ASSURE A71 – Conduct Safety Risk Management Analysis on Unmanned Aircraft Detect and Avoid Systems

Issue Report

August 30, 2024

v 1.0

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
A11L.UAS.120_A71		

4. Title and Subtitle	5. Report Date
ASSURE A71 – Conduct Safety Risk Management Analysis on Unmanned System Detect and Avoid Systems: Issue Paper	August 30, 2024
	6. Performing Organization Code

7. Author(s)	8. Performing Organization Report No.
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9. Performing Organization Name and Address	10. Work Unit No.
Kansas State University University of North Dakota Embry Riddle Aeronautical University Drexel University	**11. Contract or Grant No.** A11L.UAS.120_A71 – Detect and Avoid

12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
Federal Aviation Administration UAS COE PM: Karen Davis, ANG-C2 UAS COE Dep. PM: Hector Rea, ANG-C2	Issue Report (3/18/2024 – 8/30/2024) **14. Sponsoring Agency Code** 5401

15. Supplementary Notes
Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. Abstract
This issue paper explores DAA system functions and operations against the backdrop of the safety risk management (SRM) process to identify issues and gaps that pose challenges to assessing risks associated with DAA systems. Framing this issue paper regarding the SRM process – describing the system, identifying hazards, assessing risk, analyzing risk, and controlling risk – provides a rational way to look for issues and gaps that challenge effective SRM for DAA systems in each process step. This approach identifies issues and gaps that may be considered and addressed during the development of a DAA risk assessment framework in future research tasks.

17. Key Words	18. Distribution Statement
Safety Management Systems, Safety Risk Management, Detect and Avoid, Beyond Visual-Line-of-Sight,	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	47	N/A

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ADS-B	Automatic Dependent Surveillance-Broadcast
ANSI	American National Standards Institute
ASTM	American Society for Testing and Materials International
BVLOS	Beyond Visual Line of Sight Operations
C2	Command and Control
CNPC	Command and Non-Payload Communications
CVaR	Conditional Value-at-Risk
DAA	Detect and Avoid
DET	Dynamic Event Tree
EO	Electro-Optical
FAA	Federal Aviation Administration
FMEA	Failure Mode Effects Analysis
FOV	Field Of View
GBS	Ground-Based Sensor
GBSS	Ground-Based Surveillance System
GCS	Ground Control Station
ICAO	International Civil Aviation Organization
LIDAR	LIght Detection And Ranging
MAC	Mid-Air Collision
MoC	Means of Compliance
MOPS	Minimum Operation Performance Standards
NAS	National Airspace System
NMAC	Near Mid-Air Collision
NASEM	National Academies of Sciences, Engineering, and Medicine
QRA	Quantitative Risk Assessment
RADAR	RAdio Detection And Ranging
RPIC	Remote Pilot in Command
RTCA	Radio Technical Commission for Aeronautics
SDO	Standard(s) Development Organization
SM	Simulation and Modeling
SMS	Safety Management System
SRA	Safety Risk Assessment
SRM	Safety Risk Management
STAMP	System Theoretic Accident Modeling and Process
STPA	System Theoretic Process Analysis
sUAS	small Unmanned Aircraft System
UA	Unmanned Aircraft
UAS	Unmanned Aircraft System
VaR	Value-at-Risk

EXECUTIVE SUMMARY

As the demand for regular beyond visual line-of-sight (BVLOS) flight operations for small Unmanned Aircraft Systems (sUAS) continues to grow, so does the need to assess the safety of Detect And Avoid (DAA) systems. DAA systems play a critical role in promoting the safety of BVLOS flights, as they perform the essential function of detecting and avoiding other air traffic, mitigating the risk of mid-air collisions. However, the hazards and risks associated with using DAA systems are not entirely understood, and there is currently no reliable, repeatable process for assessing the risks related to their use.

This issue paper explores DAA system functions and operations against the backdrop of the Safety Risk Management (SRM) process to identify issues and gaps that pose challenges to assessing risks associated with DAA systems. Framing this issue paper in terms of the SRM process – describing the system, identifying hazards, assessing risk, analyzing risk, and controlling risk – provides a rational way to look for issues and gaps that challenge effective SRM for DAA systems in each process step. This approach identifies issues and gaps that may be considered and addressed during the development of a DAA risk assessment framework in future research tasks.

Issues and gaps identified within this issue report can be listed in seven key points. These points are distilled from issues and gaps identified in each step of the SRM process and summarized for brevity. Issues and gaps identified within this issue report are:

1. There are no universally accepted reliability metrics for DAA systems.
2. There are currently no accepted standards for assessing risk associated with DAA systems.
3. Much of the data available for analyzing DAA systems is incomplete, inaccurate, or unavailable.
4. Reliable data must drive analytical models that inform risk assessment for DAA systems.
5. The rapid growth and deployment of DAA technologies have outpaced the development of Federal Aviation Administration (FAA) operational guidance.
6. There is an inherent need to define the reliability of DAA systems.
7. Guidance and standards for applying risk controls are needed.

While this issue paper does not address all possible issues and risks associated with DAA systems, it highlights some of the most prominent barriers to identifying hazards and assessing risk. The issues and gaps identified in this issue paper will inform the identification of hazards and the development of a risk assessment framework in future research tasks. Additionally, the issues and gaps identified here may inform other research efforts and serve as a starting point for identifying essential characteristics of DAA systems.

1 INTRODUCTION AND BACKGROUND

Industry demand for Beyond Visual Line of Sight (BVLOS) flight operations is high. A primary bottleneck towards the acceleration of BVLOS operations in the National Airspace System (NAS) is the uncertainty regarding system and operational safety when small Unmanned Aircraft Systems (sUAS) are equipped with Detect and Avoid (DAA). Presently, new and refined Safety Risk Management (SRM) strategies are required for Unmanned Aircraft (UA) as current methods, protocols, and tools may fall short of providing meaningful output for both system safety and operational safety/risk.

The Federal Aviation Administration (FAA) utilizes Safety Management Systems (SMS) strategies to integrate safety policies, procedures, and practices. SMS strategies provide tools to systematically identify, assess, and mitigate safety risks in aviation operations. FAA Order 8040.6A (Federal Aviation Administration, 2023b) provides the guidelines for conducting a safety risk assessment for Unmanned Aircraft Systems (UAS) operations. Before 2018, UAS Operations were conducted through an exemption process using various traditional safety risk assessments – i.e., FAA Order 8040.4C (Federal Aviation Administration, 2023a), and strategies with step-by-step processes to identify hazards and associated risks. Unfortunately, traditional aviation Safety Risk Assessment (SRA) hazards and definitions for severity and likelihood differ, creating unaddressed gaps in the SRA process for unmanned aircraft and related operations using FAA Order 8040.6A.

In 2018, a report published by the National Academies of Sciences, Engineering, and Medicine (National Academies, 2018), addressed as NASEM herein, reported that current approaches to SRM used by the FAA are highly subjective for effective risk assessment of UAS operations. NASEM (2018) suggested that the qualitative nature of current SRM strategies, when applied to UAS, often leads to results that are not repeatable, predictable, or transparent. Additionally, the FAA uses multitiered safety targets for conventional aviation aircraft categories. For instance, the safety target for conventional transport aircraft is estimated to be one catastrophic event per one billion flight hours. Safety targets may differ for other aircraft categories with reduced rigor to approximately one catastrophic event per one million flight hours (e.g., general aviation; NASEM, 2018). The resulting outcome is that applying the same safety targets used for conventional aviation to UAS is impractical, as thresholds for assessing risk in commercial and general aviation have been based on the probability of a passenger fatality. According to NASEM (2018), these measures do not correspond well with risk assessment concerning UAS operations. A key recommendation is the evolution of SRM methodologies currently used by the FAA.

Due to the high variability in UAS systems design, establishing safety targets for UAS systems and operations has been challenging, resulting in highly qualitative approaches to evaluating risk for different UAS operations. The most common approach used by the industry to assess probability and consequence is a 5x5 risk "heat" matrix based on ordinal scale ranking. NASEM (2018) suggests that risk matrices based on measures of an ordinal scale are often subject to many logical inconsistencies and should be avoided as a measure of good risk practice. Unfortunately, the problem is exacerbated when applying current SRM methods, protocols, and tools on UAS sub-systems such as DAA. This presents new and unique challenges. For instance, it is inherently difficult to assess the performance of a DAA system using a 5x5 risk "heat" matrix as the risk calculated does not correspond to or consider overall DAA performance. Additionally, a lack of empirical data sets for airborne and ground-based DAA systems in this nascent industry accentuates the shortfalls between technology development and policymaking. NASEM (2018) suggests that the basis for safety decision-making may better be achieved with an approach more reliant on applicant expertise and investment in risk analysis, modeling, and engineering assessment toward quantitative probabilistic risk analysis.

2 SAFETY MANAGEMENT SYSTEMS (SMS)

SMS is essential for safety in nearly all aviation ventures, including sUAS flight operations. The FAA defines SMS as a systematic approach to safety composed of four primary components: safety policy, safety risk management, safety assurance, and safety promotion (Federal Aviation Administration, 2021). Figure 1 shows these components and provides greater detail regarding their contributions to SMS. These four components define a systematic approach to safety that integrates into operational procedures and cultural norms at an organizational level, building itself into, across, and through all levels of an organizational hierarchy.

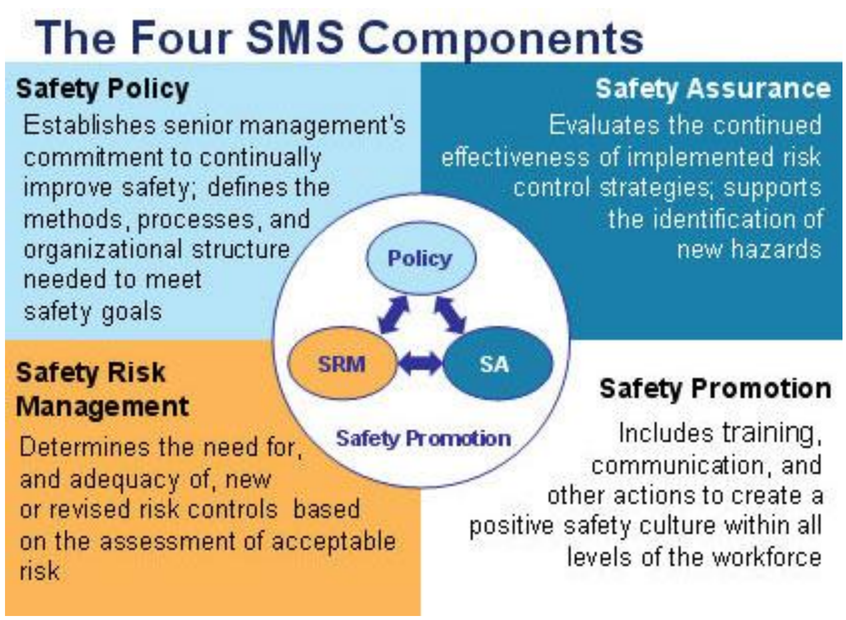

Figure 1. Four components of an SMS (Federal Aviation Administration, 2021).

Of these four components, SRM presents a unique challenge for sUAS and DAA systems. While FAA policy guidance under FAA Order 8040.6A offers an SRM framework, which includes describing a system, identifying hazards, assessing risks, analyzing risks, and applying risk controls, there are gaps and unknowns relating to DAA systems. While this report focuses primarily on SRM, it is important to note that all four SMS components are interdependent. For example, under safety policy, the accountable executive's responsibilities include the authority to approve or accept the highest level of risk within the organization. Likewise, under safety assurance, FAA Order 8040.6A describes the interdependent relationship between SRM and safety assurance regarding approvals gained through waivers or exceptions to the regulations. FAA Order 8040.6A states, "previous approvals do not eliminate the need for continuous monitoring of UAS related safety risk, e.g., Safety Assurance functions, or the potential need for updating established controls (Federal Aviation Administration, 2023).

Understanding the importance of harmonization of the four components, the following sections provide an overview of the components of SRM through the lens of DAA systems, identifying issues and gaps associated with the application of SRM strategies to DAA systems.

3 SAFETY RISK MANAGEMENT (SRM)

The SRM process is a comprehensive framework designed to enhance aviation safety by systematically identifying, analyzing, and mitigating risks. The SRM process involves a systematic approach, including describing the system, identifying hazards, and analyzing, assessing, and controlling safety risks. SRM provides decision-makers with critical information by identifying hazards, analyzing safety risks, assessing safety risks, and developing controls to mitigate risks to the lowest practical level. It requires coordination across various FAA organizations and is applied during planned changes to the aerospace system and when new hazards are discovered. The process also emphasizes the dynamic relationship between SRM and safety assurance, ensuring adequate safety risk controls and modifying them based on continuous monitoring and data analysis (Federal Aviation Administration, 2023a).

3.1 Describing the System

The first step of the SRM process is to 'Describe the System.' Within the SRM framework, this critical step is often overlooked and underappreciated. "The effects of safety hazards and associated risk management methods across multiple organizations, domains, and implementation timelines must be properly understood to achieve the highest practical level of safety. Safety risk deemed acceptable for an individual element of the NAS may lead to unintentional safety risk in another element if SRM is not conducted with a 'system of systems' philosophy" (Safety Management System Manual Air Traffic Organization, 2022). When defining the 'system,' an organization must be concerned with the sum of the parts that make up a particular system and the interaction of those parts within the system. This rationale can also be applied to system-of-system scenarios. For simplicity, consider the National Airspace System. Suppose an organization only identifies the parts of the system, such as types of airspace, regulations for communications, aircraft that fly in that system, etc., but does not consider how each of those parts and systems interact within the NAS; many hazards and consequential risks will be misdiagnosed or entirely omitted. An organization must understand its system and how other systems and parts will interact with that system before attempting the second step of the SRM process, which is identifying hazards. The following section describes a breakdown of the 'parts' of the DAA system so that it will be appropriately applied to the broader NAS in continued research.

3.1.1 Functional Breakdown of DAA Systems

Core functions common to all DAA systems, as specified in the Standard Specification for Detect and Avoid System Performance Requirements, include operating UA safely within low- and medium-risk airspace environments, particularly at altitudes below approximately 1200 feet above ground level. DAA systems must handle mixed traffic scenarios involving cooperative and non-cooperative aircraft, including those operating under instrument and visual flight rules. They must ensure UA can detect and avoid conventionally piloted aircraft without relying on air traffic control separation services, operating effectively in both visual and instrument meteorological conditions and during both day and night. Additionally, DAA systems are required to meet specific safety performance thresholds to ensure operational safety, and they must be adaptable to various architectures and integrated seamlessly with the overall UAS system. These systems are expected to be utilized by multiple contributors, including system designers, sensor suppliers, UA developers, control station designers, and flight control designers using standards such as American Society for Testing and Materials International (ASTM) F3442/F3442M-23.

