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Risk Assessment in Air Traffic Management

*Edited by Javier Alberto Pérez Castán
and Álvaro Rodríguez Sanz*



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Contributors

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Meet the editors



Javier Alberto Pérez Castán was born on March 14, 1989 in Huesca, Spain. He has a BSc degree in Aeronautical Engineering, an MSc degree in Aerospace Engineering, and a PhD in Aerospace Engineering from Universidad Politécnica de Madrid. His expertise focuses on aerospace and procedure design, risk assessment, and RPAS integration in ATM. Nowadays, Prof. Pérez Castán is a researcher and lecturer in Universidad Politécnica de Madrid and belongs to the Navigation Area Research Group (GINA).



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Preface

One of the most complex challenges for the future of aviation is to ensure a safe increase in expected air traffic demand. The growth in air traffic operations is expected to almost double its current value in 20 years. This impressive air traffic increase requires the development, validation, and implementation of new concepts of operations that have to tackle future needs. The Single European Sky in ATM Research in Europe, Next Generation Air Transportation System in the United States, and Collaboration Actions for Renovation of Air Traffic Systems in Japan are the most important research macroprograms to respond to these aviation challenges.

Nonetheless, air traffic management (ATM) must ensure and even increase current safety levels. The International Civil Aviation Organization defines safety as “The state in which risks associated with aviation activities, related to, or in direct support of the operation of aircraft, are reduced and controlled to an acceptable level.” This definition is underlain by two crucial concepts: risks and acceptable level. They have their own meaning and the implications of both are diverse, depending on the scenario and actors involved. The aviation system has evolved from a reactive to a predictive approach, and requests the assessment of risks in ATM to minimize the probability and severity of intrinsic hazards.

The primary issue that risk assessment in ATM must face is the lack of a common and widespread methodology and safety metrics in the aviation community. Multiple factors must be taken into account in ATM that, typically, are gathered into three areas: navigation, intervention capacity, and exposure to risk. However, these factors cannot be considered isolated from the regulatory framework that imposes acceptable levels for the different stakeholders, such as airports, airlines, manufacturers, pilots, air traffic controllers, and so on.

Moreover, the approach for analysis differs when the temporary horizon is introduced, as the available information, data accuracy, and goals vary. Strategic analyses focus on airspace design and define safety levels based on air traffic flows. Pretactical analyses demand different information because the network manager and airspace users provide specific information about flight plans. Tactical analyses provide insights into the air traffic network or dig into specific collision avoidance or trajectory optimization. As the reader will discover, there are as many different methodologies and safety metrics as the researcher’s goals and/or approaches.

To date, many books on aircraft and air transportation systems have been published worldwide, and particularly by IntechOpen. However, few books have brought to light the different purposes and methods developed for risk assessment in ATM.

This book entitled *Risk Assessment in Air Traffic Management* tries to motivate further research by encompassing crosswise and widespread knowledge about this critical and exciting issue. In case a novel researcher would like to delve into this area, this book could be the backbone for a comprehensive listing of references as well as a focal point for current risk assessment in ATM trends.

The first section is entitled “Airspace Design and Air Traffic” and presents different conflict or collision risk models to calculate the level of safety in particular scenarios regarding a strategic horizon.

The second section is entitled “Complexity and Regulation,” which is the most crosswise section. Works included in this section provide different methods to convert regulations to acceptable levels of safety in specific areas such as air traffic control complexity or ATM system performances.

The last section is entitled “New Airspace Users” and introduces possible ways to apply risk assessment to new airspace users such as unmanned aircraft. These works bring to the fore different methods from strategical to tactical points of view and define the process to ensure the safe operation of unmanned aircraft.

Finally, the editors would like to acknowledge and express their gratitude to all the authors for their contributions and to the IntechOpen team who made this book possible. We wish readers a fruitful and enlightening read.

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Section 1

Airspace Design and Air Traffic

Collision Risk Model for High-Density Airspaces

Francisco Javier Saez Nieto

Abstract

This chapter describes a collision risk model (CRM) of airspace scenarios to describe their safety levels when populated by given air traffic. The model requires the use of representative data, containing a description of the flown aircraft trajectories. It is a combination of deterministic and probabilistic mathematical tools able to estimate the level of safety. Furthermore, the model captures the frequency and spatial distribution of the encounters and conflicts, the time in advance the conflict is identified and the overall reaction time of the Air Traffic Control ATC system, and finally, the effectiveness of the ATC as safety layer. The model considers that the risk of an air miss depends on two different factors: on the one hand, the frequency of exposure to risks and, on the other, the chance of collision associated to this exposure. The exposure to risk is captured following a deterministic data-driven approach, whereas the associated chance of collision is derived from a statistical mathematical model, fed by the kinematics of the encounter and the statistics associated to the accuracy of the aircraft state vector when following a planned trajectory.

Keywords: risk, conflict, collision, air miss, CPA, safety barrier, level of safety, LAT

1. Introduction

Air miss in the airspace has been studied for decades since Marks [1] and Reich [2] formulated mathematically the collision risk probability associated with parallel route structures during the early 1960s. The Reich approach was used as the reference model by ICAO to determine the minimum safe separations applied in the ICAO NAT region. As E. Garcia [3] identified, it was during the 1990s when a new wave of different theoretical studies was introduced extending the Reich approach to more complex airspace scenarios [4–9].

None of these models though consider scenarios with positive control, where the a priori planned trajectory is usually continuously monitored and modified, as it is required in high-density controlled airspaces, in order to maintain the demanded flow throughput safely.

Just by using statistical concepts applied to aircraft, flying their planned trajectories with some degree of uncertainty, it is not feasible to capture the intrinsic complexity of the traffic flows flying planned trajectories but dynamically adapted to accommodate the airspace demand-capacity balance problems.

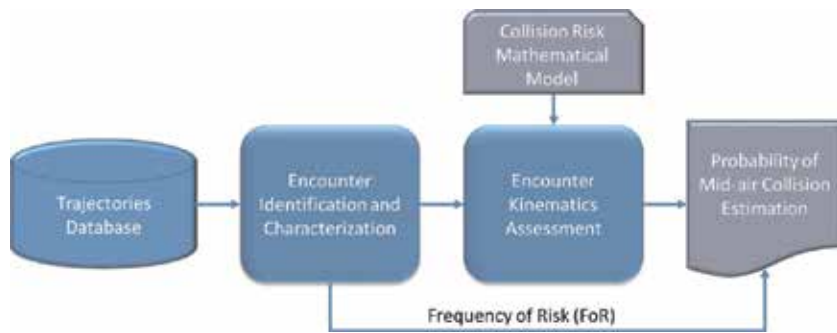


Figure 1.
Method to estimate the probability of mid-air collision.

Currently, complexity is derived from reports provided by the controllers and pilots involved in the incidents, from which the mid-air collision risk is estimated. These incidents are extremely rare events, which make them infeasible to derive any reliable statistics. Furthermore, not all incidents are reported, making it difficult to infer how many true incidents have really occurred. Finally, the used incident classification is ranked according to how close the involved aircraft finally were, omitting any associated kinematics, which could provide us with more representative information about risk.

This chapter describes how to estimate the probability of mid-air collision plus additional helpful information, used to estimate the safety level of given airspace when populated with a sample of air traffic. The process is based on an integrated hybrid approach, using flights stored in a database and a stochastic mathematical collision risk model. The database containing the trajectory description for the traffic sample is used to empirically determine the conflicts or encounters from which the frequency of risks (FoR) and the kinematics of the aircraft involved in these encounters can be determined. Whereas the mathematical model is used to estimate the probability of collision associated with each aircraft encounter, and from them the global probability of air miss [10], **Figure 1** describes the whole process:

Risk is here understood as any event that requires immediate reaction to avoid a dangerous situation which has the potential to cause damage or harm. In particular, regarding mid-air collisions, it refers to any situation where two or more aircraft are evolving toward a loss of separation; if not corrective action is taken.

Nowadays there are different databases from which the encounter identification and characterization can be derived. They can be grouped into two families: *surveillance data files*, describing the aircraft trajectories by a sequence of 3D + T positions for all flights at time intervals (around every 5 s), and *on event data files*, containing 3D + T positions or all flights at any time the aircraft speed vector changes, for example, the Demand Data Repository 2 (DDR2) of Eurocontrol. This chapter applies the results to a particular case of use, with the purpose of showing the value of the model as a powerful safety tool. There are different tools that allow us to identify and characterize the encounters from these databases, for example, the Eurocontrol's Network Strategic Tool (NEST) uses DDR2 to this end. In this work, the used tool was developed by E. Garcia [3].

2. Risk mitigation in a defensive ATM structure composed of layers and barriers

James Reason proposed in his Swiss cheese model (SCM) [11] that accidents and incidents can be traced through up to four different domains: organizational

influences, supervision, preconditions, and specific acts. Accidents and incidents in the airspace caused by the air traffic management (ATM) are known as “air miss,” and they represent a safety issue or a risk. Safety is then usually measured by its absence, using the risk as key indicator.

Safety in ATM has two opposite sides: negative and positive. The first is given by air miss caused by the ATM system failure. Luckily, as for all safety-critical systems, these are always rare events, and removing them, as much as reasonably possible, is the main objective of the safety sciences. The positive side of safety, on the other hand, relies on the background of these systems evaluated by its intrinsic resistance to operational risk.

Within ATM, the ICAO’s Annex 19 and the Safety Management Manual [12–13] contain the required guidance, to be used by practitioners, for measuring the safety’s negative side and, as well, the intrinsic resistance to risk. Derived from these documents, ATM organizations have built up the safety management systems (SMS) that, among others, deal with risk and risk events and how to make the ATM system more resistant to risks, based on these.

As previously mentioned, risk means in this chapter any dangerous situation that arises from hazards and requires immediate reaction, while hazard is something, such as a physical object, environmental variable, or a state of a process, that causes or leads to problems. In general terms, it can be stated that the airspace, particularly in high-density volumes, is hazardous, because there are objects (aircraft) sharing it, where weather conditions, or other unplanned events, might drive changes in their initial flight plans, and then, the operations have to be adapted in real time to ensure the safety while handling the required system throughput, even under the uncertainties derived from these and other circumstances.

ATM contains three different “defensive” big layers; air space management (ASM), air traffic flow management (ATFM), and air traffic control (ATC), all of them devoted to reduce the hazards and, when cannot be removed, the likelihood of risks produced by those hazards and the severity of such a risks. Briefly, it can be summarized that the ASM layer function is to determine the volumes (airspace availability) and the required conditions under which aircraft can operate within them safely. Complementary, ATFM layer is devoted to the function of making compatible the demand for flights with the available capacity of airspace and airports in the so-called demand-capacity balancing process. Finally, the ATC layer is looking after the separation between any pair of aircraft and ensuring they are always flying with these separations above the applicable minima while maintaining the system throughput and the efficiency of flights.

Within the ATC layer then, pilots and air traffic controllers are working together to minimize the likelihood of having an “air miss” or a loss of separation. ATC as such usually contains different safety barriers, for instance, MTCO and STCA, and beyond these ATC barriers, commercial aviation has an additional technologically supported barrier: the TCAS. Beyond that, the see and avoid and the providence are the very last chances to avoid an accident. Any foreseen air miss finally sorted becomes a “near air miss” or “near miss.”

The layered scheme presented above (**Figure 2**) indicates that the design of the ATM system is driven by safety. The knowledge about the contributions to the safety provided by each layer or barrier is then a paramount target in the assessment of the ATM safety performance.

This chapter focuses its interest in establishing a method to derive the level of safety produced by the ATC safety layer when a volume of airspace was populated for a given sample of flights, executing their actual trajectories, during a given timeframe. It is assumed that the sample of flown trajectories has been stored in a database.



Figure 2.
The ATM safety layers, the ATC, and beyond safety barriers.

3. Risk identification: conflict

Risk is then any dangerous situation that arises from hazards where the safety is compromised and demands an immediate reaction. When it is applied to air misses, risk is considered as any situation where two or more aircraft are in course of losing the required separation minima in the coming minutes. These events are referred here as “conflicts.”

Obviously, when we use stored data, containing just flown trajectories, almost all of them are “conflict-free,” as during their operation, the pilots and controllers, supported when required by the safety barriers, reacted and removed all of them, and, as a consequence, there aren’t dangerous situations recorded, reflecting in a hidden manner the effectiveness of the operational personnel and safety barriers but nothing regarding how hard they worked out.

This lack of information has to be sorted by performing some kind of inference to unveil where and when the conflicts appeared and how they were sorted. If the available data source contains not only the actual flown trajectories but also the planned trajectories, then it would not be so complicated to derive when a change in the expected trajectory is driven by a reaction to a conflict. But if the planned trajectories are not known, the conflict identification is inferred from the following process.

Most of the stored flown trajectories exhibit a uniform behavior during most of their flight time, that is, except for some short intervals, where the aircraft changes their vertical speed or heading, the rest of the time they broadly follow the law of the uniform movement. Consequently, the stored trajectories can be approached by an ordered sequence of straight lines (assuming flat Earth), flown at constant speed, connected by events or “joints” where some change of the vertical speed or heading is registered [3]. This model is perfectly suited for en route airspaces but can have some limitations at terminal manoeuvre areas (TMAs), where the straight segments can be modeled by polynomial splines [14]. It should be remarked that the initial data, containing aircraft positions every few seconds, is now transformed into the mentioned ordered sequence of segments parameterized with time.

Once the flown trajectories are represented by this sequence of segments parameterized with time, the current and expected positions within a predefined look ahead time (LAT) can be determined at any time (see **Figure 3**). Hence, at each time, the positions for all aircraft within the chosen LAT are well defined, and the existence of conflicts in such a time horizon can be captured.

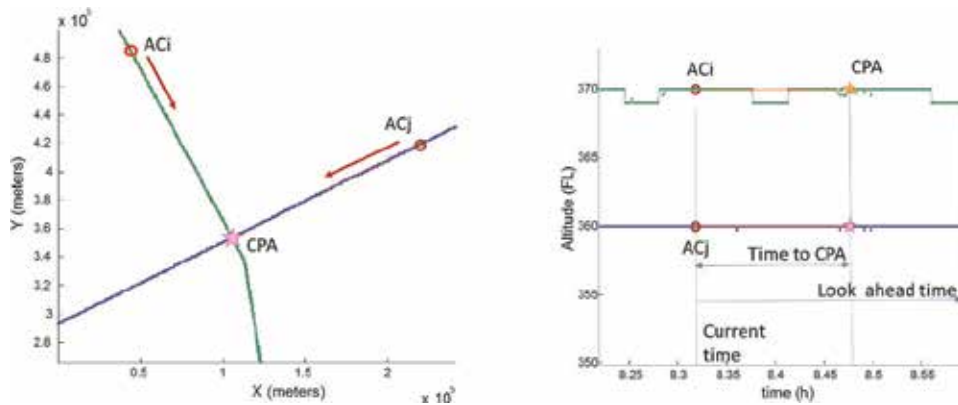


Figure 3. Identification of a conflict from the segmented trajectories (courtesy of Eduardo Garcia).

