A Quantitative Framework for UAV Risk Assessment

Version 1.0

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Abstract

This is the first public release of the draft of Altiscope's quantitative open risk framework for unmanned aerial systems. It provides a direct path to implementation in present-day scenarios, as well as the conceptual groundwork to enable increasingly complex, dense and autonomous UAS operations informed by risk. The first chapters provide the justification for the framework and situate it in relation to other efforts to identify UAS risks. Next, this framework outlines a variety of high-level use cases so that various users can understand how they might use the framework. We provide conceptual details of several derivative models using the framework. So that users of this framework can gain a better understanding of how it might be applied and implemented, we provide detailed calculations and derivations for present-day small vehicle missions. As a matter of nomenclature, a model that is implemented in software and available for operational use is referred to as a "service." A service may be available to many users and operators, or it might be used exclusively by a single user.

Note to Readers

This is a preliminary draft of Altiscope's open risk framework, provided for external consultation with the hope of generating debate and discussion on how to improve it. **Disclaimer: this is a draft document being released to invite collaboration. It should not be used to assess risk for any flight mission or operation. ALTISCOPE AND AIRBUS DISCLAIM ANY EXPRESS OR IMPLIED WARRANTIES, INCLUDING, BUT NOT LIMITED TO, THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A PARTICULAR PURPOSE.** This is an open framework because Altiscope and Airbus are providing it to the entire aviation community free of terms and restrictions. Anyone may take and adapt, modify, change or incorporate any of these methodologies into their own processes without needing a license to do so. We believe this is the best way to foster collaboration and ensure that the evolving framework meets the needs of industry, regulators and air navigation service providers, while enabling safe operations anywhere in the world.

All comments and critiques are welcome on this draft. Please submit them directly to peter.sachs@airbus-sv.com, referencing the relevant line numbers in the left-hand margin.

Many readers may be curious what relationship this framework has to the JARUS SORA (Specific Operations Risk Assessment). The short answer is that we view this framework as complementary to the SORA methodology. Altiscope's risk framework also could be used to extend SORA's abilities – for example, by providing real-time risk assessment immediately before departure, or at any point in a flight. Because this is a quantitative framework, we expect that it can be applied in high-volume, dynamic and autonomous settings in the future, for which SORA alone would not be useable in its present form.

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Readers are invited to submit comments on this draft to peter.sachs@airbus-sv.com.

1. Introduction

Altiscope's quantitative open risk framework recognizes that there are many steps between today's small UAS (sUAS) missions and the high-density autonomous flights envisioned 20 years from now. The current systems in place in manned aviation assume that all human participants are properly trained and that all equipment meets rigorous certification standards. But neither of those assumptions holds true for UAS operations today. Operators can receive a remote pilot's license in many countries without ever demonstrating competency in flying the vehicle. And the vehicles themselves may vary widely in reliability and quality, since manufacturers do not yet need to meet the same level of rigor in their design and assembly processes as in conventional aircraft.

The need for a consistent, repeatable and scalable approach to risk assessment in UAS operations is immediate. In mid-2018, a consensus study report published by a committee of the National Academies of Sciences, Engineering, and Medicine recommended that the Federal Aviation Administration create a quantifiable approach to making risk-based decisions about UAS operations (National Academies of Sciences, 2018). The FAA historically has used subjective, qualitative criteria in its approval process. But that approach leads to inconsistent findings of hazard based on every possible (not probable) harm. And it cannot be scaled to the surging demand for UAS access to all levels of airspace.

This open risk framework provides a basis for quantifying a variety of factors related to the pilot, the vehicle and the operating environment that today are analyzed by a competent pilot, dispatcher or operator. The benefit of this approach is that it can also be built into the processes that a semi- or fully autonomous system will conduct before, during and after a flight.

In other words, the open risk framework solves two problems. First, it brings clarity to the actual risks behind UAS missions happening today with a human actively involved in some portion of the flight. And it provides a quantifiable (and therefore consistent and repeatable) approach for a set of autonomous UAS traffic management (UTM) services to manage risk across all airspace operations.

2. Extending Safety Management System Principles

Manned aviation around the world currently enjoys one of the best safety records it has ever had, in terms of accident and fatality rates. In the United States, a fatality in 2018 was the first due to an accident aboard a commercially operated flight since 2009. Other countries experience similar safety records as well. The result is a popular expectation that flying, as one of the safest modes of transportation, is immune to risks that could cause death or serious injury. The truth, of course, is that risks are carefully, systematically and proactively managed by every participant in the aviation industry, from manufacturers and airport ground handling personnel to pilots and air traffic controllers.

A Safety Management System (SMS) is what helps ensure that aviation remains as safe as it is, providing a holistic and organization-wide approach to managing risk. Most aviation safety professionals recognize the term “safety culture,” which is one of the more obvious components of an SMS, and sets the tone for prioritizing safety above convenience or profit in day-to-day operations and decision-making.

Because SMS processes are so critical to modern aviation, the Open Risk Framework is intended to intersect with and enable it at many points. Many people within the unmanned aerial vehicle industry may not be familiar with SMS if they don’t have previous experience in aviation, so this section also provides a primer on how SMS is applied within an aviation organization.

The International Civil Aviation Organization’s (ICAO) Safety Management Manual (SMM), Document 9859, describes the policies that each member state must institute as part of a comprehensive Safety Management System (SMS). An SMS is a set of top-down business and management processes that prioritize safety in the operation. Not only is each ICAO member state required to have an SMS in place for its regulatory duties, but member states impose similar requirements on the organizations that provide their air traffic control services. And many ICAO member states also require certificated operators, such as maintenance facilities, cargo airlines and air carriers, to develop their own companywide SMS documentation and procedures.

An SMS helps ensure safe operations by making safety risk management and safety assurance activities central to the organization’s work. There are four broad components, though the details of each will vary significantly depending on the organization or company.

1. Safety Policy: These are the documented processes, methods and standards for ensuring operational safety, holding managers accountable and providing avenues for all employees to report safety concerns without fear of retaliation.

2. Safety Risk Management: A formal process used to evaluate threats, hazards, risks and mitigations of the operation, particularly when rules or ways of working are changed. This is often a qualitative process involving subject matter experts. The steps are commonly known by the mnemonic DIAAT: Describe the system, Identify the hazards, and then Assess, Analyze and Treat the risk. Ideally, this process should be consistent and repeatable, so that different people conducting an analysis arrive at similar conclusions.

3. Safety Assurance: This component ensures compliance with policies, procedures and rules through audits of safety practices, review of mistakes and incidents, and the use of data collection and analysis to spot trends in safety threats and hazards.

4. Safety Promotion: A robust internal safety culture is critical for an SMS to succeed. This last component enables and fosters that culture by providing relevant training and spreading lessons learned and best practices.

In practice, Safety Risk Management (SRM) and Safety Assurance are closely linked. The SRM process makes a determination that a proposed change presents an acceptable level of risk before that change is enacted. Safety Assurance collects data on the operation after the change is made to ensure that risks are in fact being effectively mitigated. It can trigger a new SRM process or other corrective actions if problems crop up.

One of the potential weak links in most SMS systems is that while data is collected at many stages of the operation, it may not be easily quantifiable or even accessible in a way that can be used in an SRM process. And in the case of evaluating the risk of entirely new procedures, there may not be available data to use as a baseline. Where data does exist that would allow a quantified analysis, there is generally no requirement that the SRM process rely on that rather than subjective, qualitative analysis. As the ICAO SMM notes, "The absence of quantitative baseline data may force a reliance on more qualitative analysis methods." (ICAO, 2015)[i] Even with available data to quantify the probability of a risk, the SRM process to assign severity generally relies on qualitative categories. Catastrophic, Hazardous, Major, Minor and Negligible are the most common terms, with more specific definitions as to the extent and seriousness of damage or injury.

Likelihood and severity of a hazard can be plotted in a risk assessment matrix such as that in Figure 1, which has the advantage of being easily interpreted and is familiar to many aviation safety professionals. The colored regions indicate whether an operation is acceptable as-is (green), tolerable with mitigations in place (yellow), or prohibited unless mitigations are added (red).

Risk probability		Risk severity				
		Catastrophic A	Hazardous B	Major C	Minor D	Negligible E
Frequent	5	5A	5B	5C	5D	5E
Occasional	4	4A	4B	4C	4D	4E
Remote	3	3A	3B	3C	3D	3E
Improbable	2	2A	2B	2C	2D	2E
Extremely improbable	1	1A	1B	1C	1D	1E

Figure 1: ICAO Risk Assessment Matrix.

Because both axes are most commonly defined qualitatively, subject matter experts evaluating a given operation may arrive at different scores given the same set of background facts and information. And depending on factors such as cost, complexity or feasibility of mitigation measures, some participants may be inclined to adjust their scoring so that the operation falls in a low-risk square instead of a yellow square where a mitigation might be required.

Conversely, when asked to evaluate a novel operation with which participants have neither data nor experience, there can be a tendency to lean in an overly conservative direction. This results in a score in the red region based on the worst conceivable outcome, however improbable that might be ("A mast arm separates from the vehicle in flight, causing it to lose control and it impacts an above-ground fuel tank adjacent to a school at recess.").

There are available methods to quantify both axes of the above chart, but consistent application will require a number of systemic changes, starting with education for SRM experts who don't normally evaluate scenarios in that way. The frequency axis can be divided into failure rate ranges, either as a rate per 100,000 operations, a rate per 1 million flight hours, or some similar metric. Intervals such as rate per number of days, months or years are less optimal, unless the operation is known to occur with relatively steady frequency across that interval, and is not expected to grow or shrink with time.

Quantifying the risk severity axis requires careful consideration of the hazard effects that need to be measured. Counts of the number of people injured or killed provide a very high-level view. Using buckets defined by severity on the Abbreviated Injury Scale or ranges of Injury Severity Score would provide a much finer tuning of the risk severity scale, and provides a means to systematically quantify the inherently qualitative nature of evaluating medical trauma (AAAM, 2015). Quantifying damage can take a more straightforward approach in selecting appropriate ranges to reflect insurance liability, replacement value, or both.

This process may not be sustainable going forward in risk assessment, though using a matrix or other visualization tool will still be important in understanding how the risks of a new operation compare with a baseline or some other point of comparison. Much of the organizational risk management that occurs today focuses on off-nominal events – that is, things that didn't quite go as expected, but don't result in a crash or collision – as precursors in an event chain that could eventually lead to a catastrophic accident. Since UAV operations are so new, and largely unfamiliar to the public at large, it may in fact be necessary in some jurisdictions to mitigate against much less severe failures. Doing so will likely require that insurance companies or regulators (or both) mandate that such data be collected and shared.

But ultimately, an approach that uses a variety of outputs from a risk model to describe the range of risks of an operation may be more adaptable for the long-term needs of the UAS industry, rather than trying to shoehorn autonomous processes into an existing risk evaluation tool designed for simplicity.

2.1. Building and Applying an SMS in an Aviation Setting

Creating an effective SMS requires not only an extensive effort to create policy, process and procedure documentation, but an equally large effort to educate everyone in an organization about the importance of those documents, and how to use them on a daily basis. Some documents may already exist, while others may need to be updated or rewritten. Establishing a blame-free environment for reporting safety concerns may also necessitate changing other organizational policies and procedures if they're in conflict.

