Understanding UAV Mission Risk

This is the first in a series of white papers documenting the process and findings behind Project Altiscope's risk framework. This is a collaborative process with a volunteer group of industry, academic and expert advisors. Interested in learning more about the risk model? Contact Altiscope's Safety & Risk Architect, peter.sachs@airbus-sv.com.

Altiscope is developing a quantitative risk model for present-day UAV mission profiles that will remain relevant as operations and technologies scale and evolve in the coming years. Scoring a mission's risk using clear and open published criteria helps everyone from manufacturers and operators to insurers and policymakers operate from the same playbook. The model reduces the influence of subjective criteria; and we can help regulators set realistic risk thresholds for different locations and mission types by providing data to illuminate the effects of those choices.

What's safe enough for one regulator may not be sufficient in a different jurisdiction for any number of reasons. The quantitative model will help users understand what investments they need to make, in terms of vehicle reliability, redundant equipment and other factors, so that they can fly their intended missions. And it will help regulators set appropriate standards for their needs, while gaining insight into how those standards may affect operations in their airspace.

Our risk model will only have value if we actively engage with other stakeholders in our industry as we develop it. This is a collaborative process with a group of volunteer advisors who have expertise in research, insurance, operational risk management, air traffic control and the backend systems that tie everything together. Our work will be shared publicly through papers like this; presentations at industry conferences and events; and ultimately in open-source documentation and software tools that anyone can use.

This paper explores where Altiscope's risk model fits in the larger realm of UAV risk assessment.

- We discuss the overall approach to developing the risk model and what the resulting model may look like (for more detail, please see Building Altiscope's Risk Framework).
- We've identified several high-level challenges, along with approaches we plan to take in tackling them.
- We review existing research literature in crash severity, vehicle separation, human factors, vehicle reliability and flight into known icing.

- There are a number of other UAV risk assessment industry efforts, and understanding how those relate to Altiscope's work is important to ensuring that this project remains relevant.
- Finally, we provide an overview of the fault tree analysis we're using to target our efforts. More details on the fault trees, including sensitivity analysis results, will be the topic of a separate paper.

What Will the Risk Model Look Like?

By the end of Q3 2018, we'll have a well-documented model and companion software tools that provide a path toward real-world testing and eventual integration with ATM and UTM software platforms. We intend for the model to be compatible with existing aviation safety policies, such as ICAO's Safety Management Manual and the Federal Aviation Administration's (FAA) Safety Management System. The model's functionality will cover a broad variety of inputs, and it will continue to be refined and updated as we gather feedback from its use in the Altiscope simulator and ultimately from real-world test ranges.

The components will most likely include:

1. Descriptions, required input variables and formulas for calculating various types of risk.
2. Identified sources for weather information and vehicle performance data.
3. Workflows for determining combined effects of multiple risk types.
4. Scripts, libraries and/or APIs that enable an ATM/UTM system or flight planning software to query the risk model; and for an implementation of the model to advise the software of changing risk conditions.
5. A toolkit for operators to understand the underlying risk of their missions, including for startup operators interested in basing their purchasing and staffing decisions on expected risks.

UAVs are sources of both air-based (i.e. near-midair collision) and ground-based risk. Mitigating one form of risk may not fully address the other, so it's important to consider a wide range of failure modes and the effects of various mitigation efforts. To do this, we hypothesize that a modular approach to building the risk model will capture those mutually independent hazards and failure modes. At the same time, the model must capture the interdependencies that multiple simultaneous failures can have on each other.

