Safety Assessment of UTM Strategic Deconfliction

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This work outlines and applies a simulation driven methodology for safety analysis of Unmanned Traffic Management (UTM) systems that are likely to emerge in the upcoming years using cooperative strategic deconfliction as the primary mitigator of collision risk. It builds on past work that examined the implications of using volume based strategic deconfliction in UTM to mitigate collision risk between uncrewed aircraft using Monte Carlo methods in simulation. We apply this methodology to asses the sensitivities of the system in terms of safety relative to key performance characteristics of strategic deconfliction such as operational intent conformance rate and strategic deconfliction participation rate. Additionally, we examine the impact of key operational characteristics, such as operational density, on system safety. Furthermore, we simulate two different operational complexities - a low complexity operational profile of uniformly distributed out-and-back operations, and a high complexity operational profile of four different operational use cases - hub-and-spoke, long-linear-inspection, point-to-point, and out-and-back operations - distributed across the Denver metropolitan area according on features of the city and population density. The simulation results generated suggest that strategic deconfliction provides a significant safety benefit that is approximately constant with operational density, and applies under both the low complexity and high complexity operational profiles simulated. The simulated benefit is sensitive to participation rate, but not to the range of operational intent conformance rates simulated in this paper.

I. Introduction

Forecasts indicate that there will be significant growth in the number of air vehicles operating in urban environments over the next 20 years [1, 2], which will have significant implications for the systems that ensure safety in our airspace. Existing air traffic management (ATM) procedures for managing urban air traffic are not expected to scale sufficiently to support these forecast future operations. For this reason, new approaches to managing air traffic beyond what is currently available through traditional air traffic control (ATC) are required. Unmanned Traffic Management (UTM) has been proposed as a digitized and automated solution for scaling to the expected volume of operations.

The UTM architecture is currently in a conceptual stage [3, 4]. Initial standards have been developed [5], and early prototypes are being tested through demonstrations. However, in order to advance UTM from demonstration to operational deployment, it is critical to suitably quantify the performance of the UTM system. This includes the verification and validation of performance-based requirements of individual services, as well as the assurance that the services and surrounding ecosystem meet desired safety targets. Simulation can contribute to this need by enabling researchers and safety analysts to investigate some of the more complex questions related to safety before a UTM system is fully operational and actual operational data is available.

In many of the architectures proposed for UTM, strategic deconfliction – resolving a predicted conflict prior to departure or well upstream of it – is proposed as a critical component to supporting separation provision. While strategic deconfliction is a function performed pre-flight, its performance depends on requirements measured by in-flight conformance and separation from other vehicles. Past work [6] evaluated the suitability of operational volumes as the

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primary data construct for strategic deconfliction in the context of a high density UAS airspace, and assessed how the formation of these volumes can impact safety of the airspace as a whole. The work analyzed how system error, specifically error in the navigation and guidance system of a UAS, can impact the ability of an operation to conform to its planned operation volumes. We connected the relationship between system error and safety to a performance requirement on conformance rate, which provides a critical pathway to quantifying the risk mitigation that strategic deconfliction can provide in the UTM ecosystem. This is consistent with the mechanism by which safety is assured in the ASTM UTM Standard [5], which recommends a performance requirement on conformance rate.

While past work [6] examined the impact of conformance rate on safety, there are other parameters that are also likely to have safety implications. Two such parameters are the underlying UAS traffic density in which the strategic deconfliction is taking place, and the rate at which operators participate in strategic deconfliction. High traffic densities are likely to increase the probability of safety events occurring, even when conformance rates are maintained, because the higher traffic density increases the likelihood of an encounter in the event of any non-conformances. Similarly, any non-participation in strategic deconfliction by operators in the airspace increases the probability of encounters, even for operations that are conformant, because intent has not been deconflicted with the non-participating operations. This paper aims to extend the previous work by quantifying these impacts, and to provide guidance on airspace capacity constraints and strategic deconfliction participation rates required to assure safety in UTM.

The past work on evaluating UTM strategic deconfliction described in Ref. [6] simulated a single operation profile of out-and-back operations distributed uniformly across a region simulating uniform demand. Real operations, however, will take place in more complex operational environments, with non-uniform demand and airspace constraints. Key locations - such as package delivery fulfillment centers, inspection sites and delivery locations - may see higher UAS traffic densities than others. Restrictions on where UAS operations are permitted are likely to constrain where UAS operations can be planned, and how UAS operations should be routed. Operational profiles may also vary, including linear-inspection type operations that must follow geographical features, and survey or mapping use cases that may loiter and be constrained to limited geographical areas. The safety implications of these complexities should be captured by the parameters considered in the safety analysis. For example, sensitivity to traffic density should suitably capture the complexities associated with a large number of package delivery UAS operating in and out of a fulfillment center, as well as any "hot-spots" that form in an airspace because UAS must route around restricted areas. However, it is important to validate that the safety analysis results are independent of operational complexities, and to identify areas in which they are not, allowing the safety analysis to be improved so that it is also applicable across such complex and realistic UAS operational scenarios. This paper takes a first step towards doing this analysis.

Section II below presents a review of relevant literature. This is followed by Section III which describes the research objectives of the paper, and Section IV which describes our methodology. Section V describes the simulation setup, while Section VI and Section VII present results and draw conclusions.