The widely accepted continuum of safety culture comprises several mileposts, each with increasing trust, information and awareness about safety (Hudson, 2001). Many organizations struggle to move past the "reactive" stage, in which resources are poured into the response after an accident or safety lapse. Even with the "calculative" systems in place at the next level, it can be hard to use the data available to progress to the "proactive" level, since doing so requires using those systems to anticipate safety problems before something occurs. The ultimate goal is to operate at the "generative" level, in which safety is deeply engrained in all aspects of an organization, and even slight irregularities are recognized and addressed.

In settings with any level of autonomy, SRM processes will take on a different flavor compared to today's groups of stakeholders working through a proposal in a conference room. As we gather more operational data and quantify both the severity and likelihood of various occurrences, we can work on making our SRM processes more predictable and repeatable. In many cases, an autonomous system will be able to conduct its own SRM process – essentially, running a validated risk model on a given operation – and assigning mitigations or changes to the operation as necessary to meet compliance thresholds set by regulators, insurers or the operator itself.

Safety Assurance responsibilities may fall to an existing quality control unit, or may require new roles. Providing the right data analytics tools to those people is crucial. While many organizations already collect large amounts of data, it may be warehoused or siloed in ways that make it difficult to unpack and visualize. An effective safety assurance program not only conducts after-the-fact investigations of errors and incidents, but also continuously reviews routine data at a high level to spot possible sources of future errors and problems. At the outset, the safety assurance team will need to scrutinize the entire organization to make sure that new and existing systems are collecting the right kinds of data. For example, who are all the people who touch a UAV from the day it (or its components) first arrive, to its last day in operation? Those people need ways to enter vehicle information – repair status, results of bench tests and flight checks, pre- and post-flight notes and anything unusual or unexpected that happens along the way – that fit with the existing data warehouse format.

2.2. Existing safety frameworks for UAS operations

Most of the frameworks we use to manage risk in aviation today are inherently qualitative. They are effective at what they do, leading a human operator (whether mechanic, pilot, controller or someone else) through an intentional checklist or set of steps to ensure that they've done everything they can in their respective domain to identify and manage any perceptible risks. Specific to UAS operations, several insurance companies have developed proprietary frameworks they use to assign risk and therefore set pricing for premiums. Details of these frameworks are not available publicly, other than listing broad categories of risk that are considered. This makes them difficult to extend to an operational setting, since there is no way to validate their underlying methodologies.

The most well developed framework in use today is the SORA developed by the Joint Authorities for Rulemaking of Unmanned Systems (JARUS). The SORA has been endorsed by the European Aviation Safety Agency for use by EU member states in deciding whether to allow a given UAS operation. SORA presents a relatively straightforward, qualitative process to determine one's Specific Assurance and Integrity Level, or SAIL, which directs the types of processes and mitigations an operator needs to have in place to enable a safe operation. The inputs are the overall width (or wingspan) of the vehicle; the type of operational scenario (VLOS or BVLOS, and density of the environment over which the flight will occur); any mitigations in place to decrease the damage a crash of the vehicle might cause; and the type of airspace and altitude of the mission.

SAIL levels range from I to VI, with higher levels requiring the operator to provide documentation or evidence demonstrating more robust maintenance and operational procedures. In many cases, to achieve the high levels of assurance required for SAIL V and VI, the operator must have their processes independently validated by a third-party organization. Especially at the SAIL VI level, the practical implication of this is that the vehicle and operator must meet guidelines that are only slightly less stringent than going through a full certification process.

While following the SORA framework results in an initial SAIL assignment, this does not immediately translate to a flight authorization. Nor does it correlate to a quantitative range for probability of vehicle loss of control, crash or fatality.

Because the SORA process does not take into account temporal risk factors, such as weather conditions, vehicle maintenance, fuel load or actual airspace occupancy levels, some operators may find that they need to conduct an additional preflight risk assessment to determine a quantifiable set of values representing that mission's predicted risk levels. That allows a comparison against benchmark safety rates, whether set by the operator themselves, the insurer or the airspace regulator – or all three.

The advantage of SORA is that is provides a holistic view of hazards and risk mitigations during the flight planning stage. Its approach is fairly conservative, assigning high SAIL levels to many types of missions. This reduces the likelihood that an airspace regulator will inadvertently decrease the equivalent level of safety in their airspace.

Since SORA is a qualitative process and not a comprehensive evaluation, its applicability to future UTM risk assessment needs is limited. SORA provides 12 categories of airspace usage and eight categories of operations (including over urban, rural or suburban areas). This does not provide a fine enough level of detail for an autonomous path planning system to optimize vehicle routes for a target risk threshold. Altiscope is working on an air risk model based on a clustering algorithm that may be able to improve the current process of conducting an expensive and time-consuming airspace usage study before seeking mission approval (see Annex C). And we are investigating methodologies to calculate ground risk using databases of people density and building footprints (see Annex B). Taken together, our hope is that validating these two approaches may be able to greatly simplify the current SORA workflow for establishing air and ground risk, making it a quantitative process that can be initiated in the background with software, and not requiring extensive knowledge on the operator's part.

SORA's scope is limited to vehicles without passengers, so the framework does not provide guidance for de-risking air taxi missions that almost certainly will want access to dense urban areas and airports. Further, SORA does not provide a mechanism to evaluate the combined risk of many UAS flights in a given volume of airspace. Even in an environment similar to today's, with most vehicles supervised closely by a human operator, this means SORA does not take into account the added risk (if any, depending on navigation and performance abilities) of two UAS missions operating in proximity to one another. While the calculations in this version of Altiscope's open risk framework are geared toward small, battery-powered vehicles (see Annex A), we intend to create similar failure mode sub-models for other types of vehicles, providing the scalability and flexibility that will be needed to accommodate future missions.

Altiscope envisions that the quantitative approaches in this framework could be used to complement and extend the SORA framework, providing operators and regulators with a single, comprehensive framework that could be used in defining mission needs (long before departure) to autonomously separating vehicles and managing airspace capacity from moment to moment.

2.3. How the Open Risk Framework enables SMS

Altiscope's open risk framework and implemented versions of its risk models can engage and enable an SMS in a variety of ways. The following notional examples are intended to illustrate some of those interactions.

1. A risk model evaluates each operation before it takes place, outputting a variety of results and providing safety risk management functionality on a systematic, flight-by-flight basis. Within a given regulatory jurisdiction, all implemented risk services must use the same underlying model, so that results generated by different services are consistent, repeatable and comparable to one another. This fundamental requirement ensures that safety policy is applied across all facets of the regulator's jurisdiction.

2. An individual operator may implement an internal risk model to aid in the flight planning process and increase the likelihood of approval without subsequent modifications. A risk service interconnected with other UTM and ATM components may recommend flight plan approval to a discrete planning service. Or a flight plan processing service may fully integrate a risk model into its system to provide both capabilities at once. Any of these permutations enable safety risk management processes across all users of a UTM.

3. The data collected from the risk model, such as how it arrived at its results, as well as inflight performance and telemetry data, is collected, stored and processed by either a standalone risk data service, or one of the same risk calculation services described in the previous step. This service, initially trained based on human-driven root cause analysis processes, is responsible for tracking and reporting flights that operate with a higher actual risk than predicted. It must also identify slight deviations that indicate an impending malfunction or a set of hazards not properly accounted for in a risk model. Taken together, these capabilities provide safety assurance at very high levels, since the service can process and aggregate large datasets to identify underlying risk factors before an unsafe event occurs.

4. The aggregate data collected from a system that relies on the risk framework enables policy and procedure decisions that are informed by a holistic understanding of the operation, not just anecdotal evidence. That same data is also the basis for learning from mistakes, incorporating best practices and the continual education that occurs within a strong safety culture.

3. Use Cases

The value of this risk framework is in how it can be applied in real-world scenarios, both today and in the future. These broad descriptions are intended to capture the needs of all participants who would interact with a service based on the risk framework. While many of these use cases apply to civil or commercial UAS operations, they may apply to military operations as well, depending on the specific mission and context.

3.1. Operator Use Cases – Present Day

Hobby/recreational drones: These vehicles are flown for fun, and as of today, we expect that operators will not need a certificate or licence to fly them. Because of this, their operations are limited to low altitudes in Class G airspace and are flown exclusively within visual line of sight. Unless the vehicle itself is available both to recreational and commercial users (and therefore may need to meet certain performance criteria for the latter), it might not be subjected to any level of risk assessment. Many of these vehicles will likely fall under future standards for *de minimis*[1] or no-risk vehicles based on their low weight and limited range and payload capabilities.

Visual line-of-sight (VLOS): sUAS flown by a commercial operator in controlled airspace below 400' AGL. Operation is limited to a small radius for surveying, photography, etc. Flights generally less than 30 minutes long, a function of battery capacity. Flights may occur at night, over groups of people or in proximity to an airport if the vehicle's capabilities reduce the risk of a crash or collision.

Beyond visual line-of-sight (BVLOS): sUAS flown by a pilot on the ground who may be co-located with the general area of operation, or who may monitor and control the vehicle from a remote station hundreds or thousands of miles away. Vehicles tend to be larger, have the capacity for flights 30 minutes or longer, and may carry specialized payloads. Includes linear infrastructure inspections, precision agricultural spraying and landscape surveying/hydrology missions.

BVLOS Package Delivery: Payload-carrying vehicle flies between a warehouse or pickup point and delivery location, then returns to the next warehouse or pickup point. Flights may operate with varying levels of autonomy in scheduling, dispatch and flight operations. A human

[1] "De minimis" here refers to the concept that some flights may fall below a very low, quantifiable risk threshold, and therefore would be exempt from a formal risk assessment process. This is not to say those aircraft wouldn't crash, but that the likelihood of resulting injury or damage would be extremely small.

pilot monitors multiple operations at once, but may only have limited capability to manually control the vehicle. A human on the ground may have functionally limited roles in loading a package onto a vehicle, doing the preflight check or checking fuel/battery levels.

Infrastructure maintenance: sUAS, remotely or visually piloted, that comes within very close proximity or direct contact with a building or object. Includes applications like wind turbine cleaning and cell tower component installation. Vehicles may pick up and release payloads between the installation site and a nearby ground location.

3.2. Operator Use Cases – Near Future

Operations in proximity to manned aircraft: These missions may either be conducted as VLOS or BVLOS, but are subject to more stringent risk thresholds to comply with higher target levels of safety associated with manned aircraft (that is, the risk calculation must take into account lethality as a primary harm, whereas a conventional VLOS mission in a sparse area may not need to meet the same level of assurance). Primary means of achieving required risk level is likely through a combination of robust/redundant and low-latency command-and-control links; precise lateral/vertical positioning; and onboard traffic avoidance as a last-resort conflict resolution tool. Coordination based on real-time manned aircraft arrival/departure corridors in use will be essential.

Emergency Response, Search-and-Rescue: Vehicles requiring priority handling and authorization in conjunction with police, firefighting or other operations critical to life. Vehicles may be deployed by a pilot at the scene of an event and operate similarly to a VLOS mission, except that they may need broader and faster access to controlled airspace that wouldn't otherwise be permitted. Depending on mission needs, flights may need to operate at altitudes above 400' AGL, or may follow a path (e.g. a wildfire containment line or aerial support of a police pursuit) or search-and-rescue grid pattern. Vehicles may autonomously launch from a storage and recharge depot to the location where needed, and either continue operating autonomously or be manually controlled once on scene.

