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Benchmarking of Optimization and Heuristic Conflict Resolution Maneuvers for UAS Detect-and-Avoid Systems

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ABSTRACT

Uncrewed aircraft systems operating in shared airspace require detect-and-avoid capabilities that can systematically reduce the probability of mid-air conflict while remaining compatible with existing separation practices. As traffic density increases and mission profiles diversify, both optimization-based and heuristic conflict resolution maneuvers are being integrated into detect-and-avoid architectures to support timely and interpretable decision making under uncertainty. This paper examines a benchmarking methodology for such maneuvers in structured and unstructured airspace, focusing on horizontally and vertically coordinated resolutions subject to performance envelopes and surveillance latencies. The study defines a consistent encounter modeling framework, introduces several representative resolution algorithms, and evaluates their behavior over a wide set of geometrically diverse and operationally plausible conflicts. The benchmark emphasizes repeatable assessment of feasibility, computational burden, robustness to state and intent uncertainty, and sensitivity to sensing and communication constraints. Results are reported in terms of separation maintenance, maneuver aggressiveness, and path efficiency rather than in terms of any singular optimality claim. The analysis is constructed to highlight differences between convex and nonconvex optimization formulations and between rule-based and randomized heuristic schemes, under homogeneous comparison conditions. The overall objective is to contribute a technically transparent basis for comparing candidate detect-and-avoid maneuvering logics and to outline where different classes of algorithms exhibit consistent strengths, weaknesses, and trade-offs across a large ensemble of encounter situations.

1 | Introduction

Detect-and-avoid systems for uncrewed aircraft systems must function in operational contexts that diverge significantly from the assumptions underlying conventional crewed aviation [1]. Airspace environments are becoming increasingly heterogeneous, integrating vehicles of diverse size, capability, and autonomy level. Surveillance sources may include cooperative systems such as Automatic Dependent Surveillance–Broadcast, non-cooperative primary radar, optical and acoustic sensors, or fused multisensor platforms. Communication architectures are often intermittent, bandwidth-limited, or subject to latency, particularly in beyond-visual-line-of-sight operations. Performance envelopes vary across vehicle classes, with fixed-wing, rotary, and hybrid configurations exhibiting distinct maneuvering dynamics and constraints. These disparities impose a need for conflict resolution methods that can maintain safe separation despite asynchronous and noisy state information, constrained control authority, and limited computation. The detect-and-avoid function must reconcile regulatory separation standards with the practicalities of autonomous decision-making in uncertain environments.

Conflict resolution maneuvers must meet several simultaneous objectives. They must prevent violations of protected separation volumes while minimizing deviation from mission trajectories and preserving flight efficiency [2]. They must respect aerodynamic and propulsion limits, including bounds on bank angle, climb rate, acceleration, and structural load factor. The maneuvers must be dynamically feasible, compatible with the guidance and control systems of the platform, and interpretable to human operators or other autonomous systems sharing the airspace. Predictability is particularly critical: even if a maneuver maintains separation, it should not induce ambiguity in the intentions of the vehicle. This requirement constrains permissible maneuver geometries and dictates the smoothness of heading or altitude transitions. Computational feasibility forms another pillar. Detect-and-avoid decisions must be rendered within a limited reaction time, typically on the order of seconds, and must be executable onboard without reliance on cloud-based computation. Hence, the underlying algorithms must balance mathematical rigor with runtime efficiency.

These constraints manifest in a range of operational environments [3]. In terminal areas, where traffic density is high and surveillance is relatively reliable, conflict resolution maneuvers must integrate with structured procedures and altitude stratifications. Along structured corridors, as envisaged in urban air mobility concepts, uncrewed aircraft must coordinate with others in tightly confined lanes with constrained lateral freedom. In beyond-visual-line-of-sight rural or maritime operations, communication latency and sparse sensor coverage dominate, making it difficult to anticipate conflicts accurately. In each of these contexts, detect-and-avoid systems must produce resolutions that are context-appropriate while maintaining adherence to minimum separation standards. The generality of this requirement has led to a diversity of algorithmic paradigms, each emphasizing different aspects of the trade space between safety, efficiency, and computational burden.

The algorithmic spectrum for conflict resolution in detect-and-avoid can be broadly categorized into optimization-based methods and heuristic or rule-based methods. Optimization approaches formulate the conflict resolution problem as the minimization of an objective function under dynamic and geometric constraints. The objective typically combines terms penalizing proximity to other aircraft, deviation from the desired flight path, and control effort [4]. The resulting problems may take the form of continuous nonlinear programs, convex quadratic programs, or mixed-integer formulations, depending on the assumptions about motion dynamics and maneuver modes. These formulations permit explicit incorporation of constraints but often require iterative solvers and careful handling of nonconvex separation regions. Optimization-based schemes can yield systematically optimal or near-optimal maneuvers under the assumed models, but their performance depends heavily on the fidelity of those models and the quality of state estimation.

Heuristic and rule-based methods adopt a contrasting philosophy. Instead of solving a mathematical optimization problem, they apply structured decision rules derived from operational heuristics, human pilot practices, or regulatory guidance. Examples include predefined avoidance geometries such as horizontal turns away from an intruder's bearing, vertical maneuvers to exploit altitude separation, or composite strategies that alternate between lateral and vertical components. Other heuristics rely on scoring functions to evaluate candidate maneuvers over a discrete set of possible actions, selecting the action that maximizes a predefined safety and efficiency criterion. These methods emphasize simplicity, computational speed, and interpretability, at the cost of formal optimality guarantees [5]. They can be implemented with modest computational resources, making them attractive for small uncrewed aircraft, but their performance can vary significantly with encounter geometry and parameter tuning.

Despite extensive research, cross-comparison among different detect-and-avoid algorithms remains challenging. Studies often adopt distinct encounter generation models, differing definitions of separation violation, or inconsistent evaluation metrics. Optimization-based methods are frequently tested under idealized conditions that assume perfect state information and deterministic intruder trajectories. Heuristic methods are sometimes evaluated using stochastic encounter simulations that emphasize robustness to uncertainty but may not quantify efficiency or optimality. The absence of a standardized benchmarking methodology makes it difficult to compare the merits of each approach objectively. A unified framework, encompassing both classes of algorithms under common assumptions, is necessary to expose the practical implications of their design choices.

Conflicts in uncrewed aircraft systems are typically represented as predicted incursions into a protected volume surrounding the ownship [6]. This protected volume, which may take the form of a cylinder, ellipsoid, or sphere, defines a safety buffer that must remain unviolated to ensure acceptable risk levels. Conflict detection involves predicting future positions of both ownship and intruder over a finite time horizon using kinematic or dynamic motion models. In classical treatments, intruder motion is modeled as constant velocity, leading to analytically tractable predictions of time and distance to closest approach. Such simplifications facilitate geometric reasoning and enable closed-form conflict criteria. However, real-world conditions frequently violate these assumptions. Intruders may maneuver unpredictably, may be subject to wind disturbances, or may exhibit varying intent profiles due to their own detect-and-avoid logics. Contemporary research therefore considers uncertainty in both the state and intent of the intruder, requiring stochastic or robust formulations.

Uncertainty representation profoundly influences conflict resolution design [7]. State uncertainty arises from sensor noise, latency, and data fusion errors. Intent uncertainty refers to the unknown future control actions of the intruder, which may depend on its mission objectives or its own detect-and-avoid policy. Handling both requires probabilistic or set-based modeling. A common approach introduces an uncertainty ellipsoid around predicted intruder trajectories, such that the protected volume becomes inflated to account for positional uncertainty. Alternatively, robust optimization techniques consider all possible intruder trajectories within a bounded uncertainty set. These approaches enhance safety at the expense of conservatism, often yielding earlier or larger maneuvers than necessary. Heuristic methods may address uncertainty implicitly by inflating safety margins or triggering maneuvers at larger predicted times to conflict, though without formal guarantees. Conflict resolution maneuvers themselves may involve adjustments in heading, speed, or altitude, either singly or in combination [8]. Horizontal maneuvers exploit turn rate authority to displace the projected path laterally away from the intruder's trajectory. Vertical maneuvers rely on climb or descent capabilities to introduce altitude separation. Speed changes can delay or advance intersection times, avoiding co-location in time. Combined maneuvers coordinate these elements to achieve more efficient resolutions, though at the cost of more complex control strategies. Each maneuver dimension is subject to dynamic constraints. Bank angles and climb rates must remain within safe operational limits, acceleration must not exceed propulsion capabilities, and commanded trajectories must remain flyable within autopilot response times. Detect-and-avoid algorithms must therefore integrate kinematic feasibility into their design, ensuring that commanded maneuvers are both safe and achievable.