II. Literature Review

Strategic airspace management has a critical safety function in traditional ATM, and is responsible for conflict mitigation over extended time horizons [7]. A number of tools and capabilities exist to help facilitate deconfliction in ATM [8–10]. However, they are designed to function with humans in the loop and are not expected to scale with the projected traffic demand in UTM. A number of frameworks have been proposed for strategic deconfliction in UTM [11–13], with the most widely accepted and demonstrated being a federated, volume-based solution.

The scope of strategic deconfliction in UTM covers conflict mitigation during the pre-flight planning stage of an operation. Prior work has explored a number of research topics in the strategic deconfliction domain such as those tied to efficiency [14], fairness [15], and safety [16, 17]. However, that research was generally abstracted from the current state of the UTM ecosystem, making it difficult to relate to forthcoming standards and regulations. A large body of literature has also covered emerging topics of interest in the broader UTM domain that go beyond deconfliction, such as those related to dynamic airspaces [18], high operational densities [19], and services necessary for multiple beyond line of sight operations [20]. However, these studies also lack a clear connection to a functional system that is implementable within the current UTM framework.

A body of work that is implementable in the near term comes from recent standards, specifically the ASTM standard specification for UTM USS Interoperability [5], which specifies interface requirements between UTM Service Suppliers (USSs) and a Discovery and Synchronization Service (DSS) for sharing operational intent, telemetry and constraint information. While the standard itself provides a pathway for operationalizing UTM, the exact nature of the safety benefit and risk reduction that the standard could provide for the ecosystem is unclear. While work has been done to begin to quantify these benefits [6], there is not an immediate path forward to assist regulators and other stakeholders in making decisions regarding standard adoption.

Evaluating the ability of a standard, a concept, or a technology to meet the needs of stakeholders through a validation and verification process can be difficult in aviation. System level risk analysis has been commonly used in traditional ATM [21, 22]. Simulation driven approaches have also been used to verify onboard and remotely situated collision avoidance systems in manned aviation like the Airborne Collision Avoidance System (ACAS X) [23, 24] and its variant for small UAS known as ACAS sXu [25]. In both cases, simulation enabled a more efficient and timely path towards certification of these systems [26]. There are also examples of UTM simulations incorporating multiple elements from Strategic and Tactical Deconfliction [27, 28]. More recently, simulation driven verification has been applied to UTM as a form of stress testing [29], but that work focuses on verification of algorithmic correctness for autonomous systems that may exist in UTM rather than considering the quality of a performance or functional requirement. Other existing work has attempted to assign risk scores to operations and modify behavior to minimize the expected risk [30].

III. Research Objectives

The objective of this research is to quantify the safety implications of key performance requirements and operational parameters in the implementation of UTM strategic deconfliction. The aim is to perform a sensitivity analysis across scenarios of different operational complexity, and to identify which results are independent and which correlate to the performance requirements and scenario complexities simulated.

The following strategic deconfliction performance requirements are examined:

1) **Operational intent conformance rate**, or how well an operation can conform to the planned operation volumes during the flight. A number of factors can influence the ability of a vehicle to conform to the planned volumes, and in this work we focus on system error that comes from onboard guidance and navigation, while leaving external disturbances such as weather conditions for future work. Directly related to conformance rate is operational volume sizing, or how an operator creates volumes relative to their intended flight path. These volumes can be sized along four dimensions — two horizontal, one vertical, and one temporal. In this work we focus on the impact of sizing in the horizontal and time dimensions.
2) **Strategic deconfliction participation rate**, or the fraction of operations participating in UTM strategic deconfliction.

The sensitivity of the system to the performance requirements described above was examined in the context of different operational complexities. The scenario complexity was varied in two ways:

(a) **Operational profile**: UAS use cases vary significantly, with corresponding variety in flight profiles. Two operational profiles are simulated. The first simulates out-and-back operations randomly distributed across the simulation area, as in Ref.[6]. The second simulates a realistic distribution of 4 different operational use cases across the city of Denver: a hub-and-spoke package delivery use case; long-linear-inspection operations; point-to-point operations; and out-and-back operations.

(b) **Operational density**: The number of operations simulated to depart across the simulated region per hour was varied, which directly impacts the operational density of UAS operations in a scenario of interest.

IV. Methodology

We apply a similar methodology here as in our previous work [6], by using the Monte Carlo approach to evaluate UTM system safety using simulation. Specifically, we perform the evaluation by simulating the UTM system in order to extract quantitative measures that would be representative of a real operational system. The UTM Simulator used consists of two key components, as shown in Figure 1: the simulation environment and the set of UTM functions necessary to test the requirements of interest. The simulation environment includes the models necessary to simulate a UAS, from an on-board guidance system to flight physics, as well as the demand profiles applied to model UAS demand in the system and operator logic associated with managing that demand.