3.3. Operator Use Cases – Future Missions

Urban air mobility/air taxi: Large VTOL vehicle that is certified by an airspace regulator, and therefore has demonstrated its robustness in design, reliability and flight handling characteristics. It carries 1-4 passengers over distances of up to 100 nautical miles and at altitudes up to 4,000' AGL. Vehicles takeoff and land at designated vertiports, but may use helipads, playing fields or other open spaces as emergency diversion locations. Vehicles may have an onboard safety pilot during initial deployment phases, and/or monitored by a human in a ground control center with limited override capabilities. Vehicle is equipped with a variety of detect and avoid (DAA) and other sensors to deviate for birds, non-cooperative aircraft or uncharted obstructions.

Flocking vehicles: UAVs with the same or similar origin, route segments or destination may flock, especially in designated UAV corridors, to maximize airspace efficiency. These vehicles share some performance characteristics but need not be the same model. All vehicles must meet equivalent CNS (communications, navigation and surveillance) requirements to receive corridor control instructions and other services from a drone traffic management system, and also to communicate amongst each other to coordinate flocking behavior. By design, all vehicles must be autonomously flown and managed, since human intervention in the flight of a single vehicle would have immediate cascading effects to all other vehicles in the flock.

3.4. Insurance Use Cases

Actuarial data is crucial to enabling a robust, competitive and economically viable insurance ecosystem for UAS operations. Insurers that lack the required data risk setting premiums too high to compensate for unknown risks and may lose out on business. Conversely, rates that are too low or coverage limits that are too generous may force payouts on claims that are unsustainable and too costly for the insurer's business model.

We expect that insurers will want to dynamically set coverage limits, premiums and other policy terms based on the predicted risks of a given mission and how those compare to past mission profiles using an algorithmic process. Therefore, the three use cases for insurers are intertwined, since the data and outputs for one will inform the others.

Individual short-term liability policy: These are issued on a case-by-case basis, for a specific mission. Since policies are in effect for a term of only a few hours, premiums are generally low, since the risk of a crash resulting in liability to a third party is low in a given time period (assuming a lightweight vehicle). These policies today generally do not cover hull loss of the vehicle, which some operators may desire especially for large, expensive or customized vehicles. Insurers using this model today are interested in refining their decision-making to take into account a greater number of variables in their prediction of risk, and determining corresponding premiums.

Individual long-term liability, comprehensive and/or hull policies: Commercial operators who fly frequent missions in many areas may prefer to have a policy similar to car insurance, which is in effect at all times and is paid monthly, quarterly or yearly. Premiums may still reflect risk-related factors such as the type of vehicle, operator experience and expected mission profiles. Just as car drivers today can opt into programs using an in-vehicle transponder that collects data on driving habits to adjust premiums, operators and insurers may be interested in similar capabilities for UAV operations. And just as with conventional car insurance, operators may want the ability to tailor their coverage limits, deductibles and other options.

Fleet coverage (any combination of liability, comprehensive and/or hull): Many commercial trucking operations today maintain group policies that cover all of their drivers. Operators with many UAVs and pilots or managers controlling their fleet may desire similar insurance to simplify expenses and ensure a standard level of coverage for all flights. Operators may also expect that, by spreading risk across a pool of pilots and vehicles performing a variety of missions, their premiums would be lower and their coverage limits more favorable than if they had to maintain a portfolio of individual policies for each vehicle and pilot. Likewise, because a company operating multiple UAVs faces different exposures than a single-person commercial outfit, that company may want a single policy that also provides robust liability protection to the company.

3.5. Regulator Use Cases (see also ANSP/Controller below)

Regulators have three envisioned uses for the risk framework, both now and in the future.

Oversight of flight plan approvals: Depending on jurisdictional requirements, the regulator may maintain control of flight authorizations, or delegate that role to an air navigation service provider (ANSP) or a U-Space/UTM flight plan processing service provider. Regardless of who performs this role, similar outputs from the risk model are required to make an informed manual or autonomous decision. These include outputs of all risk weights and access to the regulatory risk thresholds the flight must meet. The approver also needs visibility on any factors not included in the risk calculation (e.g. due to a lack of data) and how that affects the results.

Tailored risk thresholds by location and/or time: We also refer to this as "risk policy." These are factors largely independent of whether a vehicle is likely to crash or lose control, but influence the severity of the resulting harm. Risk thresholds can be based on any combination of things like:

- Probability of lethality (function of populated density, exposure/shelter factor, vehicle kinetic energy)
- Probability of a midair collision with manned aircraft
  - vehicle performance characteristics
  - airspace in use by manned aircraft (finals, traffic patterns, heliports)
  - quality of onboard traffic avoidance

    - navigation and communications equipment
- Likelihood of a compound mechanical/C2/navigation failure (“flyaway”)
- Proximity to critical infrastructure, installations vital to national security or other sensitive locations
- Stadiums and arenas, particularly during a game, concert or other event

Airspace usage and conformance data: Regulators will rely on an implemented risk model to inform them about how operators are flying, how their airspace is being used, and to help them answer a variety of questions. What types of operations are most common, and where do they occur? What are the actual operational risks, and how do those compare with the predicted risk? How closely does each flight conform to its expected flight plan or mission profile? If there is variation, is that increasing risk? And perhaps most importantly, are the regulator’s risk thresholds (risk policy regions) appropriately set and allowing or blocking flights that the regulator or the public deem excessively risky? The risk framework should complement and enhance existing quality assurance and SMS auditing processes.

3.6. ANSP/Controller Use Cases

The current approach of authorizing very-low-level UAV operations in many countries assumes that those flights have no operational impact for air traffic controllers. That is, UAVs are limited in how high they can fly, and in most cases are kept to the periphery of controlled airspace at the surface. However, this approach does not provide an obvious path toward integrated operations at higher altitudes or in proximity to manned aircraft. Therefore, we consider the following broad use cases, which are dependent on a risk-based process to filter flights.

Flight Authorizer: This person may be a safety specialist working in a specific facility or in a central location that is responsible for the ANSP’s entire jurisdiction. The role may require granting manual approval of flight requests based on guidance or recommendations output from a risk service. Or this person may deal with a relatively small number of exceptional or unusual requests that a risk service is unable to handle.

Quality Assurance/Compliance Specialist: This person needs access to much of the same airspace usage and conformance data described in the previous section. He or she may be responsible for conducting root-cause analyses of individual safety events, or they may look at aggregate trends and outcomes across large numbers of flights. This person needs to be able to compare predicted and actual risks to determine whether a given set of off-nominal operations reduced the margin of safety, and whether that effect was expected or not.

Controller on position (near term): Working at a control tower position or approach control sector, the human controller's attention must be on ensuring safe operations of conventional piloted aircraft. Therefore, a system that merges UAV flight data should prioritize and display only those flights that could require controller intervention. This could include large military vehicles flown by a pilot at a ground control station that are depicted similarly as manned aircraft and may land or takeoff from the same runways. But it must also include authorized UAVs inside of controlled airspace that experience a malfunction and are flying toward a manned aircraft. How much information does the controller need to know (and how long in advance of a conflict), assuming the controller can only issue instructions to the manned aircraft?

Controller on position (future): Assume that an autonomous traffic management system for drones handles almost all UAV flights in controlled airspace, using some combination of procedures, routes and separation rules to avoid conflicts with manned traffic. In the event of a failure of the vehicle, the communications link, or a UTM Service Provider, the controller needs awareness not just of the impending unresolved conflict, but also of any follow-on conflicts that might emerge based on the controller's response (i.e. a vector in one direction might lead to a new conflict with a third vehicle). Can a decision support tool provide the controller with the suggested best course of action so that the controller doesn't have to gain full situational awareness of a dozen vehicles in her airspace that *may* pose a conflict?

Front-Line Supervisor or Controller-in-Charge (CIC): This person has responsibility for the operational quarters, which may include several adjacent sectors, or all positions open in the tower cab. He or she needs a higher-level awareness of UAVs in the airspace, again prioritized so that those operating normally, on low-risk flight segments far from manned aircraft, are de-emphasized. The supervisor/CIC needs at-a-glance information and clear awareness about a change that increases risk. This could be a vehicle malfunction (before it reaches the proximity/criticality threshold at which it appears on the operational controller's screen), or it could be a previously approved flight happening during an unexpected change in runway configurations. In those instances, the supervisor/CIC needs a straightforward and immediate way to contact one or several pilots to convey basic instructions (return to home now, hold position until advised) and receive confirmation from the pilot. This could be done digitally through text message or notification on the UAV pilot's control device/screen.

4. Preflight Risk Model for Present-Day Missions

The preflight risk model provides ANSPs with guidance and context to understand the risk levels of present-day VLOS and BVLOS missions so that a specialist can make an informed decision (either manually or automatically) to approve or prohibit a flight. The model's inputs are a flight plan and expected conditions (weather, airspace usage patterns, etc.). The outputs are a set of probabilistic scores and guidance that identifies the the most significant factors driving those scores.

Altiscope is implementing this model as a risk service, which will provide a wealth of data on calculated and actual mission risks to further improve and refine its performance. Up until now, our previous research on UAS risk factors has guided the prioritization of modeling capabilities. Once a version of this model becomes operational, the development of future versions will be guided in large part by data that indicates relationships between inputs (existing or new) and unaccounted for risk factors. It will also be guided by the operational needs of ANSPs, including any specific needs or criteria that enable regulatory compliance.

Note that in its current draft form, the specific computations provide the rate of unrecoverable vehicle loss of control – the hazard. Work is underway to implement clustering algorithms that will enable computation of the rate of harms we wish to avoid: midair collisions, and crashes that injure or kill people on the ground. Understanding the hazard rates is an important first step in this process. It may also be useful by itself in jurisdictions that wish to account for the risk of poor public perception. While a small vehicle crashing in the middle of a street may not injure anyone or damage anything, bystanders may find it alarming and unwelcome.

4.1. Theoretical Basis

The design for the preflight risk model began with the construction of a pair of fault trees for a small UAV loss of control that would lead to a crash, collision or near-midair collision (NMAC). That approach was explored and analyzed extensively in (Sachs, 2018) and the findings informed the initial thrust of research and design into this model.

That research also revealed a greater complexity of interactions that lead to some losses of control that are commonly classified as "flyaways." In these events, several simultaneous failures result in the operator being unable to manually regain control of the vehicle, and the vehicle being unable to execute a preprogrammed "return to home" command.

To account for those complexities, the framework for a preflight risk model must be able to weigh those interactions using something other than the Boolean logic of fault trees. Therefore, we plan to pursue further analysis using Bayesian belief networks. One of the key benefits of this approach is that it allows any input to exert a causal force on several intermediate conditions, whereas in fault tree analysis, basic events must be discrete and connected to just one gate.

A notional framework for a Bayesian net may look like Figure 2. This model captures the effects of weather conditions on both battery performance and vehicle flight behavior. Note that the current modeling effort will need to expand to address other fuels, including hybrid systems (fuel cell, combustion or turbine used to generate electricity) and tethered electric supplies. It also illustrates how an operator can either directly or indirectly contribute to a loss of control, particularly if that person responds incorrectly to a malfunction and worsens the condition.