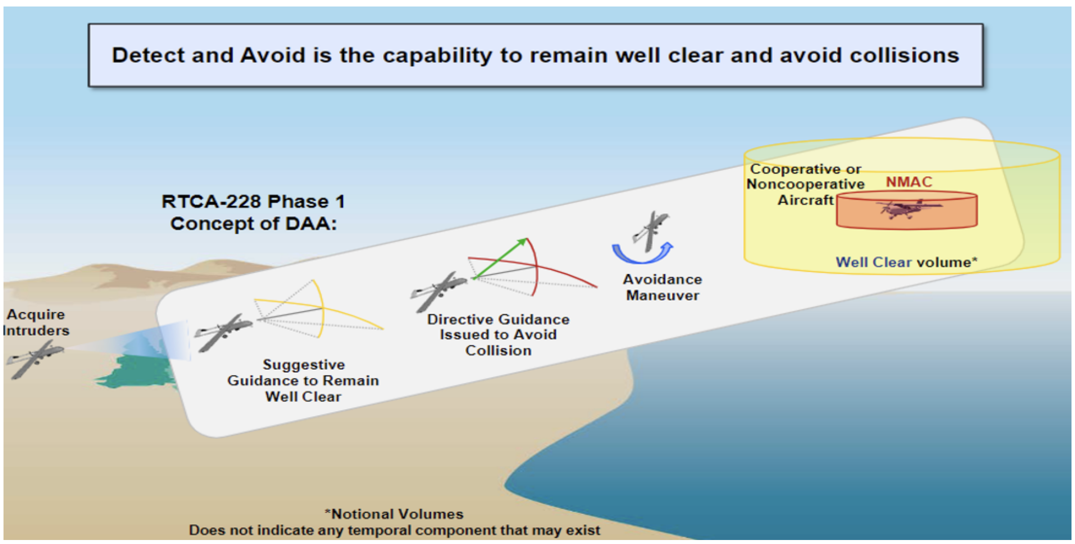

Figure 2. RTCA SC-228 Concept of DAA Systems (Chen, 2019).

Radio Technical Commission for Aeronautics (RTCA) defines DAA as a system function that enables an unmanned aircraft to maneuver within a sufficient timeframe to remain well clear of other airborne traffic. Figure 2 illustrates the RTCA SC-228 concept of a DAA system. Numerous UAS DAA system architectures can be classified into ground-based or airborne systems and automated or human-in-the-loop systems. Regardless of the specific implementation, DAA systems must perform the following basic functions, as summarized in Figure 2:

1. Detect and track airborne aircraft in the vicinity of the UAS,
2. evaluate the collision hazard of each intruder aircraft by predicting their future trajectories and comparing them against the predicted trajectory of the UAS,
3. prioritize the intruders and (if necessary) alert/declare that action is required to avoid a predicted loss of well clear, and
4. determine maneuver guidance to resolve the situation.

A DAA system has three main sub-functions, all of which may significantly affect its performance:

1. The surveillance function that detects and tracks intruder aircraft,

2. the threat alerting function to evaluate intruder tracks and declare if action is necessary to prevent an intruder from causing a loss of well clear, and
3. the guidance function to aid the UAS pilot (or autonomous DAA system) in determining a maneuver to resolve a predicted well-clear violation.

The DAA surveillance system provides an electronic means for the UAS pilot to "see" (detect and track) both cooperative (i.e., transponder-equipped) and non-cooperative aircraft. The DAA alerting and guidance system comprises a set of algorithms to alert and aid the UAS pilot in prioritizing potential traffic conflicts (i.e., a loss of well clear) and to assist the UAS pilot in performing guidance maneuvers to avoid a loss of well clear. The general functions of a DAA system are shown in Figure 3.

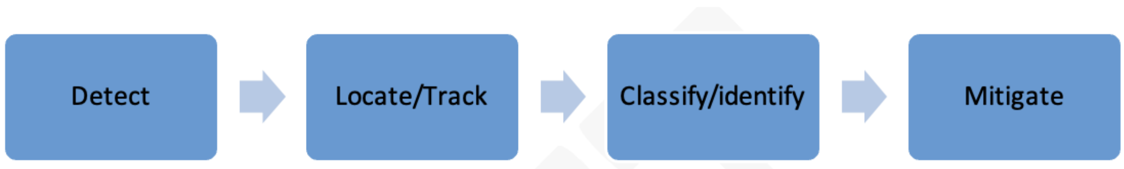

Figure 3. UAS DAA Basic Functionality (McCrink et al., 2022).

DAA systems utilize a combination of surveillance sensors to collect data on the state of cooperative or non-cooperative intruder aircraft. Cooperative traffic is equipped with Automatic Dependent Surveillance-Broadcast (ADS-B) and Mode S transponders. The ADS-B system transmits the state vector of the vehicle, such as horizontal and vertical position, velocity, and some other intent information, every second (Cao, 2007) and includes two separate components, ADS-B Out and ADS-B In. ADS-B is called dependent surveillance as it requires that the aircraft state vector and additional information be derived from the onboard navigation equipment. It is considered automated because it does not need pilot or controller input to transmit information. Mode S transponders (Orlando, 1989), consisting of ground components and an airborne transponder, have been designed to provide enhanced surveillance and communication capabilities required for air traffic control automation as part of the Air Traffic Control Radar Beacon System. DAA systems also employ active and passive sensors, which can be ground-based or airborne (i.e., mounted on the ownship UAS), to detect and track non-cooperative intruders. Current state-of-the-art active and passive sensors include Radio Detection And Ranging (RADAR), electro-optical sensors (visual/infrared cameras), Light Detection And Ranging (LIDAR), and acoustic sensors. In addition, the DAA system determines the state of the ownship UAS using navigation data from Global Navigation Satellite Systems, inertial measurement units, and vision-based sensors.

Cooperative/non-cooperative tracking data and host platform navigation data are processed using a dedicated algorithm within the central DAA processor onboard the ownship UAS. This algorithm produces an avoidance volume in the airspace surrounding each conflicting intruder/obstacle track. The algorithm ensures the rigorous mathematical treatment of the errors affecting the state measurements (correlated and uncorrelated measurements) and accounts for the host–obstacle relative dynamics and the environmental conditions affecting the aircraft dynamics.

3.1.2 Ground-Based DAA Systems

Ground-based DAA Systems are designed with a combination of onboard and ground control elements to ensure the safe operation of UAS. The architecture typically includes a variety of cooperative and non-cooperative sensors to detect and avoid potential collisions. The Ground Control Station (GCS) plays a crucial role in this architecture, housing the human-machine interfaces and facilitating Command and Control (C2) data link communication between the unmanned aircraft and the GCS. This setup allows the Remote Pilot In Command (RPIC) to oversee the operation and make informed decisions to avoid collisions, ensuring the safety of the UAS and other airspace users (Tabassum et al., 2019).

The GCS's DAA system comprises six major groups described by the RTCA Minimum Operation Performance Standards (MOPS) in Figure 4. The GCS Command and Non-Payload Communications (CNPC) equipment receives data from the ownship UAS processor and surveillance data from the ownship. The GCS CNPC may also receive guidance processing data depending on the specific system design. The GCS CNPC sends packets of maneuver command data, mode control data, and status data to the airborne CNPC equipment onboard the ownship. The GCS DAA processor processes the data received by the CNPC and forwards the information to the DAA control panel, which serves as the interface between the PIC, the ownship DAA processor, and the GCS DAA processor. The PIC can command maneuvers to the ownship UAS for execution by the onboard control/navigation system. The command functions are executed through this interface and sent to the GCS processors. Finally, they are transmitted via the datalink to the ownship UAS platform.

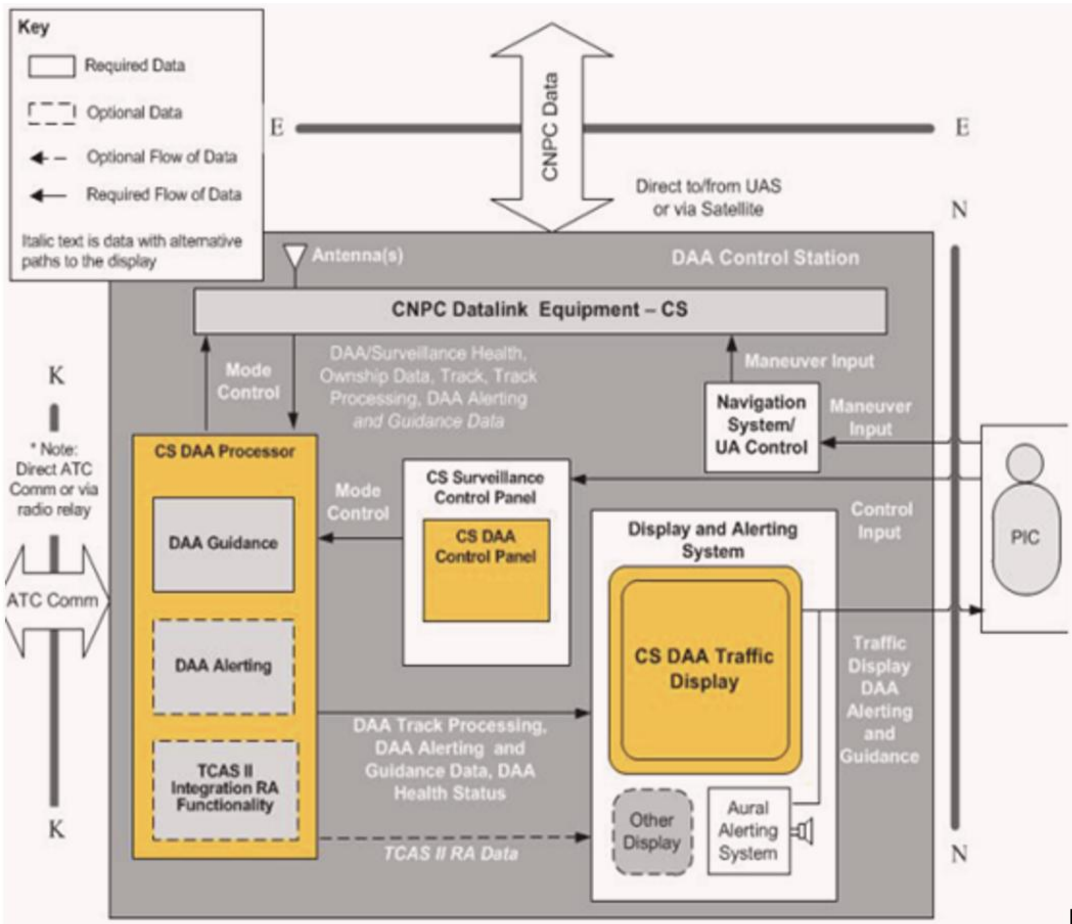

Figure 4. Major elements of the DAA system in the GCS (RTCA DO-365 2017).

Ground-Based Surveillance Systems (GBSS) can detect non-cooperative intruders in a DAA system. The GBSS provides intruder track information used by the DAA system to determine whether a maneuver is necessary to avoid a loss of well-clear. The track must be established at a sufficient range and with enough accuracy to enable the PIC to plan and execute a maneuver. The DAA system may also use the GBSS data to validate other sensors. Figure 5 shows an example from DAA MOPS illustrating the major elements of a DAA GBSS, with a single non-cooperative Ground-Based Sensor (GBS) as the surveillance sensor. The GBSS may employ more than one GBS to cover the necessary Surveillance Volume. Common GBS sensors include Electro-Optical (EO) sensors, ground-based RADAR, and acoustic sensors, which can also be combined in a multi-modal implementation. Each type of sensor has specific noise characteristics and challenges regarding potential false tracks, clutter, and environmental conditions.

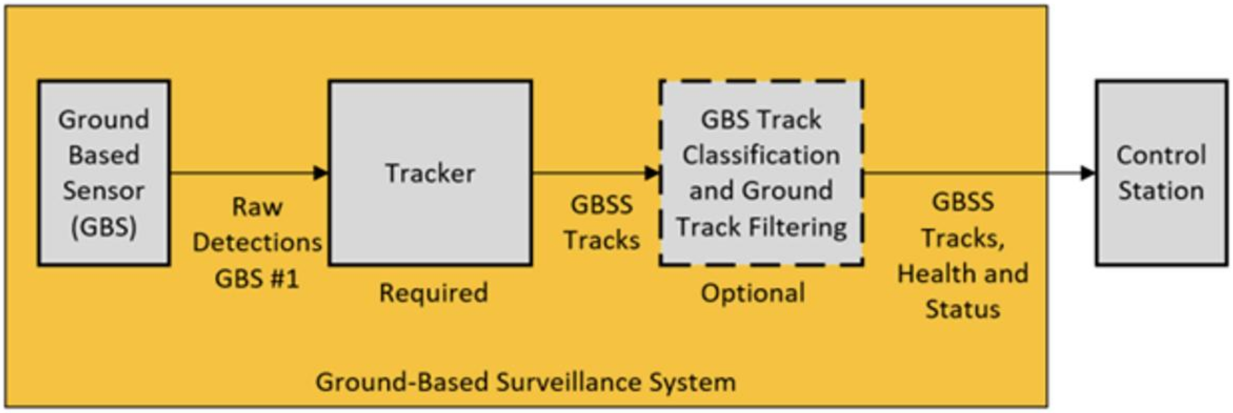

Figure 5. Ground-Based Surveillance System (McCrink, et al., 2022).

3.1.3 Airborne DAA Systems

Unlike ground-based systems, airborne DAA systems rely entirely on onboard sensors and processors to detect and avoid potential collisions. These systems integrate various sensors, including cooperative technologies like ADS-B and Mode S transponders, which communicate with other aircraft to share position and intent data. They also use non-cooperative sensors such as radar, LIDAR, and visual/infrared cameras to detect obstacles and other aircraft independently.

The onboard DAA processor fuses data from these sensors to create a comprehensive situational awareness of the airspace, enabling real-time decision-making for collision avoidance. The system processes navigation data from GNSS and inertial measurement units, ensuring accurate positioning and movement tracking. All critical DAA functions in airborne systems, including sensor data processing and avoidance maneuver computation, are performed onboard, providing a more autonomous operation (Tabassum et al., 2019).

An airborne DAA system includes four major elements: the surveillance component, the DAA processor, the onboard navigation system, and the CNPC equipment, as shown in Figure 6. Components of the overall airborne DAA system are partly located onboard the UAS platform and partly in its GCS. All cooperative surveillance systems, non-cooperative DAA sensors, and autonomous collision avoidance functions are installed onboard. All human-machine interfaces are integrated into the GCS. Both the ownship UAS and the GCS are equipped with C2 data link transceivers to transmit the data from the UAS platform to the GCS and commands from the GCS to the UAS platform. The UAS RPIC is responsible for the safe operation of the UAS and for executing directives unless they pose a hazard to the UAS.

