

# Intent-Aware MPC for Aircraft Detect-and-Avoid with Response Delay: A Comparative Study with ACAS Xu

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**Abstract**—In this paper, we propose an intent-aware Model Predictive Control (MPC) approach for the remain-well-clear (RWC) functionality of a multi-agent aircraft detect-and-avoid (DAA) system and compare its performance with the standardized Airborne Collision Avoidance System Xu (ACAS Xu). The aircraft system is modeled as a linear system for horizontal maneuvering, with advisories on the rate of turn as the control input. Both deterministic and stochastic time delays are considered to account for the lag between control guidance issuance and the response of the aircraft. The capability of the MPC scheme in producing an optimal control profile over the entire horizon is used to mitigate the impact of the delay. We compare the proposed MPC method with ACAS Xu using various evaluation metrics, including loss of DAA well-clear percentage, near mid-air collision percentage, horizontal miss distance, and additional flight distance across different encounter scenarios. It is shown that the MPC scheme achieves better evaluation metrics than ACAS Xu for both deterministic and stochastic scenarios.

**Keywords**—Model Predictive Control; Detect-and-Avoid; Aircraft Collision Avoidance; Intent Awareness; Delay-based Control

## I. INTRODUCTION

Innovative air mobility (IAM) is a rapidly emerging sector of the aerospace industry that aims to safely and efficiently integrate highly automated aircraft in the airspace, including unmanned aircraft systems (UAS) and air taxis. While in conventional (manned) air transport operations, sufficient separation between aircraft is ensured largely by air traffic controllers, in IAM operations more automated approaches for traffic management are needed [1]. A detect-and-avoid (DAA) system provides visibility on other conspicuous aircraft and supports both remote pilots (RPs) and onboard autopilots in maintaining safe separation from nearby traffic. Its remain-well-clear (RWC) function generates guidance to RPs to maintain adequate spacing and prevent potential conflicts in shared airspace.

The Airborne Collision Avoidance System Xu (ACAS Xu) is a standardized DAA system to support UAS RPs in remaining well clear and avoiding collisions [2]. The threat resolution module of ACAS Xu uses large lookup tables that were optimized by dynamic programming and a rollout approach

for the RWC function [3]. In support of systematic evaluation of ACAS Xu, an agent-based modeling and simulation environment was developed, which systematically describes interactions between DAA equipped aircraft, RP response to RWC guidance including delays, and sensor errors [4], [5]. *Livelock conditions* were found to exist in ACAS Xu supported operations, where the aircraft attain continuing fluctuations away from an intruder and back to their course *without* reaching their destination. Moreover, formal verification studies of ACAS X have identified counterexamples where the advisory logic can induce or fail to prevent near mid-air collisions in certain encounter geometries [6].

It was recognized in [5], [7] that current DAA systems only provide guidance and advisories for avoiding other traffic, which are based on state data, and that more effective RWC guidance can be achieved by including *intent data*, such as planned routes or destinations in the guidance provision. As a way forward, this study investigates the added value of an optimization-based DAA system that includes intent data. Model Predictive Control (MPC) has emerged as a promising approach [8]–[10]. MPC optimizes future control inputs over a finite prediction horizon while explicitly handling system dynamics and operational constraints. The work by Mayne et al. [11] and subsequent developments by Camacho and Bordons [12] have established MPC as a powerful tool in both industrial and aerospace applications. Unlike traditional methods, MPC’s ability to incorporate forecasted system behavior and constraints in real time makes it particularly attractive for safety-critical applications such as aircraft DAA systems.

Intent-aware controllers seek to predict the future trajectories of nearby aircraft based on their current state and expected maneuvers, modeled as a series of waypoints that the nearby aircraft will pass through. This predictive capability allows the control system to proactively plan avoidance strategies, rather than merely reacting to imminent conflicts. A recent study has demonstrated that when intent information is fused with the predictive power of MPC, yielding smoother and more efficient avoidance maneuvers compared to purely reactive methods [13]. Furthermore, [13] has proposed MPC as an efficient approach

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for incorporating such information online. However, despite these promising developments, there remains a gap in the literature regarding a direct performance comparison between intent-aware MPC strategies and established systems such as ACAS Xu using well-known evaluation metrics, particularly under more realistic conditions, such as response delays.

In this paper, we propose an intent-aware MPC framework tailored for aircraft detect-and-avoid. The proposed approach incorporates the intent of surrounding aircraft to improve decision-making and enable proactive planning. The optimal Dubins path is used to generate a complete path between the current and intended states. Response delay is included in the system modeling, and a delay-based MPC policy is designed to exploit its predictive capabilities for smoother trajectory generation. By systematically comparing the performance of our MPC-based method with the ACAS Xu standard, we aim to evaluate the benefits of integrating intent awareness into MPC schemes. An overview of the proposed intent-aware MPC for delayed multi-aircraft system is illustrated in Figure 1.

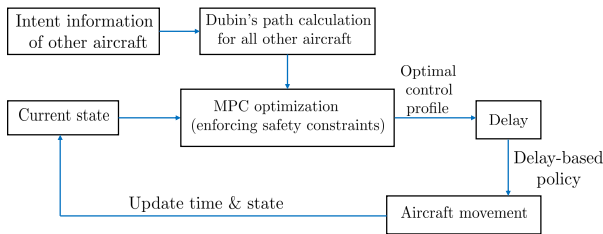


Figure 1. System diagram of the proposed intent-aware MPC framework for multi-aircraft system with response delay. Intent information is provided as the target state of surrounding aircraft. A Dubins path is used to generate the connecting trajectory. Then the MPC scheme computes the optimal control sequence, which is used to construct a delay-based policy.

Unlike conventional MPC approaches that extrapolate other aircraft trajectories using short-term flight data, our framework leverages intent in the form of waypoints and encodes kinematic feasibility via Dubins paths. This yields predictions that are consistent with realistic maneuvering constraints, rather than simple state extrapolations. The methodological contribution lies in the integration of such intent-aware trajectory predictions into an MPC formulation for DAA, enabling systematic conflict resolution under response delays and uncertainties.