Figure 2. A notional Bayesian network for a UAV loss of control.

4.2. Architecture and Computational Approach

The preflight risk model is optimized for small UAS operations that occur today: VLOS or BVLOS flights conducted with lightweight vehicles that do not require or receive separation instructions from air traffic controllers. Altitudes are generally restricted to below 500 feet AGL based on jurisdictional regulations, but the model can calculate risk for operations at any altitude.

This model chooses variables that are easily attainable from the vehicle itself, existing weather data sources and existing databases of vehicle performance characteristics. We make deliberate choices in this model's design to either omit other inputs that we know are important (especially if we know that data isn't available), or to make conservative modeling assumptions based on subject matter expertise. The intent is that once all interactions are defined in modeling software, that structure can be engineered into a developer API to run calculations using flight plans submitted to an ANSP through some kind of user flight plan application. The model, in other words, runs in the background, but provides outputs that can appear on an operator's, regulator's or ANSP's interface to help them understand mission risks and make informed decisions.

This model calculates risk using inputs from six categories (additional details in Annex A). These categories are the same ones identified in Altiscope's fault tree sensitivity analysis as having the greatest influence on the risk of loss of control of a UAV resulting in a crash or collision:

- The flight's location, time, duration, etc.
- Vehicle make, model and performance characteristics
- Operator experience
- Wind and weather conditions
- Vehicle maintenance
- Battery performance

Additional input categories allow the model to predict the chance of a flyaway and the likelihood and severity of an airborne collision and of killing someone on the ground:

- RF spectrum and communications link characteristics
- GNSS coverage and obstacles/terrain that result in degraded navigation accuracy
- Historical flight track information
- People density and exposure

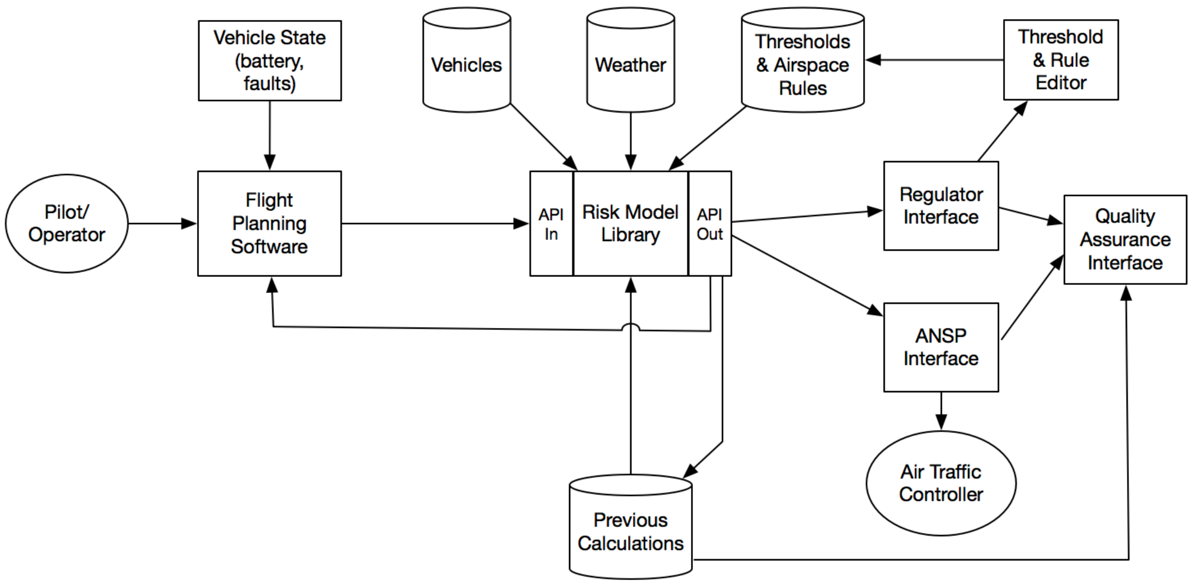

Figure 3. Architecture diagram of a near-term preflight risk service ("Risk Model Library") used to inform automatic flight approvals.

Our approach favors easily attainable data and variables to make it possible for anyone to implement a service using the model in the short term. This will start giving operators and regulators responsible for today's UAS missions greater shared insight into the safety levels and risk factors of their flights. Using our existing knowledge from our fault tree models, future data sources and other modeling techniques, we can extend this model over time to capture more of the nuance and complexity behind mission risk factors.

The ANSP's requirements for handling flight plan requests will dictate the time horizon on which the model operates. Initially, this might be several days in advance of a mission to give a human specialist time to manually review the request. The ANSP may issue a conditional approval, assuming the proposed mission is able to show a similar set of outputs within hours of the flight time. In particular, process would allow the operator to adjust their flight time to occur during more favorable wind conditions, and to ensure their battery is sufficiently charged for the duration and profile of the mission. Because of the different time horizons that may be involved for the same flight, Annex A provides guidance on how to handle calculations when some information may be missing. This same model should be able to handle risk calculations immediately before takeoff.

The preflight risk model will be capable of informing automated flight approvals, but depending on jurisdictional needs, an implemented version of it might produce a report to help a human decide whether to approve a flight or not. We expect that as usage of this model grows, we'll be able to collect aggregate data on how well it performs and whether it is accurately capturing operational risk factors. This is an important validation step that we cannot otherwise replicate, even with the extensive testing and statistical analysis we plan to apply to the model before it is deployed.

The data we collect will inform enhancements and improvements to future models: adding variables, changing the relationships between them, and so on. This makes the preflight model iterative, and it will be updated and version-tracked in this framework just like any piece of software. Ultimately, we expect that the risk framework and derivative models will be managed and updated by an international advisory or standards body, such as JARUS.

This preflight risk model will substantially inform the comprehensive preflight model.

5. The Comprehensive Preflight Model

The comprehensive preflight model takes advantage of an increasing wealth of available data about vehicles, missions and airspace usage that is shared between UTM services, operators and data providers. It assumes that flight plans are automatically approved and amended by a flight plan service component of a UTM. A key functionality here that doesn't exist in the previous model is that the outputs are used in optimizing a vehicle's route, including deconfliction before takeoff.

The plan-time deconfliction functionality assumes that an operator (autonomous or human) submits a flight plan within a few minutes of actual takeoff. This allows the flight planning service to consider all other proposed flights, including nearby vehicles that are already airborne. Operators may submit their flight plan in stages: Farther in advance, a more general intent to fly that specifies origin, destination and basic route and equipment characteristics, similar to a conventional flight today. The plan submitted shortly before takeoff would include a greater amount of data pulled from the vehicle about its battery or fuel state, maintenance condition and other parameters that might not be known farther in advance.

The comprehensive model accounts for a greater number of temporal and environmental risk factors, including:

- Real-time weather conditions reported from vehicles already in flight and weather sensing equipment installed in high-density UAV areas
- High-resolution calculations of the effects of terrain, buildings, obstacles and urban canyons
- The built environment, land use patterns and populated density on a much finer scale than is available today
- Communications signal availability (taking into account multiple means of communication and security requirements of using any shared protocol, such as 4G LTE or 5G cellular networks)
- Navigation reliability, predicted GNSS availability, accuracy and local augmentation
- Surveillance coverage requirements

This model dynamically calculates air risk, using advanced algorithms that take into account current and historical airspace usage to route vehicles away from the specific volumes of airspace used by manned aviation, such as arrival and departure corridors and traffic patterns. This approach is crucial to enabling integrated UAV operations in all classes of airspace. It is designed to account for changing traffic flows, such as a switch in the runways in use at a busy metropolitan airport as a result of a wind shift.

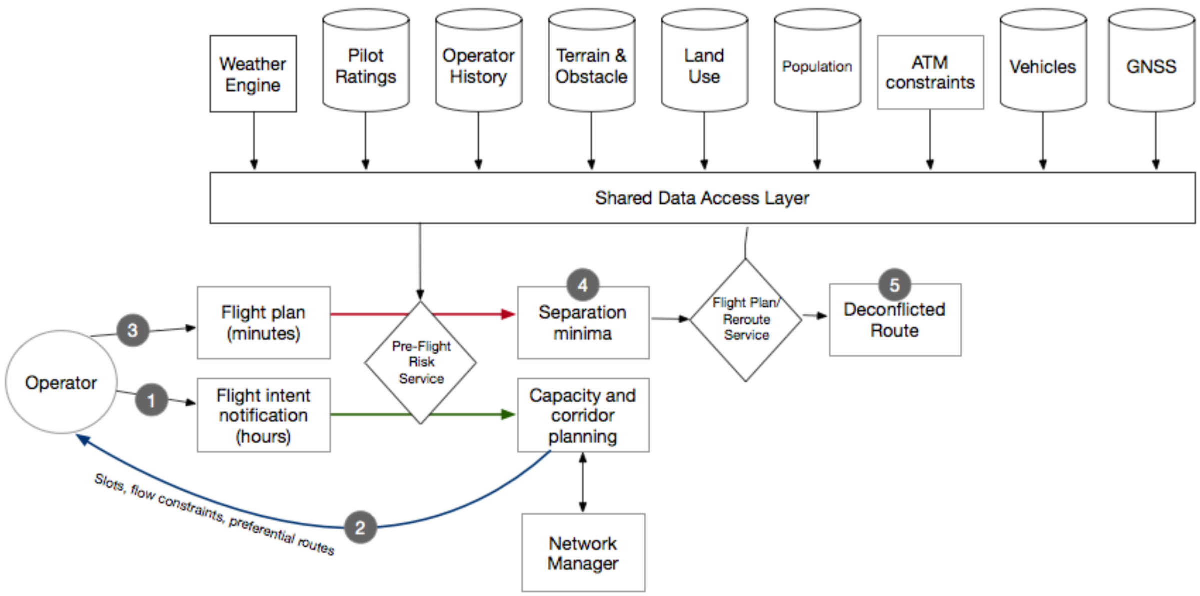

Figure 4. Architecture diagram showing the dual roles of a comprehensive preflight risk service in informing capacity management and route deconfliction.

We intend for the approach behind the preflight model to be applicable in de-risking inflight route changes as well, though further research is needed to determine at what traffic levels such flight-by-flight risk-based route changing becomes too computationally burdensome. The benefit of applying a variant of this risk model to route changes is that it can check whether a new route would enable the vehicle to stay within its range limits and safely away from adverse weather or areas of poor communications coverage. By contrast, because this model must perform algorithmic queries of several different real-time data sources, it may prove to be too computationally burdensome for use in tactical inflight deconfliction.

We expect that a large number of the components and calculations of a mature, future version of the basic risk model above will transfer directly into the comprehensive preflight model.

The model runs calculations for each flight plan it receives, taking advantage of appropriate algorithms to accurately predict battery performance, account for multiple complex interactions between variables, and suggest changes to the flight plan to bring it into compliance with the regulator’s established risk thresholds.

Recall that all implemented models must use the same underlying framework for consistency of calculations. Practically, that also means that all services would need to consult functionally identical data sources. In Figure 4, this is depicted as a Shared Data Access Layer, which would provide the same sets of data to all risk-related services.[2] In implementation, each service might individually contract with the necessary data providers, or may include its own provisions for data access that complies with the framework requirements.