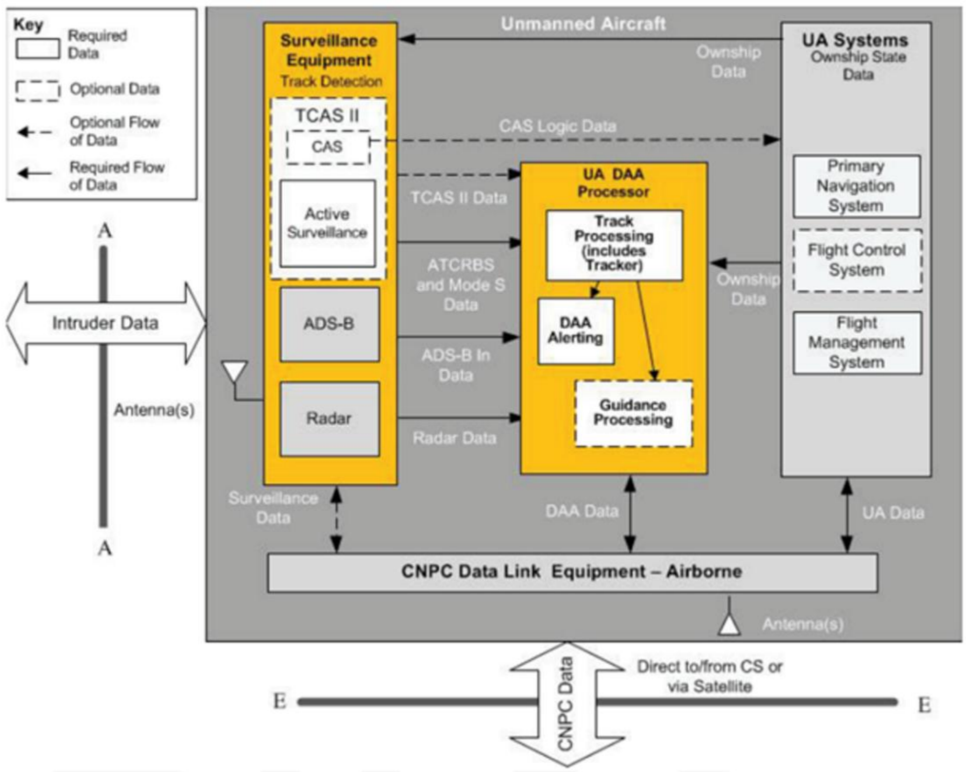

Figure 6. Major elements of an airborne DAA system (RTCA DO-365 2017).

State-of-the-art cooperative surveillance sensors include active airborne surveillance, Traffic Collision Avoidance System II, and ADS-B. Standard onboard non-cooperative surveillance sensors include RADAR, LIDAR, and EO/Infrared sensor systems. Each airborne non-cooperative sensor mode has specific noise characteristics and is subject to sensor-specific issues regarding environmental conditions, clutter, and false tracks, as will be detailed later in this report.

The UAS onboard processor receives onboard navigation sensor data, onboard airborne active surveillance data to detect transponder-equipped intruders, ADS-B receiving equipment to detect ADS-B-equipped intruders, and surveillance sensor data to detect non-cooperative intruders. The intruder data are then processed by the UA processor and used to evaluate the intended track of the intruder. Although it is assumed that the alerting algorithms are processed onboard the aircraft to help prioritize track, some manufacturers process the alerting through the GCS DAA processor (DO-365). The UA DAA processor may also provide guidance processing functionality; however, it is assumed that the architectures provided by RTCA reside in the GCS DAA processor. The initial track and other information are then sent to the CNPC datalink for transmission to the GCS for UAS RPIC operation. The airborne CNPC equipment also receives data packets from the GCS and DAA mode inputs and maneuvers from the UAS RPIC.

3.1.4 Issues and Gaps

Several issues and gaps complicate safety risk management for DAA systems in unmanned aircraft operations. One of the primary concerns is the reliability of sensor technologies, especially in diverse and dynamic airspace environments. Cooperative sensors like ADS-B and Mode S transponders depend on the compliance and proper functioning of all aircraft nearby. Non-cooperative sensors such as radar and LIDAR can struggle with detecting small or low-signature objects. Integrating and fusing data from multiple sensors can also introduce errors and delays, impacting the system's ability to make timely and accurate decisions. Furthermore, the autonomy of DAA systems requires robust algorithms to handle complex scenarios without human intervention, and these algorithms must be thoroughly validated to ensure they perform safely under all conditions. The lack of standardized performance metrics and certification processes for DAA systems exacerbates these challenges, leading to inconsistent safety levels across different systems and platforms. Additionally, issues such as common cause failures, data link reliability, and cybersecurity threats further complicate the safety risk management of DAA systems, highlighting the need for comprehensive safety assessments and robust mitigation strategies (Tabassum et al., 2019).

3.2 Identifying Hazards

Identifying hazards is a critical step in the SRM process, particularly for DAA systems within the aviation industry. This involves systematically examining the DAA systems to uncover potential safety threats that could impact their operation. By analyzing various operational scenarios and environmental conditions, one can identify risks such as system malfunctions, human errors, or external interferences that may compromise the effectiveness of DAA systems. Through this proactive approach, one can ensure that potential hazards are recognized early, allowing for the implementation of appropriate mitigation strategies to enhance overall safety and reliability.

3.2.1 Hazards Associated with DAA Systems

While DAA systems are intended to mitigate the risk associated with mid-air collisions, other hazards may result from their use. These hazards may result from specific failure modes, functional limitations, or the systems' functional characteristics. The following sections discuss hazards associated with the operation of DAA systems – ground-based and airborne.

3.2.2 Ground-Based DAA Sensors

Identifying hazards for ground-based DAA sensors is critical to ensuring their reliability and effectiveness. Potential hazards include installation errors, environmental factors, and signal interference, which can compromise sensor functionality. Specific failure modes, such as data transmission loss or sensor malfunctions, pose significant risks, impairing the system's ability to track aircraft accurately. Furthermore, functional limitations like range constraints and susceptibility to adverse weather conditions can hinder performance. One can develop targeted mitigation strategies to enhance ground-based DAA systems' safety and reliability by systematically identifying these hazards.

3.2.2.1 *Electro-Optical*

As discussed in (McCrink et al., 2022), electro-optical sensors mounted to Ground Control Stations, telescopic or permanent poles, and other elevated positions have similar sources of clutter as airborne EO sensors, including environmental effects, such as glare and reflections, and other objects, such as birds. While ground-based sensors have the advantage of not being obstructed by the ownship's airframe or affected by onboard vibrations, they have unique challenges when filtering out misinformation and false alerts. For example, depending on the placement of the ground-based EO sensor, tall objects may appear above the horizon. A low-power electrical line with multiple arms perpendicular to the pole may be misclassified as a bird or aircraft, especially if the software that detects and classifies objects in the Field Of View (FOV) has yet to be trained on a dataset including these power lines. Other tall objects may cause issues for the EO sensor if not correctly masked. Ground-based vision sensors may not have a clear line of sight to airborne collision threats and may be more susceptible to occlusions (McCrink et al., 2022).

Sources of clutter for ground-based EO sensors include aircraft and bird-shaped logos on passing trucks and buildings. Aircraft stored on runways and near hangars can also lead to false alerts and clutter. If the sensor is not trained to recognize static displays or stored aircraft, the sensor may trigger false and misleading alerts.

Infrared cameras have been employed for DAA applications, offering advantages over vision sensors, such as the ability to operate in diverse environmental conditions, such as cloud cover, low illumination, or night-time conditions. Infrared sensors are subject to some unique sources of clutter caused by various heat sources or sinks within the environment, such as variations in the heat signatures of UAS batteries (McCrink et al., 2022).

Mature EO sensors filter these ground-based specific sources out with software. However, identifying these sources influences the understanding of how these sensors filter out noise, classify tracks, and determine the most likely intruders. In addition, as with airborne EO systems, the algorithms required to classify collision threats and filter out false ones, such as approaches based on machine learning, are frequently computationally intensive and difficult to implement in real-time (McCrink et al., 2022).

3.2.2.2 *Ground-Based Radar*

Various ground-based radar systems available on the market have succeeded in separating UAS and manned aircraft. While possibly successful, the success relies heavily on understanding the limitations and hazards of each radar system used and modifying operations to reduce the risk associated with that particular system's performance and capabilities.

Factors impacting the performance of a given system include the type of radar system (e.g., 2D vs 3D), the radio frequency used, the placement of radar system(s), system delays, speed of intruder, ability to integrate with air traffic control, ability to integrate with onboard DAA systems, resolution of target, terrain, active radio interference, and environmental conditions that create false positives and clutter. These factors are all possible hazards as they all have the potential to impact the performance of a radar system to detect various UAS and manned aircraft targets accurately.

3.2.2.3 *Acoustic Sensors*

Ground-based acoustic sensors face a few unique challenges compared to airborne counterparts (McCrink et al., 2022). Specifically, traffic noise from passing vehicles may significantly contribute to clutter as the sensor is in a fixed location and cannot move away from these ground-based acoustic sources. Ground-based acoustic sensors can misclassify electrical transformers that produce low-frequency noises as traffic. Finally, other industrial equipment may enter the detectable range of the ground-based acoustic sensor and produce substantial clutter, distracting attention from the airspace the sensor attempts to monitor. All of these sources of clutter can be operationally mitigated, but it is challenging to mitigate these sources in high-volume traffic areas. The primary sources of clutter for ground-based acoustic DAA systems are summarized in Figure 7 (McCrink et al., 2022).

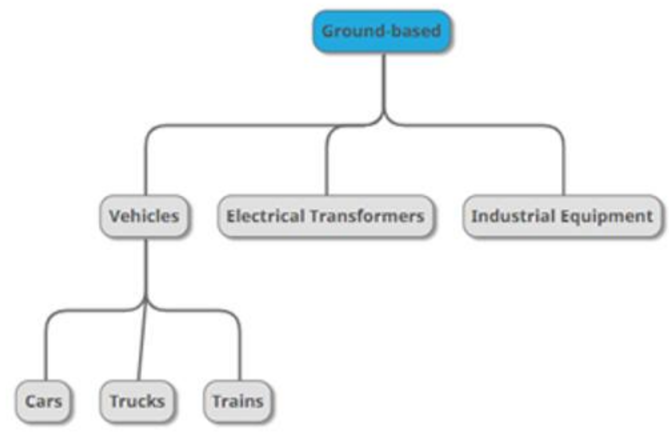

Figure 7. Sources of clutter for Ground-based DAA (McCrink et al., 2022).

3.2.3 Airborne DAA Sensors

Identifying hazards for airborne DAA sensors is essential to maintain their efficacy in preventing mid-air collisions. Key hazards include equipment failure, signal interference, and environmental challenges affecting sensor performance. Specific failure modes, such as sensor malfunctions or data inaccuracies, can lead to misidentification of potential threats. Functional limitations like range constraints and sensitivity to weather conditions can also compromise detection capabilities. By thoroughly identifying these hazards, one can implement robust mitigation strategies to ensure the airborne DAA sensors operate reliably and effectively, thus enhancing overall airspace safety.

3.2.3.1 *Airborne radar*

Airborne radar systems are susceptible to changes in ownship attitude and velocity. As many sensors are Doppler detection systems, target azimuth or velocity changes can make the targets invisible to the ownship system. Other electromagnetic interference sources on the vehicle may also provide false or misleading information. The ownship radar must carefully filter these sources to avoid spurious return signatures. Finally, the output power capability and target discrimination functionally depend on the radar size and vehicle weight. While smaller systems have been demonstrated on Group 1-2 UAS, these systems are typically low power with a limited range and azimuth scanning capability. These shortcomings are exacerbated during low altitude operations, in which case the mode of operation and error sources may be very similar to some ground-based radars (McCrink et al., 2022).

3.2.3.2 *Electro-Optical*

Figure 8 shows the classification of airborne EO noise, the sources of which can be broadly classified as environmental, configurational, instability, and others (McCrink et al., 2022).

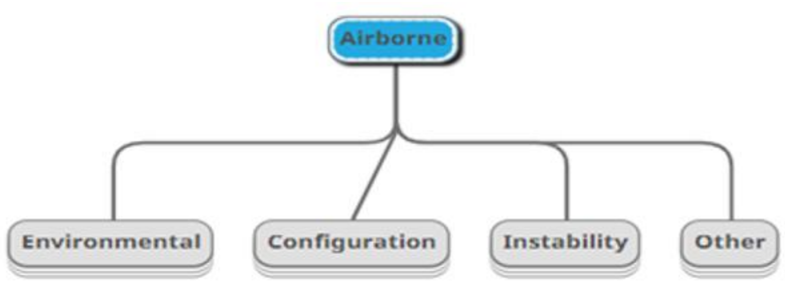

Figure 8. Classification of noise associated with airborne EO sensors (McCrink et al., 2022).

The sensor returns associated with environmental EO systems can be classified as natural and manmade, as shown in Figure 9 (McCrink et al., 2022). Natural returns include birds, reflections from water, and the sun, whereas manmade sources include glare, reflections, and spotlights from buildings, bridges, etc.

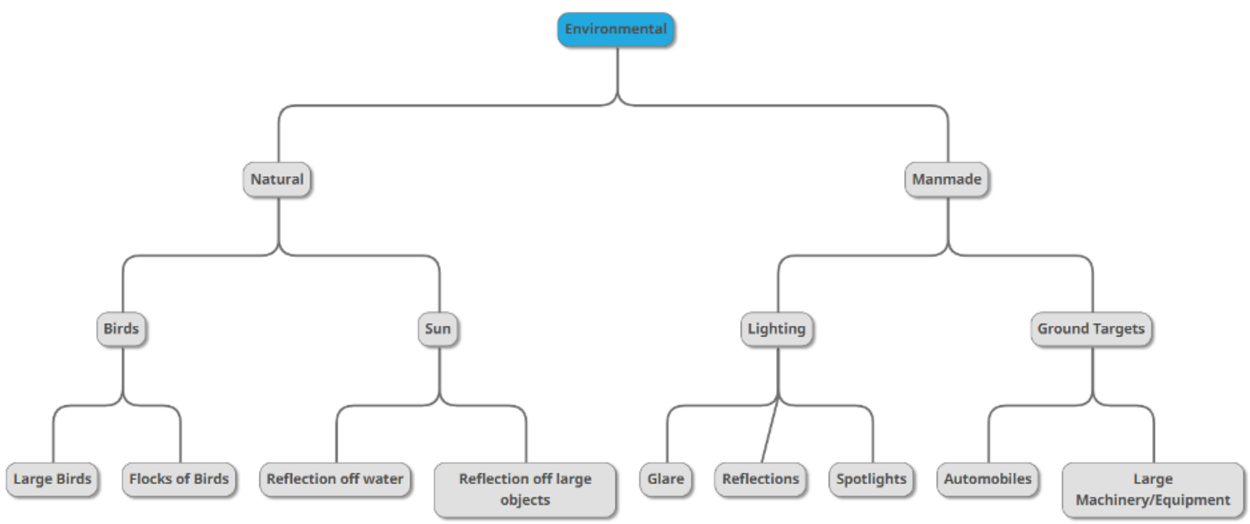

Figure 9. Classification of Environmental Noise Sources (McCrink et al., 2022).

The most common intruder for aircraft is wildlife. Large birds may produce similar profiles to distant aircraft and can be misclassified as such. Although bird strikes are often dangerous for manned aircraft and almost always result in the loss of an unmanned aircraft, bird detection is not the most crucial function of DAA systems. In the context of the DAA scenarios considered in this report, large bird encounters typically represent sources of false tracks and misinformation for UAS operators.

Flocks of birds can also generate false detections in EO DAA sensors. As many birds fly in proximity, the EO sensor and its processing algorithms may attempt to filter out that portion of the FOV to prevent clutter. As general aviation pilot studies show, the sun may cause unwanted behavior in the EO DAA sensor. Glare from large bodies of water and lens flare present challenges for optical-based DAA sensors. Lens flare can blind large portions of an EO sensor's FOV, thus causing degraded sensor performance and downstream functions. As a result, false alerts and blind spots may be produced from lens flare and reflection of water bodies.