Each simulation contains a fixed number of operations, with each operation consisting of an operation plan that meets its mission requirements (e.g., to fly from an origin to a mission location, and back to the origin). A path planner produces a series of intermediate waypoints to reach the operation's mission goals, while complying with dynamic constraints such as turn radius. The Rapidly-Exploring Random Tree Star (RRT*) algorithm [31] was used for path planning, designed to provide an asymptotically-optimal, motion-based solution. Constraints on turn rate were applied via the Dubins model to match the dynamic constraints of the UAS [32], and to allow for better recovery from unplanned

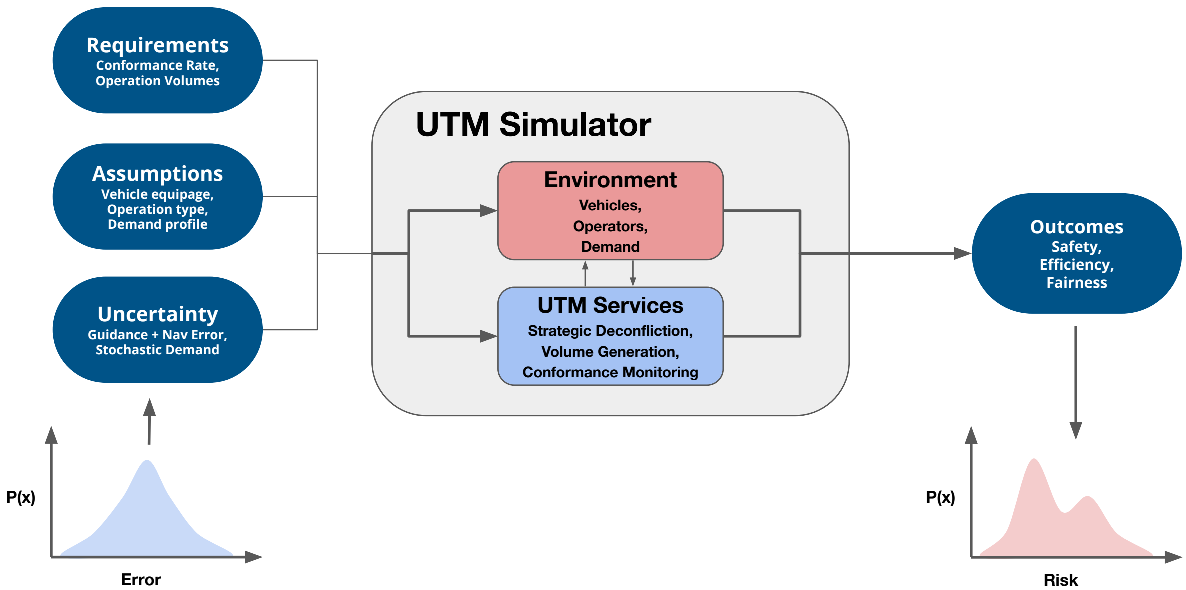


Fig. 1 Architecture for Monte Carlo analysis of UTM requirements.

disturbances like guidance error. The operational intent planning stage that exists within the simulation environment relies on two critical UTM functions - volume generation and strategic deconfliction. Volume generation enables each operation to be planned with a valid set of four dimensional operation volumes, and strategic deconfliction ensures that any new volumes created in the system are conflict free. In our simulation, these functions are performed using cloud based UTM services.

We can group all configurable parameters within the simulation into three categories, as shown in Figure 1:

1) **Requirements**, which are key system parameters we are seeking to validate through simulation. Examples include a performance requirement associated with a conformance rate, and a functional requirement to use four-dimensional operation volumes for strategic deconfliction. In this work we additionally examine the impact of UTM participation rates on safety.
2) **Uncertainty** configuration in the simulation, which is used to configure the probabilistic nature of our evaluation, such as the standard deviation of the navigation errors a UAS operation may experience during flight.
3) Necessary **assumptions** for the analysis. In this paper we take a step beyond our previous work in Ref. [6] to vary key assumptions in order to capture increasingly complex - and ultimately realistic - scenarios. These assumptions include operational use cases and underlying demand profiles.

As in our previous work, the outcomes of Monte Carlo simulations are probabilistic, resulting in a probability distribution of risk for a given set configurable simulation parameters (see Figure 1).

Strategic deconfliction is performed by an automated conflict resolution service that is based on scheduling. The service computes an optimal departure delay by solving a linear program formed by overlaps between the set of operation volumes that exist in the system and the set of operation volumes proposed by the operation being planned. The departure delay is propagated to all the volumes of a planned operation, and guarantees that the proposed set of operation volumes is conflict free from any volumes that have been previously approved. This approach allows us to ensure that regardless of the underlying operation, the size of volumes used, or the mechanism for allocation, a planned operation will always be conflict free prior to take-off so long as it participates in strategic deconfliction. To create the volumes for operations, we assume that the UAS has the ability to navigate along a four dimensional planned center-line associated with its operation. The volumes can then be created assuming a geospatial buffer in the horizontal and vertical planes and a temporal buffer in the time dimension.

Safety implications are quantified by tracking the separation between simulated vehicles and calculating two different risk metrics:

1) The number of **Mid Air Collisions (MACs)** simulated in each scenario. Because vehicles are modeled as point masses, a MAC is defined as a loss of 3 m of horizontal separation, with 3 m being a representative UAS

wingspan or maximum horizontal dimension.

2) The number of **Losses of Separation (LOS)** simulated in each scenario. MACs are intentionally rare events, so an alternative measure - a Loss Of Separation (LOS) - is defined from which we can estimate the number of MACs. We do this by assuming $P(MAC, LOS) = P(MAC \mid LOS) \times P(LOS)$. Because a MAC is always accompanied by a LOS event, $P(MAC, LOS) = P(MAC)$, so $P(MAC) = P(MAC \mid LOS) \times P(LOS)$. By using a Maximum Likelihood Estimates for MAC count, we can state that:

$$MAC = P(MAC \mid LOS) \times LOS \tag{1}$$

where MAC is the estimated MAC count, and LOS is the observed LOS count. $P(MAC \mid LOS)$ is approximately constant, allowing us to estimate MAC counts given observed LOS counts. This approach is used for crewed aviation using a LOS definition of 500 feet of horizontal separation and 100 feet of vertical separation (typically called a Near-Mid Air Collision - NMAC) [33]. It has also been proposed for small UAS using a LOS definition of 50 feet of horizontal separation and 15 feet of vertical separation (called a smaller Near-Mid Air Collision - sNMAC) [33]. While this latter definition is appropriate for estimating unmitigated collision risk, simulated losses of 50 feet of horizontal separation applying strategic deconfliction were found to be sufficiently rare that it was not possible to reliably quantify them for all scenarios simulated in this paper. We therefore define a LOS as any loss of 42.5 m (140 feet) of horizontal separation, which is the average horizontal width of operational intent volumes applied in this paper. Other values may also be appropriate. We estimated $P(MAC \mid LOS)$ from simulations in which collision risk was unmitigated and both MAC and LOS were observed.

The definitions of the safety events from which the above metrics are calculated are summarized in Table 1).

Table 1 Safety event definitions used in this paper

Event	Horizontal Separation Threshold (m)
Mid Air Collision	3
Loss of Separation	42.5

V. Simulation Setup

A series of Monte Carlo simulations were designed to evaluate the performance of strategic deconfliction in highly utilized airspace, exploring the impact of performance requirements and operational environment characteristics on safety.

A. Exploring the impact of performance requirements

The performance requirements that were varied in the simulations are operational intent volume conformance rate and strategic deconfliction participation rate, as outlined in Table 2. An example conformance rate profile for a given set of volume sizes (defined by a horizontal buffer relative to the operational intent center-line) is outlined in Figure 2. The conformance rate requirement can be empirically determined by simulating a set of on-board UAS noise configurations for speed, heading and altitude uncertainty, and operational intent volume sizes defined by horizontal, vertical and time buffers relative to the operational intent center-line. Our approach to configuring the conformance rate for a given simulation is to first empirically measure the conformance rate for a given set of noise and volume size parameters. Given a set of the measured rates, we can then determine which noise parameters in combination with operation volume sizing configurations lead to the desired conformance rate for the simulation in question. The range of noise values simulated - specifying the standard deviations for Gaussian distributions centered on zero - are described in Table 3. The range of operational intent buffers simulated are described in Table 4.

The UAS performance characteristics used in these simulations are outlined in Table 5. These operational parameters are held fixed in all the simulations exploring the impact of performance requirements. Operations are modelled to operate at altitudes between 150 and 400 feet Above Ground Level (AGL), depending on the altitude of the destination versus the origin.

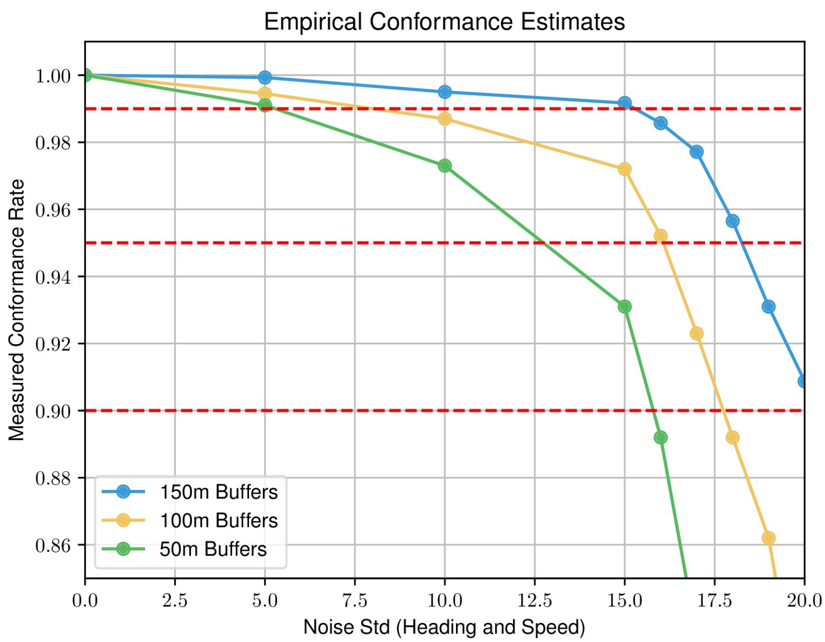


Fig. 2 Example estimate of conformance rate from configured UAS noise values.

Table 2 Requirements evaluated in this work

Study Variable	Values
Conformance Rate	[0.95, 0.99]
Participation Rate	[0.0, 0.25, 0.50, 0.75, 1.0]

Table 3 On-board UAS noise values simulated

Noise Type	Standard Deviations Simulated
Speed (m/s)	[0, 3, 6, 9, 12, 15]
Heading (degrees)	[0, 3, 6, 9, 12, 15]
Altitude (m)	[0, 3, 6, 9, 12, 15]

Table 4 Operational intent volume center-line buffer values simulated

Buffer	Values Simulated
Horizontal (m)	[15, 23, 30, 50, 100]
Vertical (m)	[10, 25, 50]
Temporal (s)	[5, 10, 30]

B. Exploring the impact of operational complexity

In this study we explore the impact of operational complexity on safety by simulating operations across a range of operational densities, for scenarios representing two operational profiles, as outlined in Table 6.

The operational profiles simulate different distributions of operational use cases. Four different operational use cases are simulated:

- **Hub-and-spoke:** Operations that model package delivery out of a fulfillment center that serves a nearby area. The operations originate and return to the fulfillment center while flying to their delivery mission location in between.