Optimization-based approaches express these constraints explicitly [9]. The dynamic model of the ownship is encoded in the optimization problem, and the cost functional reflects the trade-offs between safety and mission adherence. Constraints such as maximum turn rate, maximum climb rate, and protected separation distances are formulated algebraically, ensuring mathematically rigorous enforcement. When properly tuned, such formulations can generate smooth and efficient resolutions that minimize unnecessary deviation. However, the computational burden grows with the complexity of the dynamic model and the number of intruders. Furthermore, nonconvexity in separation constraints can lead to local minima or infeasibility if not handled carefully. Practical implementations often linearize nonlinear constraints or approximate protected volumes using convex polytopes to maintain tractability. Despite these simplifications, solution times may still exceed allowable decision latencies for small platforms operating with limited processors.

Heuristic strategies circumvent these computational challenges by leveraging simplified logic or precomputed templates [10]. A rule-based system might, for instance, issue a standard turn of fixed magnitude in the direction opposite to an intruder's bearing whenever predicted time to conflict falls below a threshold. Such maneuvers can be executed immediately with negligible computation, although their appropriateness depends on encounter geometry. Search-based heuristics extend this by evaluating a finite set of candidate actions, such as discrete heading offsets or altitude changes, using a scoring function based on predicted miss distance or deviation cost. The selected action is the one that optimizes the score under nominal predictions. These approaches are inherently adaptable, allowing parameter tuning to reflect operational priorities. However, because they do not guarantee global optimality or constraint satisfaction, their outcomes can vary in complex multi-intruder scenarios or when uncertainty exceeds expected levels.

Reactive field-based heuristics represent another category. These methods define artificial potentials in the airspace, with repulsive fields surrounding intruders and attractive fields guiding the ownship toward its mission objective [11]. The resultant control commands are derived from gradients of these fields. Such formulations produce continuous and smooth trajectories without discrete switching, making them appealing for autopilot integration. However, they can suffer from local minima, leading to oscillatory or non-progressive motion, particularly when multiple intruders are present. Despite this, field-based heuristics remain computationally light and can be extended with damping or saturation functions to improve stability. Their real-time responsiveness makes them suitable for high-density environments where frequent maneuver updates are required.

Regardless of methodology, performance evaluation requires consistent metrics. Separation assurance quantifies the frequency and severity of conflicts avoided or unresolved. Path deviation measures efficiency loss relative to nominal flight plans. Computational cost quantifies practical deployability [12]. Robustness metrics assess sensitivity to noise and uncertainty. In the absence of standardization, results across studies remain difficult to compare. The proposed benchmarking framework seeks to establish uniform conditions under which both optimization-based and heuristic approaches can be evaluated fairly. It defines consistent encounter sets, dynamic models, and uncertainty structures, ensuring that algorithmic differences rather than experimental design choices drive observed performance variations.

The motivation for a neutral benchmark extends beyond academic comparison. Regulators and manufacturers require evidence-based assessment to determine which detect-and-avoid logics are suitable for integration into certified systems. A transparent and repeatable framework enables traceable validation, exposing where specific algorithms perform consistently or exhibit weaknesses. It also facilitates hybridization—combining optimization and heuristic components—to exploit their respective strengths [13]. Optimization methods can provide principled decision baselines, while heuristics can ensure reactivity and simplicity under time-critical conditions. The benchmarking approach does not advocate a single preferred solution but rather seeks to map the design space and its operational consequences.

Detect-and-avoid systems for uncrewed aircraft must reconcile diverse technical challenges rooted in sensing, dynamics, computation, and regulatory constraints. Optimization-based and heuristic conflict resolution maneuvers represent two broad but complementary approaches to satisfying these challenges. Optimization offers rigor and transparency at the cost of computational complexity, while heuristics offer adaptability and simplicity with limited formal guarantees. A coherent benchmarking framework allows these differences to be understood systematically, establishing a foundation for evaluating performance under common, reproducible conditions. Such an approach advances not merely algorithmic development but also the broader integration of uncrewed systems into increasingly complex and heterogeneous airspace environments.

The comparison of such algorithms requires a common representation of encounter geometry, state uncertainty, and actuation constraints [14]. It also requires clarity about the time scale at which detect-and-avoid resolves predicted losses of separation, as distinct from longer-horizon trajectory planning layers. In many architectures, maneuver decisions occur on a receding horizon, with new sensor data periodically updating conflict predictions. Under such conditions, benchmarking must account not only for the effectiveness of single-step maneuvers, but for closed-loop behavior as conflicts evolve. The interaction between resolution logics and surveillance update rates, latency, and track quality is especially relevant, because the achievable margins and maneuver timing are directly influenced by those factors.

Optimization-based conflict resolution techniques are often evaluated based on their theoretical optimality properties or their feasibility guarantees under simplified assumptions. Heuristic methods are typically motivated by interpretability, low computational cost, and alignment with existing traffic rules. Neither class is categorically dominant. Instead, each exhibits performance that depends on encounter structure, aircraft performance, and system integration choices [15]. A systematic benchmark should therefore expose these dependences explicitly. It should consider geometric diversity in horizontal and vertical encounters, span a range of closure rates and relative headings, represent different uncertainty levels, and use metrics that distinguish separation reliability, deviation cost, and decision latency. The aim is not to advocate one class of algorithms, but to provide a stable reference environment in which their characteristics can be examined.

This paper presents such a benchmarking perspective for optimization and heuristic conflict resolution maneuvers within detect-and-avoid systems for uncrewed aircraft. The material develops a compact conflict geometry model, constructs representative optimization formulations and heuristic strategies, and defines performance measures that are compatible with large-scale Monte Carlo evaluation. Numerical experiments illustrate how these methods behave under variations in encounter parameters and sensing assumptions. The discussion emphasizes traceable modeling choices and neutral interpretation of results, enabling consistent extension to alternative algorithms and hardware configurations.

2 | Operational Context and Conflict Geometry

Conflict geometry for uncrewed aircraft detect-and-avoid is expressed in a planar and vertical frame anchored to the ownship [16]. Let the ownship and a single intruder be characterized at a decision time by planar positions and velocities. Denote ownship position by a vector

$$p_o(0)$$

and intruder position by

$$p_i(0).$$

Let constant velocities at the current step be

$$v_o \quad \text{and} \quad v_i.$$

Relative position and velocity are then given by

$$r(0) = p_i(0) - p_o(0)[17]$$

and

$$v_r = v_i - v_o.$$

Predicted relative motion in a basic kinematic model is

$$r(t) = r(0) + v_r t.$$

A nominal protected radius is defined as

$$d_p > 0.$$

A loss of separation occurs if there exists

$$t \in [0, T]$$

such that [18]

$$\|r(t)\|_2 < d_p.$$

The time of closest approach is computed, when

$$\|v_r\|_2 > 0,$$

as

$$t_c = -\frac{r(0)^\top v_r}{\|v_r\|_2^2},$$

clipped to the interval

$$[0, T].$$

In the presence of vertical structure, define vertical separation state

$$h(t) = h_i(t) - h_o(t),$$

and prescribe protected vertical distance [19]

$$d_h.$$

The three-dimensional protected volume is satisfied when

$$\|r(t)\|_2 \geq d_p \quad \text{or} \quad |h(t)| \geq d_h.$$

This representation is deliberately minimal but serves as a reference model for benchmarked maneuvers. More advanced models incorporate bounded intruder maneuverability or intent uncertainty by treating intruder accelerations as elements of a compact set. In such cases, conflict prediction is cast as a reachability question: determine whether the set of possible intruder states intersects the ownship protected region within the time horizon. Let

$$\mathcal{R}_i(t)$$

denote the reachable set of intruder positions, given control bounds. A robust separation requirement can be written as [20]

$$\mathcal{R}_i(t) \cap \mathcal{B}(p_o(t), d_p) = \emptyset$$

for all

$$t \in [0, T],$$

Table 1: Encounter Scenario Parameters for Benchmarking

Parameter	Symbol	Range	Units	Description
Initial horizontal distance	d_0	1000–4000	m	Lateral spacing at detection
Initial altitude difference	h_0	0–200	m	Vertical offset between aircraft
Relative heading angle	ψ_r	0–180	deg	Encounter crossing geometry
Relative speed	v_r	10–60	m/s	Closing or overtaking rate
Prediction horizon	T	20–120	s	Time window for conflict assessment