Lighting remains an important visual cue for manned aviation and can adversely affect the overall functionality of EO-based DAA systems. Airport towers with spotlights, operations in low lighting conditions near dense highway traffic, and distant aircraft lights may generate false detections and thus increase BVLOS pilot workload. For urban mobility and urban delivery, large manmade buildings can reflect light at the EO sensor and produce clutter. For rural operations, lights on towers over 200 feet above ground level and well within the operating flight regime of small UAS can also produce unnecessary alerts.

Finally, noise sources can be derived from non-essential portions of the FOV, such as clutter produced by large moving targets on the ground. For example, large automobiles contrasting with roads and large industrial or agricultural equipment can produce unnecessary tracks in an airborne EO system. Other large vehicles, such as ships or small boats, can affect airborne EO sensors operating in maritime environments. Generally, airborne systems have multiple layers of filters for sorting ground tracks from airborne tracks. Still, ground-based clutter is a significant factor in the risk analysis of airborne EO sensors.

3.2.3.2.1 Configuration

Several sources of noise may stem from the configuration and installment of the EO sensor itself, as shown in Figure 10 (McCrink et al., 2022). These sources can include obstructions, such as the ownship aircraft moving in and out of view of the sensor, motor vibration, quality of the lens, FOV, varifocal capabilities, and lost focus. These issues may become sources of a cluttered FOV or trigger a filter to mask the area, producing blind spots for the UAS operator.

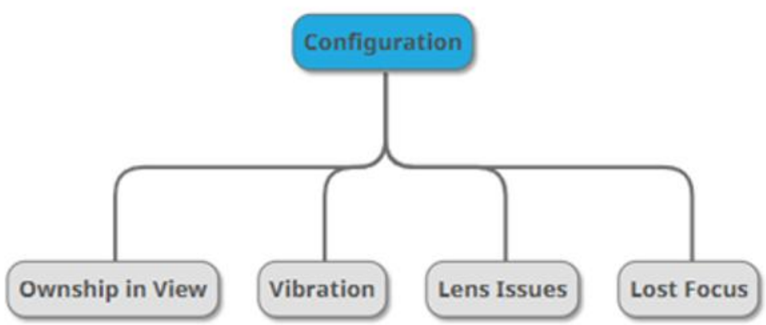

Figure 10. Classification of noise associated with configuration EO sensor (McCrink et al., 2022).

3.2.3.2.2 Instability

Several sources of noise from the instability of EO sensors may be generated from unstable reference points, unsteady or changing horizons, and unstable scenery (both from air and ground), as shown in Figure 11 (McCrink et al., 2022).

For airborne EO sensors, the identification and tracking of features or objects can be affected by changing illumination, occlusions such as cloud cover, and the vehicle's motion. The latter issue can be particularly challenging for strap-down sensors as features and objects can frequently exit and re-enter the FOV. In contrast, gimbaled sensors can help mitigate this problem at the cost of added complexity. With airborne EO sensors, the vibration of the platform can adversely affect the ability to track features accurately. In all cases, the instability of reference points can lead to false or inaccurate tracking. An unsteady or changing horizon, as might be caused by changing environmental conditions or the presence of objects near the horizon, can also adversely impact tracking since it is no longer straightforward to differentiate between airborne and ground-based clutter.

External climatic factors impact sensor data quality and the background image, which can result in misleading tracks. For instance, unstable scenery, which can be ground-based or air-borne, can induce apparent motion in the high-clutter and low-clutter backgrounds. Ground-based instabilities, such as waves and forests, can give an appearance of motion to the high-clutter background (below the horizon). A low-clutter background (above the horizon) can also be affected by unstable scenery, such as fast clouds, smoke clouds, and haze. Therefore, unstable scenery can lead to additional clutter and, in turn, an increase in false or misleading tracks.

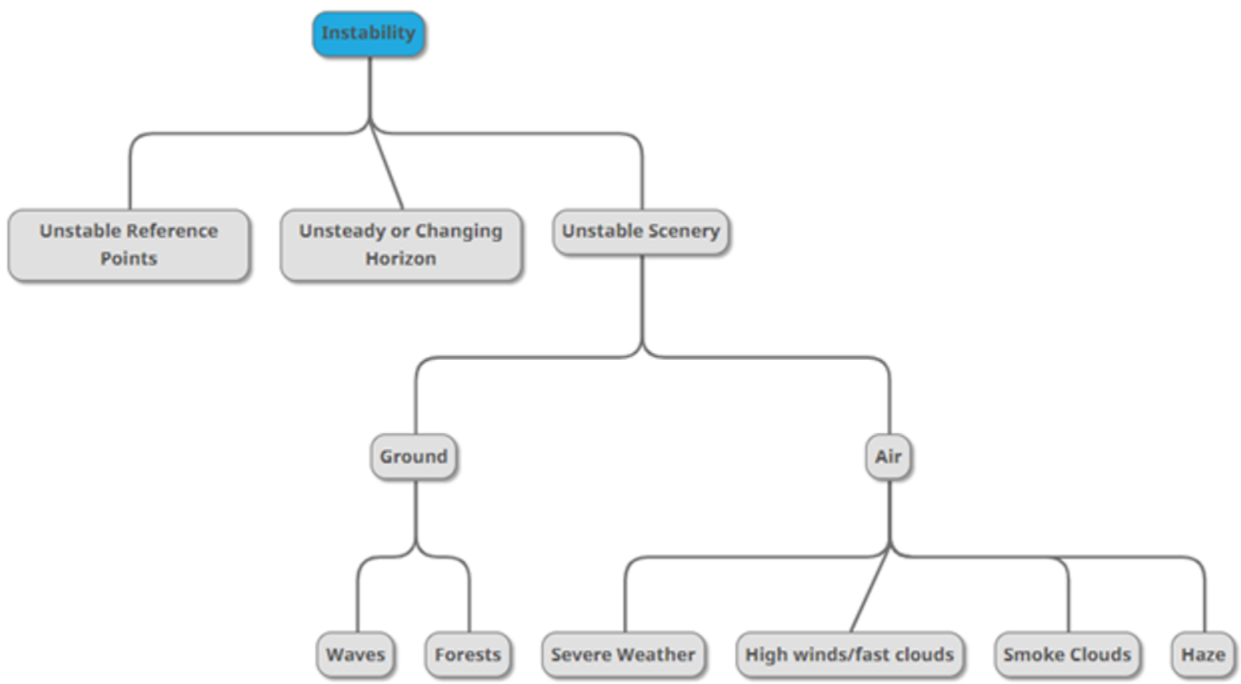

Figure 11. Classification of noise associated with instability EO sensor (McCrink et al., 2022).

3.2.3.3 *Acoustics*

Compared to optical sensors, which face the challenge of classifying moving pixels, and radar sensors, which can be adversely affected by ground clutter, acoustic sensors have relatively few sources of misinformation. Acoustic sensors have disadvantages such as the inability to classify intruders, lack of detection of silent intruders, such as birds and gliders, and lower pinpointing accuracy. For airborne acoustic sensors, as the ownship gains altitude, the effect of ground clutter decreases. Therefore, ground-based sensors need extra layers of filtering that airborne acoustic sensors may not require. Figure 12 depicts two general noise categories relevant to airborne acoustic sensors: ground traffic and non-threatening aircraft (McCrink et al., 2022).

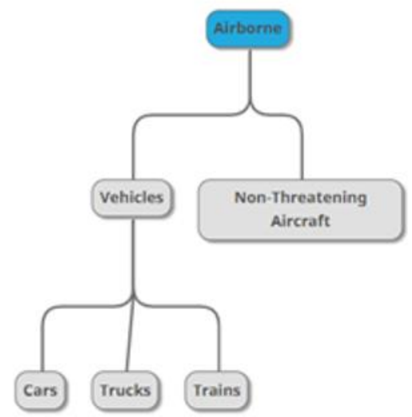

Figure 12. Sources of clutter for Airborne Acoustics DAA (McCrink et al., 2022).

As acoustic sensors are sensitive to sounds generated by engines, ground traffic such as cars, trucks, and trains represent sources of clutter. The interaction with these sources decreases when the aircraft operates away from busy roadways and in more rural airspace. As the ownship increases altitude, ground-based acoustic sources have less effect on sensor performance.

Exceptionally loud aircraft, such as jets, can clutter the air picture of an acoustic sensor without any real danger to the operation of the ownship. Turbo-propellor and large jet engine aircraft can resonate far from the airborne acoustic sensor. These non-threatening air traffic may not always pose self-separation threats but can distract the ownship's operator from nearby air traffic.

3.2.4 External/Environmental Hazards

As discussed in (McCrink et al., 2022), external climatic conditions affect the quality of sensor data, which can cause false tracks. For example, meteorological conditions, such as wind, rain, etc., interfere with radar/electro-optical sensors, leading to misclassifications (Zeyang, 2022).

Several schemes for wind compensation are provided in the literature, e.g., (Ceccarelli 2007, McGee 2006). The study by (Ragi 2013) considers wind compensation and collision avoidance in the context of a partially observable Markov decision processes framework. Recent studies (Khan 2022, J. L. Wang 2021) discuss the advantages and disadvantages of different drone detection techniques, i.e., acoustic, visual, radar-based, and radio-frequency-based, according to which visual conditions such as rain, fog, and dust do not impact the detection accuracy of radio-frequency-based methods. AirWarden (AeroDefense 2022) and the DeTect MERLIN Aircraft Birdstrike Avoidance Radar (DeTect 2022) are patented drone detection systems that utilize radio frequency to identify and classify drones and controllers. These systems are claimed to be unaffected by lighting, sound, rain, clouds, fog, background clutter, or line of sight, making them suitable for air, ground, and marine UAS detection (McCrink et al., 2022).

Highly cluttered environments, such as dense forests and urban canyons, may be challenging for drones to access. Previously unknown surroundings and narrow corridors combined with the requirements of swarm coordination can create significant challenges. Therefore, the general operational environment of the UAS affects the performance of a DAA system. Furthermore, precise location information is also necessary to adequately characterize radar echoes. For example, urban environments cause challenges for radars/electro-optical sensors by introducing high clutter generated by stationary objects such as buildings and dynamic obstacles such as other vehicles (Wellig, 2018). Clutter from land, sea, and other sources has been studied since the earliest days of radar, as clutter can heavily impact the performance of a radar system due to its high clutter signal level. Due to the high speeds involved, the radar must have a sufficient range and be capable of distinguishing between airborne traffic and ground clutter, including moving cars (McCrink et al., 2022).

Essential parameters used to characterize clutter are mean radar cross-section per unit area, amplitude statistics, Doppler spectrum, and temporal and spatial correlation (Griffiths, 2018). Siegel (1968) considered diversity in aircraft scattering, studying the behavior of the bistatic radar cross-section relative to the monostatic radar cross-section of a large civilian jet aircraft at a frequency of 250 MHz as a function of the aspect and bistatic angles. The micro-Doppler signature of drones, particularly those using rotating blades (e.g., multicopters), may provide useful information that can be extracted using signal-processing techniques (Griffiths, 2018). Measurements of the micro-Doppler signatures of a drone, with and without a payload, were realized using the UCL NetRAD in a multistatic configuration (Fioranelli, 2015).

Considerable research is now focused on filtering out and rejecting false tracks produced by sensors using different methods ranging from conventional filters to machine learning models, Hamiltonian optimization for motion planning (Lu 2020), and spatial-temporal joint optimization (Soria 2022). Background subtraction and spectral analysis can be used to estimate the range of a drone, and suitable Gaussian process regression methods can be used to refine the range and the target's angular localization. Such studies can be found in Paredes (2021) for a static environment and Ragi (2013) for a dynamic environment (McCrink et al., 2022).

According to Aerospace Testing International (Sampson, 2022), two different testing programs have been successfully concluded in the US for radar-based DAA systems: Honeywell's IntuVue RDR-84K radar system and Bell's QuantiFLYTM system. It was demonstrated that both of these systems could autonomously change the course of a drone when an aircraft on a collision course was detected during test flights. The RDR-84K radar includes an onboard processor, where monopulse technology, i.e., a system of overlapping beams, is used to increase accuracy and remove ground clutter within a range of up to 3 km. According to Honeywell, the testing of IntuVue RDR-84K demonstrated its capability to detect airborne traffic and make autonomous decisions during the mission without human intervention for the first time. The QuantiFLYTM system is a new aircraft communication unit that offers automatic flight data monitoring and is used on the Bell 429 to record aircraft telemetry data (McCrink et al., 2022).

Aircraft detection systems must be able to detect collision aircraft in three distinct sensing environments: the unstructured sky above the horizon, the structured ground clutter below the horizon, and the interface between the two near the horizon, according to recent experimental studies (Molloy, 2017). The state of the clutter is also relevant as it can be stationary or moving within the sensing environment. Depending on the ownship's altitude, a bird, for example, can be classified as moving clutter above or below the horizon. A DAA system should be able to filter out clutter regardless of its state and the sensing environment where it was detected (McCrink et al., 2022).

Most of the research available in the literature on the radar signature of drones assumes monostatic geometries, with some limited research dedicated to the analysis of multistatic experimental drone data and radar signatures, including Fioranelli (2015), Ritchie (2016), and Palama (2021) who used such systems mainly to discriminate between drones versus non-drone targets (e.g., birds that were either flying individually or as part of a flock). Implementing principles of radar signal processing (e.g., fast Fourier transform and multiple signal classification methods) can reduce the effects of environmental clutter by removing the background component from the signal (Paredes, 2021).

The design of robust systems for airborne detection and tracking of uncooperative flying targets for DAA applications should include maximizing the declaration range as a requirement (McCrink et al., 2022). Thus, the declaration range, which is defined as the range at which the sensing system declares the presence of the intruder, must be large enough to ensure that the time to the closest point of approach is sufficient to command and execute an appropriate avoidance maneuver, considering flight maneuverability and any processing delays (Opromolla, 2021). Research is underway to develop robust DAA approaches to achieve the optimal trade-off between low false alarm rates and a long declaration range (Weinert, 2018; Opromolla, 2019). This challenge becomes even more complicated when dealing with intruders from below the horizon (Opromolla, 2021).

Future research could explore condensing common paths into single representations to reduce visualization clutter and computation time (Eiris, 2020). Comparative analyses should also be conducted between the 2D and 3D visualization designs to assess the advantages and disadvantages of each approach for DAA. Such investigations will help validate the effectiveness of each design in reducing pilot stress and concentration levels and improving their navigational skills and decision-making. For autonomous operations in complex environments, such as urban environments, it is crucial to equip UAS or UAS swarms to perform guidance, navigation, and control for collision avoidance with static and dynamic obstacles. This includes planning and re-planning flight trajectories in real-time based on evolving information (McCrink et al., 2022).

Several environmental conditions may cause false target detections to occur with ground-based radar, as shown in Figure 13 (McCrink et al., 2022). Both natural and manmade objects can be detected as targets. Additionally, phenomena such as tropospheric ducting can cause multiple instances of the same target (true or false) to appear simultaneously at different ranges.