A modular approach allows us to update one part of the model while reducing the chances of unintentionally affecting the calculations in another part of the model. This path also builds in mitigation against risk calculation errors when one or more risk categories don't apply to a specific mission. Broadly speaking, the modules will cover the following categories and types of risk:

1. **Vehicle reliability, equipage and redundancy.** This includes not only failure rates for mechanical components, but predictive battery performance and quantifiable mitigation for redundant systems, navigation, obstacle avoidance and position-reporting equipment.
2. **Communications protocols and infrastructure.** Latency in receiving and acknowledging control instructions (or a lack of ability to respond at all) represents a latent risk that may be a bigger or smaller factor depending on where a vehicle is operating in relation to other UAVs and manned aircraft. This is a function of the UAV's onboard equipment, ground-based communications infrastructure and signal loss due to obstacles and terrain.
3. **Operator training, experience and performance.** Whether the vehicle is flown within a geofence by a remote pilot or programmed to fly autonomously hours ahead of time, the decisions the remote pilot or fleet operations manager makes can have subtle effects on the successful outcome of the mission.
4. **Airspace usage and rules.** Airborne collision risk increases in more congested airspace. But risk isn't merely a function of airspace class or average traffic volume: it varies significantly based on exact location with regard to approach paths, departure corridors, traffic patterns and other factors unique to each area.
5. **Environmental factors.** Weather and terrain interactions can have a significant impact on the safety of a mission. Boundary layer conditions and urban canyon effects can amplify wind conditions beyond the takeoff, landing or maneuvering tolerance of a vehicle.
6. **Population density, land use patterns and building/obstacle height/density patterns.** Regulators and policymakers may choose to limit or prohibit flights over certain areas for a variety of reasons. For example, one regulator may want to limit flights over noise-sensitive areas, while another may want to restrict flights above critical infrastructure and sensitive government buildings. They may consider any or all of these metrics in their rulemaking, which may be independent of airborne risk factors.

Challenges & Solutions

One of the biggest challenges in developing the risk model is finding data to validate our assumptions. Manned aviation safety data is widely shared and available, but in many industries, including ours, performance and failure data is closely guarded in the interest of preserving trade secrets, competitive advantages and customer privacy.

We envision several ways of addressing this gap in available data:

- Altiscope is exploring data-sharing relationships with external partners. Our goal is to collect de-identified performance data (i.e. not traceable to a specific operator or mission) to validate the model incrementally; and to share larger insights about operational best practices.

- Use the advisory group's operational expertise, including flight data that members may be willing to share.
- Gathering data from the risk model when it's applied to real-world flights on test ranges or other approved airspace.

As this paper points out, there are several qualitative models that address similar risk factors as Altiscope's model. It will be a challenge not only to avoid duplicating effort when a solution already exists, but to avoid over-complicating Altiscope's model by addressing too many variables. One of the greatest benefits of a streamlined qualitative model is that it is often straightforward for a user to understand and use, even if they do have have specialized expertise in risk management. We must be deliberate in striking the right balance between a robust quantitative model and making sure it is usable in the real world.

We also face challenges in modeling complex failure modes. For example, a communications link loss alone may not lead to a loss of control. But when combined with high winds that place the rally point (or return-to-home location) out of range, and a battery discharging at an unexpectedly high rate, a flyaway event may become unrecoverable and lead to a crash. Understanding that risk requires being able to model dynamic, temporal factors, especially when environmental conditions are expected to increase risk.

At this early stage, the model will rely on a large number of assumptions; collecting insights from the Altiscope simulator and real-world data from our partners will help narrow that uncertainty. The sensitivity analysis of our fault trees will also help us understand the impact of that uncertainty. The members of Altiscope's risk advisory group are helping with this process, and had the opportunity to provide feedback on draft versions of this paper.[1]

Even with sufficient data, the model will require real-world testing to validate its usefulness with regulators, operators and manufacturers. Thus, we expect the early versions of the model to evolve substantially once we're able to see how it works on test ranges or in shadow mode with our external partners.

Likewise, for the model to be relevant to industry and regulators, we must ensure that it remains consistent with existing safety management principles and policies. The ICAO Safety Management Manual, for example, provides detailed background and checklists for member states to ensure they collect and analyze relevant safety data. It also differentiates between hazards, unsafe events and consequences in evaluating sources of risk and mitigation strategies [27][24]. Similarly, the FAA's Safety Management System promotes

[1] We believe transparency is crucial to the success of the framework, of which the risk model is one part. The risk advisory group is an independent volunteer group. Members do not receive compensation from Altiscope, and participate with whatever amount time they have available. However, as aerospace is a small community, members of the group, including individuals or companies, may perform unrelated paid services for one or more other members of the group. All advisory group members sign a similar agreement with Altiscope stating that their contributions to the risk framework will be made publicly available. This work is not protected by NDA, so anyone can use the risk framework in any way they desire.

using a bow-tie model in risk analysis to clarify the relationships between hazards, threats and consequences [25].