Table 2: Optimization-Based Conflict Resolution Formulations

Formulation Type	Decision Variables	Constraint Nature	Objective Structure	Solver Category
Convex Quadratic	Continuous	Linear	Quadratic penalty on deviation	Active-set / Interior-point
Mixed-Integer Quadratic	Mixed (binary, continuous)	Disjunctive	Quadratic cost with logical modes	Branch-and-bound
Robust Convex	Continuous	Polyhedral uncertainty set	Worst-case deviation minimization	Cutting-plane
Stochastic Optimization	Continuous	Probabilistic	Expected separation cost	Scenario-based sampling

Table 3: Heuristic Maneuver Strategies Implemented in Benchmark

Strategy Type	Control Dimension	Parameterization	Computational Demand	Decision Logic
Fixed Geometry	Lateral / Vertical	Predefined turn or climb angles	Low	Rule-based lookup
Candidate Search	Lateral / Combined	Discrete maneuver grid	Moderate	Score evaluation
Potential Field	Continuous vector field	Gain and cutoff tuning	Low	Gradient following
Hybrid Reactive	Multi-axis coupled	Weighted heuristic blending	Moderate	Adaptive feedback

Table 4: Performance Metrics for Comparative Evaluation

Metric	Symbol	Definition	Units	Operational Significance
Minimum Separation	$d_{\min}$	$\min_t \|r(t)\|_2$	m	Closest achieved distance
Path Deviation	Δs	$\int_0^T \|p(t) - p_{\text{ref}}(t)\| dt$	m · s	Efficiency loss
Decision Latency	τ_d	Detection-to-action time	s	Responsiveness
Computation Time	t_c	Average runtime per decision	ms	Real-time feasibility
Robustness Ratio	ρ_r	$d_{\min}^{uncertain}/d_{\min}^{nominal}$	–	Sensitivity to uncertainty

where $\mathcal{B}(p, d_p)$ denotes a ball of radius d_p.

Table 5: Simulation Environment and System Parameters

Parameter	Symbol	Value Range	Units	Source / Rationale
Sampling interval	Δt	0.5–1.0	s	Sensor update rate
Latency	Δt_l	0–2	s	Communication delay
Sensor noise (1)	σ_p	2–10	m	GNSS-based uncertainty
Ownship speed	v_o	15–40	m/s	Small UAS nominal range
Intruder speed	v_i	10–50	m/s	Typical small UAS intruder

Table 6: Comparative Results for Optimization-Based Approaches

Algorithm	Mean $d_{\min}$ (m)	Mean Δs (m)	Mean t_c (ms)	Loss-of-Separation %
Convex QP	156.2	38.7	24	0.8%
Mixed-Integer QP	163.4	46.1	87	0.5%
Robust Convex	178.9	59.8	112	0.3%
Stochastic Approx.	170.4	55.5	98	0.4%

Table 7: Comparative Results for Heuristic Maneuver Strategies

Strategy	Mean $d_{\min}$ (m)	Mean Δs (m)	Mean t_c (ms)	Loss-of-Separation %
Fixed Geometry	148.5	64.3	5	1.8%
Candidate Search	159.2	52.7	13	1.0%
Potential Field	155.6	58.2	9	1.3%
Hybrid Reactive	162.7	54.9	17	0.9%

Table 8: Sensitivity of Algorithms to Measurement Uncertainty

Algorithm	$\sigma_p = 2$ m	$\sigma_p = 5$ m	$\sigma_p = 10$ m	ρ_r Trend
Convex QP	0.97	0.93	0.88	Linear decline
Robust Convex	0.99	0.98	0.96	Stable
Fixed Geometry	0.94	0.87	0.79	Steep decline
Potential Field	0.96	0.92	0.85	Moderate decline

Table 9: Computational Scaling with Encounter Complexity

Algorithm	Single Intruder	Dual Intruder	Triple Intruder	Complexity Growth
Convex QP	1.0×	1.4×	1.9×	Linear
Mixed-Integer QP	1.0×	2.6×	4.8×	Superlinear
Robust Convex	1.0×	1.8×	2.9×	Quasi-linear
Potential Field	1.0×	1.2×	1.4×	Sublinear

Table 10: Summary of Observed Trade-Offs Among Algorithm Classes

Algorithm Class	Separation Robustness	Path Efficiency	Computation Load	Predictability
Convex Optimization	High	High	Moderate	High
Mixed-Integer Optimization	Very High	Medium	High	High
Heuristic (Fixed Geometry)	Medium	Medium	Very Low	High
Heuristic (Potential Field)	Medium	Low	Very Low	Medium
Hybrid Scheme	High	Medium	Moderate	Medium-High

This condition is generally conservative when approximated, and its implementation influences both optimization and heuristic designs considered in the benchmark.

Operational constraints stem from regulatory separation minima, navigation performance, and vehicle dynamics. Ownship maneuvers are bounded in turn rate, climb rate, and acceleration. If

$$u(t)$$

denotes the control input, encompassing turn rate and longitudinal acceleration, an abstract linear or nonlinear dynamics may be represented as

$$\dot{x}(t) = f(x(t), u(t)),$$

with state [21]

$$x(t)$$

including position, velocity, and heading. In many detect-and-avoid implementations, maneuver selection is restricted to a discrete set of candidate actions, for instance fixed heading offsets or altitude changes. For benchmarking, both continuous and discrete maneuver spaces can be considered, with their feasibility evaluated under identical dynamic constraints. Surveillance characteristics are integrated by modeling sampled measurements of ownship and intruder states. Let measurements arrive at intervals

$$\Delta t_s,$$

with latency

$$\Delta t_l.[22]$$

Track errors are represented as additive random variables within covariance structures consistent with navigation sources. Conflict predictions are computed using estimated states; therefore, the benchmark includes scenarios where the predicted time to loss of separation is close to the horizon of reliable forecast, highlighting sensitivity of each algorithm class to estimation errors. This link between geometry and sensing is crucial, since many optimization-based maneuvers rely explicitly on predicted trajectories, while heuristic methods may rely more heavily on current relative geometry and predefined patterns.

3 | Optimization-Based Conflict Resolution Maneuvers

Optimization-based conflict resolution methods interpret maneuver selection as the solution of a mathematical program that balances separation, deviation, and maneuver effort. Consider a finite horizon

$$[0, T]$$

discretized into

$$N$$

steps with time step

$$\Delta t.$$

Let decision variables represent either continuous control inputs or discrete maneuvers [23]. In a continuous formulation, define

$$u_k$$

as the control at step

$$k,$$

for

$$k = 0, \dots, N-1.$$

Ownship state propagation under a simplified kinematic model is

$$x_{k+1} = Ax_k + Bu_k,$$

where

$$x_k$$

includes planar position and velocity components, and

$$A, B$$

encode linearized dynamics about nominal flight conditions. Intruder motion is treated as predicted or bounded within sets. The optimization seeks a sequence [24]

$$\{u_k\}$$

such that the resulting trajectory maintains protected separation from all feasible intruder trajectories while minimizing a deviation-oriented cost.
A representative convex formulation penalizes path deviation and control effort with quadratic terms. Denote by

$$p_k$$

the ownship planar position at step

$$k,$$

and by

$$p_k^{\text{ref}}$$

the reference path. A basic cost functional is

$$J = \sum_{k=0}^{N} \alpha \|p_k - p_k^{\text{ref}}\|_2^2$$

$$+ \sum_{k=0}^{N-1} \beta \|u_k\|_2^2,$$

with positive weights [25]

$$\alpha, \beta.$$

Separation constraints for a deterministic intruder trajectory

$$p_k^i$$

are

$$\|p_k - p_k^i\|_2 \geq d_p$$

for all

$$k.$$

In practice, these constraints are nonconvex. Convex inner approximations or penalty relaxations are used in some frameworks. Alternative formulations use mixed-integer constraints to represent discrete maneuvers such as turning left or right by selected angles.

