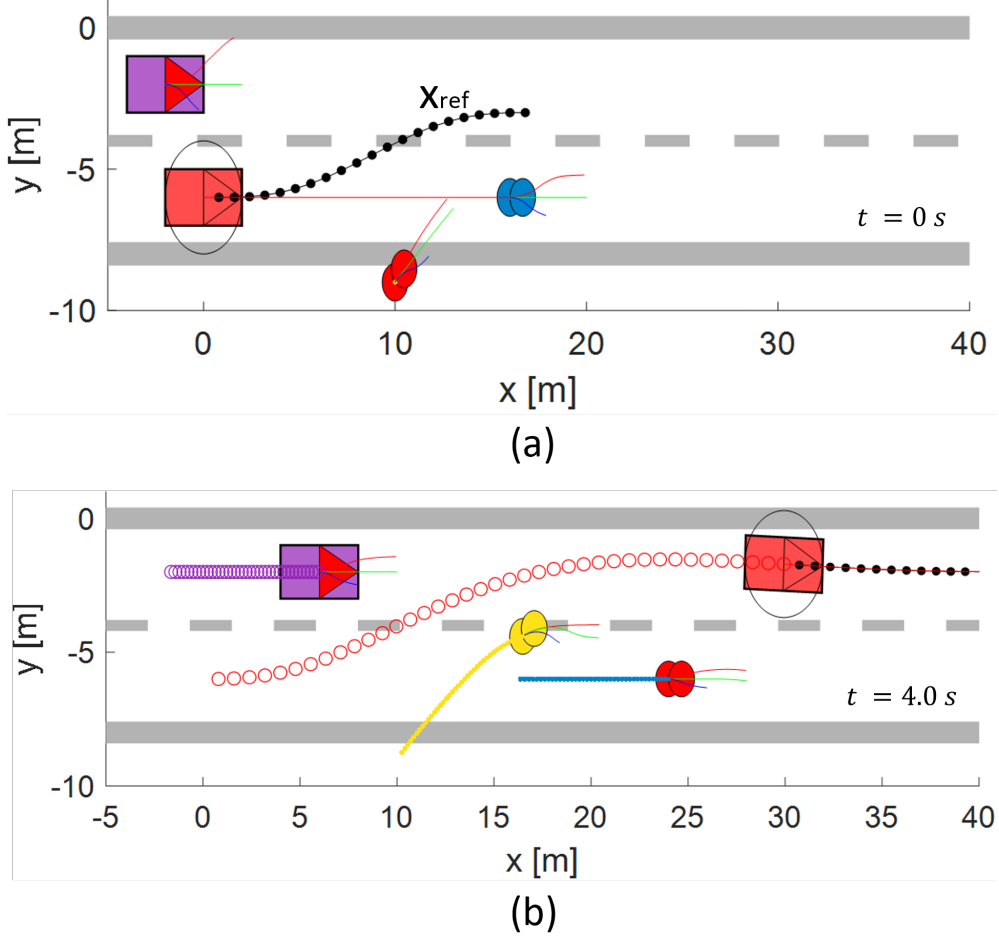


Fig. 10 A scenario using the proposed multi-priority collision avoidance strategy: (a) At $t = 0s$, AV overtakes the priority targets PLEV 1 (on the same lane as AV) and vehicle, V1 (on the adjacent lane), (b) then by $t = 4s$, AV overtakes the new priority target PLEV 2 (in red).

However, when vehicle V1 moves at a high speed of 6 m/s, the proposed multi-priority-based trajectory sampling algorithm could not find a safe lane change