Literature Review: Crash & Collision Severity

Because the current body of research is moving forward so quickly, we did not look solely at peer-reviewed articles, but also considered findings in conference papers and presentations. The pace of research has accelerated tremendously since 2011, and especially in the last two years. , Because the field is advancing so quickly, it isn't possible to capture all findings here.

We focused our review on five broad categories of research. Most discussion of risk in aviation ultimately relates to the probability of a lethal crash or collision, so research aimed at determining how UAVs behave when they crash (whether falling at terminal velocity or approaching someone from the side) merits mention. Numerous factors can contribute to a crash, including onboard systems failures and environmental factors (most UAVs are only tested to withstand winds up to a certain limit, for example). And human error will likely continue to be an issue, even in autonomous environments, just as it is in manned flight today. We identified relevant findings related to crash severity, vehicle separation, human factors, vehicle reliability and flight into known icing.

The Federal Aviation Administration (FAA) has funded a university research consortium known as ASSURE (Alliance for System Safety of UAS through Research Excellence), which published two peer-reviewed studies in 2017 assessing UAV collision impact severity. The first study [1], found that lethality rates from being hit by small, off-the-shelf UAVs (often referred to as sUAV aircraft) were much lower than previously assumed. Researchers conducted drop, impact and laceration tests and found that because many sUAVs comprise large plastic structural elements, they tend to fracture and break apart on impact, dispersing their energy over a larger area. The report found that the probability of skull fractures and neck injuries were low as long as the impact energy was below about 100 foot-pounds (136 J), making the lethality risk for many off-the-shelf sUAVs negligible for weights under about 3 pounds (1.4 kg). This provides a substantial advance over the earlier Range Commanders Council findings [26], which assumed lethality in most UAV crashes regardless of weight, since that research treated the vehicles as solid metal structures that would not break or deform on impact.

The findings are nominally consistent with a Virginia Tech study [4]. Researchers found that a given UAV would produce a range of head and neck injuries depending on the orientation and angle of impact. The group tested UAVs as large as the 11-kg DJI S1000+, which had up to a 70-percent chance of inflicting severe neck injury in a direct drop hit. If one of the vehicle's eight mast arms or rotors impacted the test dummy first, then severe injury chances were much lower.

Project Wing, an Alphabet venture, has also conducted impact tests of its proprietary vehicle. The team found that it could significantly reduce injury risk by modifying the vehicle with plastic connectors that would cause the vehicle to break apart in a side impact, but not under normal flight loads (Burgess 2017, public presentation). The team has presented its overall findings at several industry conferences and meetings, but has not published detailed study results.

ASSURE also simulated the impact risk of an sUAV striking various portions of a single-aisle airliner and of a business jet, creating and validating a precise 3D model of a DJI Phantom 3 and its internal components [19]. The results found a high risk of penetrating airframe damage in a worst-case scenario, in which the UAV's battery or a motor directly impacts the leading edge of a control surface. But damage was limited to skin deformation if other parts of the UAV struck the aircraft, especially if it was a glancing or offset impact. This is consistent with information regarding two known sUAV-aircraft impacts in 2017. In those events, the aircraft remained flyable but sustained non-structural damage to the aircraft skin and main rotor surfaces [7].

The research conclusions on the consequences of sUAS engine ingestion were limited by an inability to accurately model the proprietary compressor section of a typical high-bypass turbofan [6]. Nonetheless, simulation results indicate that an sUAS could cause the outer portions of the intake fan blades to break off. Because of the research methodology, it is not yet possible to extrapolate impact damage for larger UAS models. Testing on an out-of-service engine would clarify impact severity and possibly make the findings generalizable to different engine models.