There are different elements that characterize any conflict as:

- The look ahead time (LAT), the chosen timeframe during which the current position is extrapolated, assuming uniform movement, determining the expected “short-term” trajectories of the aircraft
- The involved aircraft, usually two, discretionally named as the reference aircraft (ACi) and the intruder aircraft (ACj)
- The closest point of approach (CPA), the physical situation in the airspace where the two involved aircraft are (or are expected to be) at minimum distance. Note that CPA encloses the 2 physical points, representing the positions of both aircraft, the distance between them, and the time of occurrence
- The time to CPA, the remaining time until the involved aircraft reach the CPA

The LAT is a key parameter that has to be adapted to the characteristics of the assessed airspace, for instance, in en route airspace, the aircraft follows extensively the assumption made considering uniform movement, unless something unexpected happens (weather, other traffic, etc.) and then extrapolating the current position through along LAT seems acceptable, say, for example, 10 min. On the other hand, in high-density TMAs, the flown trajectories have shorter straight segments, which means that is not realistic to extrapolate the current position with such LAT but with values around 2 min or less. The best value for the LAT has to be derived from the observation of the flown trajectories in the airspace of interest, establishing the average time the aircraft has been flying following uniform movement.

4. Characterization of conflicts

Working with trajectories as straight lines, parameterized with time, makes rather simple and computationally fast, using linear geometry, to find out the minimum distance between them and the time it happens. It is then applicable to explore for encounters or aircraft crossings, and particularly conflicts, at any

time (t), using the chosen LAT, just by extrapolating the position at this time (t) up to ($t + LAT$) and computing for all flights the minimum distance between possible pairs. If this distance is equal to or below the applicable separation minima, then it is declared as a conflict; otherwise, it will be a crossing.

In high-density airspaces, the separation minima are defined by building up a protection cylinder around aircraft, which shall remain free at all times of other aircraft. For example, typical dimensions for such a cylinder are a radius of 5 nautical miles (NM) and height of 2000 feet (ft), considering the aircraft in the center. From now on, this cylinder will be named as “conflict cylinder.” Analogously, the “collision cylinder” is defined by using as horizontal (λ_{xy}) and vertical (λ_z) values the characteristic dimensions of the aircraft (see **Figure 4**).

The conflict or collision events characterization can be better observed when referred to reference aircraft (ACi) axes rather than when referred to the local axis (Earth fixed). Two reference frames fixed to ACi are used, vertical (x, y, z) reference frame and the projection frame (x_1, y_1, z_1).

The vertical reference frame is defined by the local vertical axis (Oz). Then, the horizontal axis (Ox) is perpendicular to Oz and contained in the plane defined by this axis (Oz) and the vector velocity of the intruder (ACj) relative to ACi (v_{ji}). And the (Oy) horizontal axis is perpendicular to the other two axes. From this vertical frame, the projection frame (x_1, y_1, z_1) is obtained by rotating through (Oy) axis the vertical plane (y, z) until the (Ox) axis is parallel to (v_{ji}). Let us call the resulting (y_1, z_1) plane “impact plane” where the intruder (ACj) will hit this plane just when they reach the CPA.

Figure 5 shows an encounter between the reference aircraft (ACi) and the intruder (ACj), where the intruder is approaching the reference with a relative velocity (v_{ji}). The reference aircraft (ACi) has been represented with its collision (in yellow) and conflict volumes (not in scale) on the top left-hand side. On the bottom right-hand side, the projections of such cylinders onto the impact plane ($y_1 z_1$) are presented. As can be seen, depending on the foreseen impact of the intruder on the impact plane (red dot), the severity of the encounter can be derived, allowing, in a deterministic way, to establish if the intruder is in a course of having a conflict or even a collision or just a crossing without compromising the separation minima.

Applying the above method, the author and others [3] over a particular traffic sample of 1 month flying over Maastricht airspace (MUAC) that included 131,151 flights and 47,078 flown hours obtained the results shown in **Figure 6**.

From these results, the frequency of risk or FoR (situations requiring corrective action) is around 0.27, and the rounded frequency of air miss or near air miss is 1.4×10^{-4} .

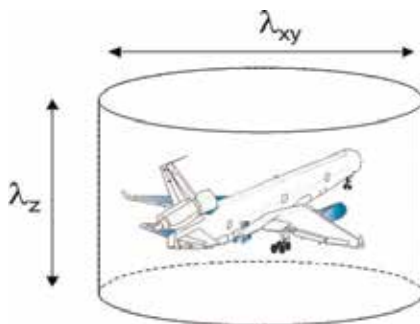


Figure 4. Characterization of the collision cylinder (courtesy of Eduardo Garcia).

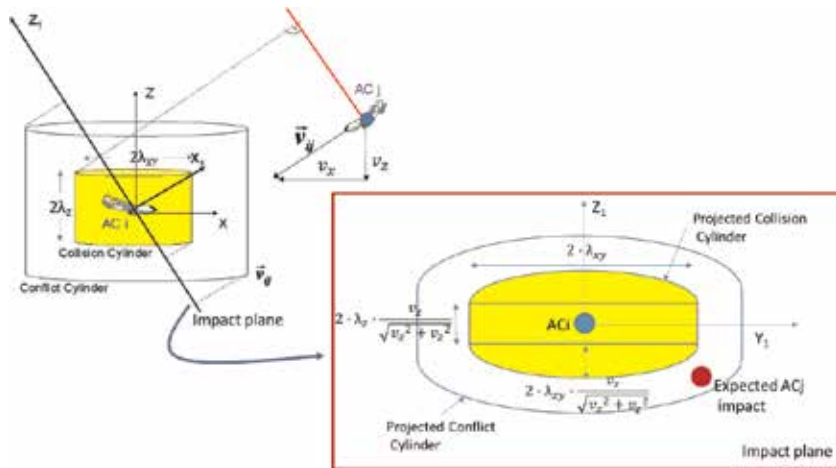


Figure 5. Identification of a pairwise encounter determining if it will come up as “safe” crossing, conflict, or collision, depending on the expected impact of the intruder onto the (y_1, z_1) plane.

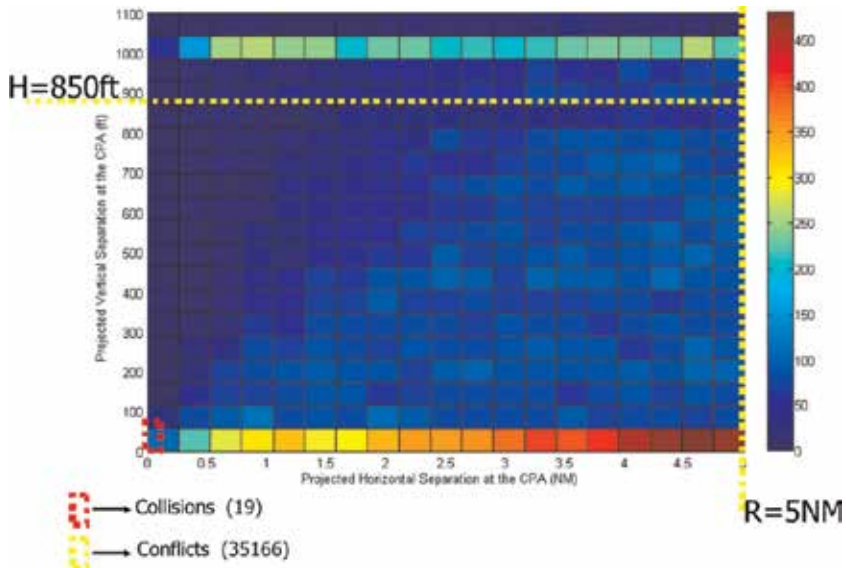


Figure 6. Separation of expected impacts of the intruder aircraft onto the impact plane of the reference aircraft for a sample of 131,151 flights.

The above description presents an aggregated deterministic model providing relevant information about the number of initial safety issues (conflicts and near-miss) for a particular traffic sample, flying in a given airspace, just by using the stored flights in the form of surveillance data files or on event data files. In the example, the former was used.

The method proposed ignores many elements that are essential to unveil relevant information related to the actual safety level of the scenario, populated with the sample of traffic, as:

- Kinematics of the encounter (relative velocity)
- The available time until reaching CPA when the conflict was initially detected

- The time taken by ATC to remove the conflict condition or the time to CPA when it was sorted
- Uncertainty of the current and, particularly, the extrapolated position of aircraft

This information is singular for each encounter, but some aggregations illustrate relevant characteristics related to safety.

5. Time evolution of conflicts and the safety barriers

The method of using current positions at any time, and their extrapolated positions, allows to track the evolution of conflicts while evolving toward the CPA [3]. There is neither common criteria nor common characteristics of the safety barriers applied in ATC. Although STCA is broadly applied, each ATC system can have a different value of the time to CPA value that triggers this alert to the controller (between 90 and 120 sec.). MTCD is a supporting tool that has not been always welcomed by controllers, and then, it is omitted in the following discussion, using instead the operational pre-tactical and tactical barriers (Figure 7).

Typically, in an ATC center, the controllers try to remove the conflicts as early as possible; this criterion is limited by the uncertainty associated with the extrapolation of the current aircraft positions. Some of the identified conflicts might not be actual conflict; then taking the removal decision of such uncertain conflict far in advance introduces undesirable disturbances in the aircraft planned trajectories. This is why operationally it is usually considered that a conflict sorted before around 4 min prior to reaching the CPA is a pre-tactical ATC action. On the other hand, some conflicts appear with a very short term in advance, even with times to CPA below these times.

When the removal of the conflict is taken later, but before reaching 2 min to CPA, then it is said it has been solved at the tactical level. Around these 2 min, most ATC systems provide the controllers with the STCA tool that triggers an aural and visual alert, preventing them that they shall take immediate corrective action.

When all the above barriers have failed, and the thread of an air miss remains, the involved aircraft triggers the TCAS TA just when the time to CPA reaches around 48 s. Once a TCAS TA is triggered, the aircraft still shall follow the

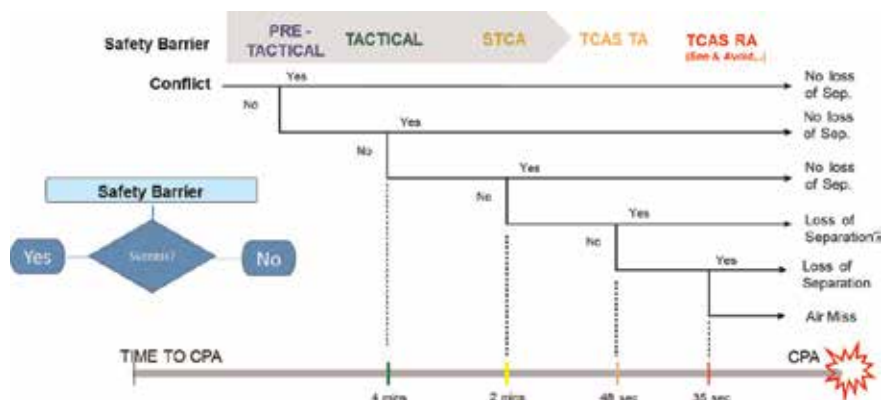


Figure 7. Example of safety barriers and their triggering times to CPA. Pre-tactical, tactical, and STCA are part of ATC. TCAS is not an ATC barrier.

controller instructions, but if the situation remains and the time to CPA reaches 35 s, the TCAS will trigger the RA and indicates to the involved pilots the vertical maneuver they shall follow; once RA is triggered, these pilots shall ignore any further instruction by the controller.

In the brief previous discussion, the relevance of exploring the relative frequency of unsuccessful removal of conflicts by a given safety barrier becomes clear.

Figure 8 shows a scatter plot with the number of conflicts for each time to go to CPA when the conflict was identified, the associated reaction, and the time required to sort it. The data used was drawn from the same sample than in the previous example.

As observed, most of the conflicts (33,185 AC out of 35,166) are identified with more than 4 min before the CPA, although there are some “sudden” conflicts that appear with less than 4 min and more than 2 min (1763 AC), and even there are those arising between 2 min and 45 s before reaching the CPA (190 AC), the latest demanding urgent attention. The figure also shows that few of them were not solved and reached the CPA without ending in an air miss. This fact (those cases represented over the diagonal of the graph) indicates that the separation minima were infringed, which is an ATC failure, but the involved aircraft still crossed each other with enough separation to avoid the air miss.

Additionally, **Figure 8** shows that around 88% (31,109 AC enclosed by the box) of the conflicts were identified between 5.5 and 10 min to go to the CPA and sorted in a time between 30 s and 2 min and 15 s.

Figure 9 represents the times used in the previous discussion, relative to the CPA time.

Barragan [15] studied the value of the frequency of conflicts associated with their time to go to CPA and the overall reaction time to produce precursors about the safety status of airspace volumes. Clearly, the airspace where conflicts are identified soon, when the involved aircraft is still far from reaching the CPA, and the overall reaction time to remove them is small exhibits good behavior, whereas if the former decays and the latter grows, some concerns should have risen about the safety in this airspace. Summarizing, if τ_1 is big (above 4 min) and τ_2 small (below 2 min) and condition $\tau_1 \gg \tau_2$ applies, then the ATC safety barriers are working properly; otherwise, some concerns arise.

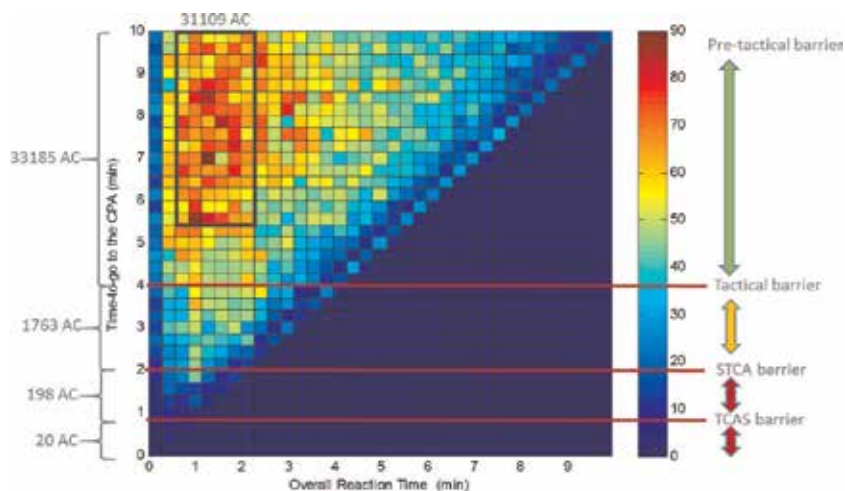


Figure 8.
Frequency of conflicts for given times to CPA and overall reaction time.