The focus of this work is on the combined effect of intent awareness, response-delay handling, and optimal conflict resolution in multi-aircraft scenarios using MPC, evaluated through comparison with the operational benchmark ACAS Xu. The goal is to demonstrate how these elements, when integrated within a unified framework, yield measurable safety and efficiency improvements under realistic flight conditions. Intent information provides anticipative guidance, MPC offers a principled means to compute optimal and constraint-satisfying advisories, and response delay is addressed through the anticipatory nature of the MPC formulation. Moreover, the receding-horizon structure of MPC inherently provides an inherent robustness: at every sampling instant, the controller observes the current system state and re-solves the optimization problem subject to real-time constraints. This continuous

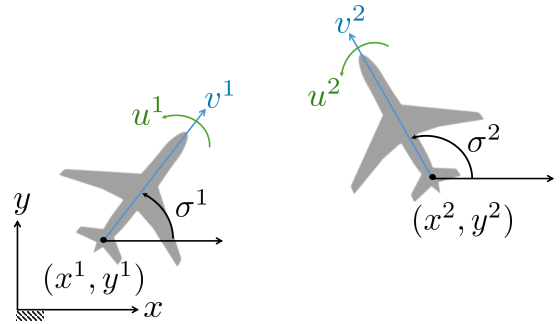


Figure 2. Two aircraft in the horizontal plane in the earth-fixed coordinate system. The black variables are the state and the greens are the angular velocities (control inputs). The linear velocities, shown in blue, are constant.

feedback correction mitigates the effect of deviations from the assumed intent maintaining safe maneuvers. The comparative evaluation with ACAS Xu quantifies the net benefit of this integration and thereby defines the scope of the paper.

The paper is organized as follows. Section II reviews the background of the aircraft model, response delay and sensor error. Section III details the proposed intent-aware MPC. Section IV presents simulation results and comparative analysis with ACAS Xu. Finally, Section V concludes the paper.

## II. BACKGROUND ON MODELING

We consider a discrete-time model with  $n$  aircraft flying in a horizontal plane without wind. The equation of motion for each aircraft  $i$  is given by:

$$\mathbf{s}_{t+1}^i = \mathbf{s}_t^i + t_e [v^i \cos \sigma_t^i, v^i \sin \sigma_t^i, u_t^i]^\top,$$

where the superscript  $i \in \{1, 2, \dots, n\}$  represents the  $i^{\text{th}}$  aircraft,  $\mathbf{s}_t^i := [x_t^i, y_t^i, \sigma_t^i]^\top$  is the state vector of the aircraft  $i$  at time  $t$ ,  $x_t^i$  and  $y_t^i$  are the position states, and  $\sigma_t^i$  is the heading angle. The constant  $t_e$  is the sampling time and is assumed to be 1 sec, and  $v^i$  is the linear velocity (air speed) that is assumed to be a constant value and  $u_t^i$  is the angular velocity (turning rate), which is considered as a control input. Figure 2 shows the geometry of two aircraft in horizontal plane. Our goal is not to capture full aircraft flight dynamics, but to evaluate the effectiveness of the proposed method in conflict resolution and to compare the performance with an ACAS Xu benchmark for horizontal RWC maneuvering. Extensions to more detailed models (e.g., including climb and descent, wind, or actuator dynamics) are possible.

In remotely piloted aircraft there is an inherent lag between the provision of an advisory and the resulting maneuver. This delay arises due to several factors, including communication latency and RP reaction time, and it can significantly affect the performance of the system. Such delays must be accounted for in the control design to ensure reliability. In this study, both deterministic and stochastic delay models are considered.

1) *Deterministic Delay Model:* A fixed delay is assumed for different scenarios in the deterministic case:

- **Automatic:** This represents the situation of an automatic response by the flight management system of the unmanned aircraft. For this a constant delay of  $\delta = 1$ s is set for each aircraft in the encounter-scenario.

- **Quick:** This represents the situation of a quick response by a RP, including the time for downlink, swift reaction of the RP, and uplink. For this a constant delay of  $\delta = 4s$  is set for each aircraft in the encounter-scenario.
- **Slow:** This represents a slower response by the RP, including the time for downlink, reaction of the RP who possibly interacts with an air traffic controller, and uplink. A constant delay of  $\delta = 12s$  is set for each aircraft in the encounter-scenario for the slow response.

2) *Stochastic Delay Model:* The delay of an aircraft is chosen from a lognormal probability distribution  $\delta \sim f(x; \mu, \sigma)$  with mean  $\mu = 4s$  and standard deviation  $\sigma = 2.5s$ :

$$f(x; \mu, \sigma) = \begin{cases} 0, & x \leq 0, \\ \frac{1}{\sigma_n x \sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu_n)^2}{2\sigma_n^2}\right), & x > 0, \end{cases}$$

$$\mu_n := \ln\left(\frac{\mu^2}{\sqrt{\mu^2 + 1}}\right), \quad \sigma_n := \sqrt{\ln\left(\frac{\sigma^2}{\sqrt{\mu^2 + 1}}\right)}.$$

With these parameter values the probability of a delay less than 1s is 0.0167 and the probability of a delay more than 12s is 0.0139. Thus, the stochastic delays are largely between the settings considered in the deterministic cases.

In addition to the uncertainty introduced by stochastic delays, sensor errors in state estimates also affect the control advisories. The position and velocity estimate errors are modeled by first-order autoregressive processes with normally distributed noise (SD is 37.8 m or 4.08 m/s; autocorrelation factors are 0.997) [4]. While the deterministic case assumes perfect sensor readings, the stochastic case accounts for these uncertainties. It is assumed that the position and speed estimates are shared with other aircraft in the encounter scenario using automatic dependent surveillance-broadcast. Both the state estimates and the shared intent data (waypoints of all aircraft) serve as inputs to the MPC formulation.

The ACAS Xu benchmark results used in this study were obtained from the Collision Avoidance Validation and Evaluation Tool (CAVEAT) of EUROCONTROL. CAVEAT provides a stochastic, dynamic, agent-based simulation environment for standardized encounter geometries and includes the validated Julia implementation of the ACAS Xu logic [2], [4], [14]. The RP model in CAVEAT can be tuned in a variety of ways [5]. For the simulations used in this study no biases in the decision-making were assumed and the pilot closely follows the (delayed) RWC guidance, such that the pilot turns towards the closest edge of the RWC bands. For instance, if the aircraft is on a course of 90 deg and the RWC bands are active from 75 to 120 deg, then the pilot would turn left to achieve a course of 75 deg. The benchmark employs surveillance inputs with realistic noise characteristics, which are similar to those used in the MPC simulations. More details and examples of ACAS Xu performance in the benchmark are provided in [7]. In this paper, the MPC simulations were conducted for the same encounter scenarios to ensure a consistent and fair comparison between the two systems.