Literature Review: Separation Standards

Other researchers have explored how vehicles might deconflict themselves from each other, and how to quantitatively determine appropriate separation standards. This is an evolving branch of research without apparent consistency. The risk model intends to incorporate some of these research philosophies to help regulators set appropriate separation standards.

Wiebel [22] uses Traffic Collision Avoidance System (TCAS) alerting criteria as a baseline to determine well-clear standards using conditional collision probabilities. The modeling allows the separation standard to vary based on what regulators determine to be an acceptable boundary risk level of a near-midair collision (NMAC) occurring. The author proposes a conservative requirement of 8,000 feet (2,440m) ahead and 3,000 feet (914m) to the side and behind, since most TCAS proximity events involve head-on/converging operations. However, these distances do not account for the flight dynamics of multirotor UAVs, which are generally very maneuverable and capable of making abrupt trajectory changes.

At the other end of the spectrum, Balachandran [2] demonstrates how UAVs can use Rapidly Exploring Random Trees to perform their own conflict resolution with other aircraft and obstacles. The author assumes that 10 meters would constitute an acceptable well-clear standard between UAVs, or 0.5% of Wiebel's forward well-clear spacing. The research is intriguing because it shows how a vehicle with suitable onboard computational resources can resolve its own conflicts in as little as 0.2 seconds, without having to rely on external ATC instructions, operator commands or collaborative resolution advisories from the other vehicle.

Research and testing of Airborne Collision Avoidance System X (ACAS X) indicates that it may also be useful for resolving conflicts between UAVs, in addition to its originally intended use as an upgrade and replacement for TCAS [9]. Whereas TCAS uses a fixed set of rules to determine how to resolve a conflict between two aircraft, ACAS X also considers aircraft performance and probabilistic models to predict aircraft positions.

Lin [15] simulated crash field dynamics for small UAVs in various wind conditions to determine the largest ground footprint over which the UAV might fall. The results could be applied to low-risk path planning algorithms to determine acceptable overflight areas in built environments.

NASA's UTM project is being closely watched for its variety of research goals and inclusion of live flight test results on protected UAV ranges. Homola's [13] findings from testing near Reno, Nevada indicated that the most likely times for a UAV to blunder outside of its assigned protected airspace volume were during takeoff and landing. This is an important discovery, since it suggests that vehicles may need to meet precise navigation and maneuverability thresholds if they are allowed to operate near one another in busy terminal environments. Homola's research also has implications on human factors issues (see below).

Literature Review: Human Factors

Altiscope hypothesizes that human factors will continue to be a source of errors, even in increasingly autonomous flight regimes. These errors may take different forms than we're accustomed to today, whether in vehicle maintenance, fleet management practices or the ability to react to unusual situations in a timely and effective manner.

McFadden and Towell's [17] paper laying out a framework for addressing human factors in aviation is one of the oldest in this review, but remains pertinent. The author encourages reporting and investigation of operational errors that don't result in an accident, because those root causes are often shared with rarer catastrophic failures. And, the author notes, poor training is often an underlying factor in numerous safety events.

In the broader aviation community, the best way to ensure pilots and controllers know how to respond to off-nominal situations is to provide them with relevant training in robust simulated environments. This allows the operators to revert to their training, which tends to increase the likelihood of a successful outcome.

To that end, Rodríguez-Fernández [20] shows how time-series clustering analysis can identify preferred operator performance traits in a simulated UAV environment. Specifically, their algorithms can detect patterns in how operators react to situations like low fuel or a weather diversion. This data can be used to construct profiles of desirable traits for training benchmarks and standards. It is, essentially, a statistically significant way of quantifying attributes like aggressiveness, agility, precision, attention and cooperation.

Homola's findings as part of the NASA UTM project included a recommendation that operator-oriented systems be designed to give clear alerts of unusual operations. Those alerts are crucial to helping operators understand not only what is going wrong, but what they should do to intervene and recover.