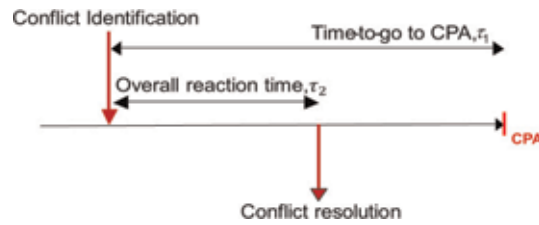


Figure 9.
Interpretation of overall reaction time and time to go to CPA.

6. Measuring the effect of the safety barriers

The previous section presented the time evolution of the airspace conflicts for a sample of traffic, deriving some deterministic results. This information unveils the degree of stress under which the controllers dealt with the air traffic encounters contained in the sample. The model is able to provide as well the effectiveness of the safety barriers comparing the predicted separation of the involved aircraft (at the CPA), when the conflict was identified, with the final separation of those aircraft that crossed each other. **Figure 10** shows the three-dimensional results.

The red dot in the bottom of **Figure 10** is defined by the coordinates:

Predicted horizontal separation (NM)	Actual horizontal separation (NM)	Number of conflicts
0	5	3

The sample then contains, among all conflicts having a “Predicted Horizontal Separation” of 0NM, 3 conflicts that finally had an actual separation of 5NM.

The bottom part of vertical plane, represented by red dotted lines, shows only two conflicts (the little peaks) with predicted horizontal separations of 2 and 4 NM that finally had an actual separation of 4NM. It can be also observed that there are no conflicts with an actual separation equal to or below 3NM.

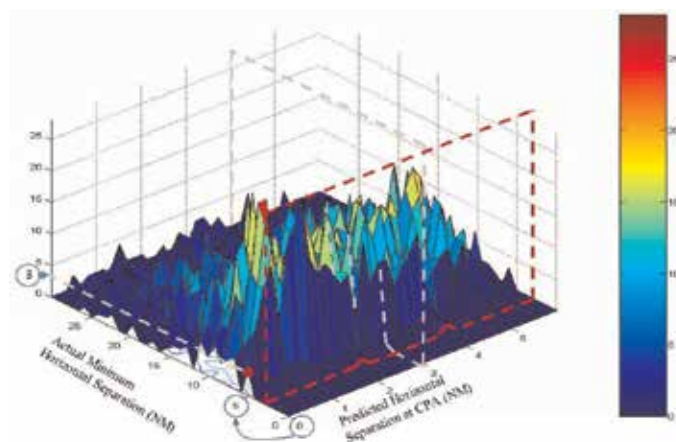


Figure 10.
Representation of the effectiveness of the safety barriers.

All the sections above use a simple linear model over the database to extrapolate the current aircraft positions until the LAT and take the resulting segments, containing the time as parameter, to determine the separation between all possible aircraft pairs. If the separation is below the required minima, then a conflict is declared, and the key elements of it are retained to perform the assessment presented for a particular case of use.

Of course, as has been shown, relevant information about safety is derived, but still, there is not a simple formula that could estimate the safety level. This is the objective of the next section.

7. Estimation of the level of safety

Let us now abandon the deterministic approach followed so far, although we still require the sample of traffic in a given scenario. Now it is assumed that both the actual position and the predicted future positions are just estimates of actual position and expected future positions of the trajectory.

The objective is to estimate the probability of an air miss associated with each crossing or among all captured pairwise encounters from the aircraft population. It is pointed out that, now, we are considering not only those encounters with an expected separation at the CPA below the separation minima (conflicts) but as well as those with separations above these limits. This is to recognize that any foresee crossing; irrespectively the expected separation at the CPA might come up with an air miss.

According to **Figure 5**, captured encounters are identified by the CPA, which is the situation where the separation between ACi and ACj will be minimum, and the intruder (ACj) will reach the impact plane after a time (τ_1) at the point, in the reference frame (x_1, y_1, z_1), of coordinates $(0, y_{1p}, z_{1p})$.

Let us assume that the probability density function of the intruder aircraft (ACj) reaching the CPA at the time (τ_1) hitting the impact at coordinates $(0, y_{1p}, z_{1p})$ is known: $f_p(y_{1p}, z_{1p})$. Then, the probability of collision, that is to say, the probability that these coordinates are within the collision area (S_{PCOL} , yellow area in the impact plane represented in **Figure 5**, right-hand side) of the reference aircraft (ACi), is given by:

$$P_2(y_{1p}, z_{1p}) = \int_{S_{PCOL}} f_p(y_{1p}, z_{1p}) dy_1 dz_1 \approx f_p(y_{1p}, z_{1p}) \cdot S_{PCOL} \quad (1)$$

The approximation made in the last term of Eq. (1) assumes that the pdf function remains constant over the collision surface, as these surface dimensions (characteristic distance below 150 ft) are very small in comparison with the characteristic horizontal (y_p) and vertical (z_p) distances of around 5NM and 1000 ft., respectively, that produce first-order changes in this pdf function.

Eq. (1) shows the way to establish the safety level of any scenario populated with known air traffic (positions and velocity). To this end, the two factors in the last term of the equation shall be determined for each encounter.

The surface of collision (S_{PCOL}), defined onto the impact plane, is given by the physical typical dimensions of the aircraft (λ_{xy}, λ_z) and, additionally, by the horizontal and vertical components of the velocity of the intruder (ACj) relative to the reference (ACi) aircraft (v_x, v_z). Therefore, it can be expressed as the area of the rectangle plus the area of the two half of ellipse, resulting in:

$$\begin{aligned}
 S_{PCOL}(\lambda_{xy}, \lambda_z, v_x, v_z) &= 4\lambda_{xy}\lambda_z \cdot \frac{v_x}{\sqrt{v_x^2 + v_z^2}} + \pi\lambda_{xy}^2 \cdot \frac{v_z}{\sqrt{v_x^2 + v_z^2}} \\
 &= 4\lambda_{xy}\lambda_z \cdot \frac{v_x}{\sqrt{v_x^2 + v_z^2}} \left[1 + \frac{\pi}{4} \cdot \frac{\lambda_{xy}}{\lambda_z} \cdot \frac{v_z}{v_x} \right]
 \end{aligned} \tag{2}$$

The probability density function $f_p(y_{1p}, z_{1p})$ determination requires a careful approach to obtain realistic results, despite the random nature of the involved variables (τ_1, y_{1p}, z_{1p}) . One key assumption is to consider that it is a bivariate normal distribution with zero mean (no biases) in (y_{1p}, z_{1p}) , while the time to go to CPA (τ_1) variable affects linearly the value of the standard deviations of those variables. Additionally, it is assumed that the two random variables (y_{1p}, z_{1p}) are uncorrelated. Then, applying the above considerations, the expression for the $f_p(y_{1p}, z_{1p})$ results in:

$$f_p(y_{1p}, z_{1p}) = \frac{e^{-\frac{1}{2} \left(\frac{y_{1p}^2}{\sigma_{y1}^2} + \frac{z_{1p}^2}{\sigma_{z1}^2} \right)}}{2\pi\sigma_{y1}\sigma_{z1}} \tag{3}$$

where the standard deviations for coordinates (y_{1p}, z_{1p}) , $(\sigma_{y1}, \sigma_{z1})$, respectively, are linearly dependent on τ_1 . Eq. (3) can be expressed in terms of the vertical reference frame (x, y, z) as presented in **Figure 5**, becoming:

$$f_p(y_p, z_p) = \frac{e^{-\frac{1}{2} \left(\frac{y_p^2}{\sigma_y^2} + \frac{z_p^2}{\sigma_z^2} \right)}}{2\pi\sigma_y\sigma_z} \tag{4}$$

Meanwhile, the time to go to CPA (τ_1), degrades the value of the standard deviations as:

$$\begin{bmatrix} \sigma_y \\ \sigma_z \end{bmatrix} = \begin{bmatrix} \sigma_{y0} \\ \sigma_{z0} \end{bmatrix} \cdot [(1 + r_y \cdot \tau_1) \quad (1 + r_z \cdot \tau_1)] \tag{5}$$

where r_y and r_z are the ratios giving the increase (in NM and ft., respectively, per minute) of the horizontal and vertical standard deviations, respectively, with the time to go to CPA. Now the stochastic model demands four parameters to determine the probability density function, $f_p(y_p, z_p)$; these are:

Parameter	Units	Comment
Horizontal standard deviation, σ_{y0}	Nautical miles	It is related to the accuracy of the position for the involved ACs as stored in the database, around several NM
Standard deviation over Oz ₁ axis, σ_{z0}	Feet	As above, around a hundred feet
Ratio of variation of the horizontal standard deviation, r_y	Nautical miles per minute	This value shall be estimated assessing the errors in the model to predict the future positions, around 1NM per minute
Ratio of variation of the Standard deviation over Oz ₁ axis, r_z	Feet per minute	Varies, when $v_z = 0$ is low, say 20 ft./minute. When $v_z \neq 0$ is high, say 500 ft./minute

Once the above parameters are defined, using any traffic sample of N aircraft, all crossings between aircraft can be captured and analyzed, determining their three main variables:

- Time to go to the CPA (τ_1) when the encounter was initially identified
- Horizontal separation at the CPA (y_p)
- Vertical separation at the CPA (z_p)

Finally, the values for the collision volume shall be determined with the parameters (λ_{xy}, λ_z).

With all these elements, the estimated probability of an air miss $E(P_{coll})$, before acting the ATC barriers, for the traffic sample is given by:

$$E(P_{coll}) = \frac{2}{2\pi N} \sum_1^{N/2} e^{-\frac{1}{2} \left(\frac{y_p^2}{\sigma_y^2} + \frac{z_p^2}{\sigma_z^2} \right)} 4\lambda_{xy}\lambda_z \cdot \frac{v_x}{\sqrt{v_x^2 + v_z^2}} \left[1 + \frac{\pi}{4} \cdot \frac{\lambda_{xy}}{\lambda_z} \cdot \frac{v_z}{v_x} \right] \quad (6)$$

where N is the number of flights in the sample, regardless of them having a crossing or not, in cases of flight without crossings, they count on N. When an aircraft has different crossings, it counts as a different flight for each.

Computationally this expression (6) is demanding, considering that the variables ($\tau_1, y_p, z_p, v_x, v_z$) are dependent on each particular aircraft pair, as they are the parameters (σ_y, σ_z) which are τ_1 dependent. The computational burden then grows linearly with the size of the sample. When applying this model to the case of use, the obtained results are the following.

Collision risk of the traffic sample before the air traffic controllers and pilots react to remove conflicts is $E(P_{coll}) = 1.23 \times 10^{-4}$. Eq. (6) can also be applied taking other times to go to CPA (τ_1); other representative times are looking for the probability of collision of encounters when triggering the STCA (say, 2 min before CPA), the result, in this case, is $E(P_{coll})_{STCA} = 6.65 \times 10^{-6}$. If it is the one triggering TCAS TA (48s), we get $E(P_{coll})_{TA} = 5.30 \times 10^{-7}$. Finally, when the conflict evolves and reaches the value that triggers the TCAS RA (35s), the value is $E(P_{coll})_{RA} = 8.25 \times 10^{-8}$ (**Figure 11**).

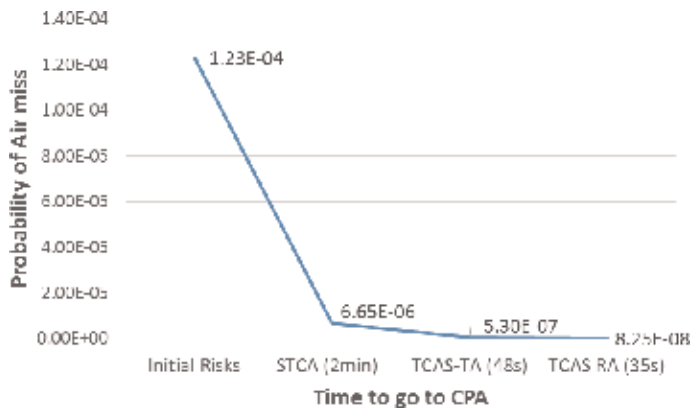


Figure 11.
 Evolution of the probability of air miss with time to go to CPA.

These values, together with the information obtained in the deterministic part of the chapter, described previously, complete the methodology CRM to assess the safety performance of a given traffic sample of flights in a defined volume of airspace.

8. Conclusions

High-density airspaces are actively managed by ATC, speeding up the traffic flows and maintaining the required separation minima at any time. Their job is based on the surveillance of the traffic flying within their volumes of responsibility (ATC sectors). The surveillance function is supported by radar and/or other sensors (multi-lateration, ADS B, etc.), and the tracks representing the state vector of the aircraft presented to controllers are, as well, usually stored in databases.

The chapter presents a collision risk model that helps to assess the safety characteristics for any volume of airspace where the above data sources are available. The model is data-driven, and most of the information comes up directly from working with the stored flown trajectories complemented with a linear prediction of future positions of the flights, up the so-called look ahead time (LAT).

In the last section, nevertheless, the stochastic nature of both, the data and the linear predictive models, have been considered, providing relevant additional information about the safety levels of the traffic in the sample for different chosen times to go to CPA.

The sampled used takes radar tracks during a month of flights through the MUAC airspace, but other sources of information can also be used, particularly DDR2 from Eurocontrol, containing significant points of the trajectories, where a special event, apart from the uniform movement, took place.

The results show interesting information closely related to the safety of the airspace volume, when populated with the flights contained in the sample, from deferent viewpoints as:

- Frequency of risks at a time (τ_1) before reaching CPA, where the ATC conflict was identified
- The overall time required to remove the conflict (τ_2)
- The initial (when the conflict was identified) and final (actual) distances at CPA for each conflict
- An estimation of the probability of air miss at different safety barriers

This set of information provides an exhaustive picture of the safety level exhibited by the flown trajectories. The airspace volume, and the data sample, can be chosen, with the only limits of making the results representative and, on the other hand, allowing our computational capabilities to work out with the amount of data, keeping in mind that the burden grows linearly with the size of the sample.

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Relationship between Air Traffic Demand, Safety and Complexity in High-Density Airspace in Europe

Tamara Pejovic, Fedja Netjasov and Dusan Crnogorac

Abstract

Air traffic performance of the European air traffic system depends not only on traffic demand but also on airspace structure and its traffic distribution. These structural (airspace structure) and flow characteristics (factors such as traffic volume, climbing/descending traffic, mix of aircraft type, military area activity) influence airspace complexity, which can affect controller workload and influence the probability of safety occurrence. In other words, all these dynamic and static complexity components can potentially have an impact upon the safety of the air traffic management (ATM) system. Having in mind fluctuation in traffic on daily, seasonal or annual level in certain airspace, a few questions arise: How changes in traffic demand influence complexity and conflict risk? Is there any correlation between traffic demand, conflict risk and complexity? and Are there any differences between seasons? For that purpose, an investigation is performed on FAB Europe Central (FABEC) airspace, based on 2 weeks of operated traffic during the summer and fall of 2017. Air traffic complexity is estimated using the EUROCONTROL complexity metrics, while conflict risk is assessed using the conflict risk assessment simulation tool. Results show that certain positive relationship exists between traffic demand, conflict risk and complexity.