A service operating under this model processes two distinct types of flight planning information. First, an operator may submit a flight intent notification several hours (or farther) in advance. This contains some elements of a flight plan, such as vehicle type, origin, destination and expected flight time. But it would not contain the specific vehicle health information necessary to perform a complete risk calculation. It would, however, be enough to inform capacity management and corridor control services about expected future demand. Knowing that allows those services to generate ad-hoc corridors to meet short term demand, and to create preferential routes or assign time-based slots to help manage capacity constraints.[3] An operator who submits notice of intent for 1,000 flights would receive a bucket of slot times, as well as corresponding preferential routes to use with those slots, depending on destination. Knowing those details in advance allows the operator to allocate the slot times best for their needs and speeds up the flight plan filing and acceptance process – almost identical to what happens today for major air carriers in United States and EUROCONTROL airspace.

Within a few minutes before departure, the operator submits detailed flight plans, which include slot assignments, preferential routes and corridors the operator expects that flight to use. The flight plan also contains the other inputs needed for a complete risk calculation, such as vehicle health and fuel state. With a 4-D flight plan, the risk service is able to do the granular checks of obstacle clearance, GNSS performance, weather conditions and other risk factors.

This model's output isn't just a probability of collision or a risk score, but also whatever information a future UTM service would need so that it can apply dynamic separation standards between vehicles. For example, a vehicle with redundant navigation and communications systems may be eligible to fly with reduced separation and over areas that other drones wouldn't be qualified to overfly. A given vehicle's minima may vary over the course of a flight. For example, passing through an area with known high-latency communications coverage, a vehicle might require greater separation distances, whereas in an area with micro-positioning navigation

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[2] In NASA's UTM architecture, this functionality is provided by one or more Supplemental Data Service Providers (SDSP).

[3] One implicit assumption here that deserves considerable further definition is how to ensure fairness in the system. Left unchecked, an operator could flood a flight plan filing service with thousands of requests, effectively tying up large airspace blocks and preventing their competitors from launching their missions. This is a complementary area of policy creation and regulation. Broadly, Altiscope's UTM architecture assumes that a central System Manager acts as a check on these types of events, ensuring that an operator's needs and requests are balanced by other system and airspace constraints – as well as the airspace access needs of other operators.

augmentation and calm winds, that same vehicle – during the same flight – may be able to take advantage of reduced separation minima.

The separation minima are appended to the flight plan and passed to a strategic deconfliction service. Knowing the separation requirements, the deconfliction service is able to plan an optimal route that takes into account other vehicles that will be flying through that area at the same time.

6. The Inflight and Capacity Management Models

Like the comprehensive flight planning model, this model anticipates the needs of an integrated, autonomous UTM system, with traffic management (tactical, strategic and flow-based) provided by multiple service providers in each jurisdiction. This model is oriented toward holistic airspace optimization assuming hundreds of vehicles in the air over a metropolitan area at any given time, including fully autonomous package delivery and passenger transport vehicles.

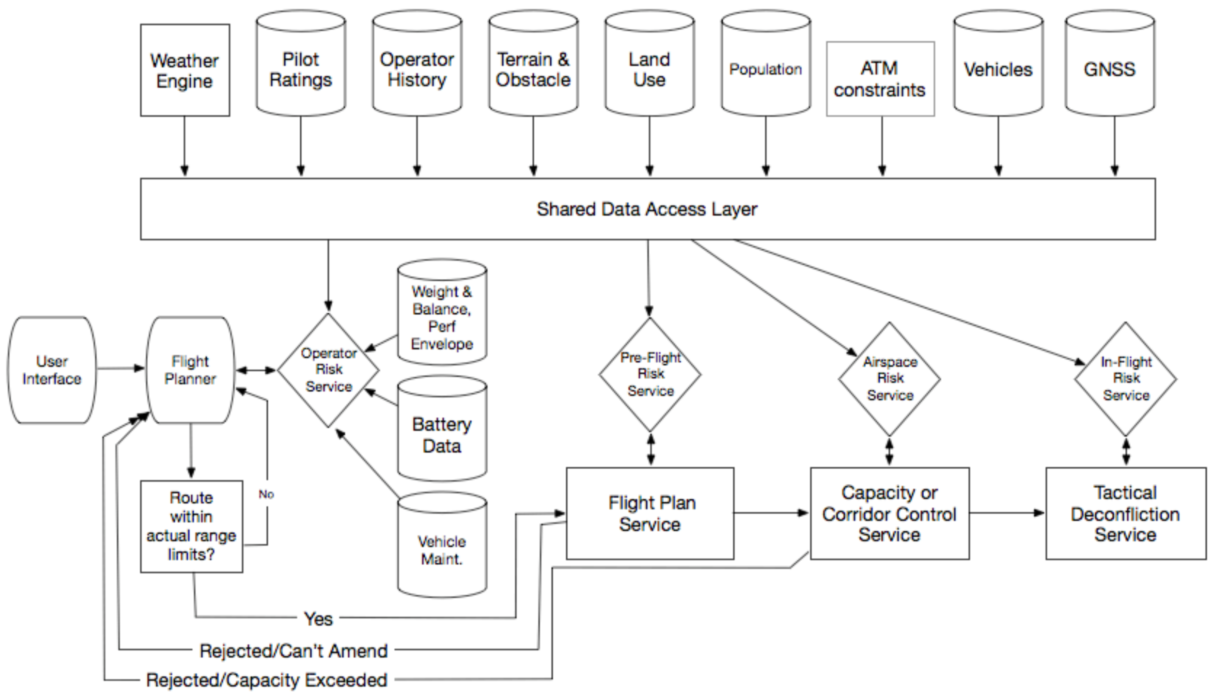


Figure 5. Architecture diagram of multiple risk services informing all phases of flight, including vehicle-level tactical deconfliction and airspace-level capacity management.

The model is most likely to be used by services that need to make routing and airspace usage decisions that will affect many vehicles at once. Assuming that multiple providers will provision services in the same physical volume of airspace, it is important that all of them reference the same risk framework to arrive at logically consistent decisions. As in the previous section, we depict the need for consistent and functionally identical data sources through the Shared Data Access Layer in Figure 5.

One or more risk services may interact with flight plans in a variety of different ways. An operator may have its own internal risk service (or subscribe to one) that helps in preparing batches of flight plans, taking into account UTM-wide airspace management initiatives that may affect those flights. A preflight risk service handles factors unique to an individual vehicle and its mission and route. As in the previous model, those calculations inform the separation criteria for each vehicle, and therefore affect the deconflicted route issued to each vehicle. An airspace risk service looks at how the interactions among large numbers of vehicles affect total airspace risk. This includes one-to-one vehicle encounter risks and more complex interactions based on density and traffic flow patterns. An airspace risk service's outputs will affect how capacity and corridor management services use their airspace. This could include creating new corridors to handle a high-demand stream (many vehicles going in the same direction, possibly assembled into a flock). It could also include time- or distance-based flow management initiatives to ensure that a given volume of airspace remains within safe density limits given the vehicles traversing it, weather conditions and any limitations due to communications, navigation or surveillance coverage.

Finally, an inflight risk service plays a critical role in helping tactical deconfliction services decide how to resolve the inevitable inflight conflicts that will emerge. As our studies have shown, even with robust preflight deconfliction algorithms to resolve many situations, the slight natural variations in individual flight behavior (e.g. exact departure time, climb profile, cruise performance and course deviation) can add up to create new conflicts between vehicles. Tactical deconfliction services resolve these encounters similar to air traffic controllers today, using a variety of tools, like vectoring, level changes and speed restrictions. A risk service that is aware of a vehicle's operational capabilities is important to identifying the most effective conflict resolution strategies.

This model treats overall airspace risk as a changing surface across which vehicles fly. Higher parts of the surface represent higher levels of risk based on a combination of factors. Some vehicles may be properly equipped or qualified to traverse those areas (and in fact would not "see" peaks in the same way, because they would not be susceptible to those risk factors), while others will naturally be pushed away from those areas to lower-risk sections of the surface.

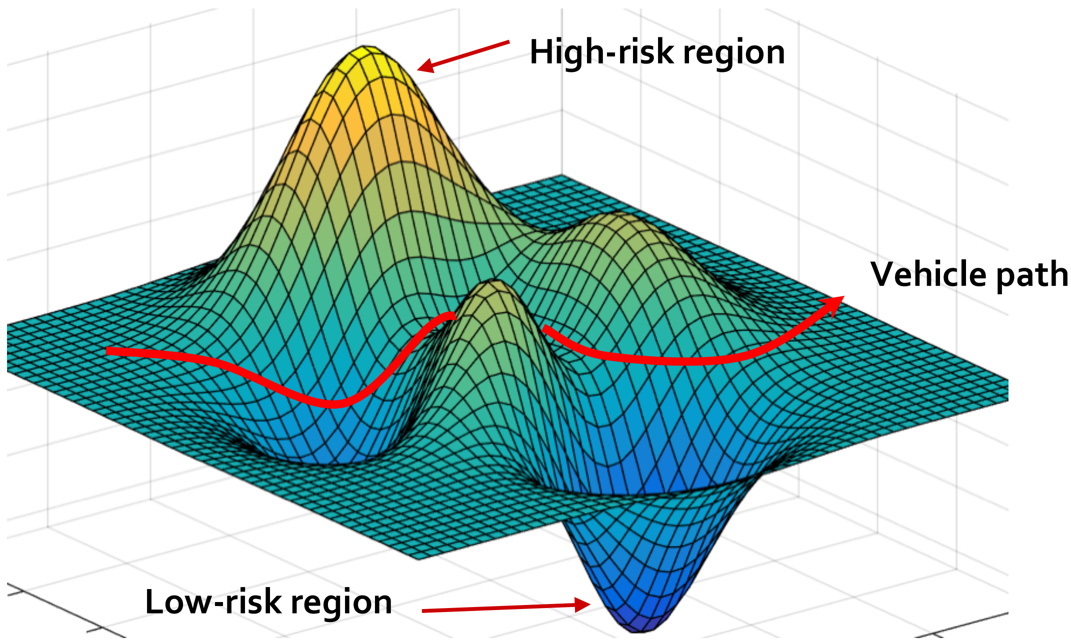


Figure 6. Notional view of varying levels of risk or density in a volume of airspace, as perceived by a given vehicle. High-risk areas are naturally repulsive, pushing vehicle routes toward nearby lower-risk areas. (Image Source: MathWorks France)

Airspace density therefore can be dynamically and temporally represented. Assuming all other risk factors are constant, less-dense areas become "depressions" in the surface and areas close to their maximum capacity for the fleet mix in the region become increasingly higher peaks. This draws vehicles toward valleys and away from peaks until the vehicles flying through dense hotspots exit the area and density levels trend toward an equilibrium for that airspace.

7. Definitions

Reserved.