Literature Review: Vehicle Reliability

At present, most vehicle reliability data is proprietary to each manufacturer. Specific numbers for component failure rates are hard to discern, although we can make some conclusions about relative likelihood of failure modes. Because off-the-shelf UAVs are not subject to airworthiness certification criteria like manned aircraft (and therefore, independently verifiable end-to-end manufacturing quality control processes), there may be large variability in the reliability of components across different examples of the same vehicle model.

In reviewing public records of military UAVs over the last 15-plus years, Hansen[12] found that between a third and half of all accidents resulted from powerplant or propulsion failures. While the powerplants differ (Jet-A powered engines on most military UAVs versus Lithium Polymer powered electric motors), those systems are still prone to failure over time.

Likewise, Caswell and Dodd [5] find that about 25 percent of UAV failures are due to problems with electronic components, including batteries, GPS and communications links. Most other crashes are due to weather encounters (particularly flight profiles in wind conditions that exceed the vehicle's performance abilities) and pilot error. Importantly, they note that electromagnetic interference susceptibility is mostly unknown -- what levels of EMI and for how long cause a given vehicle to experience a flyaway or loss of control?

Saha's [21] findings provide useful insights on battery performance issues. The authors determined that if the future mission profile (e.g. climbs, descents and cruise segments) is known in advance along with the specific type of battery, an algorithm can accurately predict the battery's state of charge for the rest of the mission, including the point at which the battery voltage will be too low to continue flying. Even if the future mission profile is unknown, as long as the vehicle's battery parameters are understood, one can still make predictions about when the battery will be discharged. However, this paper did not investigate the effect of battery temperature on state-of-charge.

Finally, Hammer [10] created and tested a set of generic fault trees for beyond visual line-of-sight (BVLOS) UAV operations. Sensitivity analysis of the trees indicated that the most significant failure modes are due to poor maintenance/pre-flight checks; weather encounters; and non-redundant mechanical design choices. Conversely, the sensitivity analysis found that any one basic event failure would not significantly increase the risk of an inflight collision. This is largely a function of how complex that branch of the fault tree is; an inflight collision requires several simultaneous and disparate failures. While the trees do not consider autonomous operations, their structure is fairly adaptable and considers a wide range of failure modes, making them a useful analysis tool.

Bayesian Belief Networks provide another tool for understanding complex UAV failure modes [16]. The author modeled the risk of NMAC and mid-air collision assuming a UAV operating within a geofence near a small airport. Given several failures that manifest simultaneously (strong wind gusts; EMI that contributes to loss of communications link; incorrect UAV waypoint programming; and a vehicle electrical system malfunction), the unmitigated mid-air collision probability is about 7E-5 per flight hour in that scenario. The model is similar to what might happen in a flyaway scenario: The geofenced area's ability to protect the vehicle from flying too close to another aircraft decreases as the number of simultaneous failures increases.

Literature Review: Icing Conditions

Research indicates that just as manned aircraft are susceptible to inflight icing conditions, UAVs can be as well, but generally with more severe effects on smaller vehicles. While several vehicle anti-ice and de-icing technologies are being developed and tested, none are commercially available.

Hann [11] conducted computer simulations of fixed-wing UAVs flying in various types of icing conditions. The research found that mixed ice, which accumulates between -10˚C and -15˚C, had the greatest effect on increasing drag, reducing lift and decreasing battery performance as the vehicle uses any excess available power to increase its thrust. The increased power usage also reduces the vehicle's range. Clear and rime ice had similar effects, but to a lesser degree because the airfoil retained more of its aerodynamic shape and could continue generating lift at lower angles of attack.

Li [14] conducted wind tunnel tests of UAV blades in icing conditions. The work found that different types of ice accrete in different ways along the leading edge of each propeller blade. Rime ice accreted evenly and therefore had the least effect, slightly increasing both thrust and drag in the tests. Clear and mixed ice tended to accumulate in greater amounts closer to the blade tips, which increased drag and vibration. After enough ice accumulated, a blade's centrifugal force would shed some of the ice, creating an imbalance on the rotor assembly which further increased vibration and increased the risk of fatigue failure. The tests found that after 105 seconds in icing conditions, an ice layer up to 5 mm thick had developed on the rotor blades, a relatively large proportion of the blade chord length (typically 1-3 cm) in small UAVs.