### III. INTENT-AWARE MPC WITH RESPONSE DELAY

#### A. Intent-aware MPC policy

Our goal is to design a decentralized control  $u_t^i$  for aircraft  $i$  using MPC such that the aircraft approaches to its intended waypoints, denoted by  $s_f^i$  while maintaining sufficient separation distances from all other aircraft. In our MPC formulation we use a soft constraint  $\rho$  for the desired minimum separation between the aircraft in an encounter, in combination with slack variables  $\epsilon$  that allow some variation with respect to this soft constraint. The reason is that due to various uncertainties such as sensor errors and mismatch of the actual paths taken by other aircraft with the assumed path based on the Dubin path, the MPC may not be able to find a feasible solution at some instances for a hard safety constraint (without slack variables).

MPC produces control policies by solving an optimal control problem at each discrete time instant based on the current system state  $s$ , over a finite, receding horizon. As one of the main benefits, MPC can directly account for state-input constraints in optimization. In particular, for aircraft  $i$  the following optimization problem is solved:

$$\min_{\hat{u}_{0:N-1|t}^i, \hat{s}_{0:N|t}^i, \epsilon_{0:N|t}} \|\hat{s}_{N|t}^i - s_f^i\|_{Q_t}^2 + \sum_{k=0}^{N-1} \|\hat{s}_{k|t}^i - \bar{s}_k^i\|_Q^2 + \quad (1)$$

$$\sum_{k=1}^{N-1} \|\hat{u}_{k|t}^i - \hat{u}_{k-1|t}^i\|_R^2 + \epsilon_k^2,$$

s.t.  $\forall k \in \{0, \dots, N-1\}$ :

$$\hat{s}_{k+1|t}^i = \hat{s}_{k|t}^i + t_e \left[ v^i \cos \hat{\sigma}_{k|t}^i, v^i \sin \hat{\sigma}_{k|t}^i, \hat{u}_{k|t}^i \right]^\top,$$

$$\rho^2 - \epsilon_{k|t} \leq (\hat{x}_{k|t}^i - \bar{x}_k^j)^2 + (\hat{y}_{k|t}^i - \bar{y}_k^j)^2,$$

$$\forall j \in \{1, \dots, M\} \setminus \{i\},$$

$$0 \leq \epsilon_{k|t}, \quad \underline{u}^i \leq \hat{u}_{k|t}^i \leq \bar{u}^i, \quad \hat{s}_{0|t}^i = s_t^i.$$

This is done recursively at each state  $s_t^i$  and produces a complete profile of control inputs  $\hat{u}_{\cdot|t}^{i,*} = \{\hat{u}_{0|t}^{i,*}, \dots, \hat{u}_{N-1|t}^{i,*}\}$  and corresponding state predictions  $\hat{s}_{\cdot|t}^{i,*} = \{\hat{s}_{0|t}^{i,*}, \dots, \hat{s}_{N|t}^{i,*}\}$ . The notation *star*  $\cdot^*$  is used to refer to the optimal value of the decision variables. In order to distinguish between the actual system trajectory and the predicted state-input profile, we use the notation *hat*  $\hat{\cdot}$  for the latter. The MPC in (1) for aircraft  $i$  consists of decision variables  $\hat{u}_{0:N-1|t}^i, \hat{s}_{0:N|t}^i$  and slack variables  $\epsilon$  with parameters  $\{s_f^i, \bar{s}_{0:N-1}^i, s_t^i\}$ . Moreover,  $\underline{u}^i$  and  $\bar{u}^i$  represents the lower bound and upper bound for the control input. The cost function in (1) minimizes the difference of the predicted trajectory  $\hat{s}_{0:N|t}^i$  with a reference trajectory  $\bar{s}_{0:N-1}^i$  in the sense of the weighted norm defined as  $\|x\|_Q^2 = x^\top Q x$  for any vector  $x$  and positive definite matrix  $Q$  along with the control deviations. The constraints respect the dynamics, separation criterion and control input limits. The reference trajectory of aircraft  $i$ , as well as those of other aircraft, is obtained using intent-based Dubins paths [13], i.e., the complete reference trajectories of other aircraft are assumed to be generated using Dubins paths and are provided as input to the optimization.



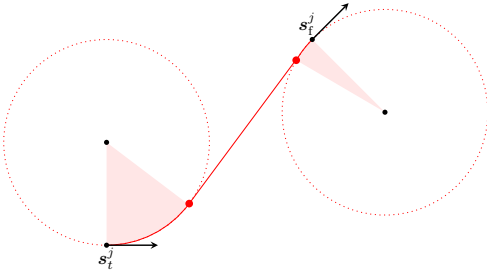


Figure 3. An LSR Dubins path for aircraft  $j$

It is worth noting that, when only one aircraft is equipped with the DAA system and the other aircraft follow their predefined paths without sensor errors or stochastic delays, the slack variables  $\epsilon$  take a value of zero. This is because the other aircraft exactly follow their predicted Dubins paths, and no additional sources of uncertainty are present. In other scenarios, the slack variables may also be zero, depending on whether the system can enforce the soft minimum separation criterion  $\rho$ .

In order to solve MPC (1) for a given aircraft  $i$  one has to feed  $s_f^i$  and  $\bar{s}_k^j, \forall j \in \{1, \dots, n\}$  and  $\forall k \in \{0, \dots, N-1\}$  as parameters to the optimization. Target state  $s_f^i$  is given for any aircraft  $i$ . However, to estimate  $\bar{s}_k^j$  for all aircraft  $\forall j \in \{1, \dots, n\}$ , we use intent information of other aircraft. Intent is modeled as waypoints of other aircraft given by  $s_f^j, \forall j \in \{1, \dots, n\}$  that is available for any aircraft  $i$ . To use these waypoints  $s_f^j$  to generate the entire predicted path  $\bar{s}_k^j, \forall k \in \{0, \dots, N-1\}$  for all other aircraft, we use Dubins path. The Dubins path is tangent to the initial conditions (position and direction) and the next waypoint. It determines the path by specifying maneuvers such as turning left (L) by a certain angle, moving straight (S) for a specific duration, and finally turning right (R) by a certain angle. Compared to a simple projection of past trajectories, Dubins paths explicitly account for kinematic constraints such as bounded turning rate and speed. This makes them better suited to represent intent, which in practice is communicated through waypoints. Thus, Dubins paths provide an appropriate mapping between the current state and target waypoint under aircraft motion constraints [15]. Figure 3 illustrates an example of such a path, denoted as LSR. The red dashed-line circles represent the maximum possible curvature based on the limitations of linear and angular speed. Both geometric [16] and analytical methods [15] are available to compute this optimal path. More specifically, the optimal Dubins path provides a mapping from the initial-target state pair to the path connecting these two states, i.e., for aircraft  $j$ , at time  $t$  the predicted path to use in (1) is given by the following map:

$$\bar{s}_k^j = D(s_t^j, s_f^j, k), \quad 0 \leq k < N,$$

where  $D$  is a mapping from the current state  $s_t^j$ , the target state  $s_f^j$ , and the time index  $k$  to the corresponding optimal connecting states  $\bar{s}_k^j, 0 \leq k < N$ , generating the optimal Dubins path. This mapping can be obtained based on different

types of optimal paths including RSR, RSL, LSR, LSL, RLR, or LRL. The rate of turn is assumed to be either  $-2, 0$ , or  $2$  deg/s. The optimization in (1) is solved simultaneously for all aircraft based on the observation of the current states of other aircraft and a predicted trajectory derived from Dubins path. Subsequently, the MPC policy is executed for all aircraft, the successor states are obtained, and the optimization process is repeated for the next state. More specifically, to incorporate feedback, only the first element  $\hat{u}_0^{i,*}$  of the input sequence  $\hat{u}^{i,*}$  is applied to the system, a successor state  $s_{t+1}^i$  is attained in the next time instance, and the optimization (1) is solved again for the new state  $s_{t+1}^i$ .

### B. MPC Policy with Response Delay

As explained in Section II, the aircraft system often has a delay in executing the control command. In traditional approaches, the computed control advisory is simply shifted by the delay and applied at the appropriate time. More specifically, at time  $t$ , we apply the following policy:

$$\pi_{\text{common}}(s_t^i) = \hat{u}_{0|t-\delta}^{i,*},$$

as the common method of applying controller for the delayed systems, where  $\delta$  is the delay time. However, this can result in poor performance and oscillations, as the system may respond suboptimally to outdated control inputs. MPC provides a more advanced approach to effectively address such delays. Instead of delivering a single control input, MPC generates an entire sequence of optimal control inputs over a specified prediction horizon. This sequence serves as a comprehensive plan that accounts for future system behavior and constraints. As illustrated in Figure 4, rather than merely shifting the control advisory based on the delay (as in common approaches), MPC allows us to align the corresponding control sequence with the system's current state. Specifically, past advisories can be adjusted, and the appropriate element of the sequence can be applied at the current time, ensuring that the control inputs are better synchronized with real-time system needs. In this method, at time  $t$ , we apply the following policy:

$$\pi_{\text{delay}}(s_t^i) = \hat{u}_{\delta|t-\delta}^{i,*}.$$

Note that in the stochastic delay case, the delay  $\delta$  can be replaced by its mean. This ability to utilize the control sequence improves system performance by reducing oscillations and enhancing overall stability as demonstrated in the simulation results (section IV). By leveraging the predictive capabilities of MPC, we ensure that the control inputs remain relevant and effective, even in the presence of delays. This approach is particularly advantageous in scenarios such as aircraft control, where precision and responsiveness are essential.

*Remark 1:* From a safety and operational perspective, the applicability of intent information in tactical DAA systems depends on the reliability of how such data are shared between aircraft. In this study, intent is modeled as waypoints or target states communicated among aircraft, representing an idealized setting in which each aircraft truthfully broadcasts its intended trajectory. While the secure and standardized exchange

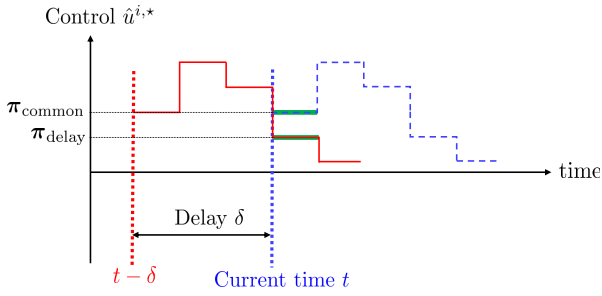


Figure 4. Comparison of the proposed MPC scheme policy for delayed systems with common approaches. The blue dotted-line indicates the current time  $t$ , while the red dotted line represents the shifted time at  $t - \delta$ , with the corresponding predicted optimal control sequence shown in red. The shifted sequence is shown in blue dashed-line. Green lines represent policies executed using common approaches (simple shifting) or by the proposed MPC policy (aligning with the corresponding predicted element).

of intent information is still an open challenge in current air traffic management—one reason why existing systems such as ACAS Xu rely primarily on state measurements—the presented framework demonstrates the potential safety benefit such information can provide once reliable communication protocols are available. In practice, intent sharing could be realized through ADS-B-like or future UTM/ATM data links with appropriate integrity and authentication mechanisms. By isolating the algorithmic benefit of intent awareness under these assumptions, the study highlights its value while remaining compatible with future developments in airspace digitalization.

#### IV. EVALUATION METRICS AND SIMULATION RESULTS

In this section, we provide standard performance and safety evaluation metrics and the results of different encounter-scenarios and response delay for two-aircraft system using the common approach for the delay systems and the proposed method utilizing the MPC control profile.

##### A. Evaluation of the Performance

The following metrics are used for evaluation of the proposed MPC scheme in encounter-scenarios.

- **Loss of DAA Well Clear (LDWC) percentage:** A loss of DAA Well Clear has been defined to occur for en-route cooperative aircraft [17] if the following three conditions all apply: (1) the projected horizontal miss distance (assuming constant speed) is  $\leq 4000$  ft (1219 m), (2) the so-called modified  $\tau$  (for large range approximately the time to pass the range) is less or equal than 35s, and (3) the vertical separation is less or equal than 450ft. The LDWC percentage is the part of the runs in a scenario configuration where an LDWC occurred.
- **Near Mid-Air Collision (NMAC) percentage:** In the ACAS validation studies traditionally NMAC events are used as a key metric. It is defined as vertical miss distance (VMD) being  $< 100$  ft (30.5 m) and horizontal miss distance (HMD) being  $< 500$  ft (152.4 m). The NMAC percentage is the part of the runs where an NMAC occurred.
- **Horizontal Miss Distance (HMD):** The HMD is the distance in the horizontal plane between a pair of aircraft at the

closest point of approach. The mean and standard deviation of the HMD are recorded for each scenario.

- **Additional flight distance (AFD):** As a result of the DAA advisories the trajectory is adapted and additional distance is traversed. The horizontal distance for each aircraft is determined by the integrals of the traversed distance for the original trajectory and the modified trajectory. The additional distance of an aircraft is the difference of the traversed distances plus the distance between the points at the end of the original and modified trajectories. The additional distance in a run is the sum of the additional distances.