Keywords: air traffic complexity, conflict risk assessment, air traffic management, safety performance

1. Introduction

In 2018, instrument flight rule (IFR) movements within the European airspace continued to grow strongly (4.65% versus 2017), making last year a new record year in terms of traffic volumes: the number of flights controlled reached an all-time record of more than 11 million [1]. The forecast growth indicates that by 2021, the European sky will handle over 12.3 million operations.

This is an incredible challenge for the safety, the en route sector capacity and impact on the environment. The implementation of two operational concepts, the free route airspace (FRA) and functional airspace block (FAB), is seen as crucial 'tools' for solving those issues.

By definition, FRA is a specified airspace wherein users can freely plan a route between a defined entry point and a defined exit point, with the possibility of

routing via intermediate (published or unpublished) waypoints, without reference to the air traffic service (ATS) route network, subject of course to availability. Within such airspace, flights remain subject to air traffic control (ATC) for the separation provision and flight level (FL) change authorizations.

The overall benefits of free route operations are distance and flight timesaving, resulting in less fuel consumption and a notable reduction of engine emissions, which benefits the environment [2]. FRA is seen as a cornerstone to improve FAB Europe Central (FABEC) structure and utilisation.

From the other side, an implementation of FABs should bring further efficiency of airspace operations because FABs are ‘based on operational requirements and established regardless of State boundaries, in which the provision of air navigation services and related ancillary functions are optimized and/or integrated’ [3]. Currently, there are nine FABs established to cover almost the whole European airspace [3]:

- Baltic FAB (Lithuania, Poland)
- BLUE MED FAB (Cyprus, Greece, Italy and Malta)
- Danish-Swedish FAB
- Danube FAB (Bulgaria, Romania)
- FAB CE (Austria, Bosnia and Herzegovina, Croatia, Czech Republic, Hungary, Slovak Republic, Slovenia)
- FABEC (Belgium, France, Germany, Luxembourg, the Netherlands and Switzerland)
- North European FAB (Estonia, Finland, Latvia, and Norway)
- South West FAB (Portugal, Spain)
- UK-Ireland FAB

However, their implementation is still too slow (according to the European Commission [3]) causing inefficiency in the European ATM system.

1.1 Complexity of air traffic

Complexity of air traffic can be defined as the level of either perceived or actual spatial and time-related interactions between aircrafts operating in a given airspace during a given period. Specifically, complexity of air traffic in a given airspace can be very high solely because of the traffic intensity and its pattern in terms of mutual interactions between different traffic flows, as well as between individual aircrafts. Such presumably high complexity could be used for both planning and operational purposes mainly aimed at reducing it. Consequently, it may be reduced at the strategic, tactical and pre-tactical level. At each of these levels, it can have a spatial-based nature (such as airspace and airfield system design and/or assignment such as air routes, sectors, terminals, runway systems, etc.) and also time-based solutions (such as schedules, slot allocations, flow management, etc.). In that context, according to Netjasov et al. [4], complexity is understood as a demand characteristic of air traffic that is to be served by an appropriate supply system.

Gianazza [5] claimed that no single universal complexity measure exists but rather a set of complexity metrics, shown to be useful and relevant in a particular context and for a particular purpose.

Over the last 25 years, concern about measuring how difficult a traffic situation is, i.e. measuring complexity, has risen. Mogford et al. [6, 7] were some of the first to deal with complexity and its influence on air traffic controllers (ATCo) workload. They identified two basic elements of ATC complexity: sector complexity and traffic complexity. Dealing with the influence of a 'free flight' on physical and mental workload of the ATCos, Pawlak et al. [8] developed a model of air traffic complexity with the hypothesis that complexity causes a great change in the ATC cognitive workload.

In order to measure the ATCo workload, Laudeman et al. introduced a concept called 'Dynamic Density' (DD), which 'includes both traffic density (a count of aircraft in a volume of airspace) and traffic complexity (a measure of the complexity of the air traffic in a volume of airspace)' [9]. DD was also applied in the studies of Sridhar et al. [10] with the aim of determining whether a DD could be predicted in the future. DD concept was further elaborated and its applicability further broadened in the studies of Smith et al. [11], Kopardekar and Magyarits [12], Masalonis et al. [13], Rantanen et al. [14] and Kopardekar et al. [15, 16].

Schaefer [17] defines complexity as a measure of difficulty that a particular traffic situation will present to an ATCo. This measure is limited to the characteristics of the traffic situation itself and may thus be considered as a factor that contributes to the workload. Schaefer used complexity as a key concept for solving the problem of the ATCo workload and sector capacity. Similarly, Chaboud et al. [18] have studied the influence of complexity on workload and air traffic service costs and Flynn et al. [19] on sector categorisation and comparison between the US and European sectors based on traffic complexity characteristics. de Oliveira et al. [20] are dealing with workload balancing using complexity. Even in the last decade, investigation of relationship between complexity and workload remained actual [21–23].

Delahaye and Puechmorel [24], Histon et al. [25] and Delahaye et al. [26] dealt with the problem of measuring complexity of air traffic. They assumed that airspace complexity is related to the traffic structure and airspace geometry. According to this assumption, they concluded that a measure of complexity would find wide application in balancing the sector load, distribution of traffic in the sense of congestion, new airway network design, dynamic sectorisation, slot allocation, traffic flow management, comparison of different airspace structure effectiveness, etc. Following previous study, Gianazza [5, 27] applied complexity metrics to airspace configuration. In its study, Hilburn [28] provides a comprehensive literature survey of different theoretical views concerning complexity, different complexity factors and data collection methods. He identified more than 100 complexity factors and almost 30 methods for elicitation, refinement and validation of complexity factors.

Other approaches to define, measure, manage or even reduce air traffic or airspace complexity have recently appeared, opening a new field for further application of the complexity metric [29–32]. The above-mentioned overview also shows that great attention was given to modelling and measuring complexity in the en route environment related to the ATCo workload.

In recent years new approaches to study air traffic complexity emerged. Hong and Kim [33] dealing with the reduction of air traffic complexity have introduced a concept of complexity map. Wang et al. [34, 35] investigated the structure of air traffic situations based on aircraft clusterisation and using complex network theory. Further on searching for objective air traffic situation measurement, they have used a dynamic weighted network [36]. Some authors have used machine learning methods (ensemble learning models) [37, 38] while others human-in-the-loop simulations [39].

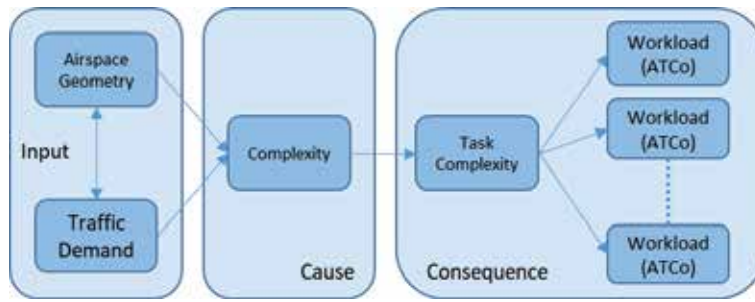


Figure 1. Scheme of the relationship between complexity, task complexity and workload (based on [4]).

Traffic complexity affects control task complexity (**Figure 1**), where the control is performed by human operator. It is expected that a more complex task will produce a higher workload. However, the workload differs between ATCos (**Figure 1**) due to differences in their working environment, perception of the traffic situation, personal experience, etc. Therefore, complexity represents a contributing factor of task complexity and ATCo workload (more on ATCo workload modelling may be found in the studies of Loft et al. [40] and Majumdar and Ochieng [41]).

The approach presented in this chapter is based on EUROCONTROL [42] methodology, with exclusion of ATCo workload issue from the explicit consideration. Approach is taking a macroscopic view, and it is considering four complexity components: adjusted density, potential vertical interactions, potential horizontal interactions and potential speed interactions. A single metric, ‘complexity score’, which incorporates these four separate parameters, was considered as the simplest for benchmarking purposes. Recently, Pejovic and Lazarovski [43] have studied the performance of the North European Free Route Airspace using EUROCONTROL approach.

1.2 Conflict risk

The International Civil Aviation Organisation (ICAO) has developed the Collision Risk Model (CRM) as a mathematical tool used in predicting the risk of mid-air collision [44]. Although aircraft collisions have actually been very rare events, contributing to a very small proportion of the total fatalities, they have always caused relatively strong impact mainly due to relatively large number of fatalities per single event and occasionally the complete destruction of the aircraft involved.

From other side, one of the principal matters of concern in the daily operation of civil aviation is the prevention of conflicts, i.e. loss of separation between aircraft either while airborne or on the ground, which might escalate to collisions. A loss of separation is a situation when two aircrafts come closer to each other than a specified minimum distance both in the horizontal and the vertical planes. One can imagine that losses of separation are more frequent event than collisions, so assessment of conflict risk is becoming important.

In order to determine whether or not loss of separation situation exists and to calculate a conflict risk value, a cylinder-shaped ‘forbidden volume’ is defined around the aircraft [45]. A loss of separation exists between two aircrafts if one of them enters the other’s forbidden volume. Losses of separation could be of a crossing or an overtaking type, depending on the aircraft trajectory relations both in horizontal and vertical planes [46].

Dealing with a conflict risk (see Section 2.2.2) instead of a collision risk (a concept established by ICAO) is enabling a proactive safety approach, which is much closer to everyday ATCo activities.

2. Study approach

To analyse how future changes in airspace structure and traffic flow could influence complexity and safety performance, this paper proposes a showcase methodology on the analysis of FABEC.

FABEC, which includes airspaces of six countries, Belgium, France, Germany, Luxembourg, the Netherlands and Switzerland (**Figure 2**), is one of the biggest FABs and is handling more than half of the European annual traffic. According to EUROCONTROL [48] this 'airspace is one of the busiest and most complex in the world' with 'most major European airports, major civil airways and military training areas located in this area'.

In addition, Air Navigation Service Providers (ANSPs) within FABEC airspace (7 ANSPs with 14 area control centres (ACCs)) handle 55% of the annual European air traffic.

FABEC would surely benefit a lot from FAB and FRA implementation; however, their implementation would cause airspace structural as well traffic flow changes which could further influence complexity and safety performance, and also indirectly ATCos workload.

Prior to assessing those potential future influences, it was necessary to create a benchmark. For that purpose, an analysis of traffic situation in terms of safety and complexity in FABEC airspace in 2017 was made, before full FAB airspace integration and full FRA implementation.



Figure 2.
FABEC airspace (source: [47]).



Figure 3.
FABEC FRA implementation status [49].

The latest information about FRA implementation status from the ATM Master Plan Portal and Local Single Sky Implementation (LSSIP) reports show that FRA implementation at the end of 2018 in some states is ongoing (green) while in some states late (yellow). The current FRA implementation of FABEC is shown in **Figure 3**. At the moment final implementation dates vary from end of 2021 for Germany and Switzerland to the end of 2024 for France.

2.1 FAB and FRA concepts in FABEC airspace

The FABEC airspace is situated in the core area of the European Air Navigation Service network. It is among the busiest (handles about 6 million flights per year—55% of the European air traffic) and most complex airspaces in the world. Most of the large European airports are also located in this area. Since June 2013, FABEC is officially in operation.

FABEC defined a stepped and gradual FRA implementation approach, whereby FABEC area control centres (including Maastricht Upper Area Control (MUAC)), in cooperation with airlines and computerised flight planning service providers, develop and implement cross-border free route airspace based on a single common FABEC concept of operations, which complies with standards defined by the Network Manager.

FABEC FRA initiative includes joint efforts of the seven service providers, and the project was launched in 2011. FABEC ANSPs agreed on one common concept of operations to ensure a harmonised process. First implementations took place in December 2017 in the MUAC airspace. By 2018, ANSPs of Germany, France and Switzerland have also implemented several direct routes.

2.2 Traffic data and scenarios

Traffic demand data used for simulation and analysis were available via EUROCONTROL Data Demand Repository (DDR2). The analysis of complexity and safety was done using the current tactical flight model (CTFM) flight

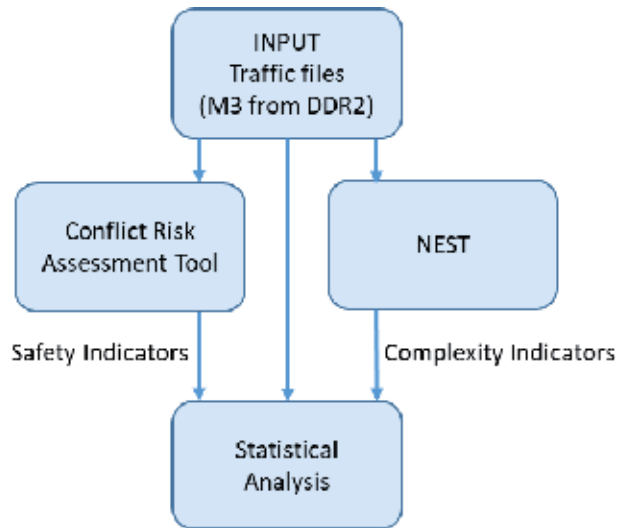


Figure 4.
Structure of the methodology.

trajectories (M3 in Network Strategy Tool (NEST [50]) terminology). These are trajectories constructed by the Enhanced Tactical Flow Management System (ETFMS) of EUROCONTROL Network Manager to tactically represent a flight being flown.

This actual trajectory refines the last filed flight plan trajectory (M1 in NEST terminology) when correlated position reports (CPRs) show a significant deviation (1 min in time, more than 400 feet in en route phase, more than 1000 feet in climb/descent phase or more than 10 NM laterally) and/or upon message updates from ATC (direct, level requests, flight plan update) [51].

In other words, an initial flight trajectory is updated with available radar information whenever the flight deviates from its last filed flight plan by more than any of the predetermined thresholds. Therefore, used trajectory represents the closest estimate available for the flight trajectories handled by controllers on the day of operations.

To allow the analysis of different airspaces of FABEC of seven ANSPs in a similar manner (in terms of static and dynamic parameters), the airspace and traffic only above FL195 were chosen for analysis (as the lowest level at which lower airspace starts in FABEC airspace = Class C airspace). The selection of traffic above FL195 excluded terminal manoeuvring area (TMA) traffic, which could have had additional implications during analysis of safety performance (different separation minima levels could be applicable at TMAs).