UAV and Aviation Risk Assessment Industry Efforts

Risk models throughout aviation take a variety of forms, from the simple mnemonics private pilots learn to qualitative versions that determine whether an airport improvement project can proceed. Each has its strengths and solves some piece of the integration challenge. Understanding the current efforts can help guide Altiscope's efforts. We are aware of several other efforts to develop risk models. Understanding those existing efforts helps us identify gaps that our model can help satisfy. Altiscope's effort is unique in that it is collaborative and open from the beginning – it's not proprietary to Airbus or A^3, and we intend to extensively document our process so that anyone can understand our methodology, assumptions and conclusions.

PrecisionHawk, which provides a variety of UAV hardware, software and data-gathering solutions, is developing an operational risk assessment model that it hopes to build into its software platforms [8]. The company expects it to be quantitative, recognizing that much of the data they need does not yet exist, nor do target risk thresholds. The company is working with MITRE, the non-profit aviation research organization funded by the FAA, to evaluate various technologies aimed at reducing human error in UAV operations.

MITRE has a separate effort to develop benchmarks for UAV safety performance [3]. The probabilistic model considers operational, vehicle and ground risk variables, arriving at several vehicle and mission profile categories to evaluate risk. The work is promising because it provides a notional path from a quantitative model to an implementation dashboard to help users understand the risk of their mission as a function of ground-base lethality likelihood.

The Joint Authorities for Rulemaking of Unmanned Systems' (JARUS) Specific Operations Risk Assessment (SORA) is nearly complete [18]. The qualitative holistic (bow-tie) risk model is intended to assess risk for BVLOS UAV operations above 150 meters AGL, weighing both air- and ground-based risk. By the model's design, ground-based risk tends to be the category that requires the most mitigation in order to allow flights over anything other than unpopulated areas. The SORA is not yet usable because several appendices, necessary to determine how to classify one's vehicle or risk mitigating equipment, won't be published until Q2 2018. However, EASA has committed to making use of the JARUS SORA mandatory in its member states by late 2019 or early 2020. In conjunction with the SORA, EASA is researching a set of procedures known as Automated Low Altitude Air Delivery, which would route vehicles over unpopulated areas as much as possible, thereby lowering ground-based risk.

As part of its Safety Management System, the FAA uses a qualitative matrix to evaluate hazard severity and likelihood in most air traffic Safety Risk Management exercises, using that to determine the need and extent of mitigations. This framework has been extended to sUAS operations in AC-107-2 [23]. The matrix dictates whether an operation is allowed, prohibited, or conditionally allowable with appropriate mitigations in place for each identified hazard.

Fault Tree Analysis

Altiscope believes that solely focusing on the root causes of catastrophic (i.e. loss-of-life) UAV failures is not sufficient to address their risks. Our perspective is consistent with ICAO guidance that to manage safety risk in complex systems, a variety of latent conditions and organizational factors must be evaluated and mitigated. The larger aviation industry has spent the last 20 years understanding lower-level failure modes and operational errors. Doing the same for UAVs can help identify root causes that may lead to undesirable situations that are costly for insurers, bad for public perception and damaging to property -- even if there is no loss of life.

Therefore, we have developed a pair of fault trees in an effort to capture as many failure modes and environmental factors as possible. Why two? A UAV, just like a manned aircraft, can experience a loss of control leading to a crash or collision. But it can also make a controlled crash due to a separate set of failures, not unlike controlled flight into terrain accidents in manned aviation.

The fault trees are an imperfect way to understand failure modes because they simplify variables that may have complex interdependencies into Boolean relationships. This is especially the case when evaluating risks leading to a vehicle flyaway situation. Because of this, Altiscope may expand this work into constructing Bayesian Belief Networks, since they allow for a finer gradation of basic event influences while depicting statistical uncertainty.