Table 5 Key simulation parameters used in this work.

Parameter	Value
Cruise speed	$15\,\mathrm{m\,s^{-1}}$
Maximum linear acceleration	$2.5\,\mathrm{m\,s^{-2}}$
Maximum UAS turn rate	$45\,^{\circ}\,\mathrm{s^{-1}}$

Table 6 Operational complexities evaluated in this work

Study Variable	Values
System Demand	[100, 200, 250, 400, 500, 600] Ops/Hr
Operational Profiles	[low complexity, high complexity]

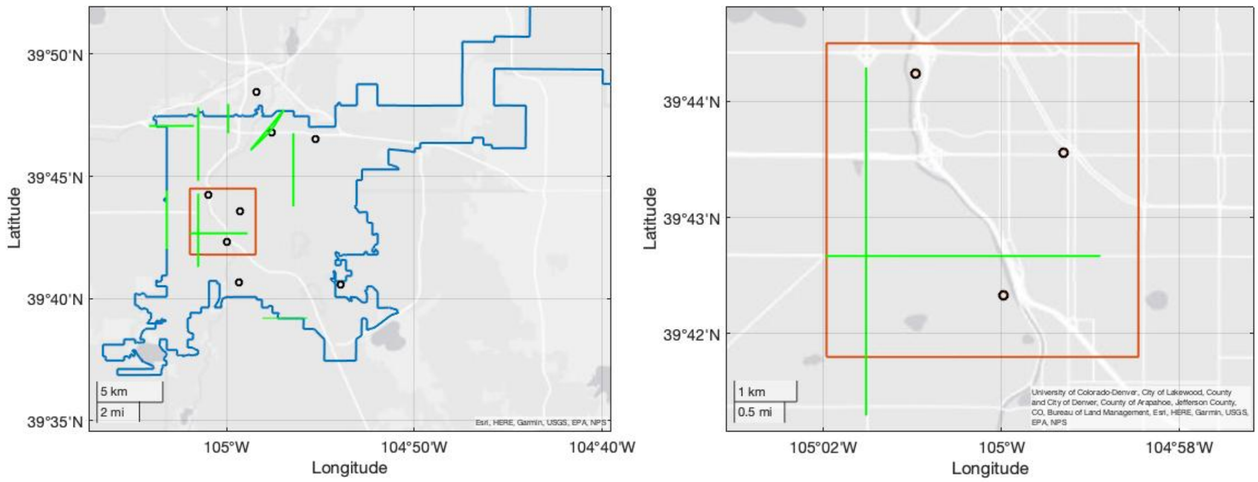
- **Long-Linear-Inspection:** Operations that follow a specified geographical feature, such as road, railway or waterway, from one point to another, representing inspection type operations.
- **Point-to-Point:** Operations that start and end in different locations while flying the shortest viable path from their origin to their destination. These operations are meant to model any point-to-point use cases such as medical delivery operations between medical practices or hospitals.
- **Out-and-Back:** Operations that start and end in the same locations while flying to a destination mission location in between. In this use case the origins/destinations are randomly distributed, and represent hobby drone operators and law-enforcement drone activity.

The first operational profile simulated - representing a low complexity scenario which aligns with the approach used in our previous work [6] - is a uniform distribution of out-and-back operations across the simulation area. The second operational profile simulates a realistic distribution of all 4 operational use cases across a real city. In this case, the distribution of operational use cases across the total demand is fixed, with the magnitude of total system demand varied as before. The composition of the operational profile is listed in Table 7, and is based on the US Federal Aviation Administration's (FAA's) expectation of the notional distribution and frequency of various operational use cases derived from existing Beyond-Visual Line Of Sight (BVLOS) waivers and exemptions. Operations are simulated in the greater Denver metropolitan area, with the locations of each operational profile based on the real locations of various features in the city, such as warehouses representing fulfillment centers for hub-and-spoke operations; and roads and railway lines for long-linear-inspection. The origins and destinations for out-and-back-operations and point-to-point operations, and the mission locations for hub-and-spoke operations and out-and-back operations, are randomly distributed across the simulated region, weighted by population density (shown in Figure 4 for the region simulated). Figure 3 shows the region simulated in Denver, and the locations of the hub-and-spoke fulfillment centers and long-linear-inspection routes.

The operational environment simulated for the low complexity and high complexity operational profiles are 25×25 km and 5×5 km regions, respectively, with no airspace constraints or restrictions. The impact of airspace constraints on operations will be explored in future work.

Table 7 Composition of operational profile simulated for Denver

Operational Use Case	Value
Hub-and-Spoke	50 %
Long-Linear-Inspection	20 %
Point-to-Point	15 %
Out-and-Back	15 %



(a) (b)

Fig. 3 Denver metropolitan area simulated, showing (a) region simulated (red square) relative to metropolitan area (blue polygon), and (b) close-up of simulated region (red square) with warehouse fulfillment centers (black circles) and long-linear inspection routes (green lines) shown.