Two traffic scenarios covered 1 week of summer (July 3–9, 2017, with 131.268 flights) and winter (November 13–17, 2017, with 94.947 flights). For each traffic scenario, calculation of complexity parameters (calculated using the NEST tool) and safety indicators (calculated using the Conflict Risk Assessment Tool [44]) was done using the same input—summer and winter traffic (**Figure 4**).

2.2.1 Assessment of complexity indicators

The assessment of complexity was done using the EUROCONTROL complexity score [42] as airspace complexity indicator. The two main metrics that define the complexity score are the adjusted density and the structural index. The latter is derived from three parameters describing potential number of interactions in specific

situations classified as vertical, horizontal and the mix of aircraft performances. These potential interactions can have additional complexity if they involve aircraft in evolution (vertical interaction) and in horizontal flights for headings of more than 30° of difference (horizontal interactions) and/or combining aircraft with different performances (speed interactions). Formulas used for the calculation of complexity score are explained in [42].

The adjusted density assesses the potential interactions resulting from density, including uncertainty in the trajectories and time, while the structural index balances the density metrics according to the interaction geometry and aircraft performance differences. The parameters used indicate the difficulty to manage the presence of several aircraft in the same area at the same time, particularly if those aircraft are in different flight phases, have different performances and/or have different headings [43].

The horizontal interactions assess pairs of aircraft depending on their relative headings, and only pairs of aircrafts with a difference greater than 30° heading are considered. The vertical interactions measure the interactions when aircraft in a climb/descend phase has vertical speeds with more than 500 feet per min difference (also when one of the aircrafts was in cruise). Finally, the speed interactions provide a value of the mix of aircraft types (it considers pairs of aircraft only if their different speed performances are greater than 35 knots in nominal cruise) [43].

Complexity is calculated for the en route traffic in FABEC airspace above FL195. The calculations are done in airspace volume in 3D cells of 20 × 20 NM × 3000 ft. The complexity is computed separately for each grid cell and for discretised 60 min periods, and finally averaged [42].

2.2.2 Assessment of safety indicators

The assessment of safety indicators was done using Conflict Risk Assessment Tool [46]. This tool is intended for the simulation of planned or analysis of realised air traffic, consisting of flight trajectories (4D trajectories) crossing a given airspace, with the aim of assessing safety performance. Conflict Risk Assessment Tool has been developed as a network based simulation model consisting of three modules, each being used for the calculation of certain safety indicators [46]:

- Separation violation detection module (dynamic 3D conflict detection model based on known flight intentions and distance-based separation minima) used for the calculation of duration and severity of potential loss of separation (PLoS) as well as determination of number of PLoS
- Traffic collision avoidance system (TCAS) activation module (stochastically and dynamically coloured Petri net model) used for the determination of number of traffic alerts (TAs), resolution advisories (RAs) and near mid-air collisions (NMACs)
- Conflict risk assessment module used for the calculation of conflict risk

The separation violation detection module simulates flights (following discrete simulation logic with constant time steps) and compares the actual separation of aircraft following certain predefined flight trajectories (both in horizontal and vertical planes) with a given separation minima in order to detect PLoS [46]. Once PLoS are detected, this module counts them and for each of them calculates its severity and duration under given circumstances. Finally, a list of PLoS is created.

Each PLoS discovered by the separation violation detection module is then considered by TCAS activation module. Namely, not every PLoS will activate TCAS. If the situation worsens, then TCAS activation module will uncover which event could occur. It counts TAs and RAs and based on vertical separation between aircraft at closest point of approach (CPA) counts possible number of NMACs [46].

Finally, the conflict risk assessment module is based on the calculation of 'elementary risk' for each specific conflicting pair of aircraft, considering both duration and severity of PLoS. Summing up elementary risks for all possible conflicting pairs of aircraft and dividing it with the observed period of time (e.g. 24 hours), a conflict risk in a given airspace can be estimated [46].

2.3 Objectives and assumptions of the study

Having in mind changes in the European airspace (such as introduction of FRA and FABs) and constantly growing traffic demand, the following research questions emerged:

- How did those changes influence air traffic complexity and safety?
- Is there any relationship between traffic demand, air traffic complexity and safety?
- Are there any differences between seasons?

The main objective of the research presented in this chapter is to find answers on above questions by analysing air traffic within FABEC airspace (a discrete simulation with fixed time step).

The main assumptions were as follows:

- A time increment of 10 sec is chosen as a result of the balance between run time and quality of loss of separation detection (smaller values could be better from the quality point of view but would last much longer).
- Consequently, all events lasting only 10 sec were excluded from further analysis in order to deal with potential trajectory inaccuracies.
- The safety minima separations used were horizontal separation (5 NM) and vertical separation (1000 ft); however, those values are relaxed for 10% (4,5 NM and 900 ft) in order to deal with potential position and altitude inaccuracies.
- The tactical actions by the pilots and ATCos as well as their behaviour in traffic separation are not analysed as their interventions were already partially included in M3 trajectory.
- Complexity in horizontal and vertical plane is homogeneous within FABEC airspace.

3. Results

Analysis of complexity and safety performance is performed in five stages:

1. Analysis of daily variations of complexity and safety indicators described above

2. Analysis of correlation between traffic, complexity and safety indicators (overall and seasonal comparison)
3. Analysis of PLoS severity and duration as well as horizontal and vertical separation at closest point of approach
4. Analysis of complexity and safety indicator values per flight levels
5. Analysis of geometrical characteristic of PLoS

3.1 Complexity and safety indicators overall analysis

Daily fluctuations of both complexity and safety indicators follow similar pattern throughout the week in both summer and winter. Traffic values indicate that traffic demand during winter is lower than during summer in a range from 22 to 37%. Similarly, the complexity score values fluctuate in a similar manner, and summer values are higher in a range between 17 and 29%. Overall, changes of daily complexity values are following the changes of daily traffic demand.

Contrary, the changes in daily number of PLoS and conflict risk do not follow strictly the changes in daily traffic demand. However, variations in the number of PLoS are following the changes in conflict risk. The number of PLoS during winter is lower in a range from 33 to 63%. Similarly, the conflict risk shows lower values in winter in a range from 28 to 65%.

Complexity analysis shows that total hours of interactions (bars, **Figure 5**) increase during winter mainly due to increase in speed interactions (yellow bars, **Figure 5**) which could indicate the greater changes in the mix of aircraft used. However, overall complexity score reduces during winter by 15–20% depending on the day of the week. This indicates that overall complexity score (black line, **Figure 5**) is mainly influenced by changes in adjusted density (green line, **Figure 5**). Adjusted density assesses aircraft interactions resulting from density, including uncertainty in the trajectories and time. Adjusted density shows that interactions are not only related with the traffic volume, however also with how this traffic is dispersed in airspace.

The analysis of number of interactions and number of PLoS per hour of flight (**Figure 6**) show that the total number of interactions per hour of flight reduces



Figure 5.
Complexity parameters.

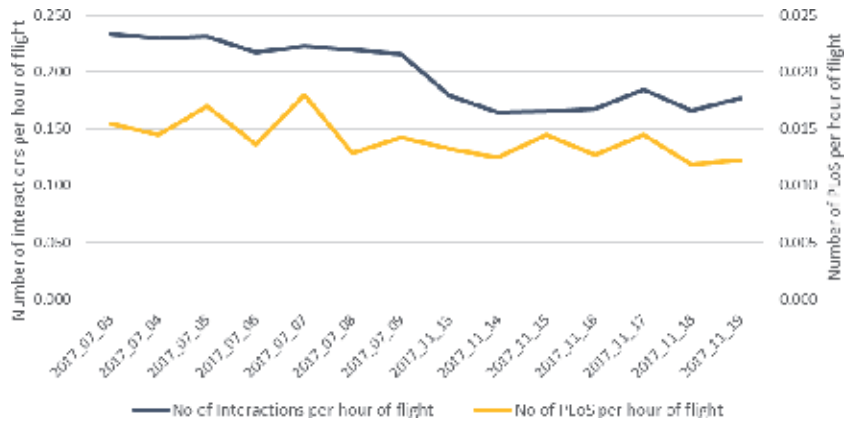


Figure 6.
 Number of aircraft interactions and PLoS per hour of flight.

Both seasons	Complexity	PLoS	Conflict risk
Number of flights	+0.9807	+0.8819	+0.8008
Complexity	—	+0.9138	+0.8296

Table 1.
 Linear correlation coefficients for both seasons combined.

during winter by over 23% (0.224 in summer vs. 0.172 in winter). The number of PLoS per hour of flight is somewhat more stable and does not change much with decrease in traffic. Overall change is approximately 13% (0.015 in summer vs. 0.013 in winter).

3.2 Correlation between traffic, complexity and safety indicators

A very strong correlation ($R^2 = 0.9807$) was found between the daily number of flights and complexity (**Table 1**). Strong correlations were also found between safety indicators (slightly better correlation with the number of PLoS) and the total number of flights. Similarly, strong correlations exist between safety indicators and complexity.

These findings could lead to a conclusion that with increase in traffic, one can expect the higher complexity, which is mostly influenced by the number of PLoS and conflict risk. In other words, this means that ATCo task load will increase, leading to a higher ATCo workload.

3.2.1 Seasonal comparison

The results of correlation analysis between traffic demand, complexity and safety indicators (conflict risk) show the positive correlation between the number of flights and complexity score (as dependent variable) that is stronger in winter (summer $R^2 = 0.7163$ (**Table 2**) vs. winter $R^2 = 0.9022$ (**Table 3**)). This is expected as daily complexity scores follow the daily number of flights (see Section 3.1). Moreover this could be explained by the fact that during the winter traffic is more uniform, while during summer there are more charter and business flights (un-scheduled flights) that could change traffic flows and locations of potential conflict points, which in turn is decreasing predictability and increasing complexity score. Operationally, this could also potentially increase ATCo's workload during summer.

Summer season	Complexity	PLoS	Conflict risk
Number of flights	+0.7163	+0.3716	+0.3114
Complexity	—	+0.6980	+0.5144

Table 2.
Linear correlation coefficients for summer season.

Winter season	Complexity	PLoS	Conflict risk
Number of flights	+0.9022	+0.5005	+0.2207
Complexity	—	+0.5640	+0.2843

Table 3.
Linear correlation coefficients for winter season.

Moreover, the positive correlation between the number of flights and conflict risk (as dependent variable) is not significant (in both seasons, although in summer is somewhat stronger). Similarly, the positive correlation between complexity score and conflict risk is not significant (R^2 is higher in summer than in winter).

Correlation between the number of flights and number of PLoSs is not significant (although somewhat higher in winter). Contrary, correlation between complexity scores and the number of PLoS shows a significant positive correlation (stronger in summer).

Overall, it can be concluded that correlation between complexity and the number of PLoSs is stronger than between complexity and conflict risk (Tables 2 and 3). Similar behaviour can be observed in the case of correlation between the number of flights and the number of PLoS. However, it has to be noted that the conflict risk as an indicator contains more information about the loss of separation than just the total number.

3.3 Analysis of potential losses of separation

3.3.1 PLoS duration and severity

Each PLoS is characterised by the combination of severity (related to the breach of separation) and duration. The severity of the PLoS depends on the minimum distance (spacing) between the pair of aircraft (S_{min}) and the applied separation minima (Sep_{min}). The severity presents the level of aircraft proximity and is defined either for the violation of separation in the horizontal or the vertical plane, or both [45]:

$$Severity = \frac{(Sep_{min} - S_{min})}{Sep_{min}}$$

where $0 < = Severity < = 1$.

Severity could be 1 in the case when both aircrafts are at the same point in the horizontal plane (although they could be properly separated vertically) or in the case when both aircrafts are at the same altitude (however they could be properly separated horizontally).

Results of PLoS duration analysis show that majority of PLoSs are short, up to 30 sec (roughly two-thirds, i.e. 372 cases), while almost 90% do not last more than 1 min (Figure 7). Results of severity analysis (Figure 8) show that in 80% of cases severity is 1, which means that both aircrafts were at either the same flight level or at the same point in the horizontal plane.

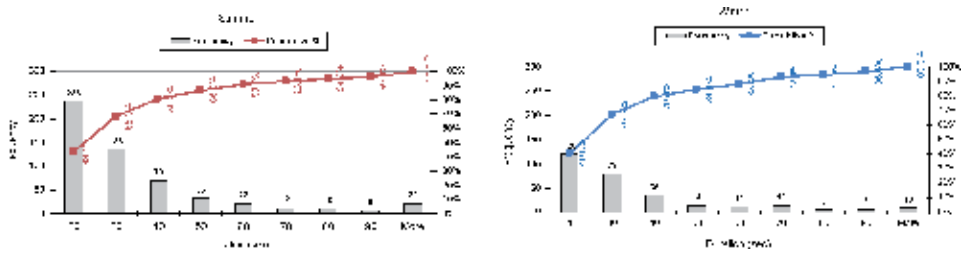


Figure 7.
 Distribution and cumulative distribution of PLoS duration.

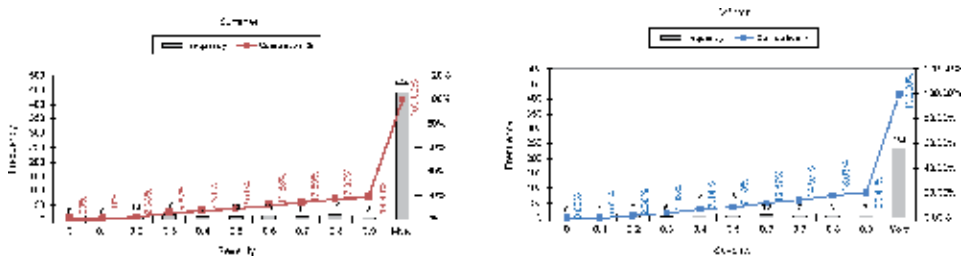


Figure 8.
 Distribution and cumulative distribution of PLoS severity.

3.3.2 Horizontal and vertical separation at CPA

The results of the distribution of minimum vertical separation at the CPA show that almost 80% of PLoSs are at the same flight level or are separated vertically up to 100 ft. (top **Figure 9**). The results of horizontal distribution show that roughly 50% of PLoSs have breach of less than 3 NM (bottom **Figure 9**).

3.4 Complexity and safety per flight level

Both complexity and conflict risk can change with flight level. The distribution of an average daily complexity and average daily number of PLoS per FLs (grey lines show a standard deviation) is shown on **Figure 10**.

The highest average values of complexity are on higher altitudes (FL350 to FL380) which correspond to the level used for en route cruise. Somewhat increased values of complexity could be also seen between FL220 and FL240 (corresponds to situations in which flights are entering or leaving lower airspace), however, the number of PLoSs is not increased at this level band.

Distributions of average daily complexity and average daily number of PLoS per FL are similar, with lower values during winter days (**Figure 10**). Additionally, it can be concluded that traffic demand is influencing higher complexity values; moreover, the number of PLoSs evidently contributes to higher complexity values (**Figure 11**).