The first tree considers a controlled crash, collision or near-midair collision as the top-level failure. There are three second-level failures in this tree, for failures originating from route conflicts, deconfliction errors, or human-in-the-loop errors. Keep in mind, this tree is designed to capture both flights with a remote pilot and autonomous flights, so some of the basic events are speculative based on our assumptions of high-level architecture and design for future ATM systems.

The second tree considers an uncontrolled crash, collision or near-midair collision as the top-level failure. We have adopted Hammer’s design paradigm in assigning a fixed probability that any of the second-level failures leads to a crash [10]. This is an elegant way to account for the fact that some failure modes may be recoverable. This tree considers any one of four second-level failures leading to an unrecoverable loss of control. These failures include hardware and electronic failures like battery problems, motor failure and blade separation. This tree also models flyaway events -- those in which the vehicle may technically still be controllable, but in which its behavior is unpredictable to the operator, making it difficult to recover the vehicle. Finally, the other two failure branches in this tree cover inflight weather conditions and preflight/maintenance actions, respectively.

The results of the sensitivity analysis of both trees will be discussed in-depth in the next white paper. At a high level, they are consistent with the findings of Hammer’s sensitivity analysis. Basic events related to weather conditions, operator error and a vehicle’s inability to maneuver in accordance with a deconfliction command have the greatest influence in increasing the probability of a top-level failure in the trees.

Conclusions

The pace of research and development gives us a wealth of resources — and also raises the prospect of making the risk advisory group’s collaborative effort obsolete if it fails to engage with industry and regulators more broadly. For example, how can our risk model inform or complement future iterations of the JARUS SORA, which EASA has already committed to using for some UAS missions in Europe?

What can we learn from other risk modeling efforts at places like PrecisionHawk and MITRE? We should remain open to partnerships or collaboration arrangements to share knowledge and reduce the amount of time we all spend re-inventing the wheel.

The existing research provides meaningful insight as to how to evaluate ground and air collision lethality using quantitative measures of terminal velocity, kinetic energy and vehicle weight. Less clear is how to evaluate vehicle reliability. How often do battery failures manifest? How controllable does a given UAV remain if a single motor or rotor fails? These rates likely vary by vehicle model and how heavily it is flown. How should the risk model evaluate missions where those variables aren’t known?

Based on the existing research and other risk framework efforts, we see an opportunity to construct a notional model for evaluating a vehicle’s proposed routing against its weight, battery capacity (and therefore range) and wind conditions to determine its probability of completing a mission successfully. This has relevance in any instance where an operator may need to mitigate ground-based risk (i.e. probability of a lethal crash into people) by flying a longer route over sparser geography. This could also be useful for an ATM/UTM system that needs to issue a longer route around weather or restricted airspace.

Glossary of Terminology

ANSP: Air Navigation Service Provider. A public or private entity that is responsible for air traffic control. May be the same as a regulatory body, or may operate as a separate organization.
ATM: Air Traffic Management. A set of operational and policy concepts related to air traffic control, aircraft performance, system safety and airspace usage.
EASA: European Aviation Safety Agency. Aviation regulatory body for 32 member states in Europe.
EUROCONTROL: The ANSP for most of Europe.
FAA: Federal Aviation Administration. The regulator for aviation in the United States and its ANSP.
HITL: Human-in-the-Loop. A set of theories focused on how people interact with and interpret information provided from automated systems.
sUAS: Small Unmanned Aerial System. Depending on context, a vehicle weighing less than 55 pounds.
TCAS: Traffic Collision Avoidance System. Cooperative hardware mandated to be installed on most commercial aircraft as an added layer of safety to avert imminent midair collisions.
UAS: Unmanned Aerial System. Refers to all components of a pilotless platform, including the aircraft, ground station, communications link and remote pilot.
UAV: Unmanned Aerial Vehicle. The pilotless aircraft itself, also commonly referred to as a drone.
UAM: Urban Air Mobility. Research and policy focused on how to integrate UAV operations into existing airspace, whether segregated or heterogeneous.
UTM: Unmanned Aerial System Traffic Management. An automated system (or network of systems) that manage and separate UAV traffic.

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