Annex A: Computational Approach for a Preflight Risk Model

Required Inputs:

- Vehicle model
- Percentage of time flying in manual or programmed mode
- Drone pilot hours
- Latitude and Longitude of flight location, path or polygon
- For polygonal regions, total distance to fly (km)
- Flight duration (minutes)
- Date and time of flight
- Operating altitude (AGL feet)
- Count of hardware faults recorded by vehicle in last five flights
- Indication of any repairs completed to vehicle since last hardware fault
- Verification of preflight check completed
- Initial battery voltage measurement (sum of all cells)
- Payload weight (kg)

Calculated Inputs

Based on vehicle model:

Platform Length (m)	Max Range (mi)	Airframe
Platform Width (m)	Max Altitude (ft)	Rotors Enclosed
Platform Height (m)	Wind Resistance Speed (knots)	Launch
Wing Span (m)	Min Operating Temp (C)	Recovery
Wing Span Area (m^2)	Max Operating Temp (C)	Communication/Data Link
Platform MGTOW (kg)	Payload Weight (kg)	Operating RC Bandwidth
Max Speed (knots)	Power (kW)	Operating Conditions
Cruise Speed (knots)	Propulsion	Navigation/Control
Max Ascent Speed (ft/s)	Energy Source	Navigation Method
Max Descent Speed (ft/s)	Battery Type	BLOS Capability
Endurance (mins)	Battery Weight (g)	

Based on location and time:

MSL takeoff and operating altitude

Cruising airspeed (knots)

Peak wind speed (including gust, kt)

Ceiling (lowest BKN or OVC value, feet)

Visibility (SM)

Count of each frozen precipitation code (FZ, SN, PL, IC, GR, GS, SG)

Count of each thunderstorm-related code (TS, SQ, FC or CB in cloud group)

Temperature (Celsius)

Outputs

(All expressed in units of "per flight hour" and "per operation")

$R_{weather}$, the risk of loss of control due to Weather

R_{pilot}, the risk of loss of control due to Pilot

R_{maint}, the risk of loss of control due to Maintenance

$R_{battery}$, the risk of loss of control due to Battery

R_{param}, the risk of loss of control due to flight parameters outside of the vehicle's performance limits

R_{flight}, the total risk of loss of control, a simple summation of the above five risk values above

A moderately conservative normalized percentage score for each risk category can be calculated by the formula:

$$RiskPercent = 1 - \frac{\ln(R) + 15}{25}$$

Finally, a total risk score can be found by averaging the percentage risks of each of the first five output risk scores.

Battery Risk

The battery model is given by the equation

$$\widehat{Rbattery} = -12{,}180 + 1.98IV + 1.67 * 10^{-1}D - 7.68 * 10^{-1}Ve - 4.86 * 10^{-3}A - 121.9Du$$

With the given inputs:

IV, initial voltage measurement (millivolts)
D (total Haversine[4] distance) (m)
Ve (average total velocity) (km/sec)
Du (total flight time) (min)
A (difference between highest and lowest altitude) (mm)

And where

$$Ve = \frac{D}{Du}$$

The derivation of this model is provided in Annex B.

Pilot Risk

$$Rpilot = (tm\ x\ Fm) + (tp\ x\ Fp)$$

Where t_m and t_p are the percentage of time (expressed as a value between 0 and 1) spent operating in manual (F_m) and programmed (F_p) flight modes, respectively.

F_m is given by the equation:

$$F_m = 6.4103E\text{-}13h^5 - 4.3725E\text{-}10h^4 + 1.1121E\text{-}07h^3 - 1.2499E\text{-}05h^2 + 5.2364E\text{-}04h + 2.5007E\text{-}03$$

When Pilot hours (h) ≤ 200, otherwise F_m = .0025

Similarly, F_p is given by the equation

$$F_p = 2.4318E\text{-}14h^6 - 1.6940E\text{-}11h^5 + 4.4357E\text{-}09h^4 - 5.2312E\text{-}07h^3 + 2.4663E\text{-}0hx^2 - 1.7112E\text{-}04h + 1.0986E\text{-}03$$

When Pilot hours (h) ≤ 200, otherwise F_p = .0011

The basis for these equations is provided in Annex C.

Weather Risk

These calculations are a function derived by the vehicle's peak wind tolerance and assume, even in BVLOS operations, that the vehicle must remain in VMC (visual flight rules) weather

[4] The haversine distance determines the arced distance between two points on a sphere given their longitude and latitudes.

conditions. The weather calculation may vary slightly based on the amount of time between flight plan filing and proposed departure; the availability of nearby weather sensing equipment; and the precision of any forecast models used. For additional details, refer to Annex D.

$$Rweather = (Rwind + Rceiling)x\ (TS + FZ + V)$$

Where wind risk is a bounded third-order polynomial for peak winds less than 75 percent of the vehicle's tolerance, and otherwise a bounded forth-order polynomial. As an example, for a vehicle with a 23-knot maximum wind tolerance, the equations would be:

$$Rwind = 9.64357\mathrm{E} - 05w^3 + 0.001361059w^2 + 0.006376812\mathrm{w} + 2.77556\mathrm{E} - 17$$

For winds less than 75 percent of the peak tolerance, and:

$$Rwind = -3.81169\mathrm{E} - 06w^4 + 0.000608811w^3 - 0.036084856w^2 + 0.939636531\mathrm{w} - 8.05952381$$

for winds greater than or equal to 75 percent of the vehicle's peak tolerance. In both cases, *w* is the measured or predicted wind at the flight location.

$$Rceiling = (2\ x\ 10^{-8})\delta^3 - (1\ x\ 10^{-5})\delta^2 - 0.002\delta + 1.0144$$

when the difference between the vehicle's operating altitude and the ceiling, ∂, is less than 400 feet, and otherwise is

$$Rceiling = 0.03e^{-0.002\delta}$$

TS is the Count of each thunderstorm-related code (TS, SQ, FC or CB in cloud group)

FZ is the Count of each frozen precipitation code (FZ, SN, PL, IC, GR, GS, SG):

V is the parameterized visibility in statute miles

Maintenance Risk

$$Rmaint = \left(\frac{0.0001e^{2.7081\ x\ \mu}}{R}\right)^{1/P}$$

where μ is an integer value between 0 and 5 representing the number of hardware faults recorded by the vehicle in the last five flights. For values of μ > 5, *Rmaint* =1.

R is a parameterized integer value between 2 and 4 based on whether the operator performed a preflight check of the vehicle; and whether the operator performed a repair since the last hardware fault.

P is a parameterized value between 1 and 3, with increasing values as the payload weight approaches and exceeds the vehicle payload limit.

Flight Parameter Risk

$$Rparam = 0.001^{1/(Sr+Tr+Er)}$$

Sr is a parameterized value between 0.3 and 10 based on the vehicle's calculated airspeed and maximum speed.

Tr is a parameterized value between 0.3 and 10 based on the air temperature and the vehicle's minimum and maximum operating temperature.

Er is a parameterized value between 0.3 and 10 based on the vehicle's maximum endurance and the filed flight duration.

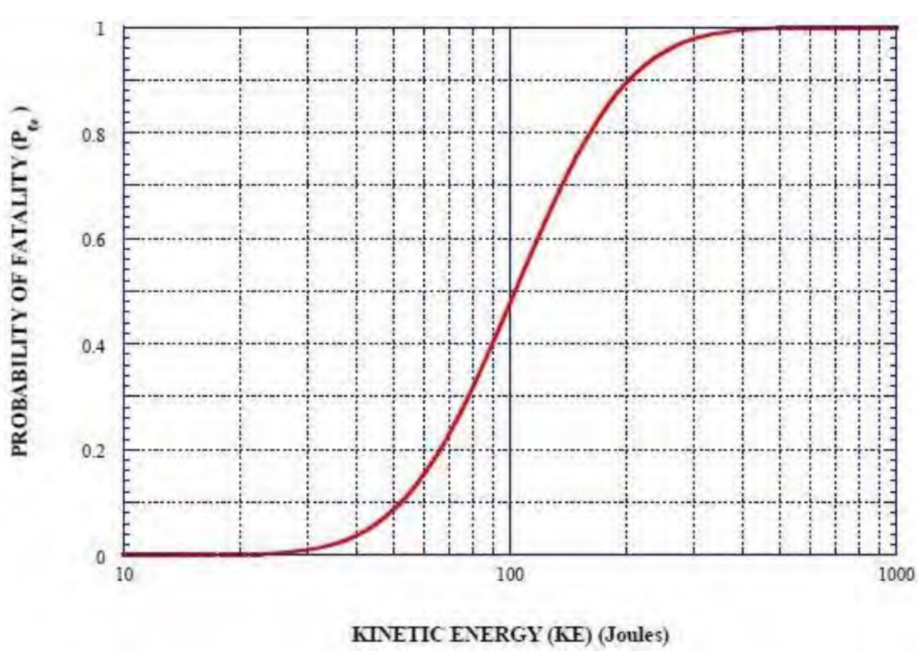
Annex B: Quantitative Ground Risk Calculation Approach

We quantitatively calculate ground risk by computing the vehicle's path over one or more LandScan people density tile squares (or other data source as appropriate). The ground risk output is the probability of a third-party lethality on the ground per flight-hour. The following methodology does not account for mitigations like a parachute or the vehicle's ability to self-select an emergency landing site in the event of a partial propulsion failure.

Ground risk (that is, the number of lethalities per flight hour) for each waypoint and/or path segment can be calculated from the equation

$$Rgrid \;= Grid_{TMR} \;* D_{People} * A * P_{Lethal} * ShelterFactor$$

$Grid_{TMR}$ is the total time-based mission risk for a grid square, A is the vehicle's frontal area (see below) and P_{Lethal} is the probability that if a person is hit, they will be killed. This is a function of the vehicle's kinetic energy at impact and can be looked up from a curve such as this one:



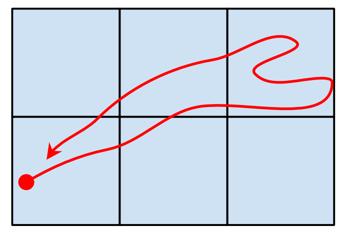
1. To determine kinetic energy, we must know the vehicle's terminal velocity at impact for multi-rotors. For fixed-wing vehicles, V_{term} is the vehicle's best glide speed (this assumes the vehicle auto-trims for that speed in the event of a propulsion failure).
2. For each waypoint, calculate the vehicle's terminal velocity as a function of its altitude, frontal area and weight.

$$V_{term} = \sqrt{\frac{2w}{Cd\ x\ \rho\ x\ A}}$$

a. Where *w* is the vehicle weight, C_d is the drag coefficient from a lookup table, $\rho$is the gas density, and *A* is the vehicle's frontal area (wingspan * height for fixed-wing, or πr^2 for a multi-copter).

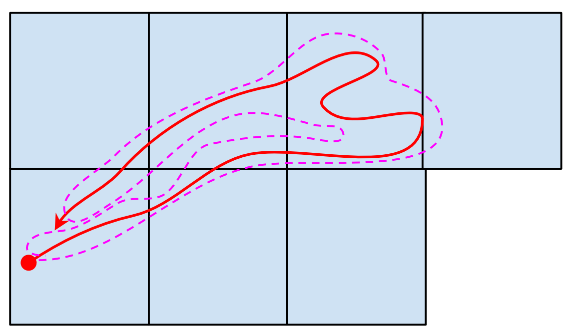
b. Gas density can be calculated given MSL altitude, temperature and dewpoint (or relative humidity) using a calculation like these: https://www.brisbanehotairballooning.com.au/calculate-air-density/

3. Kinetic energy from terminal velocity and weight eqn
4. **[Simplistic calculation]** For each route segment, determine the time (t = d/V) the vehicle spends overflying each square immediately below its route. Consider the flight path distance will vary from one square to the next, depending on how it traverses the square.



a. A more **robust calculation** entails a convolution of the vehicle's path with the underlying footprint. This is because, if the vehicle fails while turning, its trajectory will be a tangential vector that could cause it to travel into an adjoining grid square that otherwise wouldn't be overflown.

b. Thus, the calculation needs to consider the vehicle's (x,y) velocity vector and descent angle. Assume a 1:1 glide ratio for multi-copters, since they may have some autorotation capability and will have a forward velocity vector unless hovering at the time of failing. Where-ever possible, look up the actual glide ratio for the vehicle, since these can vary greatly for fixed-wing and tilt-rotor vehicles.