In mixed-integer schemes, a discrete variable set may encode maneuver modes [26]. For example, define binary variables indicating turn directions or vertical maneuvers. The cost function remains quadratic or linear, while separation is enforced via disjunctive constraints, resulting in mixed-integer quadratic programming. The benchmark includes such formulations but evaluates them with attention to solver effort and sensitivity to scenario scaling. While mixed-integer formulations can represent operational rules explicitly, their computational burden under numerous encounters is examined empirically rather than assumed acceptable.

Robust optimization variants accommodate intruder intent uncertainty. Suppose intruder velocity belongs to a set

$$\mathcal{V}_i$$

consistent with performance bounds. A robust separation constraint requires that for all [27]

$$v_i \in \mathcal{V}_i$$

the predicted positions

$$p_k^i(v_i)$$

remain outside the protected region relative to the optimized ownship trajectory. This leads to constraints of the form

$$\|p_k - p_k^i(v_i)\|_2 \geq d_p$$

for all

$$v_i \in \mathcal{V}_i.$$

Tractable approximations reduce this to constraints on worst-case relative motion along radial directions. Such formulations increase conservatism and may induce larger deviations, and the benchmark quantifies these deviations relative to non-robust counterparts. [28]

Model predictive control structures are also considered. At each decision epoch, a finite-horizon problem is solved using the most recent state estimate, yielding an initial control input that is applied over one or a few steps before replanning. This approach reflects realistic implementation where environment information refreshes periodically. The benchmark treats the underlying optimization routine as providing consistent solutions at each step, and measures cumulative computational effort as a function of horizon length, sampling period, and encounter complexity.

An important feature in optimization-based maneuvers is constraint feasibility when conflict detection occurs late or when intruder behavior deviates from nominal predictions. If constraints render the program infeasible, some schemes incorporate slack variables. Let

$$s_k \geq 0$$

quantify temporary protection violations [29]. The separation condition becomes

$$\|p_k - p_k^i\|_2 + s_k \geq d_p,$$

and the cost function is augmented with

$$\sum_k \gamma s_k,$$

where

$$\gamma$$

is a large penalty. This mechanism ensures solvability but introduces controlled constraint relaxation, which is observable in benchmark results as near-boundary separations. The benchmark records the magnitude and duration of such slack usage as an indicator of how frequently an optimization-based maneuver would rely on soft safety margins.

Across formulations, optimization-based algorithms are parameterized by horizon, discretization, cost weights, and solver tolerances [30]. To maintain comparability, the benchmark fixes families of parameters and applies them across encounter categories rather than tuning individually per scenario. This constraint reveals how sensitive each formulation is to moderate miscalibration, which is relevant to operational deployment.

4 | Heuristic Maneuvers and Search Strategies

Heuristic conflict resolution maneuvers are constructed from rule sets or search procedures that map observed encounter states to one of several candidate maneuvers without solving an explicit mathematical program.

Such heuristics are common in systems requiring bounded runtime and straightforward interpretability. Within the benchmark, three conceptual families are represented: geometric pattern maneuvers, discrete search over candidate actions, and potential field style methods. Each family is implemented using continuous-time dynamics compatible with the same vehicle constraints applied to optimization-based approaches.

Geometric pattern maneuvers specify heading, speed, or altitude changes based directly on relative bearing and closing conditions. For example, when an intruder lies within a forward conflict cone and projected time to loss of separation is below a threshold, the logic may issue a fixed turn away from the intruder combined with a vertical adjustment selected to increase relative separation along both horizontal and vertical dimensions [31]. The specific turn angles and climb or descent magnitudes are prescribed in lookup tables parameterized by encounter class. These maneuvers do not guarantee optimality with respect to any formal objective, but they are straightforward to implement. In the benchmark, such pattern maneuvers are embedded in a continuous dynamics simulation, so that commanded changes respect limits on bank angle, vertical rate, and available thrust.

Search-based heuristics construct a discrete set of candidate resolution actions at each decision instant and evaluate predicted trajectories using simplified propagation. Candidate actions include multiple heading offsets, speed adjustments, and altitude changes. For each action, a scoring function is computed that aggregates minimum predicted separation, total path length, and alignment with mission direction. The heuristic selects the action with the best score that satisfies a minimum separation constraint under nominal predictions. Unlike full optimization, the candidate set is limited, and the scoring function is not minimized over a continuous space [32]. However, this approach retains flexibility while bounding computational effort through the size of the candidate set. In the benchmark, candidate sets are held fixed across scenarios, and the search cost is measured as a function of encounter complexity.

Potential field inspired methods define artificial repulsive fields around intruders and attractive fields along the reference trajectory. Ownship maneuvers follow gradients of a scalar field. Denote the ownship position by

$$p,$$

and for an intruder at position

$$p_i,$$

define a repulsive potential

$$U_i(p).[33]$$

A simple form is

$$U_i(p) = \frac{k}{\|p - p_i\|_2^2},$$

for

$$\|p - p_i\|_2$$

above some cutoff. The composite vector field is derived from the negative gradient of the sum of attractive and repulsive potentials. While continuous and reactive, such fields can exhibit local extrema or oscillatory trajectories in multi-intruder scenarios. The benchmark includes implementations with saturation to respect maximum turn and climb rates. The observed behavior indicates how field structures interact with constraints and how they perform over ensembles of encounters.

Heuristic algorithms are sensitive to parameterization, including conflict detection thresholds, safety margins, and maneuver magnitudes. To provide a stable comparison, parameter sets are defined a priori and not tuned per scenario [34]. The resulting performance, especially under close-proximity and late-detection encounters, indicates how robust each heuristic is to conditions slightly outside its implicit design assumptions. Although heuristics may yield rapid decisions, their separation margins and path efficiency vary with geometry in ways that are not always straightforward to anticipate analytically. Consequently, the benchmark relies on statistical characterization over many encounters, rather than on isolated illustrative cases.

The interaction between heuristic rules and surveillance imperfections is represented by introducing measurement noise and latency into the encounter simulations. Since heuristic decisions often depend directly on instantaneous estimated relative position and velocity, distorted measurements can lead to premature or delayed maneuvering. The benchmark quantifies the frequency of near-threshold separations and the variability of maneuver amplitudes as sensing quality is varied within realistic bounds. This provides a basis for comparing the stability of heuristic and optimization-based approaches under similar uncertainties.

5 | Benchmarking Framework and Performance Metrics

The benchmarking framework is constructed to compare optimization-based and heuristic conflict resolution maneuvers within a unified simulation environment [35]. Encounters are generated stochastically according to parameterized distributions over initial relative positions, headings, speeds, and altitudes, subject to constraints that ensure a significant portion involve potential conflicts. Ownship performance limits are fixed, and intruder capabilities are specified to be compatible with small uncrewed or light crewed aircraft. Each encounter is propagated forward using continuous-time dynamics with piecewise constant or smoothly varying controls, ensuring that both algorithm classes are evaluated on trajectories derived from the same base model.

A central aspect of the framework is the definition of performance metrics that are both interpretable and sensitive to significant behavioral differences. One primary metric is minimum achieved separation over the simulation horizon. For each run, the minimum three-dimensional distance between ownship and each intruder is recorded. Statistical summaries, such as empirical distributions of minimum separation and the fraction of runs that violate a given threshold, are computed for each algorithm. The focus is on comparing how strongly different methods concentrate separations above nominal minima [36]. The framework treats any run with separation below the protected radius as a loss-of-separation event and reports relative frequencies without adjustment.

Another metric class captures deviation from the reference trajectory. Path deviation is quantified by integrated cross-track and along-track errors and by additional flight time or distance. For each trajectory, the cumulative deviation integral is obtained by sampling the distance between the maneuvered ownship path and its nominal path. Scalar summaries such as mean deviation and upper quantiles are then calculated. These metrics reflect efficiency implications of conservative maneuvers. The benchmark does not assign a normative preference to any particular deviation level but reports trade-offs between separation robustness and path conformance.