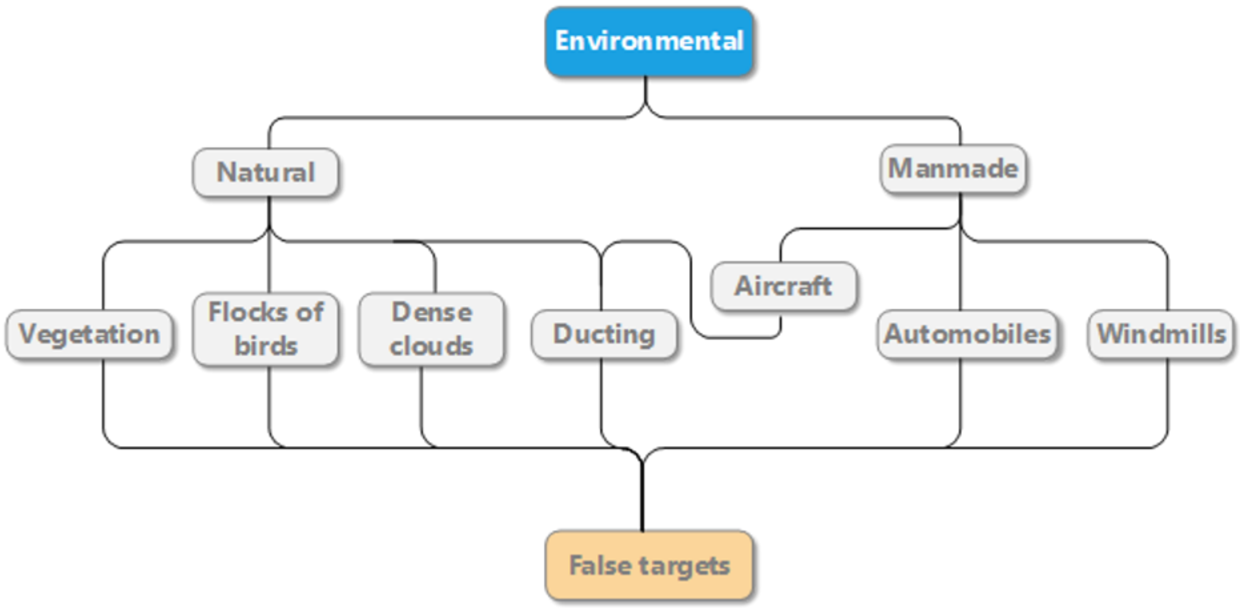

Figure 13. Classification of noise associated with environmental Radar sensors (McCrink et al., 2022).

3.2.5 Issues and Gaps

Identifying hazards in DAA systems, both ground-based and airborne, presents several issues and gaps that require due attention to ensure comprehensive safety management. One significant challenge is the variability in environmental conditions, such as weather and terrain, which can affect the performance of DAA sensors, leading to inconsistent hazard detection. Additionally, the integration of DAA systems with existing air traffic management infrastructure often reveals gaps in data compatibility and communication protocols, potentially leading to information silos and delayed hazard identification. Additionally, technological limitations exist, such as the sensitivity of sensors to external interferences and the range constraints of ground-based systems, subsequently compromising the reliability of hazard detection. Notably, the evolving nature of airborne threats and the continuous development of aviation technology necessitate an ongoing reassessment of potential hazards and reoccurring scrutiny of how hazards are reassessed.

3.3 Analyzing Risk

Analyzing risk involves a structured process to identify, assess, and mitigate potential hazards. The primary goal of this process is to ensure that safety risks are reduced to an acceptable level, facilitating the safe integration of UAS into the NAS. This involves a comprehensive system analysis to understand the components, operations, and interactions within the UAS environment. Identifying hazards includes examining equipment failures, human errors, environmental conditions, and other factors. The risk associated with each identified hazard is then analyzed in terms of severity and likelihood, using data-driven methods to quantify potential impacts. Safety risk controls are developed and evaluated to mitigate these risks, and residual risks are monitored to ensure ongoing compliance with safety standards. This iterative process is critical in managing the safety of UAS operations, particularly in the dynamic and complex airspace where both manned and unmanned aircraft operate (Federal Aviation Administration, 2023a).

3.3.1 *Overview of Existing Guidance – FAA Order 8040.6A*

FAA Order 8040.6A contains guidance for analyzing risk in UAS DAA contexts and emphasizes a structured SRM process. This process involves several critical steps: identifying potential hazards, analyzing the associated risks, and developing appropriate mitigation strategies to reduce these risks to acceptable levels. The guidance specifies the roles and responsibilities of various stakeholders, including program leads and safety analysts, who must ensure thorough documentation and coordination across different FAA lines of business. It outlines the need for a comprehensive system analysis, considering all aspects of the UAS operation, including technical components, operator qualifications, and the operating environment. The guidance also emphasizes the importance of continuous monitoring and validation of mitigation measures to maintain safety standards. Following these detailed procedures, the FAA aims to ensure that UAS operations within the NAS are conducted safely and effectively, addressing existing and emerging risks.

3.3.2 *DAA Metrics*

FAA Order 8040.6A (Federal Aviation Administration, 2023b) provides metrics for assessing risk, broken out into two components—severity and likelihood. For DAA, severity determination is generally easier than likelihood, though this depends upon the severity scale used. In the ASSURE project Shielded UAS Operations: Detect and Avoid (DAA) (henceforth referred to as A45), the highest (catastrophic) severity outcome for air risk was a Mid-Air Collision (MAC) (Askelson et al., 2023). This simplifies the evaluation of severity as it does not require a determination of collision severity, which is a topic of ongoing research since not every collision between a UA and a manned aircraft is guaranteed to produce a fatality (e.g., Oliveras et al., 2017). This approach is not utilized in FAA Order 8040.6A (Federal Aviation Administration, 2023b), which identifies a catastrophic outcome as "An expected unintentional effect that includes any of the following:

- 3 or more fatalities,
- Manned aircraft hull loss with at least 1 fatality."

While this approach is more aligned with what would be considered catastrophic, it requires the determination of airborne collision severity, which is still unresolved. Thus, severity determination as part of risk can be challenging and result in subjective outcomes.

Likelihood is also challenging for DAA; FAA Order 8040.6A (Federal Aviation Administration, 2023b) defines likelihood in terms of occurrence per number of flight hours or occurrence over some time, assuming a given number of flight hours per calendar year. For airborne DAA risk, things like the occurrence rates of MACs must be determined. Such likelihoods can be placed within a framework of the successive events of encounter, well clear violation, Near Mid-Air Collision (NMAC), and MAC, as illustrated, for instance, by Askelson et al. (2023). However, this approach still requires determination of the likelihood of encounter. Determining this is challenging given the relative lack of information for (e.g., Weinert et al., 2019; Weinert and Barrera, 2020) and inherent variability of (e.g., Theisen et al., 2010) low-altitude aircraft densities. While examples of estimating encounter likelihoods exist (e.g., Askelson et al., 2023), the inherent uncertainties complicate using such an approach for risk evaluation, with uncertainties possibly masking benefits associated with hazard mitigations.

Another approach to understanding DAA performance is through the risk ratio, which is defined as the ratio between the probability of an event (e.g., well clear violation, NMAC, or MAC) with a system and the probability of an event without a system (ICAO, 2006; ASTM International, 2023). For a DAA system, the risk ratio depends upon its characteristics, the characteristics of intruder aircraft (e.g., flight speeds), encounter characteristics (e.g., geometries), and environmental conditions. An overall risk ratio for a DAA system is defined by evaluating system performance across all independent variables at the expected frequencies of occurrence. Such a risk ratio is a logic risk ratio, which holds for nominal system performance and is used by ASTM International (2023) to define DAA performance requirements—including failures (corrupted logic, faults, etc.) resulting in system risk ratios.

3.3.3 Issues and Gaps

Analyzing risk in UAS DAA contexts presents several issues and gaps complicating effective safety risk management. One major challenge is the need for comprehensive and consistent data on UAS operations and their interactions with manned aircraft, which hampers accurate risk assessments. Additionally, the rapid evolution of UAS technology outpaces the development of standardized safety metrics and regulatory frameworks, leading to inconsistencies in hazard identification and risk mitigation strategies. Integrating multiple sensor technologies with different detection capabilities and limitations adds complexity to the risk analysis process, as does the need to ensure these technologies perform reliably in diverse operating environments. Furthermore, there are gaps in DAA systems' validation and verification processes, particularly in ensuring that safety risk controls are effective across various operational scenarios. These issues underscore the need for continuous improvement in data collection, regulatory development, and system validation to ensure the safe integration of UAS into the NAS.

3.4 Assessing Risk

Assessing risk is a pivotal component of the SRM process, particularly in the context of detect and avoid systems. This phase involves a detailed evaluation of identified hazards to determine their potential impact on safety and operational effectiveness. Risk assessment in ground-based and airborne DAA systems involves analyzing the likelihood, severity, and exposure of various events, modes, environmental influences, and functional limitations. By systematically quantifying these risks, decision-makers can prioritize mitigation strategies, ensuring that resources are allocated to address the most significant threats. Effective risk assessment not only considers the risk of a given setting but juxtaposes this risk with the potential gain of an operation.

3.4.1 Introduction to Risk Management

As described by both the International Civil Aviation Organization (ICAO) and the FAA, risk generally considers two variables: likelihood and severity (ICAO, n.d.; FAA, n.d.). The likelihood variable attempts to ascertain the probability of an event occurring or not, while severity contemplates the consequences of an event or behavior should the event occur. The two variables are then combined and simultaneously considered to assess overall risk. The result is generally depicted as a two-dimensional matrix, with the more likely and severe events classified as riskier. Medium-level events often require at least some mitigation, while low-level risk events require no additional safety measures, and normal operations can ensue.

Risk in unmanned aircraft operations and DAA systems refers to potential loss or harm due to uncertainties inherent in the operational environment. These uncertainties can stem from various sources, such as unpredictable weather conditions, technical malfunctions, human errors, and other airborne traffic. Risk encapsulates both the likelihood of adverse events occurring and the severity of their potential consequences. For instance, in DAA systems, a risk might involve the failure of sensors to detect an incoming aircraft, leading to a possible collision. Understanding risk as a combination of probability and impact is crucial for developing effective mitigation strategies that can enhance the safety and reliability of UAS.

The specific relevance of risk management to DAA systems lies in their critical role in ensuring the safe operation of UAS within shared airspace. DAA systems are designed to detect and avoid other cooperative aircraft (equipped with transponders, ADS-B, etc.) and non-cooperative (without transponders, ADS-B, etc.), thereby preventing mid-air collisions. The inherent uncertainties in sensor performance, data processing algorithms, and the dynamic nature of air traffic introduce significant risks that must be carefully managed. Effective risk management in DAA systems involves continuously monitoring and assessing these uncertainties, implementing robust detection and avoidance algorithms, and maintaining reliable communication links between the UAS and ground control stations. By systematically addressing these risks, DAA systems can significantly reduce the likelihood of accidents and enhance the safety of unmanned aircraft operations in controlled and uncontrolled airspace.

Two additional variables are sometimes included in risk assessment. These are exposure and weight. In this sense, exposure is simply the time spent with risk present, and weight refers to the confidence in the variables. Several methods are used in risk assessment, including qualitative, quantitative, and mixed methodology.

3.4.2 Importance of Risk Management

Risk management is critical to any operational framework, especially in DAA and UAS. It involves the systematic identification, assessment, and mitigation of risks to ensure the safety and efficiency of operations. Effective risk management is essential for maintaining high operational safety and reliability standards, mitigating hazards to prevent collisions, and enhancing system performance while ensuring compliance with regulatory standards.

Ensuring operational safety and reliability is paramount in the aviation industry, especially for UAS operations. Effective risk management practices help identify potential risks and implement strategies to minimize their impact. By proactively and predictively addressing possible hazards, organizations can prevent accidents and ensure the smooth functioning of their systems. This protects human lives and property and builds trust in the technology and its operators. Robust risk management contributes to the reliability of UAS by ensuring that systems are resilient to various threats and can continue to operate safely under different conditions.

One of the primary goals of risk management in UAS operations is to mitigate hazards and prevent collisions. UAS operate in complex environments with various obstacles and other aircraft, making collision avoidance a significant challenge. Through comprehensive risk assessment and management, potential hazards can be identified, and effective mitigation measures can be implemented. This includes developing advanced DAA systems, establishing safe operational procedures, and continuously monitoring the airspace for potential threats. By systematically addressing these hazards, the likelihood of collisions can be significantly reduced, ensuring the safety of both manned and unmanned aircraft.

Enhancing system performance and ensuring compliance with regulatory standards are also crucial aspects of risk management. Regulatory bodies set stringent standards to ensure the safety and efficiency of UAS operations. Effective risk management ensures that UAS systems meet these standards, which are essential for gaining approval for operations and maintaining compliance. Additionally, organizations can optimize system performance by identifying and mitigating risks and reducing downtime and maintenance costs. This leads to more efficient and cost-effective operations, allowing UAS operators to deliver better services and maintain a competitive edge in the market.

3.4.3 Qualitative Analytical Methods

This subsection provides a brief overview of some of the most common and relevant qualitative analytical methods for risk assessment; an overview of quantitative analytical methods for risk assessment is given in the subsequent subsection. The following qualitative analytical methods are reviewed below: i) fault tree analysis (Section 3.4.3.1), ii) dynamic event trees (Section 3.4.3.2), iii) Failure Mode Effects Analysis (FMEA) (Section 3.4.3.3), iv) System Theoretic Process Analysis (STPA) (Section 3.4.3.4), and v) System Theoretic Accident Model and Process (STAMP) (Section 3.4.3.5).

3.4.3.1 *Fault Tree Analysis*

Fault tree analysis is a deductive process that examines a specific undesirable event and its associated causes (Vesley et al., 1981). It is a process that promotes analysis of a system within its environment to model credible outcomes of undesirable events (Vesley et al., 1981). The process is highly dependent on choosing a representative top-level event that reflects a credible fault state, and it typically assumes a system or portion of a system has failed in a certain way (Vesley et al., 1981). To that end, fault tree analysis is valuable for understanding system fault states and relationships between system components.

Fault trees may be beneficial for analyzing DAA systems due to their flexible nature and rational, structured approach to modeling system faults. When properly constructed, fault trees enable an understanding of how different components of a DAA system may affect overall system function when in a fault state. Developing a thorough understanding of system fault states provides valuable inputs for risk assessments and more detailed system analysis.

While there are various DAA system types – i.e., ground-based, airborne, and sub-types DAA systems can be described as discrete functions that govern their basic operation. These functions are listed in ASTM F3442/3442M *Standard Specification For Detect And Avoid System Performance Requirements* (ASTM International, 2023):

1. Detect,
2. Alert, and
3. Avoid.

These basic functions can describe nearly any element of a DAA system and provide a means for describing faults and degraded operational states regardless of the type or architecture of a DAA system. Taking a system-agnostic approach that emphasizes common functions offers the opportunity to standardize methods for system analysis and risk assessment that are common to all DAA systems. Figure 14 illustrates a simple example of a fault tree that examines causes related to a failure of the detect function resulting from power loss. Note that the fault state can be generic (top-level event) while the causes of the fault, using *AND* logic, can be tailored to the specifics of a given system.