Statistics related to cases with stochastic delays or sensor errors are obtained based on 10 Monte Carlo simulation runs.

##### B. Simulation Results

As parameter values for the MPC optimization we have set the soft separation constraint  $\rho = 1.8$  NM, the size of the receding horizon  $N = 120$ , the cost matrix for distances with respect to the waypoints as  $Q_f = Q = 500I$ , and the costs matrix for control input variations as  $R = 1000I$ . The weights in the cost function were set once, by manual tuning within reasonable ranges, to balance trajectory tracking, safety margin enforcement, and advisory smoothness. Importantly, the same parameter set is used across all scenarios without case-specific adjustment, thereby avoiding bias and reflecting a realistic controller configuration. Other parameter values are the same as those used in the ACAS Xu benchmark evaluations [7].

In the considered encounter-scenarios, two aircraft, AC1 and AC2, operate under specific conditions where either only AC2 is equipped with the intent-based MPC strategy or both aircraft are equipped with it. There is no wind, and both aircraft follow planned trajectories that are straight, remain in the horizontal plane, and maintain constant speeds. They fly at the same altitude of 8000 ft (2438 m). All planned aircraft trajectories in an encounter have a HMD of 0 m. AC1 follows a heading of 0 deg, while AC2 may have a heading of 45, 90, 135, or 180 deg. The speed of AC1 is fixed at 120 kt (61.7 m/s), whereas AC2 may travel at either 120 kt (61.7 m/s) or 140 kt (72 m/s). The maximum allowed turning rate is 2 deg/s for both aircraft. Moreover, different delays have been considered as described in Section II, and in some scenarios, sensor errors have also been incorporated.

Figure 5 compares the common MPC policy  $\pi_{\text{common}}$  with the proposed delay-based MPC policy  $\pi_{\text{delay}}$ . As shown, the proposed method reduces the oscillations caused by system delays by leveraging the prediction capabilities of the MPC scheme tailored for delayed systems. Delay-dependent oscillations may arise in DAA sociotechnical systems, as discussed in in [5], [7].

Figures 6–12 visualize different encounter scenarios for two-aircraft conflicts under different delay settings, equipage configurations, and error models. In each subplot, the trajectories of AC1 (red) and AC2 (blue) are shown from their initial positions. A black line connects the points of closest approach, and the corresponding minimum horizontal separation is labeled.

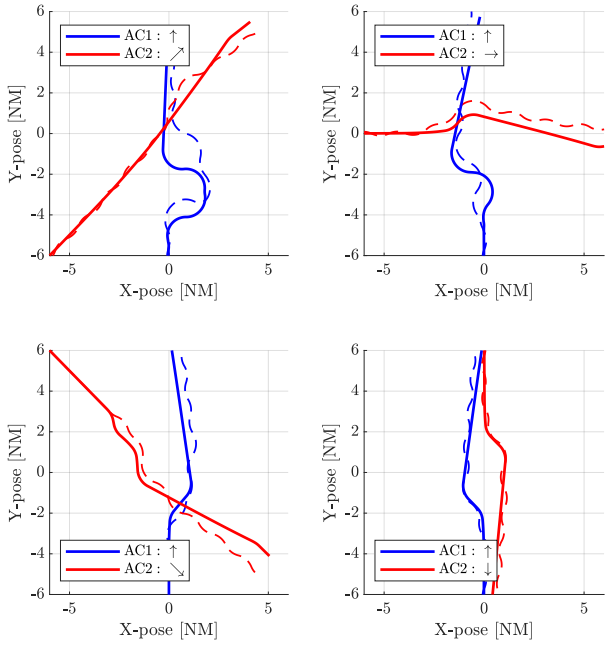


Figure 5. Comparison of the MPC policies  $\pi_{\text{common}}$  (dashed line) and  $\pi_{\text{delay}}$  (solid line) without sensor errors and for both aircraft equipped, with “slow” response delay and same speeds for relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

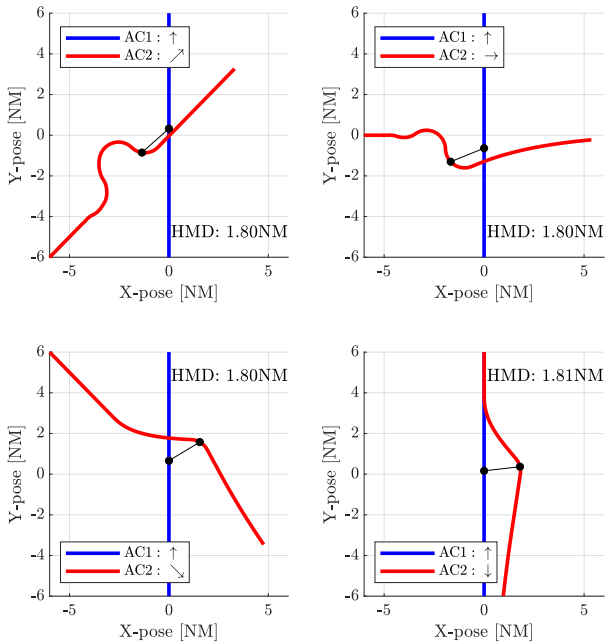


Figure 6. Two-aircraft deterministic encounters (no sensor errors). Only AC2 equipped; “auto” response delay (1 sec); same speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

Figure 6 shows a baseline case where only AC2 is equipped and reacts almost instantly (“auto” delay). The avoidance maneuvers are initially away from the intruder, while later the aircraft turns back to its intended trajectory. The thus induced extra flying distance leads to sufficient separation in the encounters.