Figure 11 shows that in the summer period increase in the number of PLoS at high complexity altitudes is of higher magnitude than in winter months. This could be related to the fact that summer traffic is less predictable (due to the existence of increased number of charter flights and summer destinations traffic).

3.5 Geometrical characteristics of PLoS

To better understand the influence of PLoSs on complexity scores, it is necessary to investigate geometry between aircraft in PLoS encounters. Three types of PLoS,

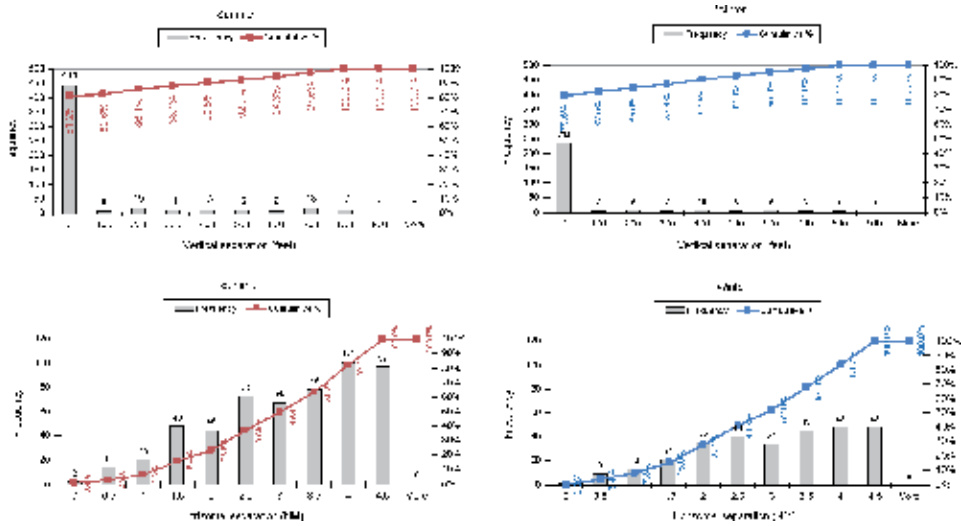


Figure 9. Distribution and cumulative distribution of vertical and horizontal separation at CPA.

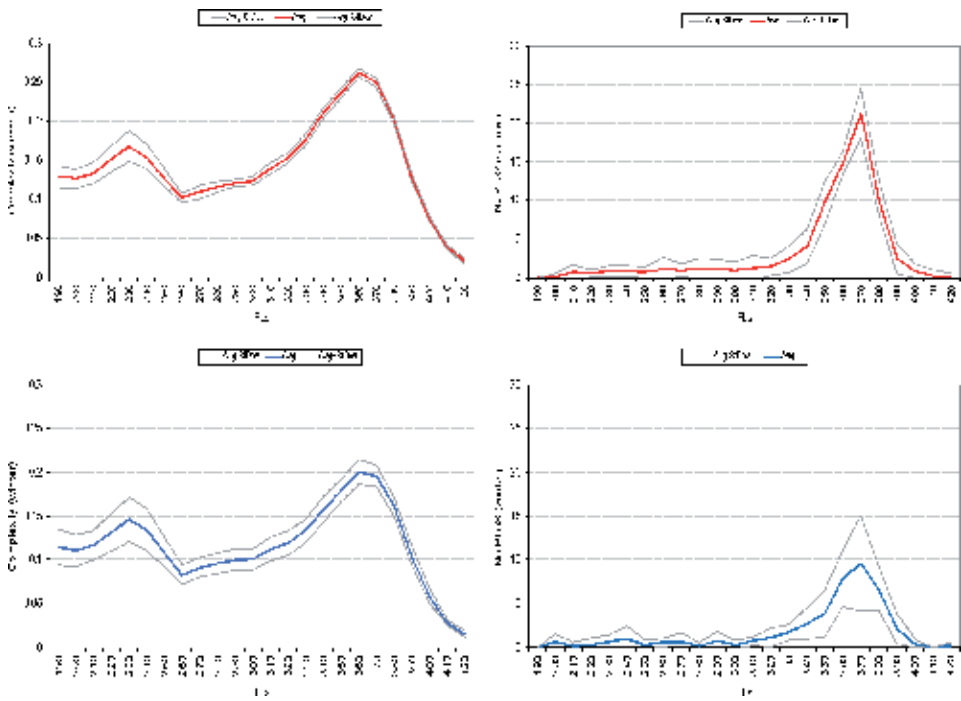


Figure 10. Complexity and the number of PLoS per FL.

based on special position of two aircraft in PLoS, are used: overtaking (difference between headings is $\pm 70^\circ$), crossing (difference between headings is in a range between ± 70 and $\pm 160^\circ$) and head-on encounters (difference between headings is in a range between ± 160 and 180°).

Figure 12 (top) shows the share of each encounter type. In summer sample percentage of overtaking and crossing PLoSs is almost similar (51 vs. 46%) while in winter there are more overtaking PLoSs (71%). Daily values (**Figure 12** bottom)

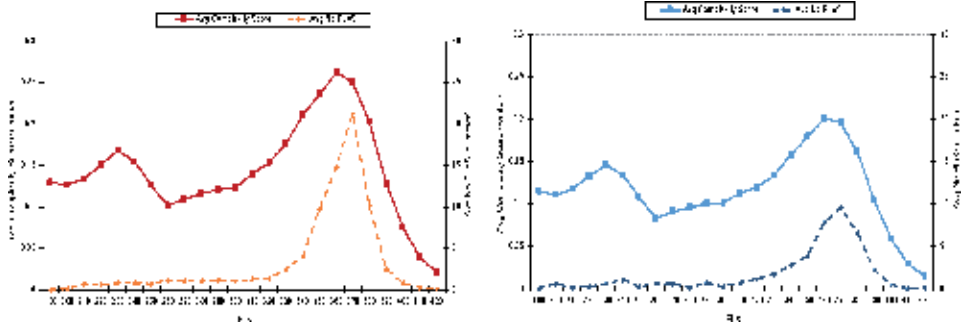


Figure 11.
 Distribution of complexity and the number of PLoS per FL.

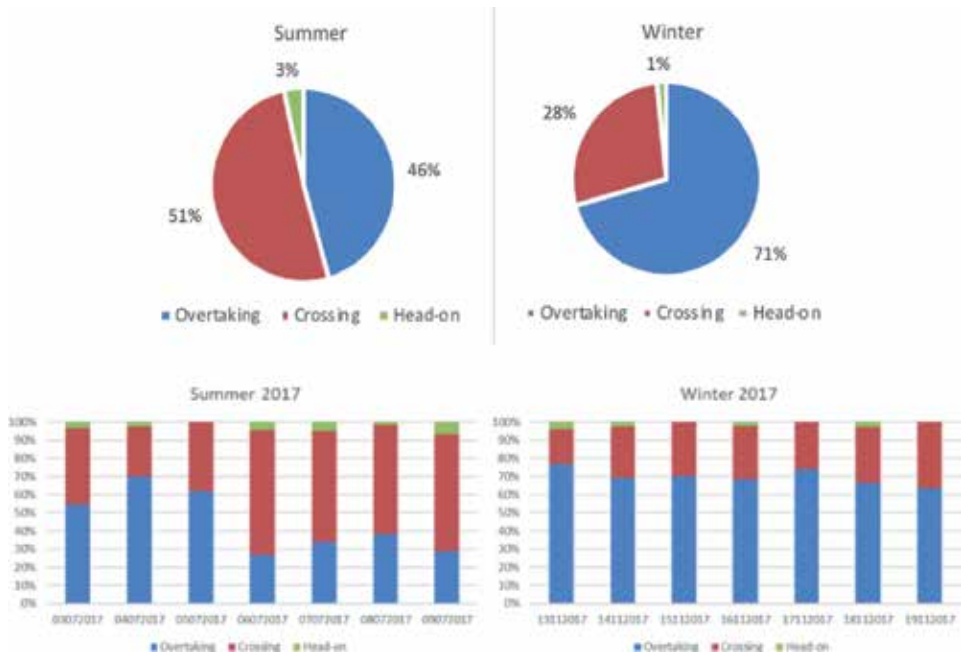


Figure 12.
 Shares of encounter types.

show that daily share of encounter types are more stable during the winter which could be related to more uniform traffic flows during winter months (e.g. no seasonal and charter flights).

4. Conclusion

Air traffic performance of the European air traffic system depends on traffic demand but also on airspace structure and its traffic distribution. These structural and flow characteristics influence airspace complexity, which can affect controller workload and influence the probability of safety occurrence.

An investigation is performed on FABEC airspace in Europe, based on 2 weeks of realised traffic during summer and fall of 2017, with aim to answer several questions: How changes in traffic demand influence complexity and conflict risk? Is there any correlation between traffic demand, conflict risk and complexity? Are there any differences between seasons?

Daily fluctuations of both complexity and safety indicators follow a similar pattern throughout the week in both summer and winter. Analysis of complexity parameters shows that overall complexity score is mainly influenced by changes in adjusted density which show that interactions are not only related with the traffic volume but also with how this traffic is dispersed in airspace.

The changes in the number of PLoS and conflict risk do not follow strictly the changes in daily traffic demand, and the numbers of PLoS and the conflict risk are lower in winter. This could be related to the fact that traffic demand is lower in winter months and that traffic is more predictable.

Strong correlations were found between traffic demand, safety and complexity indicators. These findings could lead to conclusion that with increase in traffic, one can expect the higher complexity, which in turn influences the number of PLoS and conflict risk. In other words, this means that ATCo task load will increase, leading to a higher ATCo workload.

Both complexity and conflict risk can change with flight level. The highest average values of complexity and number of PLoS are on higher altitudes (FL350 to FL380) which correspond to the level used for en route cruising. Increase in number of PLoS at these altitudes is higher, in relation to increase in complexity, during summer. This could be related to the fact that summer traffic is less predictable (due to existence of increased number of charter flights and summer destinations traffic).

In a conclusion, this small-scale analysis showed that changes in traffic demand do influence complexity and safety performance (both in terms of the number of PLoS and conflict risk). Moreover, this analysis set a benchmark for future monitoring of safety and operational performance after FRA implementation at FABEC airspace. Further analysis should investigate whether dispersion of traffic after FRA implementation is enough to create complexity decrease and whether change in complexity have not compromised safety and ATCo workload. Moreover, analysis could increase credibility by considering traffic flows, sectors, types of flights (charter, low cost, business, etc.) and vertical profiles of flight.

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Conflict Risk Assessment Based Framework for Airspace Planning and Design

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Abstract

This chapter presents a conflict risk assessment based framework for airspace planning and design developed for the purpose of preventing aircraft conflicts and collisions. During airspace planning and design process, airspace designers are often guided by the need to increase capacity and/or reduce air traffic controller (ATCo) workload. In order to consider safety risks in a systematic way, the proposed framework contains an additional step—safety risk assessment, performed by safety analysts guided by the risk reduction need. In such a way, they are providing feedback to airspace designers regarding safety issues of their solutions. This chapter presents four conflict risk assessment models, each one developed for different airspace planning level (strategic, tactical, operational, and current day) contained in the proposed framework. Basic development principles for every model were explained together with specific objectives, assumptions, conflict risk concepts, and required input data. Models are illustrated by the simple numerical examples.

Keywords: conflict risk assessment, airspace planning, airspace design, air traffic control, aviation safety

1. Introduction

Air traffic is growing with an average annual rate of about 4–5% in the last 30 years [1, 2]. The increase of the air traffic volume in Europe up to 2050 is forecasted in the European Commission (EC) document “Flightpath 2050” [2] to be almost a threefold relative to the year 2011 (25 million commercial flights in 2050 relative to 9.4 million expected in 2011), i.e., with an expected average annual rate of about 4%. Also, an increase of 25% in aircraft operations is predicted up to 2039 relative to 2019 in the USA [3], i.e., 1,25% annually in average. Simultaneously, an increased level of safety is required [2].

In order to accommodate such a growth, a development of new air traffic operational concepts is expected [4]. But accommodation of growing traffic with requirement to increase safety presents a significant challenge for the research and scientific community since an increase of traffic should not lead to a decrease in safety. That is why a development of new safety measures and system safety performance indicators is also expected [4].

The air traffic system is a complex, socio-technical, safety-critical, and dynamic system with three main components at macro level—airlines, airports, and air traffic control/management services. Those components mutually interact at different

hierarchical levels. At microlevel air traffic system presents a very complicated, highly distributed network of human operators, procedures, and technical/technological systems within different operational environments. Safety of flight operations in such a complex system is influenced by interactions between the various components and elements [5, 6]. Airports and the air traffic control/air traffic management (ATC/ATM) system as an air traffic system infrastructure are expected to be able to support such growth safely and efficiently with adequate capacity.

The research presented in this chapter is focused on the ATC/ATM system and more specifically on airspace planning, design, and organization.

An airspace as main infrastructure resource of ATC/ATM system is characterized by the capacity, which is usually given as the maximum number of aircraft passing through a given airspace in a given time period [7]. Capacity depends on the air traffic flows and the aircraft separation minima applied. One of the possibilities to increase airspace capacity is to reduce the separation minima [8]. This approach is driven by the fact that suitable communication, navigation, and surveillance technology (COM/NAV/SUR) already exist [9]. The reduction of separation minima could increase the traffic throughput but also could affect the safety of the flight operations. This is the reason for the development of models for safety assessment of such a change and for balancing between an increase in capacity and any possible decrease in safety.

The main objective of the research described in this chapter is the development of a framework for airspace planning and design based on a conflict risk assessment. The main purpose of such a framework should be prevention of aircraft conflicts and collisions.

To enable implementation of the proposed framework, it was necessary to develop a risk assessment model for airspace planning, design, and organization purposes at the strategic, tactical, operational, and current day planning levels.

This chapter is organized as follows. Section 2 presents an overview of different risk modeling approaches in air traffic system. Section 3 describes the proposed framework. Section 4 explains the development of a conflict risk assessment model for strategic, tactical, operational, and current day planning levels as well as illustrates their application. Finally, Section 5 draws conclusions and presents further research directions.

2. Risk modeling approaches

2.1 Overview of risk modeling approaches

The main concern in the daily operation of ATC system is prevention of conflicts between aircraft either while airborne or on the ground, which could possibly become a collision [5, 6].

The main reason for developing risk models since the 1960s was the need for increasing airspace capacity (in order to accommodate growing traffic demand) by reducing both space and time aircraft separation minima. However, due to the reduction of this separation, an air traffic safety could be jeopardized. That is why an assessment of the risk of conflicts and collisions has been studied using different models. It was expected from using those models to show whether a reduction of separation would be sufficiently safe. The following models were in use [5, 6]:

- The Reich-Marks model was developed in the early 1960s [10]. It is based on the assumption that both aircraft positions and speeds are random variables. The model computed the probability of aircraft proximity and the conditional probability of collision given the proximity [11, 12].