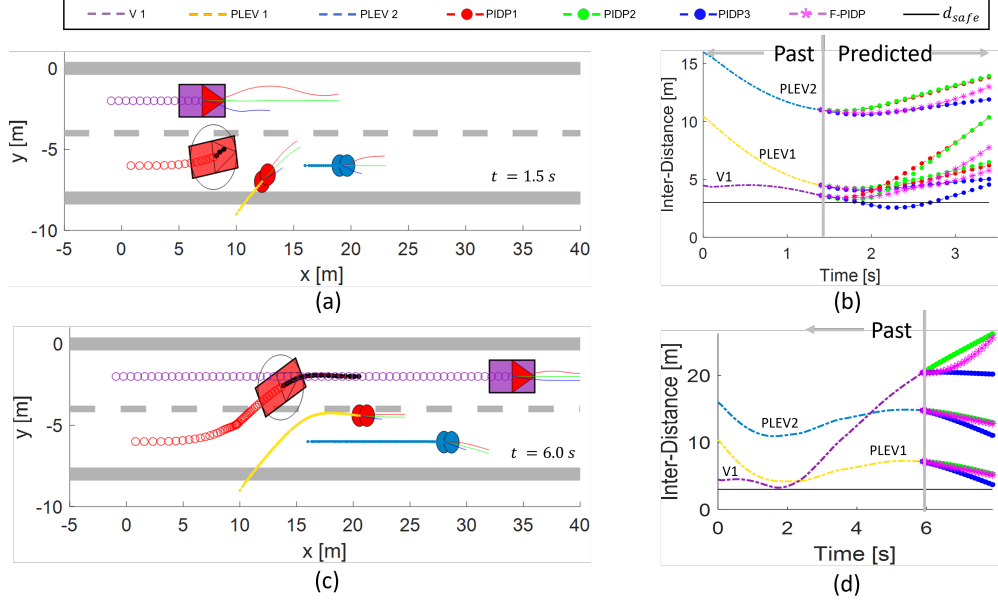


Fig. 11 A scenario using the proposed multi-priority collision avoidance strategy: (a) At $t = 1.5$ s, AV cannot overtake the priority targets PLEV 1 and V1 (in red), (b) predicted F-PIDP and PIDP of the agents on the inter-distance plot indicates possible collision, (c) then at $t = 6.0$ s, the AV is able to complete the lane change maneuver, (d) with the inter-distance plot showing no predicted collision (all PIDP are above d_{safe}).

maneuver. As seen in Figure 11 (a), at $t = 1.5$ s, the AV decelerates to wait for V1 to pass to avoid collision with the two priority agents as indicated by the predicted F-PIDP and PIDP of the agents on the inter-distance plot (cf. Figure 11 (b)). Then, at $t = 6.0$ s the AV is able to complete the lane change maneuver (cf. Figure 11 (c)) with the inter-distance plot showing no predicted collision (all PIDP are above d_{safe}) (cf. Figure 11 (d)). The proposed approach, with an average computation time of 24 ms for solving the QP problem, is limited by the number of trajectory samples. However, even when processing a substantial set of 464 trajectory samples, the multi-priority collision avoidance algorithm maintains an efficient average computation time of 63 ms, which can be further optimized.

7 Conclusion

In this paper, we proposed a novel method for risk assessment and management to enable autonomous navigation among Personal Light Electric Vehicles (PLEVs). Our approach models PLEV behavior using multi-modal predictions, which are then simplified through the Fusion of Predictive Inter-Distance Profiles (F-PIDP). This fusion process reduces the complexity of handling multiple predictions by generating a single F-PIDP for each agent. To manage collision risks, we develop a multi-priority-based collision avoidance strategy that identifies and prioritizes the most

dangerous agents. Safe control actions are subsequently computed using an MPC-based trajectory tracking method. Our method integrates F-PIDP for risk assessment with multi-priority-based trajectory sampling and MPC-based trajectory tracking for risk management, providing a less conservative alternative to conventional MPC approaches.

Simulation results, derived from varying agent behaviors, demonstrate the efficiency of the proposed method for both risk assessment and management. Compared to standard MPC and the single priority agent collision avoidance strategies, the proposed method is less conservative while maintaining a high level of safety. This approach prevents the vehicle from coming to a complete stop in response to every potential risk, thereby avoiding overly conservative behaviors that could render the system impractical for real-world deployment. Future work will focus on incorporating disturbances in the predicted agent states and optimizing the method for real-time experimental applications.

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Declarations

7.1 Conflict of interest

The authors declare no competing interests.

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