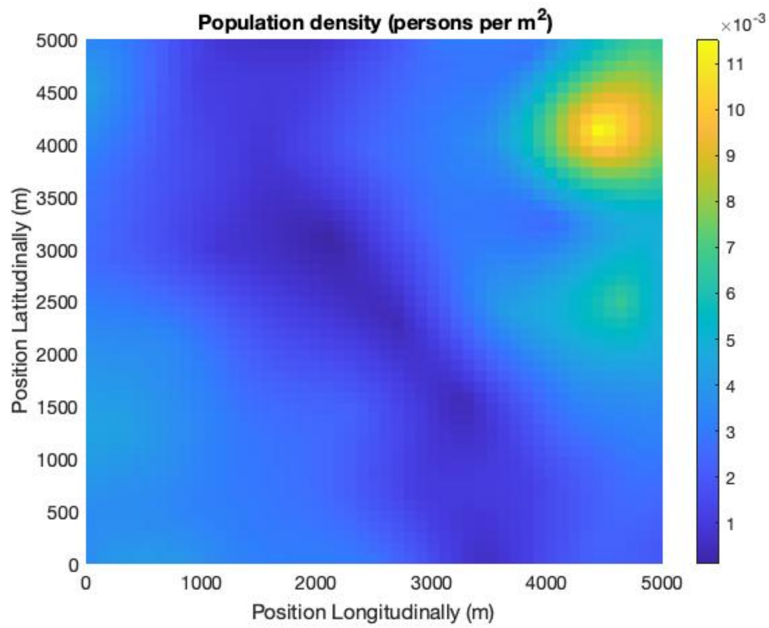


Fig. 4 Denver metropolitan area population density in the simulated region.

VI. Results

A. Low complexity operational profile

For the low complexity operational profile simulating uniformly distributed out-and-back operations across a 25×25 km region, the relationship between safety and operational density is outlined in Figure 5. The figure shows the simulated number of MACs per year between cooperative uncrewed aircraft, calculated from observed LOS counts by applying equation 1, and assuming a 10 hr operational day. A $P(MAC \mid LOS)$ of 0.176 is applied, calculated from

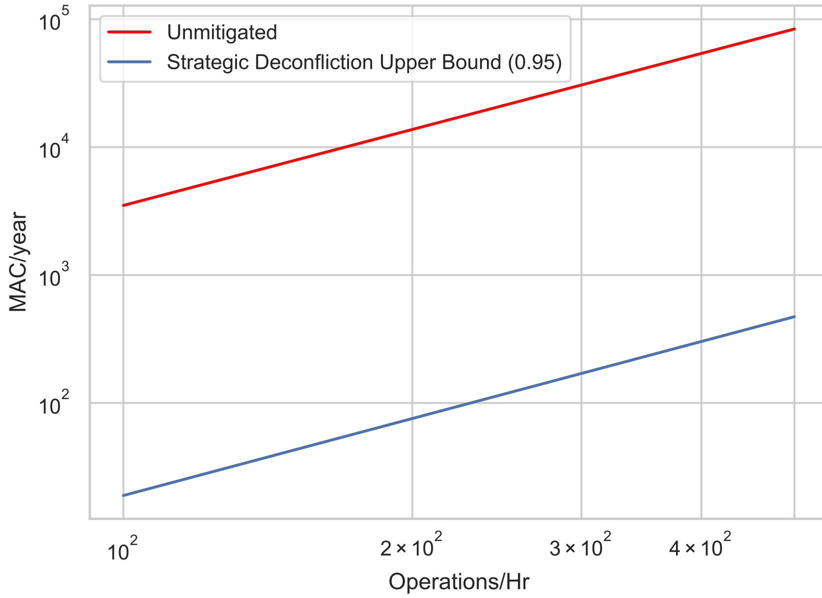


Fig. 5 Relationship between a safety metric (Mid Air Collisions per Year) and system demand, with no risk mitigation and with strategic deconfliction, for a low complexity scenario with uniform distribution of out-and-back operations.

the unmitigated simulation runs in which both MACs and LOSs are observed. LOSs are counted for pairs of aircraft by event, so if the pair of aircraft remain separated by less than the specified threshold for multiple time steps, it is only counted as a single event. Two lines are plotted in each of the subplots in Figure 5 - one showing unmitigated results when no strategic deconfliction is applied (red line), and a second showing the impact of strategic deconfliction on safety when operations are meeting a conformance rate of 0.95 (blue line). For both the unmitigated and strategic deconfliction cases, MACs/year increase with system demand in operations/hr according to a power law (straight line on a log-log plot). That relationship is similar in both cases - the lines are parallel - implying a constant reduction in the risk of collision due to strategic deconfliction, that is not a function of operational density (within the range of system demand simulated). In this simulation that scaling is an approximately 99% reduction in MAC/year. The results for each configuration plotted in Figure 5 were generated by simulating approximately 28,000 UAS flight hours on average.