5. For a failure that causes the vehicle to plummet straight down, the flight-hour probability of impact can be calculated for each square by multiplying "total-mission-risk" for the waypoints in that grid square by the time value, t_{grid}, from the previous step (units of hours).

$$Grid_{TMR} = (TMR_1 + TMR_2 + \cdots + TMR_n) * t_{grid}$$

Annex C: Quantitative Air Risk Calculation Approach

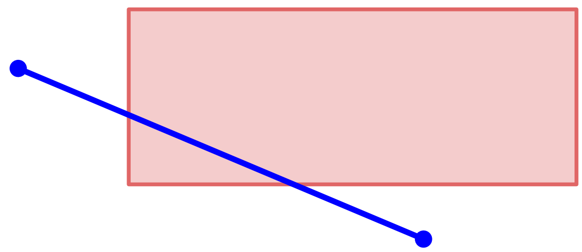
We calculate air risk quantitatively based on a UAV flight path's proximity to known commercial aircraft volumes, and the average hourly historical traffic counts in each volume. The output is a probabilistic rate of collision with a manned (conventional) aircraft.

1. Using historical ADS-B data and/or radar track data, run a clustering algorithm around all airports in the jurisdiction to identify arrival and departure volumes.
    a. Departure ADS-B tracks are identified from the time that an aircraft on the ground applies takeoff thrust.
        i. Radar track identification methodology will need to be tested. One approach would be to count tracks that initiate within 1 nautical mile of the end of a runway at an altitude less than 500' above the airport elevation.
    b. Arrival ADS-B tracks are identified in reverse, from the time an aircraft touches down on a runway and decelerates.
        i. Radar track identification methodology will need to be tested. One approach would be to count tracks that terminate within 1 nautical mile of the end of a runway at an altitude less than 400' above the airport elevation.
    c. Compute and store in a lookup table the average hourly departure and arrival traffic count, DRh, and , ARh, respectively, and standard deviation for each volume.
        i. Expected DRh values will be between 0 and 100, inclusive.
        ii. Expected ARh values will be between 0 and 60, inclusive.
2. Each volume is a 3-D shapefile encompassing at least 90% of the arrivals or departures for a given runway. A lookup table should identify the runway associated with each volume, and the criteria under which it is used (wind speed and/or bearing ranges; and/or times of day).
3. For each UAV flight, query a SWIM source for the active runways in use at the airport(s) nearest the UAV flight path.

4. Calculate the closest slant range distance of the path to each of the extents (sides and edges) of the runway arrival and departure volumes returned in the previous step.

    a. If the active runways are not known, then perform Step 4 for all arrival and departure volumes (most conservative).

5. If any flight plan waypoint or segment is within a volume, assign a collision value of $\frac{DRh}{3600}$ or $\frac{ARh}{3600}$for the waypoints. In the transverse view at right, neither waypoint is within the volume, but part of the segment is. In this case, **both waypoints** should be assigned an air risk collision value of $\frac{DRh}{3600}$ or $\frac{ARh}{3600}$ per flight hour.



6. For all other waypoints, the air risk is a function of the "mission-risk" value for that waypoint, and the shortest distance to the edge of an arrival or departure volume.

    a. $\alpha \ = \frac{mission-risk}{\delta c} x \left(\frac{DRh}{3600} + \frac{ARh}{3600}\right)$

        i. Where $\delta c$is the closest slant-range distance in kilometers and $\alpha$is the air risk per flight hour.

7. Total air risk, $\alpha_{\text{tot}} = \sum_{wpt-1}^{wpt-n} \alpha$

8. Note that this initial model is overly conservative because it does not take the vehicle's velocity into account. Based on the validation results of this model, we expect that future models will compensate for velocity, with a higher risk value for segments that spend more time in or near an arrival or departure volume.

Note: a suggested alternative definition.

1. Build small voxels using ADS-B or ground radar tracks as discussed above. For any given airspace configuration, calculate a rate r_i, measured in flights per second, for voxel i. This is just the average number of flights that enter that voxel per time unit, calculated by the number of tracks observed to intersect the voxel divided by the duration of logs considered.

2. For a flight path P, compute the accumulated risk of crossing a region of airspace as the probability that the path will occupy at least one (or more) voxels at the same time as an aircraft is in that voxel. If the probability that there is an aircraft in voxel i in a period of length t is $P_i(t)$, then the cumulative probability of encountering at least one other aircraft when traversing over a path $P = (0, 1, \ldots, i, \ldots, n)$ is $1 - \Pi^n{}_{i=0} \quad (1 - P_i(t_i))$.
3. We can approximate $P_i$by assuming Poisson arrivals, so $P_i(t) = e^{-r_i t}$.
4. We can compute t_i, the amount of time that the vehicle spends in voxel i, by computing the entry and exit points of the path through the voxel's faces, finding the distance between the points, and dividing by the average speed through the voxel.
5. Limitations in this model so far:
    - This does not account for the time that an aircraft (from the ADS-B or radar tracks) spends in the voxel. Keep in mind that it isn't just the aircraft itself; any wake should be accounted for as well. This will increase the value of $P_i(t)$.

      This can possibly be addressed by defining $P_i(t)$ as the probability that there is an aircraft arriving in the voxel in a period t, or that there was an arrival $\leq w$before, where w is the time required for the aircraft to clear the voxel (which may be the time from entering to exiting the voxel plus time for any wake to dissipate). This could be computed $P_i(t) = e^{-r_i(t+w)}$.

      However, the risk of encountering wake should probably be treated differently from the probability of encountering the aircraft itself.
    - This only addresses the probability of encounter (approximately probability of collision). This does not say anything about the harm outcome from that hazard.

Annex D: Battery Life Analysis – Practical Variable Model

Erin Dienes, Ph.D. and Chris Dienes, Ph.D.

Linear Regression Model

Altiscope derived the preliminary battery performance model using drone telemetry logs on 137 inspection flights. We intend to conduct additional flights and analyze data from a greater number of completed missions to refine the battery models. All vehicles used the same vehicle performing similar (though not identical) preprogrammed mission routes in similar VFR weather conditions with surface winds less than 10 knots. This model is presented as an operational example. Implementations of the preflight risk model must take into account varying battery chemistries, characteristics and operating limits; care should be taken in generalizing this model to other flight profiles.

The drone telemetry logs contained data on 137 flights ranging in duration from 0.47 minutes up to 22.93 minutes. Two of the flights were dated in 1969 and based on their trajectories were determined to be outliers. These flights were removed from this analysis. Out of the 526,311 data points in the logs (generally 10 per second), there were 430 observations with a measured altitude less than 100 millimeters. The observations less than 100 were deemed to be outliers and were set to "missing". In this analysis we are interested in modelling the relationship between battery life, using voltage as a proxy, and various practical predictors including initial voltage, total haversine distance, and total flight time. Linear regression was used to model the end of flight voltage measurement.

From the flight variables recorded in the telemetry logs we created 8 flight summary measures, ranges of which are likely known prior to the flight. Descriptions of these variables are provided in the table below.

Variable Name	Model Variable	Variable Description	Correlation with End Voltage
init.voltage	IV	First voltage measurement.	-0.049
tot.distance	D	Sum of the Haversine distance between time points.	-0.585
duration	Du	Total flight time.	-0.734
avg.tot.velocity	Ve	Average total velocity; total velocity is the	-0.693

		square root of the sum of squared velocity in the x, y, and z directions.	
del.alt	A	Maximum altitude measured minus minimum altitude measured.	-0.427
ascent.rt	ARt	Average rate of ascent (rate of ascent = positive change in altitude/change in time).	0.032
descent.rt	DRt	Average rate of descent (rate of descent = negative change in altitude/change in time).	-0.024
avg.vz	Vz	Average velocity in the z direction.	0.655

Stepwise linear regression resulted in the following final model.

```
Residuals:
    Min      1Q  Median      3Q     Max
-631.75  -85.43    6.74  103.81  489.61

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)      -8.241e+03  6.176e+03  -1.334 0.184529
init.voltage      1.684e+00  4.993e-01   3.373 0.000992 ***
tot.distance      2.159e-01  2.905e-02   7.434 1.46e-11 ***
avg.tot.velocity -1.184e+00  2.445e-01  -4.844 3.69e-06 ***
del.alt          -3.424e-03  1.773e-03  -1.931 0.055728 .
ascent.rt        -3.389e-03  1.553e-03  -2.182 0.030982 *
duration         -1.510e+02  1.682e+01  -8.980 3.46e-15 ***
avg.vz           -2.253e+00  1.022e+00  -2.206 0.029239 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 189 on 125 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.7256,   Adjusted R-squared:  0.7103
F-statistic: 47.23 on 7 and 125 DF,  p-value: < 2.2e-16
```

Residual analysis, the likelihood ratio test, and the Multiple R-squared value all indicate a good fit. Using the abbreviations from the above table the model’s linear equation is given by

$$\hat{y} = -8{,}241 + 1.68IV + 2.16 * 10^{-1}D - 1.18Ve - 3.42 * 10^{-3}A - 3.39 * 10^{-3}ARt - 151Du - 2.25Vz.$$

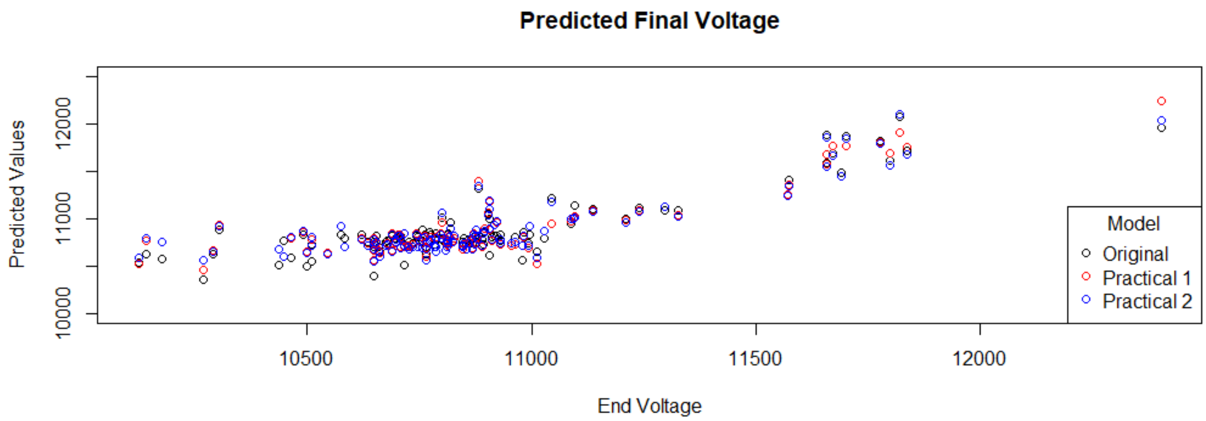
Predetermined values for the rates of ascent and descent may not be readily available. In that case the best fitting practical model is given below.

```
Residuals:
    Min      1Q  Median      3Q     Max 
-646.75  -87.27   31.52  106.25  425.37 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)      -1.218e+04  4.534e+03  -2.687  0.00818 ** 
init.voltage      1.977e+00  3.672e-01   5.385 3.38e-07 ***
tot.distance      1.665e-01  2.313e-02   7.198 4.73e-11 ***
avg.tot.velocity -7.675e-01  1.816e-01  -4.226 4.50e-05 ***
del.alt          -4.858e-03  1.732e-03  -2.804  0.00583 ** 
duration         -1.219e+02  1.309e+01  -9.313 4.84e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 193.2 on 127 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.7088,   Adjusted R-squared:  0.6974 
F-statistic: 61.83 on 5 and 127 DF,  p-value: < 2.2e-16
```

The fit of this model is slightly worse than the other model but practically speaking the differences are negligible. Using the abbreviations from the above table the model's linear equation is given by

$$\hat{y} = -12{,}180 + 1.98IV + 1.67 * 10^{-1}D - 7.68 * 10^{-1}Ve - 4.86 * 10^{-3}A - 121.9Du.$$

The following plot shows the predicted values for the best fitting model (‘Original’ proposed in the 06/28/2018 report), the first model given above (‘Practical 1’), and the second model presented (‘Practical 2’).