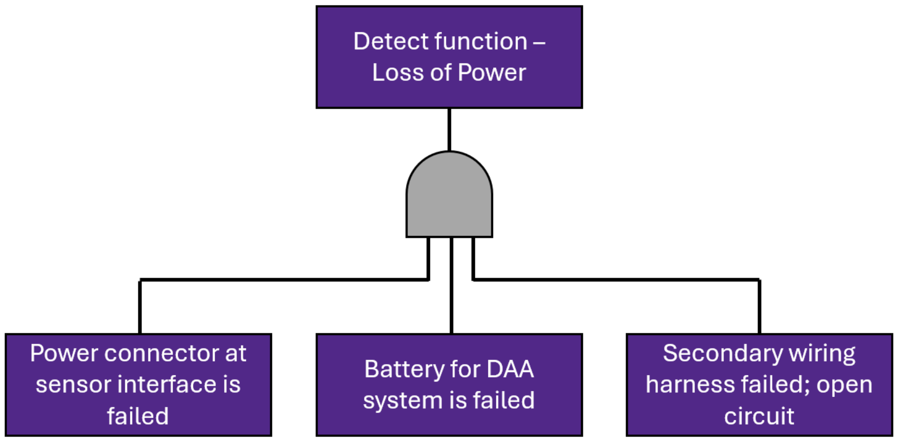

Figure 14. Simple Example Fault Tree for Detect Function.

While Figure 14 illustrates a simplified example of a fault tree for a given failure state of the detect function, it is by no means representative of every case. Applying fault trees with standardized top-level fault states, logical operators, and system-specific inputs may provide a tool to link hazards to system fault states to assess safety risk.

3.4.3.2 *Dynamic Event Trees*

An added advantage of fault trees is that they can easily integrate into other processes that link event decision chains to events and fault states. A Dynamic Event Tree (DET) provides a mechanism to link fault trees to higher-level processes and events that make up an encounter. Figure 15 outlines an example framework for a system of DETs that can model an entire encounter scenario. The process in Figure 15 provides a detailed model overview that accounts for the various steps in an encounter. The model combines a high-level event tree that describes the conflict, a generic sub-tree related to the DET, and fault trees that account for system faults in the encounter (Noh and Shortle, 2020).

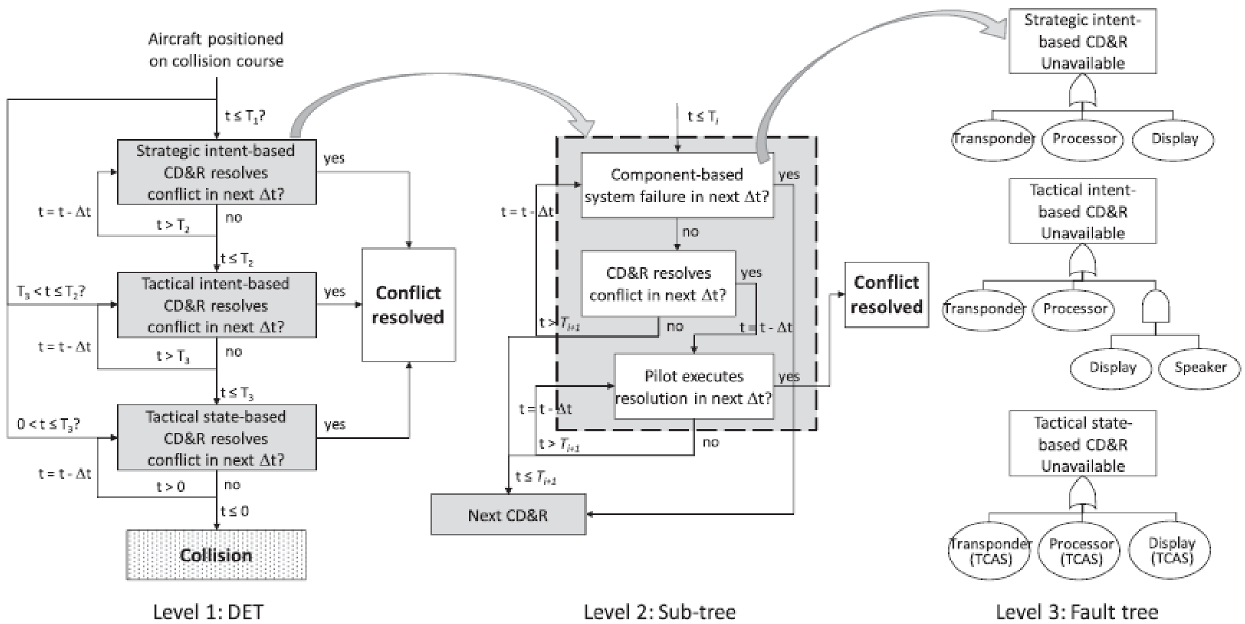

Figure 15. Dynamic Event Tree (DET) Framework (Noh and Shortle, 2023).

The DET model provides a detailed overview of the encounter and offers a means to account for events, timing, and system faults that contribute to outcomes. However, it is essential to acknowledge the assumptions built into the DET framework, as Noh and Shortle (2020) identified.

> *Assumption 1:* Each component fails randomly according to a component-dependent fixed rate.
>
> *Assumption 2:* All components are statistically independent of each other.
>
> *Assumption 3:* All components are unrepairable.
>
> *Assumption 4:* Each conflict detection and resolution system (CD&R, synonymous with a DAA system) has a random time to detect a conflict and propose a resolution maneuver successfully, according to some probability distribution function.
>
> *Assumption 5:* The time for the flight crew or remote operator to correctly respond to a proposed resolution maneuver is random, according to some probability distribution function.

As the five assumptions above imply, the DET framework relies on a series of assumptions about component states, component failure rates, system timing, and flight crew response times. Of interest are the (1) component-dependent fixed failure rates, (2) the conflict resolution time(s), and (3) the flight crew reaction time(s). These variables may be driven by known or computed values determined by probability functions.

The DET framework offers a potential avenue for modeling a complete DAA cycle while accounting for the events of the encounter, including flight crew actions and system faults that may contribute to the outcome. This approach represents an opportunity to model DAA system functions and crew responses throughout an encounter. The implication is that this modeling technique may offer a toolset capable of establishing some baseline for assessing the likelihood of

DAA system failures and their effect on airborne encounters, given the proper probability distribution functions for critical variables.

3.4.3.3 *Failure Mode Effects Analysis (FMEA)*

Failure Mode and Effects Analysis (*e.g.*, (American Society for Quality, 2024), (Stamatis, 2003), (Stamatis, 2015)), abbreviated as FMEA, is described by the American Society for Quality (2024) as follows:

"Begun in the 1940s by the U.S. military, failure modes and effects analysis (FMEA) is a step-by-step approach for identifying all possible failures in a design, a manufacturing or assembly process, or a product or service. It is a common process analysis tool."

The general FMEA process involves many steps not listed here but described in detail in the above references. A critical part of the process involves completing an FMEA form (table), such as the one shown in Table 1. As shown in the Table 1, the FMEA process requires the enumeration of functions, identification of each function's potential failure modes, the effects of those failures, the possible causes of those failures, the process controls, the recommended actions, the responsibility for those actions and the target completion date, and the achieved results of those actions.

Table 1. An FMEA Example (American Society for Quality, 2024).

Function	Potential Failure Mode	Potential Effects(s) of Failure	S	Potential Cause(s) of Failure	O	Current Process Controls	D	RPN	CRIT	Recommended Action(s)	Responsibility and Target Completion Date	Action Results					
												Action Taken	S	O	D	RPN	CRIT
Dispense amount of cash requested by customer	Does not dispense cash	Customer very dissatisfied Incorrect entry to demand deposit system Discrepancy in cash balancing	8	Out of cash	5	Internal low-cash alert	5	200	45								
				Machine jams	3	Internal jam alert	10	240	24								
				Power failure during transaction	2	None	10	160	16								
	Dispenses too much cash	Bank loses money Discrepancy in cash balancing	6	Bills stuck together	2	Loading procedure (riffle ends of stack)	7	84	12								
				Denominations in wrong trays	3	Two-person visual verification	4	72	18								
	Takes too long to dispense cash	Customer somewhat annoyed	3	Heavy computer network traffic	7	None	10	210	21								
				Power interruption during transaction	2	None	10	60	6								

3.4.3.4 *System Theoretic Process Analysis (STPA)*

System Theoretic Process Analysis (*e.g.*, (Leveson STPA, 2018)) is a hazard analysis technique created by Professor Nancy Leveson (M.I.T.). The novelty of STPA, relative to other hazard analysis techniques, is that it is (quoting from (Leveson STPA, 2018)):

"...based on an extended model of accident causation. In addition to component failures, STPA assumes that accidents can also be caused by unsafe interactions of system components, none of which may have failed."

STPA builds upon and integrates with the STAMP (described below) and is a forward-looking, anticipatory hazard analysis technique. Figure 16 shows the four steps of the STPA method (from (Leveson STPA, 2018)).

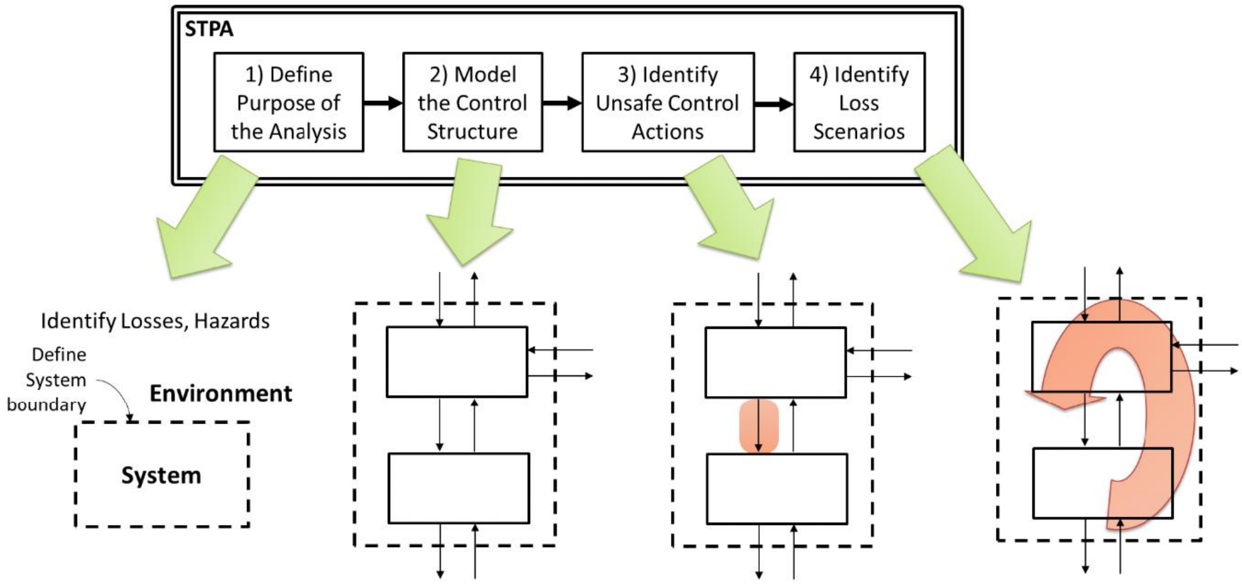

Figure 16: STPA method overview, from (Leveson STPA, 2018).

The asserted advantages of STPA, relative to other hazard analysis techniques, are its capabilities to (summarizing (Leveson STPA, 2018)):

1. Analyze very complex systems;
2. Integrate in early concept analysis;
3. Include software and human operators in the analysis;
4. Provide documentation of system functionality;
5. Integrate into system engineering processes.

3.4.3.5 *System Theoretic Accident Model and Process (STAMP)*

System-Theoretic Accident Model and Processes (*e.g.*, (Leveson STAMP, 2002) (Leveson STAMP, 2020), (Zhang, 2022)), abbreviated as STAMP, was developed by Professor Nancy Leveson (M.I.T.) as an accident model and process framework. Notably, it is *not* intended for accident analysis but to serve as a "base layer" that may be profitably integrated with an accident analysis methodology, such as STPA (described above). The following quote (from (Leveson STAMP, 2002)) highlights the philosophy of STAMP:

"Accidents (loss events) occur when external disturbances, component failures, and dysfunctional interactions among system components are not adequately controlled, i.e., accidents result from inadequate control or enforcement of safety-related constraints on the system's development, design, and operation.

...Safety is managed by a control structure embedded in an adaptive socio-technical system. The goal of the safety control structure is to enforce safety-related constraints (1) on system development, including both the development process itself and the resulting system design, and (2) on system operation.

In this framework, understanding why an accident occurred requires determining why the control structure was ineffective. Preventing future accidents requires designing a control structure that will enforce the necessary constraints."

Figure 17, from (Leveson STAMP, 2020), illustrates the role of STAMP within the broader context of accident and hazard analysis.

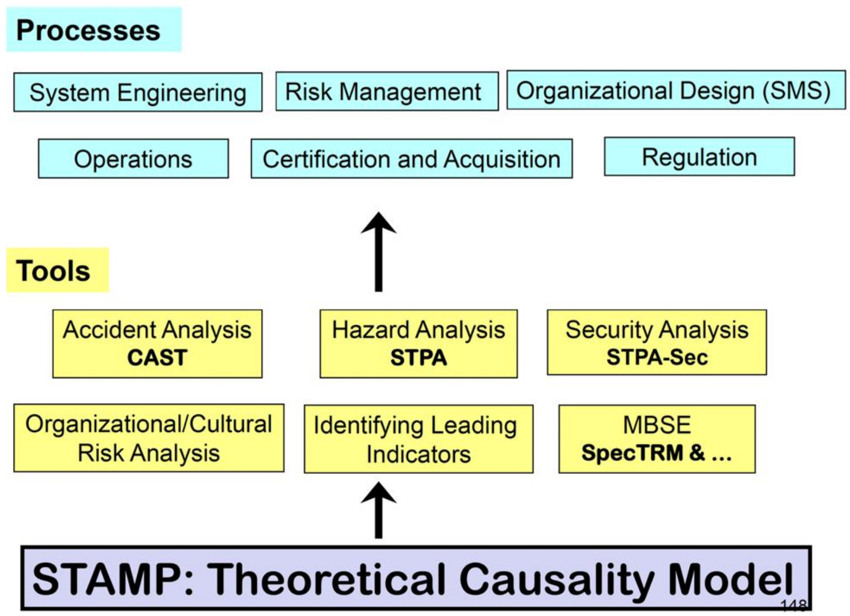

Figure 17: STAMP forms the basis for accident and hazard analysis (Leveson STAMP, 2020).

The three components of STAMP are *i)* safety constraints, *ii)* hierarchical safety control levels, and *iii)* process control loops. In particular,

1. Safety constraints "specify those relationships between system variables that constitute the nonhazardous system states" (Leveson STAMP, 2002).
2. Hierarchical safety control levels capture the fact that "socio-technical systems can be modeled as a hierarchy of levels of organization with control processes operating at the interfaces between levels to control processes at the lower levels" (Leveson STAMP, 2002).
3. Process control loops "between the various levels of the hierarchical control structure create or do not handle dysfunctional interactions leading to violations of the safety constraints" (Leveson STAMP, 2002).