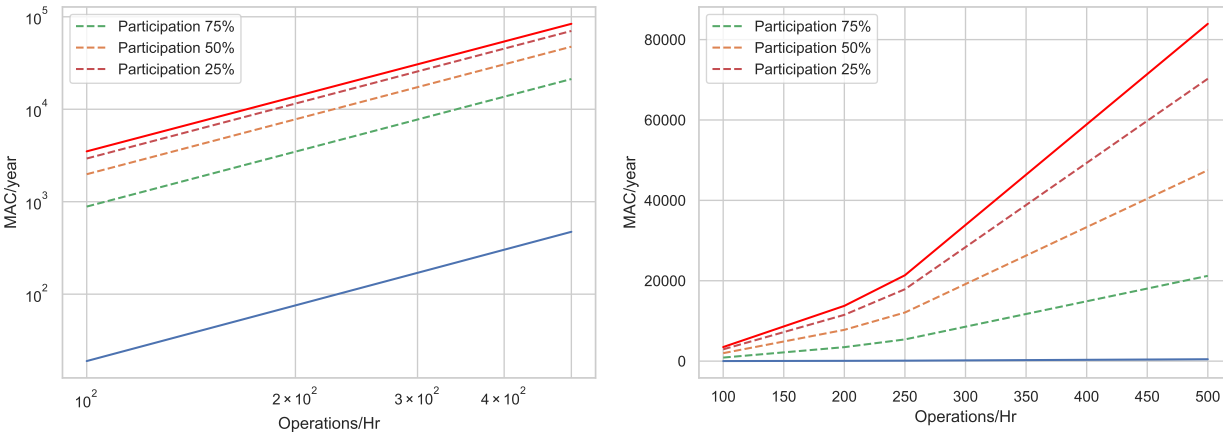
The relationships between safety, strategic deconfliction participation rate, and operational density are shown for the low complexity operational profile in Figure 6 (plotted on log-log axes in Figure 6a, as in Figure 5, and on linear axes in Figure 6b).

This figure clearly illustrates that reduced participation rate reduces the safety benefit of strategic deconfliction, with a 75% participation rate reducing the safety benefit in MAC/year by 25% on average relative to the 100% participation rate case. This approximately linear relationship is more clear in Figure 7, which illustrates the relationship between safety, conformance rate, and strategic deconfliction participation rate. These results also indicate that participation rate has a more significant impact on safety than conformance rate in analyses run in this paper.

B. High complexity operational profile

For the high complexity operational profile simulating 4 different operational use cases across a 5×5 km region in the Denver metropolitan area, the relationship between safety and operational density is outlined in Figure 8. This plot is comparable to Figure 5, and shows similar trends. The results for each configuration plotted in Figure 8 were generated by running approximately 400,000 UAS flight hours each, on average.

The results in Figure 8 for the high complexity operational profile show higher MAC/year values for any given operations/hr value than for the low complexity scenario in Figure 5. This is expected given that the demand in the high complexity operational profile is distributed across a 5×5 km region, while for the low complexity scenario it is



(a) **(b)**

Fig. 6 Relationship between safety, strategic deconfliction participation rate, and system demand for a low complexity scenario with uniform distribution of out-and-back operations, (a) log-log axes, and (b) linear axes.

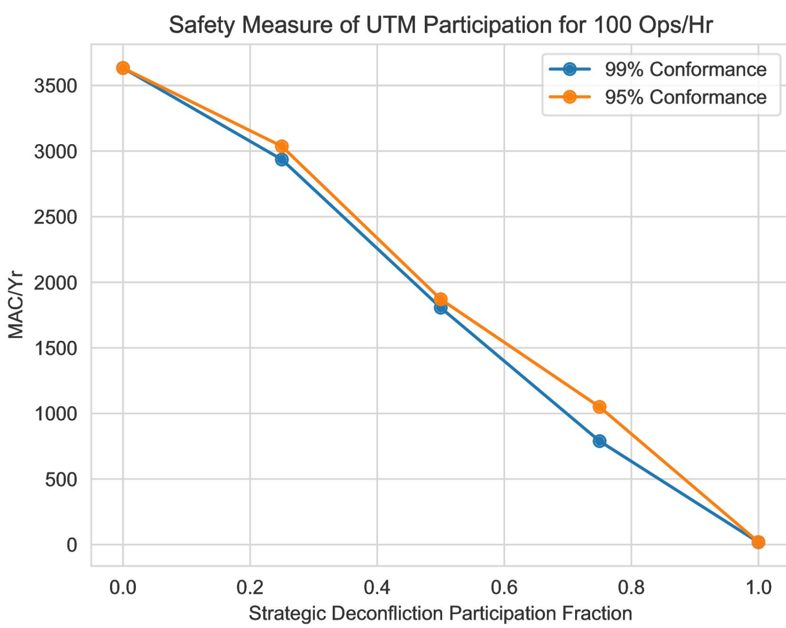


Fig. 7 Relationship between conformance rate, participation rate, and safety for system demand of 100 operations/hr for a low complexity scenario with uniform distribution of out-and-back operations.

distributed over a larger 25×25 km region.

As in the low complexity operational profile, Figure 8 for the high complexity operational profile shows MAC/year increasing with system demand according to a power law (straight line on a log-log plot). The results for the unmitigated and strategic deconfliction cases are approximately parallel, implying an almost constant reduction in the risk of a MAC due to strategic deconfliction that is not a function of operational density (within the range of system demand simulated). Like in Figure 5 for the low complexity operational profile, the average reduction in MAC/year from strategic deconfliction in Figure 8 for the high complexity operational profile is 99%.