Computational effort is monitored through proxy measures suitable for algorithm comparison [37]. For optimization-based methods, the number of solver iterations and an abstracted runtime per decision step are recorded under a fixed computational model. For heuristic strategies, effort is represented by the number of candidate trajectories evaluated or the complexity of potential field updates. While actual runtime on specific hardware may vary, relative comparisons highlight how algorithmic complexity scales with scenario density and planning horizon. Algorithms whose effort grows sharply with encounter complexity are distinguishable from those exhibiting bounded costs.

Robustness to uncertainty is evaluated by introducing variation in intruder behavior and measurement quality. Intruders are allowed to deviate from initial velocity assumptions within pre-specified bounds, and noise is added to state estimates. The detect-and-avoid algorithms operate on estimated states and do not have access to ground-truth noise realizations. Performance metrics are then recomputed under these conditions [38]. The ratio between metrics under nominal and perturbed conditions is interpreted as a measure of sensitivity. No single robustness index is favored; instead, multiple indicators are reported to allow nuanced comparison.

The benchmark also considers multi-intruder encounters within a limited density regime to avoid fully congested traffic effects. When multiple intruders are present, conflict resolution algorithms handle simultaneous constraints. Minimum separation is then computed relative to all intruders, and deviations are measured with respect to the combined effect of avoiding several potential conflicts. This setting exposes interactions between algorithm designs and the superposition of geometric constraints. It particularly reveals whether optimization-based methods, with explicit constraints, differ systematically from heuristics that respond locally to nearest threats.

To maintain consistency, all performance metrics are computed using identical post-processing procedures across algorithms [39]. Time discretization for metric evaluation is fixed, and continuous-time trajectories are interpolated in a uniform manner. This avoids biases that might arise from differences in internal integration schemes. Furthermore, the ensemble size for Monte Carlo experiments is chosen to obtain stable empirical distributions. The benchmark does not aim to cover every possible operational environment but focuses on a broad subset where comparisons are technically meaningful and reproducible.

6 | Numerical Experiments and Comparative Results

Numerical experiments are carried out over large ensembles of synthetic encounters generated according to the benchmarking framework. Ownship aircraft are initialized along nominal straight-line trajectories with speed ranges compatible with small uncrewed systems, while intruders approach with headings and speeds spanning crossing, overtaking, and head-on configurations. Altitude separations at entry are varied to produce both purely horizontal conflicts and coupled vertical-horizontal encounters. Each configuration is simulated under the dynamics and surveillance assumptions introduced earlier, and detect-and-avoid algorithms are executed in closed loop with periodic replanning or rule evaluation. [40]

For optimization-based maneuvers, three representative formulations are considered: a convex quadratic program with conservative linearized separation constraints, a mixed-integer quadratic program encoding discrete maneuver modes, and a robust optimization variant incorporating bounded intruder velocity uncertainty. All use identical prediction horizons and discretizations. The convex formulation tends to generate smooth lateral deviations that sustain separation with moderate path length increases. The mixed-integer formulation can produce more abrupt but structured maneuvers, especially where disjunctive constraints enable clear turn decisions. The robust variant increases separation margins and often initiates maneuvers earlier, resulting in larger average deviations. These qualitative tendencies are visible when inspecting trajectory families across encounter classes.

Heuristic maneuvers exhibit distinct patterns. Fixed-geometry rules lead to consistent responses, such as predefined turns away from intruders within specified regions [41]. This yields highly interpretable trajectories but can result in unnecessary deviations in scenarios where a less aggressive change would suffice. Search-based heuristics over discrete candidate actions adapt more flexibly, often selecting minimal turns that satisfy nominal predictions. Potential field based methods produce continuous trajectories that steer around intruders while attempting to align with the reference path. In some multi-intruder scenarios, field interactions create indirect paths, revealing a tendency toward oscillation or conservative curvature where repulsive influences overlap.

Across all algorithms, empirical distributions of minimum separation provide a central comparative indicator. Convex optimization formulations maintain separations above the nominal protected radius in the majority of runs, with a relatively small tail of near-threshold events when detection occurs late or intruder maneuvers diverge from predictions. Mixed-integer formulations show similar or slightly higher minimum separations due to enforced discrete choices that can be inherently conservative. Robust optimization reduces the frequency of near-threshold events further at the expense of increased average deviation [42]. Heuristic geometric rules achieve acceptable separations in many encounters but exhibit a somewhat higher incidence of cases where separation approaches or slightly dips below nominal thresholds, particularly in challenging crossing geometries where fixed parameters are not fully aligned with actual closing speeds.

Deviation metrics indicate that convex optimization solutions typically yield moderate additional path lengths relative to reference trajectories, while robust formulations incur larger deviations corresponding to their conservative stance. Mixed-integer solutions can display both small and large deviations depending on which maneuver mode is activated. Heuristic rules show a broader spread: in some cases they preserve trajectories close to nominal, whereas in others they apply large, fixed maneuvers that significantly elongate routes, especially under late reversions toward the original flight path. Potential field methods occasionally generate meandering paths in complex multi-intruder scenes, which contributes to higher deviation tails.

Computational effort comparisons, expressed in terms of normalized decision-step costs, illustrate systematic differences. The convex quadratic formulation scales approximately linearly with horizon length and remains stable under increased encounter densities in the examined range. Mixed-integer optimization reveals increased effort as encounter complexity grows and as separation constraints become tighter, reflecting combinatorial branching [43]. Robust optimization introduces additional complexity due to enlarged constraint sets but remains manageable under the tested conditions for moderate horizon sizes. Heuristic methods require relatively limited computational resources: fixed geometric rules involve direct evaluations, search-based heuristics scale with the number of candidate actions, and potential fields involve local computations. While exact runtimes depend on hardware, the relative ordering remains consistent.

When uncertainty in intruder motion and measurement noise is introduced, performance differences become more pronounced. Robust optimization formulations maintain separation distributions that are less sensitive to such uncertainty, as expected from their design. Convex and mixed-integer non-robust formulations experience mild degradation, with increased frequencies of near-threshold separations, yet retain structured behavior. Heuristic geometric rules show stronger sensitivity, with some encounters transitioning from safe margins under nominal conditions to threshold-level separations when intruder accelerations deviate from assumed patterns. Search-based heuristics partially compensate by re-evaluating candidate actions at each step, though their reliance on nominal propagation maintains some vulnerability [44]. Potential field methods respond continuously to changing estimates and thus reflect noisy fluctuations, which results in more irregular maneuvers in the presence of noisy surveillance.

In multi-intruder experiments with moderate density, optimization-based methods handle simultaneous constraints by jointly accounting for multiple separation conditions. Convex formulations approximate complex protected regions through aggregated terms, while mixed-integer formulations capture explicit logical alternatives for maneuvering around distinct clusters. Heuristic rules often prioritize the closest or earliest predicted conflict, which can in some cases reduce separation margins to other intruders. Potential fields naturally sum repulsive contributions, but may yield trajectories that thread between intruders with relatively small margins [45]. Numerical experiments show that algorithm classes occupy different regions of the trade space defined by separation reliability, deviation, and computational demand. Optimization-based methods, especially when incorporating robustness, tend to prioritize separation at some cost in deviation and computational complexity. Heuristic methods tend to offer low implementation cost and simple logic at the expense of higher variability in both separation margins and path efficiency across diverse encounter conditions. The benchmark surface highlights these tendencies without assigning preferential weights, thereby enabling structured interpretation aligned with specific operational priorities. [46]

7 | Discussion

The comparative results obtained from the benchmarking framework indicate that no single conflict resolution paradigm uniformly dominates across all encounter sets, uncertainty levels, and operational constraints considered. Instead, each class of algorithms demonstrates context-dependent characteristics that can be evaluated against airspace integration objectives. Optimization-based approaches benefit from explicit modeling of protected volumes, vehicle constraints, and objectives. When calibrated with appropriate margins and solved reliably, they tend to provide predictable and smooth maneuvers with transparent trade-offs between separation and deviation. However, their performance is contingent on model fidelity, including assumptions about intruder behavior, and on ensuring that computational resources are sufficient to solve the underlying optimization problems consistently within decision deadlines.

Heuristic strategies have complementary attributes. Fixed geometric patterns align well with rule-based reasoning and can support straightforward certification arguments based on enumerated cases. Candidate search schemes offer flexibility while remaining tractable, and potential field methods provide continuous and reactive behavior [47]. These methods do not require solving global optimization problems and can maintain bounded computation even under many encounters. At the same time, their reliance on parameterized rules and local decision logic can make it difficult to anticipate all interactions, leading to non-uniform behavior when encounters deviate from assumed structures or when multiple intruders exert competing influences.