In Figure 7, the delay is extended to a “slow” 12 s and the

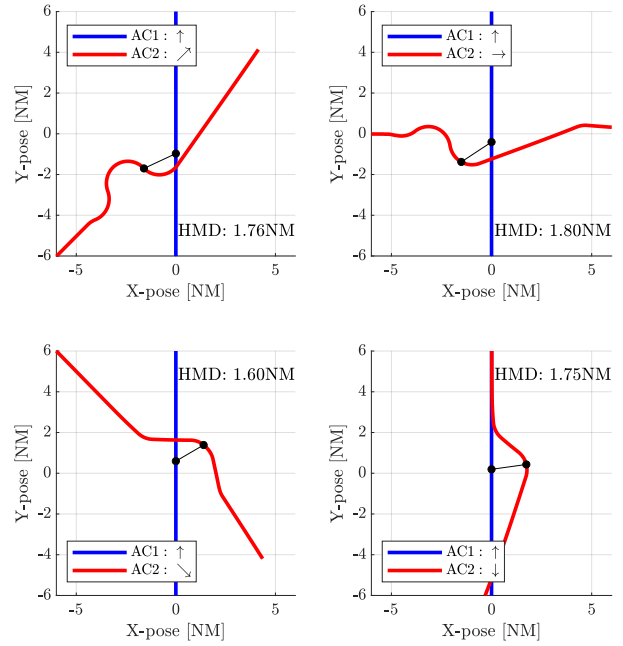


Figure 7. Two-aircraft deterministic encounters (no sensor errors). Only AC2 equipped; “slow” response delay (12 sec); different speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

aircraft fly at different speeds. The minimum distances are reduced compared to Figure 6 up to a HMD of 1.60 NM, thus using some of the slack space w.r.t. the desired minimum distance of 1.8 NM.

Figure 8 considers the case where both aircraft are equipped under the short “auto” delay. Here the avoidance becomes cooperative: each aircraft deviates moderately rather than one aircraft shouldering the full avoidance maneuver. This results in smoother and more symmetric paths, as well as slightly larger horizontal miss distances compared to the single-equipped case of Figure 6.

Figure 9 illustrates the case with both asymmetric speeds and a “quick” 4 s delay while both aircraft are equipped. The MPC again distributes avoidance across both vehicles, producing timely adjustments and maintaining larger separations. The cooperative nature is evident from the symmetric trajectory bending.

Figure 10 shows the result for stochastic delays and sensor errors with only AC2 equipped. The paths show some variability due to uncertainty in sensing and timing.

Figure 11 shows the stochastic setting with both aircraft equipped and “slow” delay. Cooperative behavior again produces conservative separations: each aircraft contributes to the avoidance, leading to wider spacing than in the single-equipped counterpart. Despite the long response lag and noisy state information, sufficient separation is consistently achieved.

Finally, Figure 12 represents a case with both stochastic delays and sensor errors with only AC2 equipped. The 45 deg encounter shows a bifurcation in the strategies: turning towards or away from the intruder based on the stochasticity. The results indicate that the MPC policies are less effective if

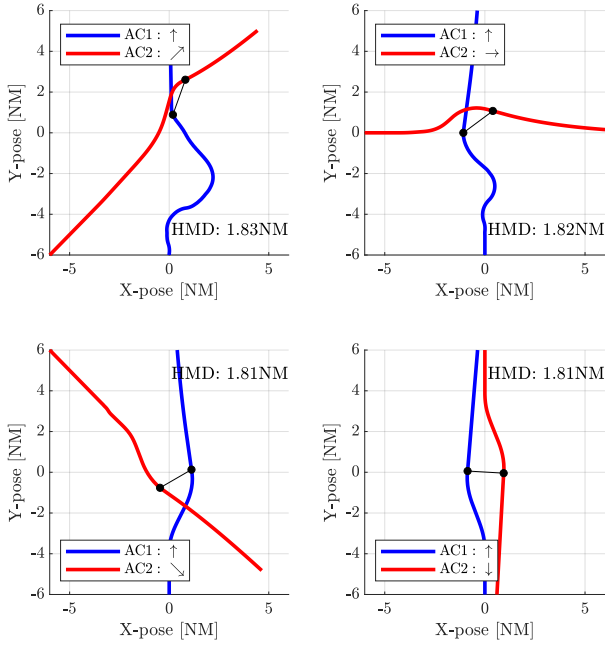


Figure 8. Two-aircraft deterministic encounters (no sensor errors). Both aircraft equipped; “auto” response delay (1 sec); same speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

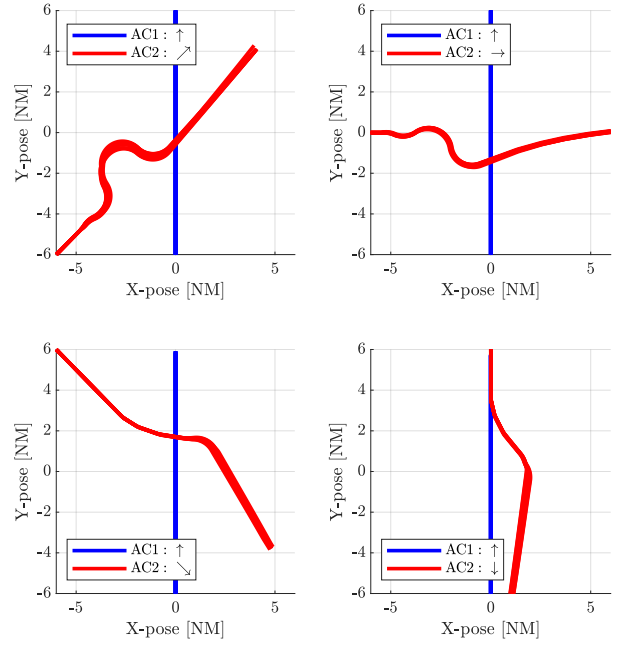


Figure 10. Two-aircraft stochastic encounters with sensor errors. Only AC2 equipped; “quick” response delay (4 sec); different speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

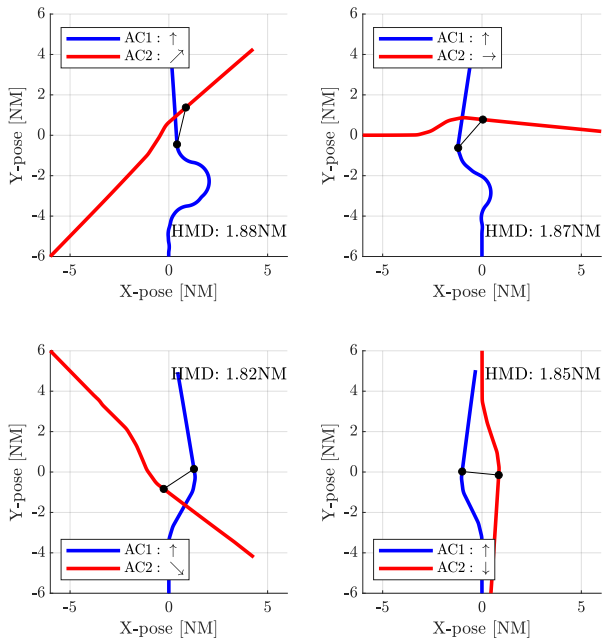


Figure 9. Two-aircraft deterministic encounters (no sensor errors). Both aircraft equipped; “quick” response delay (4 sec); different speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