- The Machol-Reich model was developed in 1966 with the idea of developing the Reich-Marks model as a workable tool, as well as to increase airspace capacity over Atlantic. Consequently, the ICAO adopted the threshold for risk of collision of two aircraft due to the loss of separation [11, 13].
- Intersection models are simplest among collision risk models. They assume that aircraft follow predetermined crossing trajectories at constant speeds. Using the intensities of traffic flows on each crossing trajectory, aircraft speeds, and airways geometry, the probability of collision at the crossing point is computed [14–18].
- Geometric conflict models are similar to intersection models. They are developed in the 1990s with the main assumption that aircraft speed is constant, but their initial three-dimensional positions are random. The conflict occurs when two aircraft are closer than the prescribed separation minimum [19–23].
- The generalized Reich model was developed during the 1990s by removing restrictive assumptions from the Reich model [9, 24–27].

Collision risk models have gradually been developed since the 1960s, but their main purpose has always been to support decision-making processes during system planning and development.

2.2 ICAO risk modeling approach

The ICAO has developed the collision risk model (CRM) as a mathematical tool used in predicting the risk of mid-air collision [28–30]. The CRM model became a crucial part of the Airspace Planning Methodology for the determination of separation criteria [28] which purpose is to determine separation minima based on calculated collision probability.

CRM calculates probability of collision as the lateral or vertical overlap probability, given the probability density functions of position errors at a given moment [31, 32]. However, [33, 34] CRM is not able to model all situations, especially operational errors.

2.3 Conflict vs. collision risk modeling

What is a conflict? A conflict is an operational situation in which two (or sometimes more) aircraft come closer to each other than a specified separation minimum distance (both in the horizontal and the vertical planes). In order to detect conflict situation, a cylinder-shaped “forbidden volume” [35] (“protected zone” [22] or “conflict cylinder” [34]) is defined around the aircraft. The dimensions of this volume are defined by the minimum horizontal S_{min} (cylinder radius) and vertical H_{min} separation (cylinder height). Whenever one aircraft enters the other’s forbidden volume (**Figure 1**), a potential conflict situation occurs. Conflicts could be of different types—crossing or overtaking—depending on the relations between aircraft trajectories both in horizontal and vertical planes [35].

What are collisions? Collisions are defined by forbidden volumes which are much smaller than in the case of conflicts (**Figure 1**). The dimensions of those volumes are defined by the size of the aircraft [10, 16, 30].

As already mentioned, one of the principal matters of concern in the daily operation of ATC system is the prevention of conflicts between aircraft (incidents) either while airborne or on the ground, which might escalate to collisions (accidents).

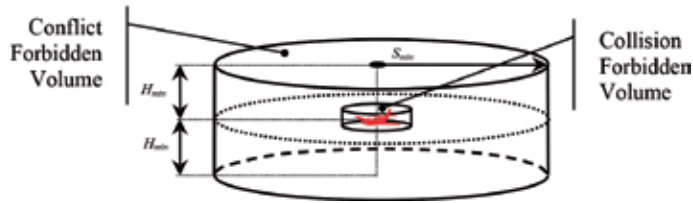


Figure 1.
Conflicts vs. collision forbidden volumes.

3. Conflict risk assessment based framework for airspace planning and design

The basic idea of the proposed framework is that different risk assessment models are required for different planning levels in ATC/ATM system [35, 36]. Their main purpose of those models is to support decision-making during airspace planning and design process through evaluation of safety risks of proposed changes (either in the existing or the new system).

Generally, airspace designers are often guided by the need to increase capacity and/or reduce air traffic controller (ATCo) workload, during planning and design process. Usually, the safety risk assessment is not explicitly performed, but in order to consider safety risks in a systematic way (explicitly), the proposed framework contains an additional step. In this step a safety risk assessment is performed by safety analysts driven by the risk reduction need (**Figure 2**). Safety analysts in such a way are providing feedback (both positive and negative) to airspace designers regarding safety issues of their solutions [9]. It is important for provision of objective feedback that safety analysts are independent of airspace designers.

A proposed conflict risk assessment modeling framework contains four planning levels (strategic, tactical, operational, and current day). It is developed to be complementary to ICAO CRMs and not as its replacement. The main differences between proposed framework and ICAO CRM are the following [37]:

- They are considering different events: the proposed framework considers risk of conflict (incidents) while CRM considers risk of collision (accidents);
- They are used for different purposes: the proposed framework considers airspace designs based on conflict risk, while CRM uses collision risk for determination of separation minima which further allow increase of airspace capacity.

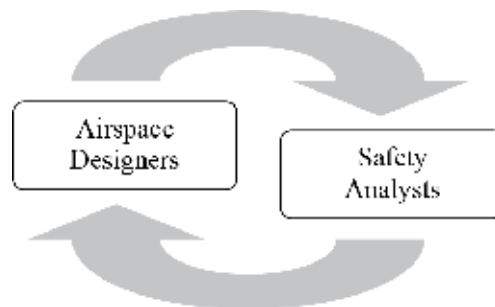


Figure 2.
Iterative process for airspace design and planning (compiled from [9]).

- They use protection volumes of different sizes: the proposed framework considers the forbidden volume around aircraft, while CRM considers the physical dimensions of aircraft.
- They use different separation minima types: the proposed framework uses distance-based separation minima only, while CRM uses both distance- and time-based.
- The resulting risk values are not the same: the conflict risk value is always bigger than collision risk value due to the fact that conflicts are more frequent than collisions.

The proposed framework is intended for use by the safety analysts (as presented in **Figure 2**). For each of the four planning levels, the necessary (not exhaustive) inputs are listed, and possible types of models are proposed (**Figure 3, Table 1** [35, 36]).

From **Figure 3** it can be seen that proposed framework is sequential in nature, meaning that outputs obtained after the application of conflict risk assessment models at one planning level are used as inputs into another planning level.

Starting from the initial larger set of scenarios, applying the suitable conflict risk assessment models, a gradually reduced set of scenarios (positively evaluated from the safety point of view) is obtained as outputs from the model application [37]:

- The output at strategic planning level is a list of airspace scenarios A_1, \dots, A_n chosen to be used on the tactical planning level.
- The output at tactical level is a list of airspace scenarios B_1, \dots, B_m ($m < n$ from the strategic planning level) chosen to be used on the operational planning level.

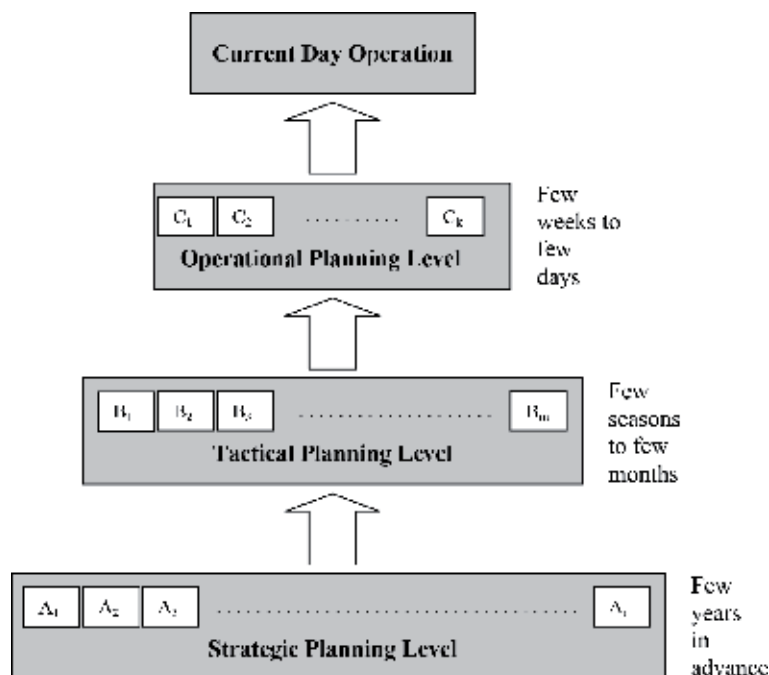


Figure 3. Planning levels in conflict risk assessment modeling framework (based on [35–37]).

- The output at operational level is a list of airspace scenarios C_1, \dots, C_k ($k < m$ from the tactical planning level) chosen to be used in current day operation.

At the current day level, risk assessment model should help decision-makers to timely organize sectorization based on a given list of sectors and confirmed flight plans.

Planning level	Time horizon	Inputs and assumptions	Flight path characteristics	Nature of the Models
Strategic	a year or more in advance	<ul style="list-style-type: none"> - given airway/trajectory network; - assumed aircraft fleet; - estimated traffic flows per airway; - average ground speed per traffic flow; - given separation criteria (horizontal and vertical). 	<ul style="list-style-type: none"> - intent based (flight plans) - linear propagation 	Analytical Models
Tactical	from one week up to a season in advance	<ul style="list-style-type: none"> - given airway/trajectory network; - known aircraft fleet; - known temporal and spatial distribution of aircraft on airways; - average ground speed per aircraft type; - given separation criteria (horizontal and vertical). 	<ul style="list-style-type: none"> - intent based (flight plans) - linear propagation 	Simple Simulation Models
Operational	one or more days in advance	<ul style="list-style-type: none"> - given airway/trajectory network (fixed/free route); - known aircraft fleet; - known temporal and spatial distribution of aircraft on airways; - average ground speed per aircraft type; - given separation criteria (horizontal and vertical); - ground and airborne systems failure rates; - operational procedures followed (ATCo vs. pilots); - human factor issues included (situation awareness, workload, fatigue, ...); - weather conditions; - conflict detection and resolution algorithms. 	<ul style="list-style-type: none"> - state based - linear propagation 	Complex Agent-based Simulation Models (e.g. Petri Nets under TOPAZ methodology or ICAO Collision Risk Model)
Current day	few hours in advance	<ul style="list-style-type: none"> - given airway/trajectory network (fixed/free route); - known aircraft fleet; - known temporal and spatial distribution of aircraft on airways; - average ground speed per aircraft type; - given separation criteria (horizontal and vertical); - operational procedures followed (ATC vs. pilots); - human factor issues included (situation awareness, workload, fatigue, ...). 	<ul style="list-style-type: none"> - intent based (flight plans) + state based - linear propagation 	Decision support models

Table 1.
Inputs for conflict risk assessment vs. planning levels.

It is evident from **Table 1** that moving closer to the current day planning level, safety risk assessment models become more detailed and complex. Actually, the level of abstraction is getting smaller due to availability of specific information, while their nature also changes (from analytical models to simulation models and further to decision support systems).

In the following text, a framework is described separately through the developed conflict risk assessment models for each planning level as well as illustration of their application.

(compiled from [35–37]).

4. Conflict risk assessment models

All conflict risk assessment models developed under the proposed framework are sharing the few general characteristics [37]:

1. The main starting point is that the risk depends on airspace geometry (static element) and the air traffic using it (dynamic element).
2. All models are based on the concept of critical sections, as part of the aircraft trajectory, which are traversed by the aircraft during level flight or while climbing or descending through these sections. A critical section was defined as portion of trajectory j in which aircraft should not be at the same time, if other aircraft is in intersection point O flying on trajectory i , in order to prevent occurrence of conflict (similarly is in the case of flying on the same trajectory).
3. A conflict is defined as a situation in which two aircraft are coming closer than a separation minimum distance (both in horizontal and vertical planes).
4. In order to detect conflict situations, around the aircraft a cylinder-shaped forbidden volume (protected zone) is defined (its dimensions are defined by the minimum horizontal S_{min} and vertical separation H_{min}).
5. The following assumptions are introduced in developing the models for risk assessment:
 - Risk is antonym for safety.
 - If there is no traffic, there is no risk.
 - Risk values are not constant.
 - Risk values usually positively correlate to traffic demand and negatively to airspace volume.
6. All models, under certain conditions, could be applied both for en route and terminal maneuvering (TMA) airspace.
7. The risk values calculated using the developed models are only the relative measure of safety. This means that there are intended for the purpose of comparison between numerous scenarios, not for comparison with a Target Level of Safety (TLS) given by the international regulations [38–40].

4.1 Conflict risk assessment model for airspace strategic planning

4.1.1 Objectives and assumptions

The conflict risk assessment model for the airspace strategic planning level [35, 37] is intended to facilitate comparisons and sensitivity analyses of different airspace designs (sector shapes) and organizational scenarios (sector configurations) under different air traffic flow levels a year or more in advance. Conflict risk is assessed using two variables [35, 37]: the conflict probability and the number of conflicts in the given airspace under the given circumstances.

In order to detect conflicts, length and flying time through critical section (critical length and critical time) are defined. Those two values enable calculation of the conflict probability, which is (for a given pair of aircraft) defined as the product of the probability that an aircraft is in a given critical section of its own trajectory and the conditional probability that another aircraft is simultaneously in a corresponding critical section of its (crossing) trajectory. The number of conflicts is defined as the product of conflict probability and estimated traffic flows for the given airway [35, 37].

Taking into account all available flight levels and airway combinations in the given airspace, it is possible to calculate total conflict numbers. Details of the model development are provided in [35, 37].

Proposed conflict risk assessment model is intended for airspace planning purposes at the strategic level, based on risk assessment of the current, and future airspace, following its modifications (changes of sector shapes or sector configurations).

The main inputs for conflict risk assessment using the proposed model are [35, 37]:

- Airspace geometry and characteristics (sector shape/boundaries, number and spatial distribution of available airways, length of the airways, number of intersecting points, available flight levels, etc.)
- Traffic characteristics (special and temporal distribution of traffic flows, proportion of level flights (in cruising phase) vs. flights in climb/descent, share of specific aircraft category in total traffic volume, etc.)

Human operator (pilots and ATCos) issues and behaviors are not considered.

4.1.2 Illustration of the model application

In order to illustrate the developed model, a hypothetical en route sector is used containing two unidirectional airways, one bidirectional airway, and four flight levels (**Figure 4**).

In this example traffic flow increase (e.g., on AWY₃) as well as airspace volume change (e.g., length extension of AWY₃) was considered together with the change in separation minima applied. Details of the model application illustration are provided in [35].

Experimental results show the following:

- Higher risk of conflict can be obtained in the case of traffic demand increase in airspace volume that does not change (sector volume and airway length, **Figure 5**).
- Decrease in risk of conflict can be obtained in the case of an increase of airspace volume (sector volumes and airway lengths), with traffic demand that does not change (**Figure 6**).