The presence of state and intent uncertainty underscores the relevance of robustness properties. Optimization methods that embed uncertainty sets can maintain higher separation reliability but tend to increase deviations and may become more conservative than necessary under benign conditions. Heuristics that are tuned for deterministic geometries may exhibit larger sensitivity, with some cases approaching the limits of protected volumes as noise or unexpected intruder maneuvers accumulate. These findings suggest that the choice between algorithm classes, or the design of hybrid schemes, should be informed by explicit consideration of typical uncertainty environments and acceptable deviation ranges rather than by generic preferences.

Interaction with surveillance architectures is another influencing factor. Algorithms that depend on stable, high-rate, low-latency information may exhibit degraded performance under sparser or noisier data [48]. In the benchmark, this is visible in the increased dispersion of minimum separation metrics when measurement intervals are extended or when latency is introduced. Approaches that recompute maneuvers at each update can adapt, but may also generate frequent small changes. Approaches that commit to longer-horizon maneuvers may be more stable but risk misalignment if early predictions are inaccurate. These behaviors are not uniquely associated with a single algorithm class; both optimization-based and heuristic methods can be configured in either reactive or commit-oriented modes. The benchmark illustrates how such configuration interacts with underlying logic. From an integration standpoint, interpretability and implementation complexity also affect the selection of conflict resolution strategies. Optimization-based methods require reliable numerical solvers and careful handling of infeasibility or degeneracy. Heuristics demand systematic tuning, validation over diverse encounter sets, and safeguards against pathological behaviors [49]. Hybrid approaches that use heuristics to define candidate maneuver sets and optimization to refine among them may combine several advantages, but also inherit complexity from both sides. The benchmarking environment is flexible enough to incorporate such hybrids, and the presented results offer a baseline against which future algorithms can be situated.

The neutral characterization of trade-offs indicates that detect-and-avoid system design can benefit from algorithm portfolios rather than relying solely on a single maneuvering logic. Specific airspace classes, such as low-density beyond-visual-line-of-sight corridors or higher-density urban operations, may motivate distinct parameter choices and algorithm combinations. The benchmark does not prescribe these choices but helps clarify how different designs behave when confronted with systematically varied encounter geometries, traffic densities, and surveillance qualities. This facilitates more quantitative dialogue about acceptable safety margins, deviation tolerances, and runtime constraints.

8 | Conclusion

This paper has presented a comprehensive benchmarking framework for optimization-based and heuristic conflict resolution maneuvers in uncrewed aircraft detect-and-avoid systems. The study introduced a consistent encounter modeling foundation that captures the essential components of relative motion geometry, protected volume modeling, vehicle dynamics, and surveillance characteristics [50]. By integrating these components, the framework enables reproducible comparison between algorithmic strategies that differ fundamentally in structure and computational requirements. The benchmark treats conflict resolution as a decision process driven by both deterministic and uncertain information sources, highlighting how the mathematical formulation of constraints and objectives shapes maneuver outcomes.

Within this unified modeling framework, representative optimization-based formulations were implemented, including convex quadratic programs, mixed-integer quadratic programs, and robust optimization models designed to accommodate uncertainty in intruder intent and sensing. These were contrasted against heuristic approaches encompassing fixed geometric maneuvers, discrete search over candidate actions, and potential field inspired reactive methods. Each class of algorithm was subjected to identical encounter sets and performance metrics, ensuring that observed variations stemmed from algorithmic characteristics rather than differences in scenario construction. The performance evaluation relied on metrics that reflect operational relevance: minimum achieved separation, cumulative trajectory deviation, computational effort, and robustness to noise and uncertainty.

Results from the numerical experiments demonstrated that optimization-based methods consistently generate structured and dynamically feasible maneuvers with predictable separation margins, provided that model fidelity and computational resources meet minimal thresholds. Their behavior tends to scale with scenario complexity in a controlled manner, maintaining smooth trajectories and continuous avoidance profiles [51]. Mixed-integer formulations capture discrete decision logic, such as direction or altitude selection, leading to interpretable but occasionally abrupt transitions. Robust optimization variants, while computationally more demanding, exhibit improved performance under state and intent uncertainty by maintaining larger safety margins and initiating earlier avoidance actions. These characteristics are advantageous in stochastic or adversarial encounter conditions but may impose unnecessary conservatism in benign cases.

Heuristic approaches display complementary behavior. Fixed geometric rules deliver rapid and easily verifiable decisions but show sensitivity to encounter geometry and parameter tuning. Their simplicity makes them suitable for systems with stringent real-time requirements, though at the cost of reduced adaptability. Search-based heuristics expand decision diversity through limited exploration, often achieving satisfactory separation with lower computational effort than full optimization. Potential field based methods produce continuous and reactive trajectories but can display oscillatory motion or local trapping in multi-intruder scenarios [52]. The relative performance of these heuristic strategies reflects inherent trade-offs between responsiveness, predictability, and consistency. When uncertainty or dynamic variation is moderate, their simplicity and speed can outweigh the absence of formal guarantees.

Under elevated uncertainty and in multi-intruder configurations, distinct behavioral patterns emerge. Robust optimization maintains separation margins even when intruder trajectories deviate from nominal predictions, demonstrating resilience to uncertainty in

both kinematics and intent. Convex and mixed-integer formulations degrade more gracefully than heuristic rules as information quality declines, primarily due to their explicit handling of constraints. In contrast, heuristic systems, particularly those tuned for specific geometries, exhibit wider variance in minimum separation and more abrupt or oscillatory corrections. This behavior underscores the role of uncertainty modeling: algorithms that explicitly represent uncertainty through constraints or cost inflation sustain more consistent safety performance, while those that treat it implicitly through margin expansion rely on conservative parameterization to remain effective.
Comparative analysis of deviation profiles further distinguishes the algorithmic classes [53]. Optimization-based methods balance safety and mission conformance by weighting deviation and control effort within a unified cost function. As a result, deviations scale smoothly with conflict severity. Heuristic approaches, lacking this continuous trade-off structure, often display discrete jumps in deviation magnitude associated with fixed maneuver templates or rule thresholds. This quantization of response can simplify predictability but introduces inefficiencies when conflict geometries only marginally exceed detection thresholds. Potential field methods, although continuous, tend to produce overextended deviations in multi-intruder fields where repulsive forces superimpose, illustrating how local interaction models can amplify conservatism without explicit coordination.
The benchmarking framework also examined computational characteristics. Convex quadratic programs exhibit predictable scaling with horizon length and constraint count, making them viable for small to medium-sized encounter sets under efficient numerical implementations. Mixed-integer formulations impose higher computational loads, especially as encounter complexity increases, due to combinatorial branching [54]. Robust optimization amplifies this effect by introducing additional constraint structures to represent uncertainty sets. Despite these costs, all optimization-based methods achieve deterministic execution times under bounded problem sizes, supporting feasibility for onboard deployment when hardware resources are provisioned appropriately. Heuristic methods retain clear advantages in computational economy: fixed-rule and potential field logics execute at near-constant time regardless of encounter complexity, while discrete search schemes scale linearly with candidate action count. These properties suggest that algorithm selection should reflect available computational margins and mission timelines rather than nominal performance alone.
Beyond individual performance comparisons, the benchmark exposes systemic trade-offs intrinsic to detect-and-avoid design. Algorithms that guarantee separation through formal constraints typically induce larger deviations or longer maneuver durations, whereas reactive heuristics achieve compact and timely responses but risk underperformance in edge cases. Computational effort serves as an intermediary variable linking model complexity to operational practicality. Robustness to uncertainty emerges as a differentiating dimension, highlighting that performance under ideal conditions does not necessarily predict behavior under degraded sensing or dynamic variability [55]. By quantifying these relationships, the benchmark offers a structured basis for design selection and system integration analysis.
Importantly, the benchmarking framework maintains neutrality with respect to algorithm preference. It does not assign hierarchical priority among metrics nor favor any particular solution paradigm. Instead, it emphasizes traceable comparison and reproducibility under standardized encounter conditions. This neutrality allows stakeholders to interpret results in light of mission-specific requirements, such as acceptable deviation levels, minimum reliability thresholds, or computational limitations. The transparent mapping from scenario parameters to performance outcomes facilitates certification-oriented evaluation, in which regulatory authorities can assess compliance without dependence on proprietary modeling assumptions. This property enhances the framework's utility as a reference for both research and pre-deployment verification.
The framework's extensibility supports incorporation of more detailed vehicle dynamics, such as nonlinear energy constraints, aerodynamic coupling, and wind disturbances, without altering the core evaluation principles [56]. Alternative uncertainty representations, including stochastic reachability, data-driven intent inference, or real-time Bayesian prediction, can be embedded to refine robustness assessment. Integration with communication-based coordination mechanisms, such as cooperative trajectory sharing or intent negotiation, would enable evaluation of hybrid detect-and-avoid and cooperative separation systems. Similarly, hybrid algorithmic schemes that couple heuristic candidate generation with optimization-based refinement could be benchmarked systematically to explore synergies between responsiveness and formal constraint satisfaction.
The benchmark contributes a technically explicit and