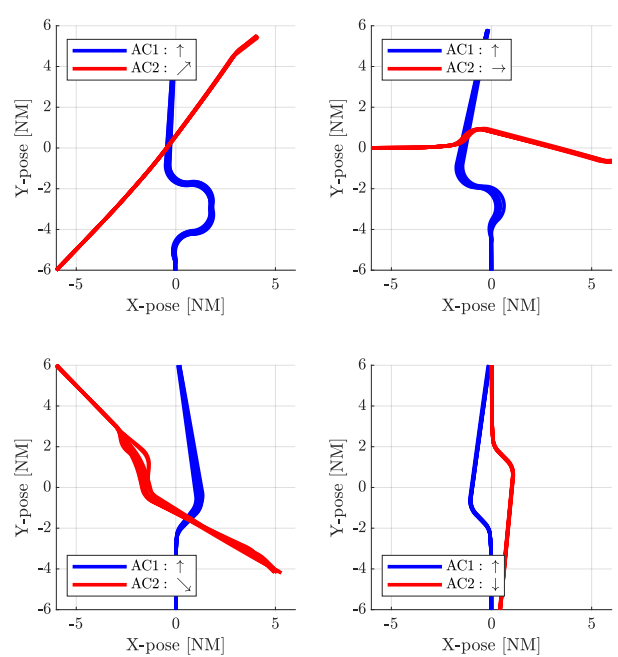


Figure 11. Two-aircraft stochastic encounters with sensor errors. Both aircraft equipped; “slow” response delay (12 sec); same speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

the actual delay differs from the delay assumed in the policy.

In scenarios with longer delays (e.g., Figures 7 and 11), the predictive capability of MPC effectively mitigates the impact of delayed responses and enables efficient avoidance maneuvers. When both aircraft are equipped, mutual intent-awareness facilitates more cooperative behavior, resulting in smaller deviations from planned paths compared to scenarios

where only one aircraft is equipped. This is because each aircraft contributes to the avoidance maneuver, leading to somewhat larger separation distances. In contrast, when only one aircraft is equipped, the avoidance is unilateral and the resulting HMD is closer to the desired minimum separation criterion. This cooperative adjustment therefore explains the

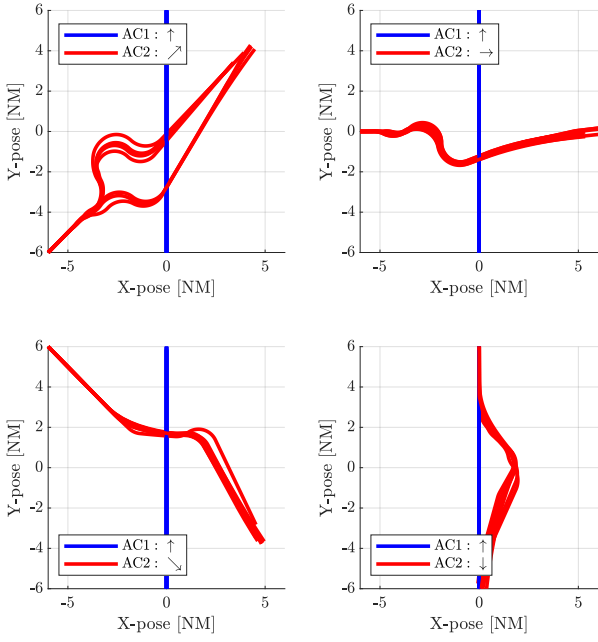


Figure 12. Two-aircraft stochastic encounters with sensor errors. Only AC2 equipped; stochastic response delays (lognormal); same speeds. Subplots: relative headings 45 deg (top-left), 90 deg (top-right), 135 deg (bottom-left), 180 deg (bottom-right).

increase in HMD in the dual-equipped scenarios. The proposed MPC approach shows robustness across all conditions, by achieving the desired destination while maintaining sufficient separation even under delays and sensor noise, regardless of whether only one or both aircraft are equipped with the DAA system. Figure 13 illustrates the distance between two aircraft across various encounter scenarios, along with the minimum distance observed in each case. The minimum distance for the hard constraints in the set of encounters is 2 NM, while the minimum distance for the soft constraints over all encounters is 1.2 NM, demonstrating the effectiveness of the proposed MPC in maintaining safe distances. Note that, through the soft constraints, feasibility of MPC is always ensured.

Figure 14 shows the computation time for a single aircraft in the two-aircraft simulation scenario for different encounter-scenarios, providing insight into the computational complexity of the proposed method. The simulations were executed on a standard laptop equipped with an 11th Gen Intel(R) Core(TM) i5-1145G7 processor (2.60GHz, base frequency 1.50GHz). As shown, the average computation time is approximately 300 sec to simulate 600 sec of aircraft operation. Note that, one MPC optimization is solved per equipped aircraft at every one-second sample time. The variance in computation time reflects differences across scenarios (e.g., deterministic vs. stochastic and encounter geometry), and the reported times are from a MATLAB implementation on a standard laptop.

For brevity, only a representative subset of encounter scenarios is illustrated in these figures. These cases were selected to highlight the most characteristic behaviors observed in the study—such as differences between single- and dual-equipped configurations, deterministic and stochastic delay

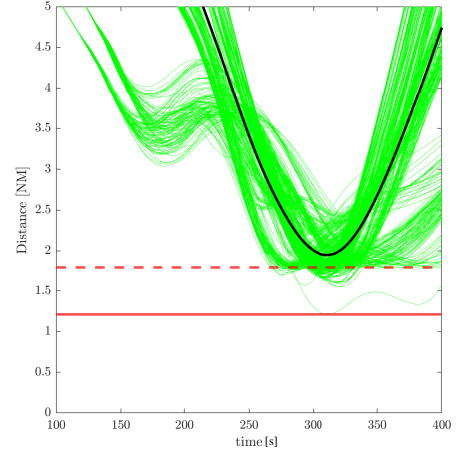


Figure 13. The distance of two aircraft for the different encounter-scenarios using the proposed intent-aware MPC approach. The minimum distance among all encounter-scenario is shown in solid red, the soft constraint threshold of MPC is shown in dashed-line and the average is shown in black.