3.4.4 *Quantitative Analytical Methods*

This subsection provides a brief overview of some of the most common and relevant quantitative analytical methods for risk assessment; an overview of qualitative analytical methods for risk assessment is given in the previous subsection. Section 3.4.4.1 reviews probabilistic risk assessment, while Section 3.4.4.2 reviews the role of simulations and modeling in quantitative risk analysis.

3.4.4.1 *Probabilistic Risk Assessment*

Risk Quantification by FAA Risk Assessment Matrix According to the *Risk Management Handbook (FAA-H-8083-2A)* (Federal Aviation Administration, 2022), hazards and their associated risks should be evaluated to ascertain each hazard's overall risk level. This evaluation should commence before the flight. While risk assessment might initially seem subjective, pilots can develop proficient risk-management capabilities through regular practice and application. Risk can be defined as the combined probability of an outcome and its consequences, which may vary in intensity. Risk likelihood can be described by: (i) Probable: An event likely to occur repeatedly; (ii) Occasional: An event that could happen at some time; (iii) Remote: An event that is not likely to occur but is still possible; and (iv) Improbable: An event that is extremely unlikely to occur. In addition, risk severity is categorized by; (i) Catastrophic: Results in fatalities and/or total loss of the aircraft; (ii) Critical: Causes serious injury or significant damage to the aircraft or property; (iii) Marginal: Leads to minor injuries or slight aircraft damage; and (iv) Negligible: Inflicts minimal injury or damage.

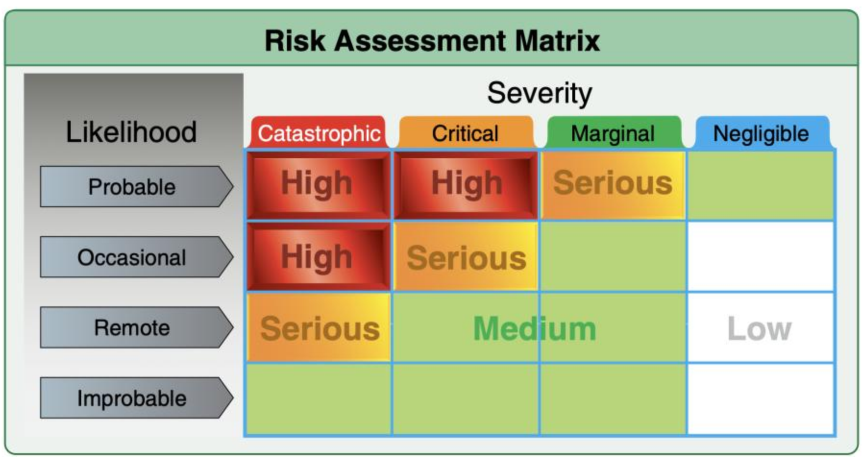

Figure 18. FAA Risk Assessment Matrix (Federal Aviation Administration, 2022).

Upon determining the likelihood and severity of risks, pilots can utilize a matrix (Figure 18) to assess the combined impact of these factors. For example, the risk of thunderstorm penetration, marked by 'catastrophic' severity and either 'probable' or 'occasional' likelihood, is assessed at a high-risk level. Conversely, the risk of a runway overrun, with 'critical' severity and 'occasional' likelihood, is considered a serious risk.

Assigning risk levels using a matrix can lead to errors due to several factors. *Accuracy*: The matrix results depend on correctly assigning risk likelihood and severity. If uncertain, pilots should opt for more conservative assessments. Inexperienced pilots are encouraged to consult more experienced colleagues or instructors. *Skewing*: There is a tendency to understate risk levels due to a desire to proceed with flights. *Obsolescence*: Matrix outcomes may become irrelevant if hazards alter before the flight. Pilots must reassess risks based on the latest conditions and information.

Risk Quantification in Robotics A common approach to dealing with stochastic costs involves focusing on expected case performance (Figure 19). While using **expectation** is mathematically convenient, it has limitations, particularly in safety-critical situations. The main issue with expectation as a metric is its risk neutrality; it fails to consider the potential risks associated with uncertainty. For instance, the fact that a drone can, on average, navigate safely through a cluttered environment does not guarantee its performance in extreme or challenging scenarios, where the risk of a crash may be higher. An alternate approach is to evaluate the **worst-case** performance (Figure 19). However, this method can lead to overly conservative planning that can be inefficient and not always practical in dynamic environments. For example, a drone might choose unnecessarily long routes to avoid obstacles despite the low probability of encountering these obstacles.

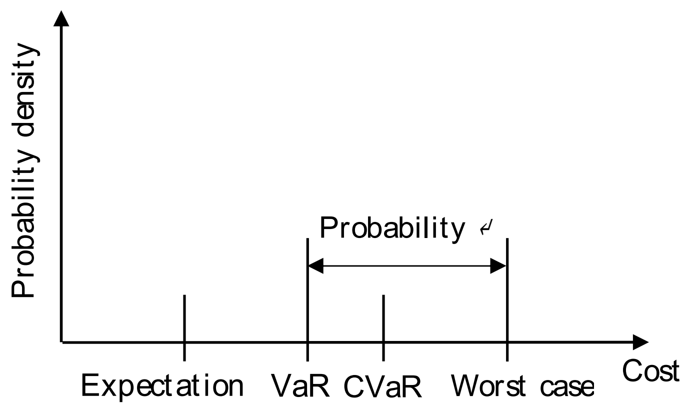

Figure 19. An illustration of four risk metrics---expectation, worst case, Value-at-Risk (VaR), and Conditional Value-at-Risk (CVaR). VaR represents the $(1-\alpha)-$ quantile of the cost distribution. CVaR calculates the expected value of the cost within the upper $(1-\alpha)-$ tail of the cost distribution.

The expected cost assessment represents risk neutrality, while the worst-case assessment represents extreme risk aversion. These represent extremes. Recent trends favor more nuanced metrics that lie in between these extremes to capture risk or safety better. These include the *mean-variance* (Mannor & Tsitsiklis, 2011), *chance-constraint, also called Value-at-Risk (VaR)* (Charnes & Cooper, 1959), and *Conditional-Value-at-Risk* (Rockafellar & Uryasev, 2000). The mean-variance risk metric expressed as $E(Z)+\lambda\delta^2(Z)$, uses a weighting parameter to combine the expected value ($E(Z)$) and the variance ($\delta^2(Z)$) of stochastic cost Z, with λ serving as a parameter to balance the expected performance against risk (i.e., variance). Despite its popularity in robotics and reinforcement learning, the mean-variance metric is criticized for underestimating risk, neglecting the fat tails of the distribution, and failing to differentiate between beneficial and harmful risks. Furthermore, it has been argued that this metric does not satisfy essential axioms for sensible risk quantification in robotics, leading to potentially unreasonable decision-making in autonomous systems (Majumdar & Pavone, 2020). On the other hand, the chance constraint, or the VaR, is another popular risk metric widely used in robotics for motion planning under uncertainty. In particular, VaR sets an upper bound on the probability of incurring costs above a specified threshold (Figure 3). It is defined as: $VaR\_\alpha(Z) = \min\{\mathbb{P}[Z \leq z] \leq \alpha, z \in \mathbb{R}\}$ with $\alpha \in [0, 1]$ denoting the user-prescribed risk tolerance level. VaR is particularly effective for risks associated with binary events, such as obstacle collisions. However, capturing risk in scenarios requiring consideration of a spectrum of cost outcomes is unsuitable, as it does not account for variations in the tails of cost distributions. Similar to the mean-variance metric, VaR also falls short of fulfilling all necessary axioms for a sensible risk metric, and it can lead to questionable and unsafe behaviors (Majumdar & Pavone, 2020). Instead, a better risk metric is the Conditional Value-at-Risk (CVaR) for risk-aware decision-making. CVaR builds upon the concept of VaR and has the definition: $CVaR\_\alpha(Z) = E[Z|Z \geq VaR\_\alpha(Z)]$. Here, $CVaR\_\alpha(Z)$ represents the expected value within the conditional distribution of Z's upper $(1 - \alpha) -$tail. This metric effectively quantifies the severity of "bad" outcomes (tailed cases), providing a more comprehensive view of risk than just a singular point on a distribution, as is the case with the expectation, worst-case, and VaR (Figure 19). CVaR's strength lies in its ability to encompass the entire spread of a distribution, making it a coherent and sensible risk metric (Rockafellar & Uryasev, 2000). It also fulfills all critical axioms necessary for a reliable risk metric, such as monotonicity, translation invariance, positive homogeneity, subadditivity, monotone additivity, and law invariance (Majumdar & Pavone, 2020). Notably, with the user-defined risk tolerance level α, metrics such as mean-variance, VaR, and CVaR offer the flexibility to balance risk and reward. A low risk tolerance leads the system to avoid risk, resulting in more conservative decisions. Conversely, a high risk tolerance level allows for riskier decisions, which could potentially yield higher rewards.

3.4.4.2 *Role of Simulations and Modelling in Quantitative Risk Analysis*

Simulations and Modeling (SM) are indispensable tools in the Quantitative Risk Analysis (QRA) of UAS and their integration into the NAS. SM significantly improves the validation and verification process of guidance, navigation, and control algorithms and provides interactive tools for the visualization and assessment of risks, facilitating the development of potential mitigation solutions.

SM methodologies allow for systematically examining potential risks associated with UAS operations, supporting several flight scenarios, environmental conditions, and system failures to identify potential hazards and assess their impacts. This process is essential for comprehensively analyzing risks, enabling more effective mitigation strategies, and increasing overall safety.

Performing QRA requires the implementation of safety cases along with documentation demonstrating the safety of UAS operations under various conditions. SM tools facilitate this by providing detailed data on system performance, reliability, and potential failure modes. Simulations, testing, and validation of different operational scenarios will ensure that UAS operations meet safety standards and regulatory requirements. Operational risk management is another critical area where simulations and modeling prove invaluable. Simulation models allow for developing and testing risk management strategies under diverse conditions. This includes the performance of collision avoidance systems, evaluation of emergency procedures, assessment of the impact of UAS on air traffic management systems, testing of the effectiveness of different operational protocols, and performance analysis of UAS components and subsystems under adverse conditions.

SM provides a comprehensive framework for identifying and assessing risks, developing safety cases, managing operational risks, ensuring performance and reliability, and achieving regulatory compliance. Recent studies have included risk metrics as part of their SM tools to calculate a hazard's severity and expected occurrence rate through Monte Carlo simulations (Breunig et al. 2019; Gutierrez et al. 2022; Kaabouch and Moncayo 2024). For example, the sUAS Airworthiness Assessment Tool developed by the MITRE Corporation was used in (Breunig et al. 2019) to quantify fatality risk to third-party people by accounting for aircraft and mission characteristics. In that work, the rate of fatality due to sUAS failure was given by:

$$C = P_{fail} * \rho_{people} * S * A_{lethal} * P_{collide} * P_{fatality}$$

Where C is the number of fatalities per flight hour, P_{fail} is the probability of aircraft failure per flight hour affected by different factors such as loss of control, component failure, and damage to aircraft, among others. This probability depends on the failure rate that depends on the UAS weight category, as shown in Table 2.

Table 2. Nominal aircraft failure rates by weight class from (Breunig et al. 2019).

Weight Category	Failure Rate Per Flight Hour
Micro (0.55 lb.)	1E-2
Mini (0.56 – 4.4 lb.)	1E-3
Limited (4.5 – 20.9 lb.)	1E-4
Bantam (21-55 lb.)	1E-5

ρ_{people} is the density of people at risk per square unit area. S is a shelter factor (a dimensionless quantity between zero and one) that estimates a percentage of the population safely covered by buildings or other objects from the direct impact of a sUAS crash.

A_{lethal} is the lethal area of the aircraft on impact, and it represents the likelihood that the aircraft is on a collision course with a pedestrian. It is based on the aircraft characteristics and surrounding population density. $P_{collide}$ is the probability of collision that could be reduced by implementing a mitigation strategy. $P_{fatality}$ is the probability of fatality that can be calculated based on the kinetic energy representing the transferred energy from the aircraft to the obstacle.

Another example of the implementation of SM for QRA studies is presented in (Barr et al. 2017). This study used SM tools to estimate third-party casualties from single-vehicle ground collisions and mid-air collision accidents. The work introduced a preliminary risk analysis that employed two distinct methodologies: Standard Risk Analysis and Probabilistic Model-Based. The Standard Risk Analysis approach followed a safety risk management process that involved identifying hazards, determining their potential causes, and evaluating existing safety controls or proposed mitigation strategies within various sUAS operational applications and scenarios. The Probabilistic Model-Based approach focuses on the feasibility of implementing a comprehensive probabilistic model for risk estimation. This model aimed to capture the complex interdependencies among multiple factors and their failure modes, incorporating internal and external parameters such as aircraft failure types, environmental conditions, and mitigation strategies.

SM tools were also used by (Primatesta et al., 2020) to propose a path planning strategy that computes optimum paths based on risk assessment of operating UAS over populated areas. Using SM, the risk level was quantified through a probabilistic approach based on the risk of flying over a specific location, vehicle parameters, and environmental characteristics. Then, the algorithm computed an asymptotically optimal path by minimizing the overall risk and flight time. SM tools corroborated the approach, proving the proposed risk-based path planning computed an effective and safe path in urban areas.

3.4.5 Issues and Gaps

An important issue and gap in DAA quantitative and qualitative risk assessment is the successful integration of the six key components of data, modeling, analysis, algorithms, hardware/software implementation, and policy. While extensive work has been done on each of these components in isolation or conjunction with one or two other components, there still needs to be a comprehensive and integrated framework containing all six components in a coherent DAA system. Roughly speaking, i) data on key operational and environmental variables must be gathered to understand their joint empirical distribution; ii) this data should inform parsimonious risk models; iii) the data and models together facilitate analysis of key safety-related performance indicators; iv) algorithms are then developed based upon this analysis to ensure operations will adhere to required safety constraints and margins; v) these algorithms are implemented in hardware and software; and vi) policy is developed to ensure the DAA systems are operating within the tolerances for which they have been designed.

3.5 Controlling Risk

The final step in the SRM process is controlling risk (Federal Aviation Administration, 2021). A risk control application is an SRM output informed by multiple facets of the process – e.g., hazards, assessed risk, residual risk, etc. According to FAA Order 8040.6, this step in the SRM process includes identifying where additional controls may reduce the risk for hazardous conditions outside of tolerances; in short, the application of controls is intended to minimize the risk to acceptable levels (Federal Aviation Administration, 2023b).

For completeness, this section incorporates safety risk acceptance, safety performance monitoring, and hazard tracking as components of controlling risk. These concepts are natural extensions of risk controls, allowing for an analysis of residual risk and regular review and monitoring for continuous improvement. They offer a rational extension of the process for controlling risk that extends to the entire unmanned system and the DAA system in and of itself.

3.5.1 Safety Risk Acceptance

Safety risk acceptance involves accepting safety risk with applied mitigations, alternatives, and risk controls (Federal Aviation Administration, 2023b). This process may also include the application of new controls or mitigations if residual risk is unacceptable (Federal Aviation Administration, 2023b). It is a crucial element of the SRM process.