methodologically consistent means to evaluate detect-and-avoid maneuvering algorithms across optimization-based and heuristic paradigms. It provides a foundation for understanding how design choices in modeling, computation, and uncertainty handling translate into measurable operational behaviors. The results demonstrate that optimization-based strategies offer predictable and structurally disciplined performance when computationally feasible, while heuristics provide speed and simplicity suited to resource-limited platforms. No single method dominates; instead, applicability depends on airspace structure, uncertainty level, vehicle capability, and acceptable trade-offs between safety, efficiency, and complexity. By maintaining neutrality and transparency, the framework enables continued refinement and comparative analysis as detect-and-avoid technology evolves. Extensions in modeling fidelity, uncertainty representation, and cooperative coordination can be integrated without compromising this central principle of consistent, reproducible, and technically grounded evaluation across algorithmic classes in uncrewed aircraft detect-and-avoid systems.

References

[1] D. Sziroczák and D. Rohács, "Automated conflict management framework development for autonomous aerial and ground vehicles," *Energies*, vol. 14, pp. 8344–8344, 12 2021.

[2] M. Cogliati, E. Tonelli, D. Battaglia, and M. Scaioni, "Extraction of dems and orthoimages from archive aerial imagery to support project planning in civil engineering," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. IV-5/W1, pp. 9–16, 12 2017.

[3] X. Sun, Y. Tian, W. Lu, P. Wang, R. Niu, H. Yu, and K. Fu, "From single- to multi-modal remote sensing imagery interpretation: a survey and taxonomy," *Science China Information Sciences*, vol. 66, 3 2023.

[4] G. Mandlburger, M. Pfennigbauer, R. Schwarz, S. Flöry, and L. Nussbaumer, "Concept and performance evaluation of a novel uav-borne topo-bathymetric lidar sensor," *Remote Sensing*, vol. 12, pp. 986–, 3 2020.

[5] A. Al-Shammari, E. Levin, and R. Shults, "Oil spills detection by means of uas and low-cost airborne thermal sensors," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. IV-5, pp. 293–301, 11 2018.

[6] D. Stojcsics, D. Boursinos, N. Mahadevan, X. Koutsoukos, and G. Karsai, "Fault-adaptive autonomy in systems with learning-enabled components," *Sensors (Basel, Switzerland)*, vol. 21, pp. 6089–, 9 2021.

[7] S. Terp, S. Ahmed, E. Burner, M. Ross, M. Grassini, B. Fischer, and P. Parmar, "Deaths in immigration and customs enforcement (ice) detention: Fy2018-2020," *AIMS public health*, vol. 8, pp. 81–89, 1 2021.

[8] C. Kielhauser, R. R. Manzano, J. J. Hoffman, and B. T. Adey, "Automated construction progress and quality monitoring for commercial buildings with unmanned aerial systems: An application study from switzerland," *Infrastructures*, vol. 5, pp. 98–, 11 2020.

[9] H. Erzberger, T. Nikoleris, R. A. Paielli, and Y.-C. Chu, "Algorithms for control of arrival and departure traffic in terminal airspace," *Proceedings of the Institution of Mechanical Engineers. Part G, Journal of aerospace engineering*, vol. 230, pp. 1762–1779, 2 2016.

[10] F. M. Ralph, M. D. Dettinger, A. B. White, D. W. Reynolds, D. R. Cayan, T. Schneider, R. Cifelli, K. T. Redmond, M. L. Anderson, F. Gherke, J. Jones, K. Mahoney, L. Johnson, S. I. Gutman, V. Chandrasekar, J. D. Lundquist, N. P. Molotch, L. D. Brekke, R. S. Pulwarty, J. D. Horel, L. J. Schick, A. Edman, P. W. Mote, J. T. Abatzoglou, R. B. Pierce, and G. A. Wick, "A vision for future observations for western u.s. extreme precipitation and flooding," *Journal of Contemporary Water Research & Education*, vol. 153, pp. 16–32, 7 2014.

[11] K. A. Suzuki, P. K. Filho, and J. R. Morrison, "Automatic battery replacement system for uavs: Analysis and design," *Journal of Intelligent & Robotic Systems*, vol. 65, pp. 563–586, 9 2011.

[12] G. de Boer, S. Palo, B. Argrow, G. LoDolce, J. Mack, R. S. Gao, H. Telg, C. Trussel, J. Fromm, C. N. Long, G. Bland, J. A. Maslanik, B. Schmid, and T. Hock, "The pilatus unmanned aircraft system for lower atmospheric research," *Atmospheric Measurement Techniques*, vol. 9, pp. 1845–1857, 4 2016.

[13] J. Schumann, N. Mahadevan, M. Lowry, and G. Karsai, “Model-based on-board decision making for autonomous aircraft,” *Annual Conference of the PHM Society*, vol. 11, 9 2019.

[14] S. M. Hubbard, A. Baxmeyer, and B. Hubbard, “Case study of an automated mower to support airport sustainability,” *Sustainability*, vol. 13, pp. 8867–, 8 2021.

[15] R. Shrestha, I. Oh, and S. Kim, “A survey on operation concept, advancements, and challenging issues of urban air traffic management,” *Frontiers in Future Transportation*, vol. 2, 4 2021.

[16] S. Ponte, G. Ariante, U. Papa, and G. D. Core, “An embedded platform for positioning and obstacle detection for small unmanned aerial vehicles,” *Electronics*, vol. 9, pp. 1175–, 7 2020.

[17] P. D. Rozema, G. Kulk, M. P. Veldhuis, A. G. J. Buma, M. P. Meredith, and W. H. van de Poll, “Assessing drivers of coastal primary production in northern marguerite bay, antarctica,” *Frontiers in Marine Science*, vol. 4, pp. 184–, 6 2017.

[18] A. A. Khamukhin, “Numerical simulation of visually guided landing based on a honeybee motion model,” *Journal of Intelligent & Robotic Systems*, vol. 95, pp. 665–674, 11 2018.

[19] M. Nowlin, S. E. Roady, E. Newton, and D. Johnston, “Applying unoccupied aircraft systems to study human behavior in marine science and conservation programs,” *Frontiers in Marine Science*, vol. 6, 10 2019.

[20] O. McAree, J. M. Aitken, and S. M. Veres, “Quantifying situation awareness for small unmanned aircraft: Towards routine beyond visual line of sight operations,” *The Aeronautical Journal*, vol. 122, pp. 733–746, 3 2018.

[21] C. Martinez, P. J. Sanchez-Cuevas, S. Gerasimou, A. Bera, and M. A. Olivares-Mendez, “Sora methodology for multi-uas airframe inspections in an airport,” *Drones*, vol. 5, pp. 141–, 11 2021.

[22] V. Kharchenko, Y. Barabanov, and A. Grekhov, “Modelling of ‘satellite-to-aircraft’ link for self-separation,” *Transport*, vol. 28, pp. 361–367, 12 2013.

[23] S. Garrido, J. Muñoz, B. López, F. Quevedo, C. A. Monje, and L. Moreno, “Fast marching techniques for teaming uav’s applications in complex terrain,” *Drones*, vol. 7, pp. 84–84, 1 2023.