This plot suggests there tends to be only small differences in the predicted final voltage between the three models. It seems reasonable to conclude that the simplest model (‘Practical 2’) is sufficient for this data.

Prediction Intervals

Prediction intervals for each of the three models can be calculated using the equation

$$\widehat{y_h} \pm t_{(\alpha/2,df)}\sqrt{MSE + se(\widehat{y_h})^2}$$

where

$$se(\widehat{y_h}) = \sqrt{MSE(X_h^T(X^TX)^{-1}X_h)}.$$

In the above

- $\widehat{y_h}$ is the predicted end voltage for a given set of inputs X_h,
- X is the design matrix,
- MSE is the mean squared error, and
- $t_{(\alpha/2,df)}$ is the $(1 - \alpha/2)^{th}$ quantile from the t distribution with df equal to the number of flights minus the number of predictors.

The width of the prediction interval is dependent on X_h and hence we can only compare these intervals based on the three models for specific input vectors. To give an example we compare the three models using the following inputs:

init.voltage = 12563

tot.distance = 10469.83

avg.tot.velocity = 890.2622

del.alt = 121870

duration = 19.85698

The prediction intervals are

Model	Predicted End Voltage (millivolts)	95% Prediction Interval	Width
Original	10760.38	(10395.09, 11125.68)	730.59
Practical 1	10719.22	(10345.26, 11093.18)	747.92
Practical 2	10732.45	(10344.54, 11120.37)	775.83

Conclusion

The final model was based on a dataset with end voltage readings ranging from 10124 to 12403 millivolts and therefore all inferences are restricted to that range. We found the initial voltage, haversine distance, average total velocity, maximal difference in altitude, and duration were all significant predictors of the battery voltage at the end of the flight. The validity of our models are dependent on the predictor values that were observed and it can be dangerous to extrapolate outside of the ranges of the training data. The five number summaries of the response and final predictors are given below.

```
  end.voltage     init.voltage    tot.distance       avg.tot.velocity     del.alt           duration
 Min.   :10124   Min.   :12177   Min.   :    2.104   Min.   :  3.607   Min.   :  54730   Min.   : 0.4732
 1st Qu.:10707   1st Qu.:12520   1st Qu.: 6294.917   1st Qu.:833.735   1st Qu.: 120420   1st Qu.:13.4036
 Median :10826   Median :12549   Median :10447.614   Median :899.726   Median : 120620   Median :18.9538
 Mean   :10879   Mean   :12518   Mean   : 8727.234   Mean   :818.885   Mean   : 200838   Mean   :15.9786
 3rd Qu.:10930   3rd Qu.:12566   3rd Qu.:10470.896   3rd Qu.:926.981   3rd Qu.: 120830   3rd Qu.:19.5138
 Max.   :12403   Max.   :12605   Max.   :16986.419   Max.   :986.205   Max.   :1126480   Max.   :21.5105
```

Annex E: Pilot Hour Risk Calculations

The preflight risk model's computation of pilot risk is based on research conducted for the Federal Aviation Administration (Knecht, 2015) correlating manned aircraft accidents to the number of hours the pilot-in-command held at the time of the accident, and whether the pilot held an instrument flight rules (IFR) rating. The research derives two weighted models based on the pilot's rating, as depicted in the images on the next page. The parameter values from Knecht's model are:

TFH, total flight hours

A, the y-axis amplitude parameter

α, the shape parameter for the model

β, the scale parameter for the model

δ, the x-axis location parameter

b, the baseline annualized accident rate, and

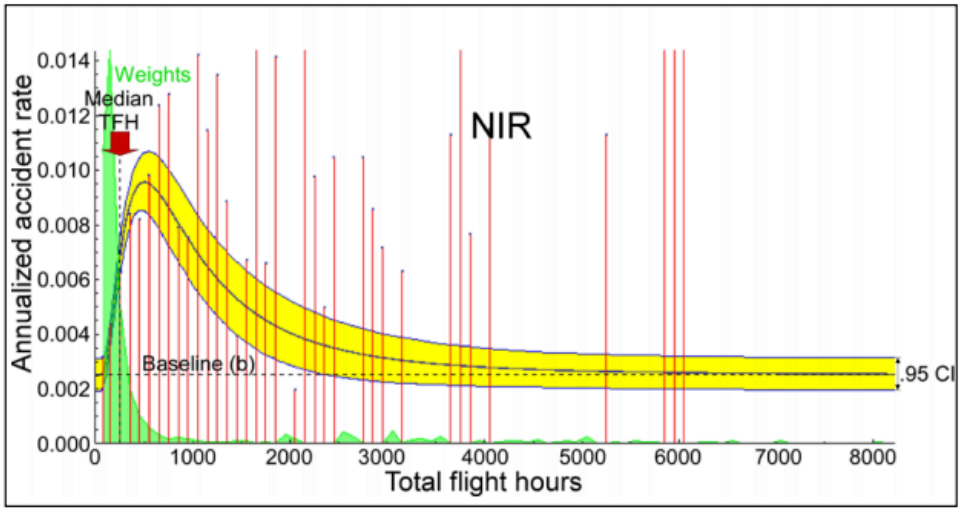
R^2_w, the weighted goodness-of-fit of the model curve.

In both images, red bars indicate counts of accidents in each 100-hour bin, while the green shading indicates the relative weight assigned to each bin.

Based on this research, we derived the equations used in the pilot risk sub-model to approximate the shape of Knecht's curves, with a few crucial differences in assumptions. We apply the non-instrument-rated model's peak and baseline rates to manually piloted flights, with the same numeric value expressed per flight hour without converting from annualized rate. This is because currently, most vehicles do not last in regular operation for more than 18 months (whether due to accident or proactive retirement/replacement at signs of impending wear and failure). Additionally, since most missions are less than 20 minutes in duration, we expect that the baseline is reached by about 170 pilot hours (equivalent to more than 500 twenty-minute flights).

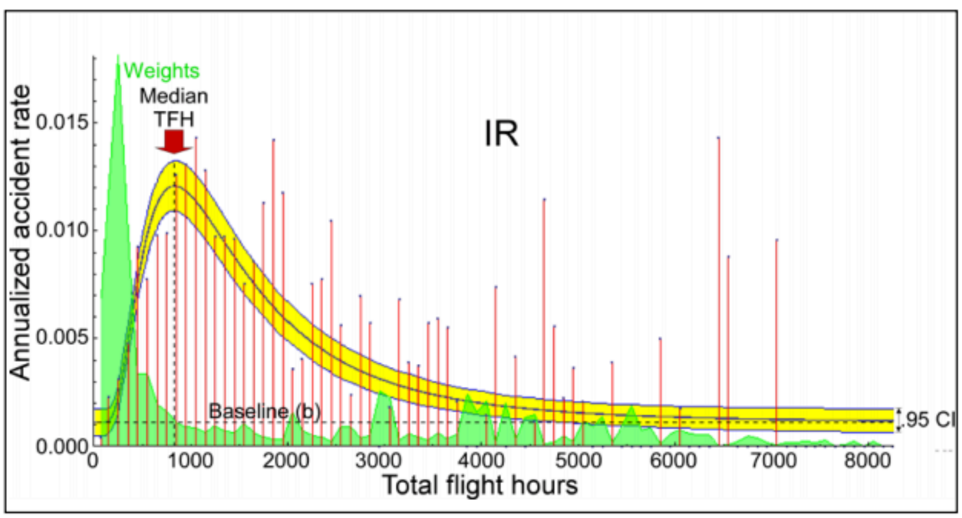
For managed flights (i.e. flying in an automatic or autonomous mode with a human monitoring and able to take manual control), we adopt the instrument-rated model's peak and baseline values in the same fashion. The higher peak value (1.74E-2, versus 1.3E-2 for manual flight) is reasonable given that when a vehicle experiences a malfunction in managed mode, human intervention may make the problem worse, until the human pilot has amassed sufficient flight hours and experience (in either a managed or manual mode) to know how to respond correctly.

The current models are expected to change as data that matches UAV accidents to pilot hours becomes available in sufficient quantity and quality. Additionally, in jurisdictions where more extensive training, certification, proficiency and currency requirements are mandated, these curves will be adjusted accordingly to capture the efficacy of those training mitigations.



Parameter	A	α	β	δ	b	R^2_w
N=39327	.0130	64.38	.0924	.3648	.0025	.654

Figure 8. Non-IR GA accident rates (median TFH=250.5).



Parameter	A	α	β	δ	b	R^2_w
N=28360	.0174	51.35	.0890	2.243	.0011	.775

Figure 9. IR GA accident rates (median TFH=823.5).

Annex F: Weather Impacts in Risk Model Calculations

Reserved.

References

AAAM. (2015). *Abbreviated Injury Scale (AIS)*. Retrieved from https://www.aaam.org/abbreviated-injury-scale-ais/

Hudson, P. (2001). Aviation Safety Culture. *Safeskies, 1*, 23.

ICAO. (2015). *Safety Management Manual.*

Knecht, W. (2015). *Predicting Accident Rates From General Aviation Pilot Total Flight Hours.* Federal Aviation Administration, Office of Aerospace Medicine.

Kochenderfer, M. J. (2010). Airspace encounter models for estimating collision risk. *Journal of Guidance, Control, and Dynamics, 33*(2), 487-499.

National Academies of Sciences, E. a. (2018). *Assessing the Risks of Integrating Unmanned Aircraft Systems (UAS) into the National Airspace System.* Washington, D.C.: The National Academies Press.

Sachs, P. (2018). *Using Fault Trees to Compute UAV Mission Risk.* Technical Report, Altiscope (A^3 by Airbus).