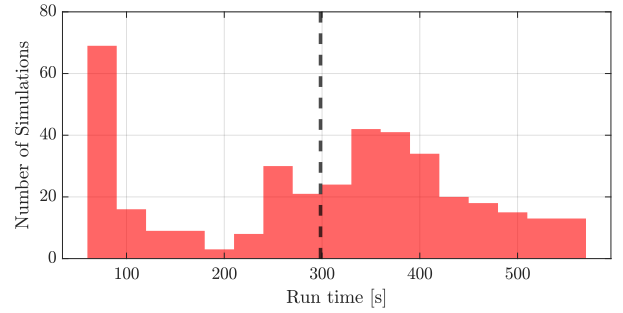


Figure 14. Computation time for different encounter-scenarios using the proposed MPC method on a standard laptop.

models, and cooperative versus unilateral avoidance responses. The complete set of evaluated scenarios follows the same qualitative trends and is fully reflected in the quantitative results summarized in Table I.

The evaluation metrics in Table I show that the MPC approach achieves substantially fewer well-clear violations, with 0% in the deterministic case and 2.5% in the stochastic case, compared to ACAS Xu with 12.5% and 24.65%, respectively. Moreover, MPC produces no NMACs in any scenario, whereas ACAS Xu averages 2.08% in the deterministic case and 0.15% in the stochastic case. Overall, MPC consistently outperforms the ACAS Xu benchmarks. The table also summarizes improvements in HMD and AFD, further validating the effectiveness of the proposed method under various uncertainties.

A closer examination of individual scenarios reveals the qualitative differences between the two approaches. ACAS Xu advisories may induce oscillatory or livelock-type maneuvers—consistent with observations in [5], [7]—because the RP model turns the aircraft to the closest edge of the RWC bands and steers back to its original course if possible. The MPC controller, by contrast, generates a smooth, cooperative avoidance through its horizon-based optimization and continuous feedback update, thereby maintaining larger horizontal miss distances and less well-clear losses. These

TABLE I. STATISTICS OF DETERMINISTIC AND STOCHASTIC ENCOUNTER-SCENARIOS USING MPC (BLUE-DOWN) AND ACAS XU (BLACK-UP).

Scenario				Results					
Delay	Sensor Errors	DAA Equipped	Type	LDWC (%)	NMAC (%)	HMD (m)		AFD (m)	
						Mean	SD	Mean	SD
auto	no	partial	det.	12.50 %	0.000 %	1905	162	4767	4605
				0.000 %	0.000 %	3339	9	2133	1205
quick	no	partial	det.	12.50 %	0.000 %	1923	173	4920	4603
				0.000 %	0.000 %	3327	35	2217	1042
slow	no	partial	det.	12.50 %	0.000 %	2048	330	5974	4496
				0.000 %	0.000 %	3217	122	2520	653
auto	no	all	det.	12.50 %	0.000 %	2357	267	12564	11847
				0.000 %	0.000 %	3368	22	1763	1331
quick	no	all	det.	0.000 %	0.000 %	2183	117	12474	12026
				0.000 %	0.000 %	3405	47	1867	1252
slow	no	all	det.	25.00 %	12.50 %	2292	1071	7544	2854
				0.000 %	0.000 %	3932	322	2691	1231
<i>Average</i>				12.50 %	2.08 %	2118	513	8041	8375
auto	yes	partial	stoch.	27.00 %	0.000 %	2024	492	4979	4691
				12.50 %	0.000 %	3347	56	2221	1194
quick	yes	partial	stoch.	29.25 %	0.000 %	2036	536	5300	4806
				0.000 %	0.000 %	3327	72	2259	1044
slow	yes	partial	stoch.	50.63 %	0.250 %	1861	666	6244	5036
				12.50 %	0.000 %	3210	184	2660	1082
auto	yes	all	stoch.	13.50 %	0.125 %	2235	476	12898	14352
				0.000 %	0.000 %	3367	56	1751	1255
quick	yes	all	stoch.	14.75 %	0.375 %	2196	526	12190	12873
				0.000 %	0.000 %	3393	63	1863	1146
slow	yes	all	stoch.	38.00 %	0.375 %	2134	729	10207	9376
				0.000 %	0.000 %	3962	286	2705	1225
stoch	no	partial	stoch.	15.00 %	0.000 %	1935	180	4971	4629
				0.000 %	0.000 %	3296	114	2212	864
stoch	no	all	stoch.	10.63 %	0.250 %	2123	257	11227	13894
				0.000 %	0.000 %	3396	46	1879	1154
stoch	yes	partial	stoch.	31.25 %	0.000 %	1996	533	5289	4822
				0.000 %	0.000 %	3312	87	2150	683
stoch	yes	all	stoch.	16.50 %	0.125 %	2183	526	11981	12826
				0.000 %	0.000 %	3531	209	1987	1230
<i>Average</i>				24.65 %	0.15 %	2072	529	8529	10189
				2.50 %	0.000 %	3414	243	2169	1143

behavioral differences explain the quantitative performance gaps observed in Table I.

## V. CONCLUSION

In this paper, we proposed an intent-aware Model Predictive Control (MPC) for multi-aircraft detect-and-avoid and compared its performance with ACAS Xu using standard evaluation metrics. By leveraging intent information and optimizing advisories over a receding horizon, the proposed MPC improves decision-making under various conditions, including sensor errors and deterministic and stochastic delays. Our comparative analysis across various encounter scenarios showed that the MPC reduces the risk of near mid-air collisions and improves safety metrics, thereby outperforming ACAS Xu in all tested scenarios. Furthermore, our results highlight the advantage of utilizing the entire predicted control sequence to mitigate delay effects, rather than simple shifting strategies. While our evaluation is conducted on a two-aircraft horizontal kinematic model, the methodological elements of the framework are general and can be extended to richer dynamics and multi-aircraft settings. Future work will focus on extending this approach to more complex air traffic environments and improving computational efficiency for real-time large-scale multi-agent systems.

The present study focuses on horizontal conflict resolution between multi fixed-wing aircraft under standardized encounter geometries. Although this setting allows a direct and fair

comparison with ACAS Xu, it does not yet capture the broader variability in multi-vehicle dynamics. In particular, multicopter platforms exhibit distinct maneuverability characteristics, including the ability to hover or stop, which would require modified kinematic models and control formulations. Similarly, operation in very low-level environments with static or dynamic obstacles would necessitate incorporating more obstacle avoidance constraints within the MPC optimization. Furthermore, while MPC offers transparent optimization and constraint handling, it also entails higher computational demands and parameter-tuning effort compared to the rule-based ACAS Xu logic. These aspects define the main limitations of the current work and outline promising directions for future extensions.

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