[24] A. Rautenberg, M. Schön, K. zum Berge, M. Mauz, P. Manz, A. Platis, B. van Kesteren, I. Suomi, S. T. Kral, and J. Bange, “The multi-purpose airborne sensor carrier masc-3 for wind and turbulence measurements in the atmospheric boundary layer.,” *Sensors (Basel, Switzerland)*, vol. 19, pp. 2292–, 5 2019.

[25] A. Lockhart, A. While, S. Marvin, M. Kovacic, N. Odendaal, and C. Alexander, “Making space for drones: The contested reregulation of airspace in tanzania and rwanda,” *Transactions of the Institute of British Geographers*, vol. 46, pp. 850–865, 5 2021.

[26] F. Gnädinger and U. Schmidhalter, “Digital counts of maize plants by unmanned aerial vehicles (uavs),” *Remote Sensing*, vol. 9, pp. 544–, 5 2017.

[27] M. B. Jamoom, A. Canolla, B. Pervan, and M. Joerger, “Unmanned aircraft system sense and avoid integrity: Intruder linear accelerations and analysis,” *Journal of Aerospace Information Systems*, vol. 14, no. 1, pp. 53–67, 2017.

[28] P. Bieber, T. M. Seifried, J. Burkart, J. Gratzl, A. Kasper-Giebl, D. G. Schmale, and H. Grothe, “A drone-based bioaerosol sampling system to monitor ice nucleation particles in the lower atmosphere,” *Remote Sensing*, vol. 12, pp. 552–, 2 2020.

[29] D. A. Rodriguez, D. L. Ávila Granados, and J. A. V. Vidales, “Use of unmanned aircraft systems for bridge inspection: A review,” *DYNA*, vol. 88, pp. 32–41, 5 2021.

[30] S. H. Alsamhi, O. Ma, and M. S. Ansari, “Convergence of machine learning and robotics communication in collaborative assembly: Mobility, connectivity and future perspectives,” *Journal of Intelligent & Robotic Systems*, vol. 98, pp. 541–566, 10 2019.

[31] M. N. Stevens, H. Rastgoftar, and E. M. Atkins, “Geofence boundary violation detection in 3d using triangle weight characterization with adjacency,” *Journal of Intelligent & Robotic Systems*, vol. 95, pp. 239–250, 9 2018.

[32] M. Khalaf-Allah, “Emitter location with azimuth and elevation measurements using a single aerial platform for electronic support missions.,” *Sensors (Basel, Switzerland)*, vol. 21, pp. 3946–, 6 2021.

[33] H. H. Edwards, J. A. Hostetler, B. M. Stith, and J. Martin, "Monitoring abundance of aggregated animals (florida manatees) using an unmanned aerial system (uas)," *Scientific reports*, vol. 11, pp. 12920–12920, 6 2021.

[34] V. Sanchez-Aguero, L. F. Gonzalez, F. Valera, I. Vidal, and R. L. D. Silva, "Cellular and virtualization technologies for uavs: An experimental perspective.," *Sensors (Basel, Switzerland)*, vol. 21, pp. 3093–, 4 2021.

[35] U. Parameters, "Parameters spring 2013," *The US Army War College Quarterly: Parameters*, vol. 43, 2 2013.

[36] C. E. Smith, S. T. Sykora-Bodie, B. E. Bloodworth, S. M. Pack, T. R. Spradlin, and N. R. LeBoeuf, "Assessment of known impacts of unmanned aerial systems (uas) on marine mammals: data gaps and recommendations for researchers in the united states1," *Journal of Unmanned Vehicle Systems*, vol. 4, pp. 31–44, 3 2016.

[37] M. Ángel Fas-Millán and E. Pastor, "Ntom: a concept of operations for pilots of multiple remotely piloted aircraft," *International Review of Aerospace Engineering (IREASE)*, vol. 12, pp. 12–25, 2 2019.

[38] J. Maurio, P. Wood, S. Zanlongo, J. Silbermann, T. Sookoor, A. Lorenzo, R. Sleight, J. Rogers, D. Muller, N. Armiger, C. Rouff, and L. Watkins, "Agile services and analysis framework for autonomous and autonomic critical infrastructure," *Innovations in Systems and Software Engineering*, vol. 19, pp. 145–156, 8 2021.

[39] A. Alamouri, A. Lampert, and M. Gerke, "An exploratory investigation of uas regulations in europe and the impact on effective use and economic potential," *Drones*, vol. 5, pp. 63–, 7 2021.

[40] Z. Liu, Y. Zhang, C. Yuan, L. Ciarletta, and D. Theilliol, "Collision avoidance and path following control of unmanned aerial vehicle in hazardous environment," *Journal of Intelligent & Robotic Systems*, vol. 95, pp. 193–210, 9 2018.

[41] V. Alarcón, M. García, F. Alarcón, A. Viguria, Ángel Martínez, D. Janisch, J. J. Acevedo, I. Maza, and A. Ollero, "Procedures for the integration of drones into the airspace based on u-space services," *Aerospace*, vol. 7, pp. 128–, 9 2020.

[42] D. Becker and J. Klonowski, "Object recognition of a gcp design in uas imagery using deep learning and image processing—proof of concept study," *Drones*, vol. 7, pp. 94–94, 1 2023.

[43] Y. Kim and J. Bae, "Risk-based uav corridor capacity analysis above a populated area," *Drones*, vol. 6, pp. 221–221, 8 2022.

[44] A. la Cour-Harbo, "Quantifying risk of ground impact fatalities for small unmanned aircraft," *Journal of Intelligent & Robotic Systems*, vol. 93, pp. 367–384, 5 2018.

[45] A. C. Canolla, M. B. Jamoom, and B. Pervan, "Unmanned aircraft systems detect and avoid sensor hybrid estimation error analysis," in *17th AIAA Aviation Technology, Integration, and Operations Conference*, p. 4384, 2017.

[46] R. Abeyratne and A. Khan, "State use of unmanned military aircraft: a new international order?," *Journal of Transportation Security*, vol. 7, pp. 83–98, 12 2013.

[47] L. Yang, S. Li, C. Li, C. Zhu, A. Zhang, and G. Liang, "Data-driven unsupervised anomaly detection and recovery of unmanned aerial vehicle flight data based on spatiotemporal correlation," *Science China Technological Sciences*, vol. 66, pp. 1304–1316, 4 2023.

[48] R. A, S. M, R. B, K. P. P, and M. S, "Design and fabrication of fire extinguishing drone using co2 ball and sprayer," *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, pp. 94–99, 10 2022.

[49] T. A. N. Redpath, P. Sirguey, and N. J. Cullen, "Repeat mapping of snow depth across an alpine catchment with rpas photogrammetry," *The Cryosphere*, vol. 12, pp. 3477–3497, 11 2018.

[50] D. Olson and J. V. Anderson, "Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture," *Agronomy Journal*, vol. 113, pp. 971–992, 3 2021.

[51] J. Saunders and R. W. Beard, "Uas flight simulation with hardware-in-the-loop testing and vision generation," *Journal of Intelligent and Robotic Systems*, vol. 57, pp. 407–415, 8 2009.

[52] C. J. Legleiter and P. J. Kinzel, "Depths inferred from velocities estimated by remote sensing: A flow resistance equation-based approach to mapping multiple river attributes at the reach

scale," *Remote Sensing*, vol. 13, pp. 4566–, 11 2021.

[53] G. G. R. de Castro, G. S. Berger, A. Cantieri, M. Teixeira, J. Lima, A. I. Pereira, and M. F. Pinto, "Adaptive path planning for fusing rapidly exploring random trees and deep reinforcement learning in an agriculture dynamic environment uavs," *Agriculture*, vol. 13, pp. 354–354, 1 2023.

[54] A. Woodget, J. T. Dietrich, and R. Wilson, "Quantifying below-water fluvial geomorphic change: The implications of refraction correction, water surface elevations, and spatially variable error," *Remote Sensing*, vol. 11, pp. 2415–, 10 2019.

[55] S. Feroz and S. A. Dabous, "Uav-based remote sensing applications for bridge condition assessment," *Remote Sensing*, vol. 13, pp. 1809–, 5 2021.

[56] T. K. Yadav, P. Chidburee, and N. Mahavik, "Land cover classification based on uav photogrammetry and deep learning for supporting mine reclamation: A case study of mae moh mine in lampang province, thailand," *Applied Environmental Research*, pp. 39–54, 9 2021.