For DAA systems, this could include acceptance or modification of risk controls as applied to a particular DAA system within a known environment. In these cases, a risk assessment may be modified to reflect additional hazards and reduce risks to an acceptable level when residual risk is beyond allowable tolerances. This reflects procedures captured in FAA Order 8040.6A.

3.5.2 Safety Performance Monitoring and Hazard Tracking

Safety performance monitoring and tracking represents the cyclical nature of the SRM process and serves as a connecting element to the safety assurance process. It consists of regular system safety assessments via operational tracking, data acquisition, and analysis. It is intended to verify the effectiveness of mitigations and controls that bind safety risk (Federal Aviation Administration, 2023b). It verifies safety performance targets and residual risk (Federal Aviation Administration, 2023b).

3.5.3 Issues and Gaps

A key issue and gap regarding the application of risk controls for DAA systems is the lack of standards that outline the application of common controls and mitigations. While FAA Order 8040.6 A provides a rudimentary list of mitigations (Table 3) and approaches to address the hazard, “unable to detect and avoid,” the guidance stops short of providing detailed information on how to apply mitigations.

Table 3. Unable to Detect and Avoid (Federal Aviation Administration, 2023b).

Hazards	Hazard Definition	Causes (if applicable)	Mitigations	Outcomes
Unable to Detect and Avoid	Beyond Visual Line of Sight (BVLOS) operations and the design of the UAS give the aircraft a limited ability to sense intruding aircraft and yield right of way as required by 14 CFR Parts §91.113 and §107.37	• Transponder failure • Communication failure between VOs • Traffic conflicts; helicopter routes/uncharted landing surfaces • Inability to comply with 14 CFR Parts §91.113 and §107.37 • Low altitude, General Aviation (GA) operations • Manned aircraft unable to see UA (due to the small size of the UA) • Pilot and crew errors • UA maneuverability (due to UA performance limitations)	• Visual Observers (VOs) (communication between pilot and observers) • Detect and avoid (DAA) system • Airspace of operation and adjacent airspace • Time of day • Operating restrictions • Restricting operations within certain boundaries or airspace volumes • Restricting operational flight time • Low altitude • ATC separation services • Traffic Alert and Collision Avoidance System (TCAS) • Proximity to structures • Unmanned aircraft systems traffic management (UTM)	• Collision between UAS and a manned aircraft in the air • Collision between two or more UAS • NMAC between UAS and a manned aircraft in the air, • Manned aircraft making an evasive maneuver to avoid UA (proximity from UA remains greater than 500 feet) • A collision between a UAS and terrain (CFIT) • Collision between UAS component(s) and persons and/or property • Collision between package/cargo and persons and/or property

The mitigations listed in Table 3 are examples highlighted within Appendix B of FAA Order 8040.6A. While these mitigations are linked to the hazard, “unable to detect and avoid,” they do not address the DAA system itself. Moreover, there is no specific guidance regarding how and when to apply these mitigations or other risk controls. This gap leaves room for standards and best practices to define how and when to apply given risk controls and mitigations within common, representative operational scenarios.

4 ROLE OF INDUSTRY STANDARDS FOR DAA RISK ASSESSMENT

This research could inform a standard, or set of standards, for approaches to SRM for DAA systems. Industry consensus standards, such as those from ASTM and RTCA, provide a mechanism for industry stakeholders to define alternative Means of Compliance (MoC) for meeting FAA safety requirements. In the case of DAA systems, defining SRM processes within industry standards offers a way to specify MoCs that are scalable and applicable to the wide variety of DAA architectures and configurations that may emerge, including airborne and ground-based systems.

The American National Standards Institute (ANSI) *Standardization Roadmap for Unmanned Aircraft Systems, Version 2.0* (2020) identifies multiple Standards Development Organizations (SDOs) that are working to address various aspects of DAA. Some of these SDOs include RTCA, NASA, and ASTM International. Of these SDOs, ASTM has been primarily focused on DAA for low-altitude UAS operations. While standards from other SDOs have relevance to this research, standards from ASTM emphasize UAS in the size, weight, and performance classes that are most compatible with the scope of this research – SRM for low-altitude DAA systems. Thus, this report addresses current efforts from ASTM to develop standards for DAA performance, test methods, and the need for unique approaches to SRM. The following sections

4.1 ASTM DAA Performance Requirements

ASTM F3442/3442M-23 *Standard Specification for Detect and Avoid System Performance Requirements* (ASTM International, 2023) defines minimum performance requirements for DAA systems for UAS that meet the following criteria:

1. Maximum dimension – e.g., wingspan ≤ 25 feet.
2. Maximum airspeed < 100 knots.
3. Of any configuration or category.

In addition to these basic criteria, the standard applies to UAS operating in a "lower risk" airspace environment where encounters with other aircraft are not expected to occur often (ASTM International, 2023). In short, while ASTM F3442/3442M-23 does not exclusively apply to sUAS, it does apply to UAS that operate in low-risk environments.

ASTM F3442/3442M outlines guidance for determining minimum DAA system performance. It offers processes and guidance for defining the system itself, system timing, and basic functions common to all DAA systems – i.e., detect, alert, and avoid. It also highlights mechanisms for capturing incidents and events that may result in an NMAC. Finally, the standard offers appendices [non-mandatory information] that identify surveillance performance characteristics, guidance for deriving system timing, and areas of future work.

While ASTM F3442/3442M does not explicitly outline SRM practices for DAA, it does offer a starting point for considerations regarding DAA system performance. Identifying DAA system performance constraints, including baseline functions, limitations, and optimal and suboptimal functional states, can inform decision-making regarding risk. ASTM F3442/3442M provides a standardized roadmap to quantify the function of a DAA system based on a system-agnostic functional breakdown. This may offer valuable inputs to risk assessment tools.

4.2 ASTM DAA Test Guidance Standard

An ASTM standard for DAA test methods is being worked on at the time of this report. The standard, presently titled WK62669 *New Test Method for Detect and Avoid*, is a companion to ASTM F3224/3442M. The *New Test Method for Detect and Avoid* provides methods to demonstrate that a DAA system meets the performance requirements described in ASTM F3224/3442M. Outputs from WK62669 may offer qualitative and quantitative assessments of a DAA system to show that it meets given performance metrics. This data may inform risk assessment tools by providing datasets that drive decision-making processes.

4.3 Standards for DAA Risk Assessment

Presently, no standards address the risk associated with DAA systems in and of themselves. While ASTM F3442/3442M and WK62669 specify standard practices for defining DAA performance requirements and test methods, respectively, they do not directly outline a risk assessment framework for DAA systems or their operation. ASTM F3178-16 *Standard Practice for Operational Risk Assessment of Small Unmanned Aircraft Systems (sUAS)* (ASTM International, 2017) guides performing an operational risk assessment for sUAS flight operations. Still, it stops short of offering guidance tailored explicitly for DAA systems. Moreover, F3178-16 addresses operational risk and misses design aspects of sUAS. ASTM F3178-16 assumes that Original Equipment Manufacturers have met basic design criteria to meet relevant safety targets (ASTM International, 2017).

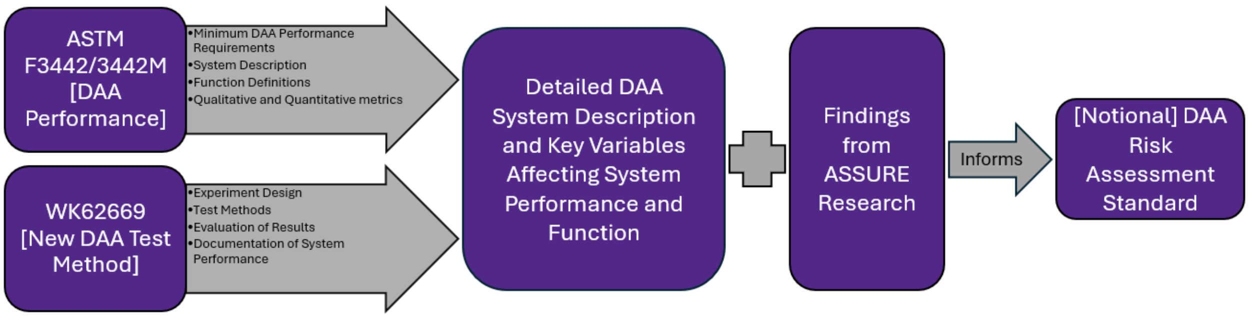

Figure 20. Framework for a notional DAA SRM standard.

Figure 20 outlines a potential path to standards that inform SRM processes for DAA systems. ASTM F3442/3442M and WK62669 provide a path to establishing a detailed description of a given DAA system. Data from DAA testing and simulation (WK62669) that conforms to given performance requirements (F3442/3442M) provides qualitative and quantitative metrics for a given system and functional limitations. This data and the results from ASSURE research could be used as input to inform a [notional] standard that defines a standard practice for SRM for DAA systems.

5 CONCLUSIONS

This issue paper examined the current state of DAA systems for sUAS through the lens of the SRM process. This approach aided in identifying issues and gaps in the current state of DAA technology and operations. The findings of this report will inform future tasks and sub-tasks for ASSURE A71, providing input for the development of risk assessment practices for DAA systems. The following sections summarize issues and gaps identified for DAA systems, list recommendations for baseline for hazard identification and risk assessment frameworks, and identify areas of future research.

5.1 Summary of Issues and Gaps

While exploring the application of the SRM process to DAA systems, the research team identified several issues and gaps. These issues and gaps point to areas of future work and serve as starting points for discussion surrounding hazard identification and risk assessment for DAA systems. While the list identified here may expand because of future developments and explorations of DAA systems, the issues and gaps identified here were seen as having a significant impact on the current state of DAA systems and operations. They are important factors for future tasks within the A71 research effort.

5.1.1 Describing the System

A major challenge in describing DAA systems is the difficulty in describing their overall reliability – both in overall function and the physical longevity of their parts and components. While more mature technologies such as ADS-B and Mode S transponders are vetted for compliance with regulatory requirements via standards and rigorous certification practices, the same is not so for DAA systems. DAA systems represent a broad spectrum of technologies, and they incorporate a variety of sensors, computational algorithms, and varying levels of autonomy. The interactions between the sensors, algorithms, and autonomy must be understood to identify the functional reliability of a DAA system and its components.

While it is presently difficult to quantify the performance of a DAA system, standards bodies are working to address this gap. ASTM International has drafted a standard for identifying DAA system performance requirements (ASTM F3442/3442M). It is currently developing a standard that describes guidance for evaluating the performance of a DAA system. While these standards are a step in the right direction, there are still challenges associated with defining overall system and component reliability. There is room for standards bodies to define further performance and reliability requirements for DAA systems to meet safety targets. The need for existing standards and metrics in this area at the time of this report represents a gap.

5.1.2 Identifying Hazards

Issues and gaps relating to identifying hazards associated with DAA systems and their operations were primarily related to the high variability of environmental conditions, integration with existing air traffic management systems, and technological limitations – such as challenges in filtering out certain types of interference that may affect reliability. These issues and gaps stem from challenges with inconsistencies in detection and tracking that may result from wind, rain, and other environmental phenomena that may create difficulties with filtering noise. This results in a need for more data regarding how various types of sensors operate, suitable thresholds for interference, and periodic reassessment of hazards.

The team also noted issues integrating DAA systems with air traffic management systems. The team noted that information regarding DAA actions may not be communicated in a way that follows existing communication or data transmission protocols. This creates a need to ensure data compatibility and protocols aimed at integrating DAA systems in a way that allows them to interact with air traffic management systems when needed.

5.1.3 Analyzing Risk

Analyzing risks associated with DAA systems is complex and complicated, and numerous issues and gaps make effective risk management challenging. There is a distinct lack of comprehensive data regarding UAS operations and their impact on traffic in the NAS. What data does exist may not be consistent or conform to any known convention. This makes assessing the risk associated with UAS operations in the NAS difficult. The rapid development and fielding of UAS and associated technologies compound this problem. The result is a landscape where UAS are developed and evolve faster than the regulatory framework that defines how and where they may operate. The rapid pace of technological advancement and integration of UAS into the airspace create inconsistencies in hazard identification and risk management. These problems are exacerbated by the inclusion of DAA systems, which add complexity to risk analysis by adding more variables in the form of novel combinations of sensors, computer algorithms, and levels of autonomy, all with their unique characteristics. These challenges are amplified by the need for more verification and validation processes for DAA systems that enable the collection of meaningful data about system performance. Findings in this area reinforce the need for standards and data-driven methods to describe a DAA system and quantify its reliability.

5.1.4 Assessing Risk

A significant issue and gap relating to quantitative and qualitative risk assessment resides in the ability to fuse key data to generate reliable risk assessments for DAA systems. Performing a reliable risk assessment requires six key components – data, accurate models, processes for effective analysis, algorithms that reflect reliable analytical approaches to existing models, knowledge of hardware/software, and policy. These six components reflect critical variables needing definition for effective analysis. While all six of these components have been explored independently, there is little work exploring the fusion of these components to inform a more detailed analysis of a DAA system. This reflects a critical gap: the lack of a comprehensive data-driven analytical framework that defines an adequate quantitative and qualitative basis for assessing risk for DAA systems.

5.1.5 Controlling Risk

Controlling risk associated with the operation of DAA systems is complicated by the lack of standardized risk controls. While there is existing guidance in FAA Order 8040.6 regarding the generalized hazard, "unable to detect and avoid," no listed mitigations specifically address failures or degraded operations of a DAA system of any type. This represents a significant gap. This gap is reinforced by gaps and issues in other areas that reflect the need for data and analytical models for DAA systems, as data drives the effectiveness of risk controls.

5.1.6 Key Takeaways

The research team identified the issues and gaps above as posing significant challenges to assessing the risk associated with DAA systems. The issues and gaps identified in this report will inform the identification of hazards and the development of risk assessment framework(s) in subsequent tasks. While this report does not necessarily capture all possible issues, gaps, and hazards associated with DAA systems, it does capture some of the more significant issues and gaps that pose barriers to effective hazard identification and risk assessment. The following represent summarized themes and concepts derived from the issues and gaps identified above:

1. There are no universally accepted reliability metrics for DAA systems.
2. There are currently no accepted standards for assessing the risk associated with DAA systems.
3. Data required to assess the risk associated with DAA systems is often incomplete, inaccurate, or unavailable.
4. Models driven by reliable data and a robust analytical framework are essential to assessing the risk associated with DAA systems.
5. The evolution of DAA technologies is occurring rapidly and extends beyond the current UAS operational guidance.

6. There is a need for effective verification and validation of DAA systems to ensure reliability.
7. Guidance and standards are needed to define and apply risk controls for DAA systems.

These themes emphasize the need for standards and data-driven analytical models that inform risk assessment practices for DAA systems.

5.2 Future Work

The issues and gaps identified in this paper indicate a need for future work exploring various topics relating to DAA systems. Beyond the need for a repeatable process for assessing the risk associated with DAA system operation, there is an obvious need for continued exploration of data collection and validation, analytical models, and standards. Future work should address these issues and gaps, as well as the ones listed above. Building standardized approaches for developing and applying analytical models to identify hazards and assess risks for DAA systems will be crucial. More importantly, standardized methods for applying risk controls are needed to provide context for applying analytical models.

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