The relationships between safety, strategic deconfliction participation rate, and operational density are shown for the high complexity operational profile in Figure 9 (plotted on log-log axes in Figure 9a, as in Figure 8, and on linear axes

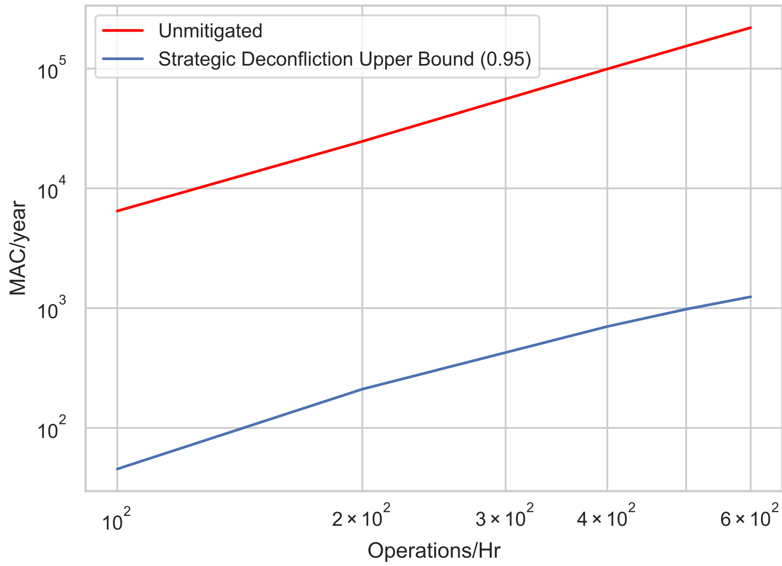


Fig. 8 Relationship between a safety metric (Mid Air Collisions per year) and system demand, with no risk mitigation and with strategic deconfliction, for a high complexity operation profile with 4 operational use cases distributed across the Denver metropolitan area.

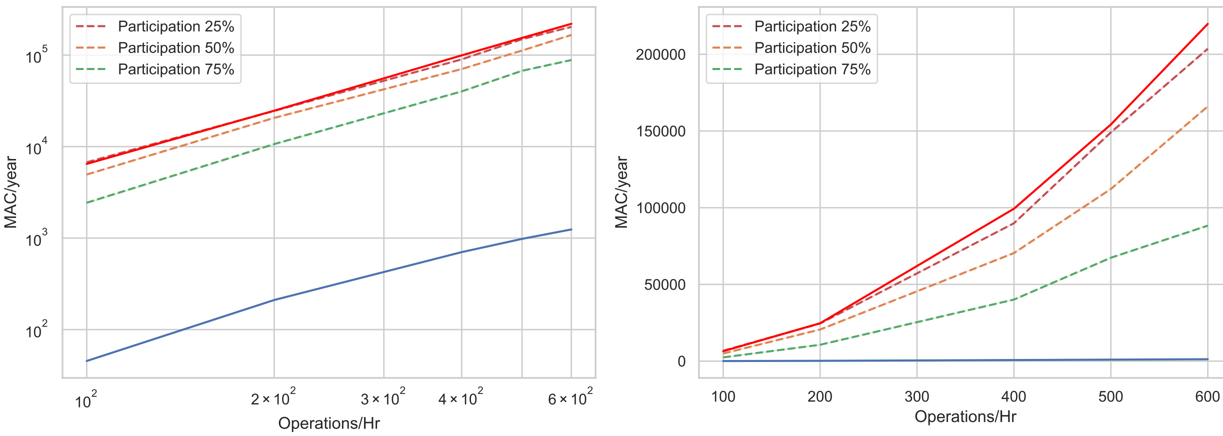
in Figure 9b). As for the low complexity operational profile, this figure shows that reduced participation rate reduces the safety benefit from strategic deconfliction. In this case a 75% participation rate reduces the safety benefit in MAC/year by 41% on average relative to the 100% participation rate case - somewhat higher than the 25% observed for the low complexity operational profile. This suggests that the impact of participation rate on the safety benefit of strategic deconfliction may be affected by the complexity of the operational scenario simulated.

The 99% operational intent conformance rate case was not simulated for the high complexity operational profile, but the impact of conformance rate is expected to be small, consistent with the results from the low complexity profile in Figure 7.

VII. Conclusions

For this paper, a series of simulations were run to explore the safety implications of key performance requirements (conformance rate and strategic deconfliction participation rate), and operational complexity (operational profile and operational density) in the implementation of UTM strategic deconfliction. The results presented show that metrics describing operational safety (MAC/year) increase with increasing operational density according to a power law. This applied to both unmitigated traffic and when applying strategic deconfliction, and for both a low complexity operational profile and a high complexity operational profile in a real city (Denver). Strategic deconfliction was observed to reduce the calculated safety metrics significantly across a range of operational densities, and in both the low complexity and high complexity operational profiles, by an approximately constant value of 99%. However, reduced participation rate in strategic deconfliction was found to reduce the safety benefit from strategic deconfliction. In contrast, the results were found to be much less sensitive to the difference in conformance rates simulated (95% and 99%). Given a target level of safety in terms of allowable MAC/year, an allowable airspace capacity could be specified to constrain system demand to ensure that the target level of safety is not violated. The value with strategic deconfliction in place would be significantly greater than without, and would increase with increasing participation rate.

The results presented in this paper show that benefits of strategic deconfliction simulated for the low complexity operational profile are also generally applicable for the high complexity operational profile - i.e., that strategic deconfliction - with a conformance rate of 95% - provides a significant safety credit for UAS flight operations, but that participation rate must be high to realise that benefit. These results suggest that such benefits may also be applicable for



(a) **(b)**

Fig. 9 Relationship between safety, strategic deconfliction participation rate, and system demand for a high complexity operation profile with 4 operational use cases distributed across the Denver metropolitan area, (a) log-log axes, and (b) linear axes.

real UTM operations, in which operational complexity is further increased.

While some operational complexities were explored in this paper, there are many more that were not. Most importantly, the impact of operational constraints, such as restricted airspace, was not explored in this paper. Operational constraints may cause traffic density hot spots resulting in an increase in collision risk, and a study of their impact is therefore recommended for future work.

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