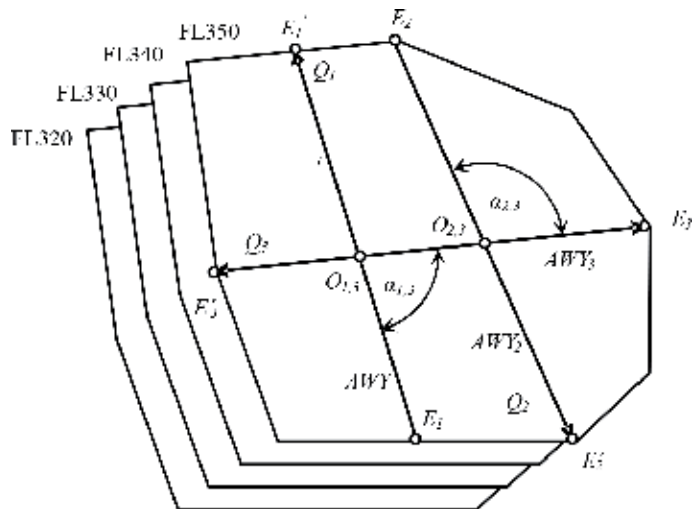


Figure 4.
 Sector geometry (compiled from [35, 37]).

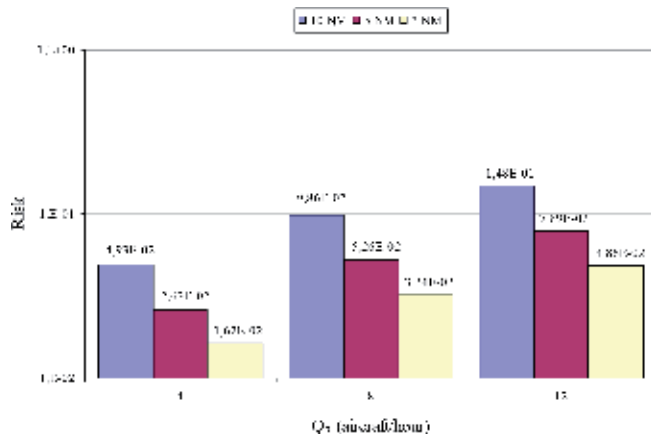


Figure 5.
 Risk for the given sector dependent on traffic flow on AWY_3 [35, 37].

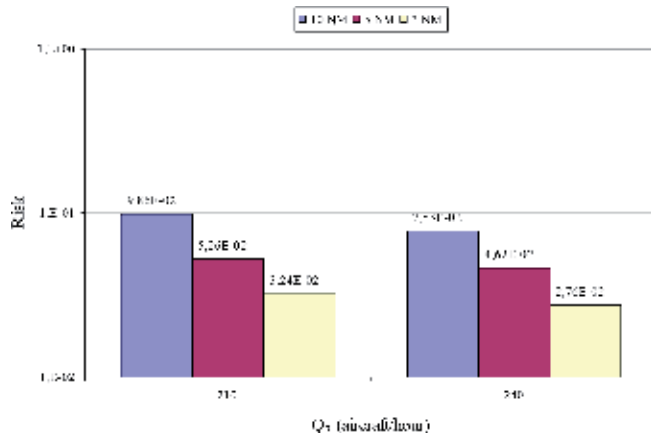


Figure 6.
 Risk for the given sector dependent on length of AWY_3 (change of sector volume) [35, 37].

- Reduction of separation minima is causing higher conflict risk values (**Figures 5 and 6**).

4.2 Conflict risk assessment model for airspace tactical planning

4.2.1 Objectives and assumptions

The conflict risk assessment model for airspace tactical planning level is intended for evaluation and comparison of different alternative flight scheduling scenarios for a given airspace sectorization, or comparison of different alternative airspace sectorization scenarios for a given flight schedule, from 1 week up to a season in advance [36, 37].

Assessment of conflict risk is based on two variables [36, 37]: duration and severity of conflict situation in the given airspace. Both, duration and severity, depend on different factors: aircraft entry time into given airspace, aircraft speed, relative speed between conflicting aircraft, trajectory crossing angle, separation minima, etc. The conflict risk is defined as the ratio between the “elementary risk” and the observed period of time. “Elementary risk” is calculated as the ratio between [36, 37] (1) the surface limited by minimum separation line (from above) and function representing the change of conflicting aircraft separation (from below) and the surface limited by minimum separation and time moments presenting the conflict duration (beginning and ending of conflict) and (2) abscissa. Conflict risk is being calculated for each aircraft pair, as well as for all conflicting pairs, i.e., total conflict risk in the given airspace. Details of the model are provided in [36, 37]. The proposed conflict risk model is intended for [36, 37]:

- Assessment of conflict risk in given airspace under given flight schedules
- Approval of filed flight plans or suggestions for their modifications (flight re-scheduling or slot assignments with the aim to reduce conflict risk)

The main inputs for conflict risk assessment using this model are [36, 37]:

- Known airspace geometry and characteristics (e.g., sector shape/boundaries, number and length of the airways, airway tracks, number of intersecting points, available flight levels, etc.)
- Known traffic demand characteristics (flight plans—planned routes, speeds, altitudes, aircraft types, temporal and spatial distribution of air traffic flows over specific airspace entry points, etc.)

The main assumption of this model is that flight perfectly follows their planned routes (trajectories) and altitudes. Also, human operator (pilots and ATCos) issues and behaviors are not considered.

4.2.2 Illustration of the model application

In order to illustrate the developed model, a hypothetical en route sector is considered containing two unidirectional airways and one flight level (**Figure 7**).

For illustration purposes only, flights on one flight level are considered. Five flights entering the sector in a 6-minute period are considered (**Figures 8–10**). For each flight, an entry time, together with aircraft type and assigned airway, was the input.

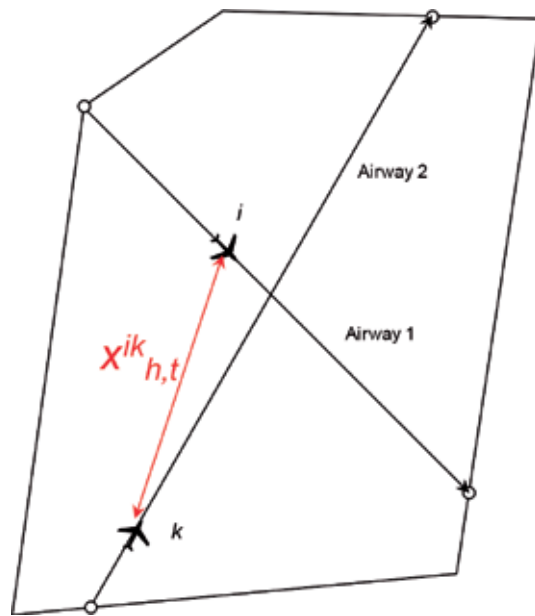


Figure 7. Sector geometry with flights (compiled from [36, 37], $x^{ik}_{h,t}$ is horizontal separation between flights i and k at time t).

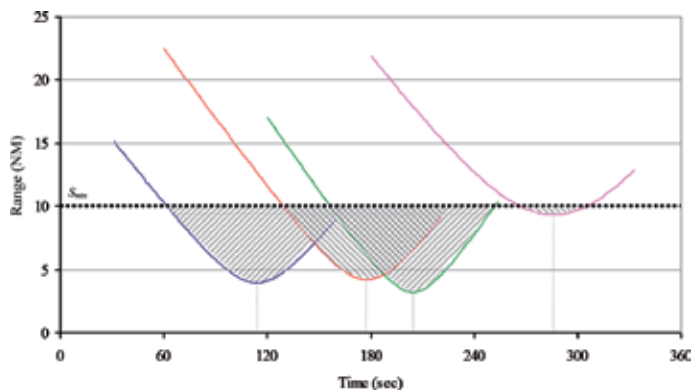


Figure 8. Change of spacing between aircraft pairs and the potential conflicts in the horizontal plane ($S_{min} = 10$ NM), compiled from [36, 37].

Potential traffic separation violations in the horizontal plane between succeeding aircraft pairs are observed in the simulated situations for the case of separation minima of $S_{min} = 10$ NM (only intersecting conflicts are presented (shaded areas in **Figure 8**)). The calculated total risk was $3.08 \cdot 10^{-3}$.

In order to examine the influence of changes in flight entry time on the individual and total risk values, a simple change is introduced.

Namely, allowing one flight to enter into the system 30 seconds earlier (red line, **Figure 9**), the total risk value is reduced from $3.08 \cdot 10^{-3}$ to $2.86 \cdot 10^{-3}$.

Additionally, a previous situation is simulated with a lower separation minima $S_{min} = 5$ NM resulting in lower total risk. The risk value is now reduced from $2.86 \cdot 10^{-3}$ to $1.39 \cdot 10^{-3}$ (**Figure 10**). Details of the model application illustration are provided in [36, 37].

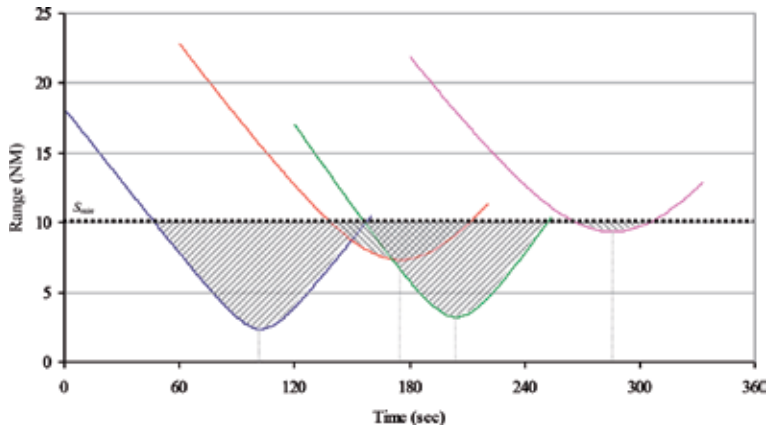


Figure 9. Change of spacing between aircraft pairs and the potential conflicts in the horizontal plane ($S_{min} = 10$ NM) with modified entry time case, compiled from [36, 37].

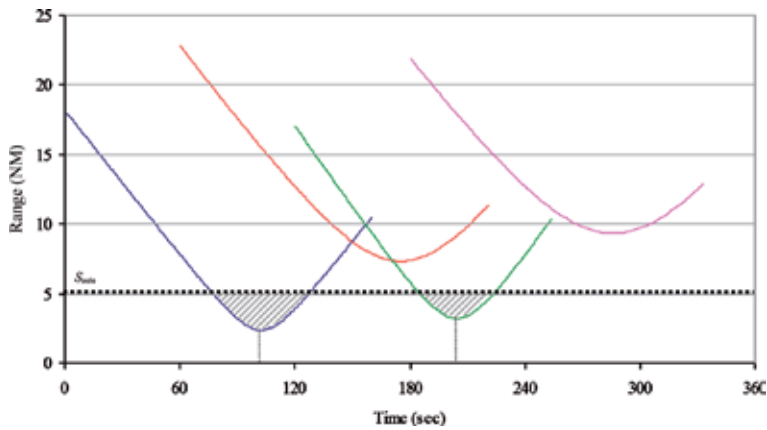


Figure 10. Change of spacing between aircraft pairs and the potential conflicts in the horizontal plane ($S_{min} = 5$ NM), compiled from [36, 37].

4.3 Conflict risk assessment model for airspace operational planning

The conflict risk assessment model for airspace operational planning level is intended for evaluation and comparison of different alternative operational scenarios (different separation minima, delegation of responsibility between pilots and ATCos, introduction of different ground and/or airborne-based decision support systems and tools, etc.) one or more days in advance [37].

In order to assess conflict risk, two variables are used [37]: duration of single or all conflict situations and severity of conflict situations.

The main inputs for this model are [37]:

- Airspace geometry
- Characteristics of the COM/NAV/SUR system equipment (technical characteristics and reliability)
- Actual traffic data (aircraft types, entry time in the airspace, exit time from the airspace)

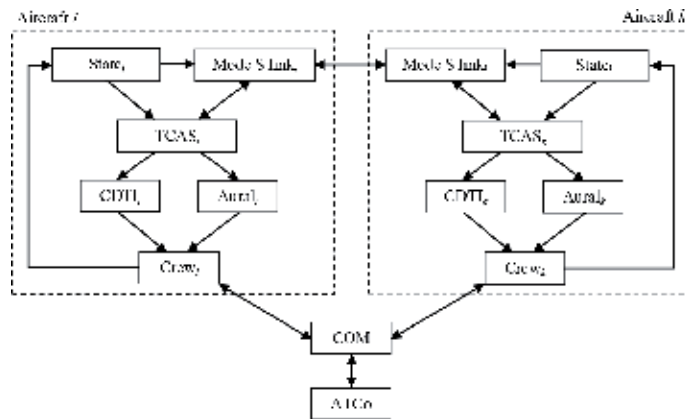


Figure 11.
 High-level representation of TCAS agents [37, 43].

- Data on aircraft behavior during the flight, reliability of certain aircraft technical parts, etc.

The influence of human operators (pilots, ATCos, etc.) at this level is considered through the modeling of their state (situational awareness, workload, etc.) [37].

An example of conflict risk assessment model for airspace operational planning level (one or more days in advance) is presented in the work of [41–43]. Although those papers are not directly related to the developed framework, they are showing the type of models which could be used for risk assessment at operational planning level. The goals of the research described in those papers were to assess the potential collision risk reduction for a historical en route mid-air collision event by using traffic collision avoidance system (TCAS).

This model (**Figure 11**) contains the technical elements (Cockpit Display of Traffic Information (CDTI), speakers for aural annunciation, TCAS, Mode S airborne-airborne communication link, airborne-ground communication link (COM)), human elements (pilot crews and ATCos), and procedural elements of TCAS operations (change of ATCos and pilots' roles during TCAS encounters) and fully supports mathematical analysis as well as rare event agent-based Monte Carlo simulation of aircraft encounters [43].

4.4 Conflict risk assessment model for airspace current day planning

4.4.1 Objectives and assumptions

A final step of the proposed framework is presented by the conflict risk assessment model for airspace current day planning level [37, 44].

The main objective (purpose) of this model is to support decision-making processes during sectorization (for a given set of available elementary sectors determined at operational planning level) through evaluation of the number of conflicts, the conflict probability, and the risk of conflict as well as their distribution at intersections or along airways, and ATCo task-load according to the approach of [45] for a given airspace and traffic load [44], few hours in advance. Decision-makers, using the proposed model and the results obtained, could decide whether or not to accept the estimated risk with a certain specified probability as well as the estimated task-load. Based on these results, they could decide, in advance, to keep the existing sectorization or not, at current day level [37, 44].

The following input data are used in this model [37, 44]:

- Known traffic data (confirmed flight plans and flight schedules with known aircraft types)
- Known airspace geometry (sector shapes and boundaries, number and length of airways, as well as airway tracks) determined as the most appropriate from a conflict risk point of view at the operational level

The influence of humans is considered through the ATCo task-load. Details of the model are provided in [37, 44].

Apart from the main assumptions, an additional one is introduced here: risk is a random variable and one aircraft at an airway can be simultaneously in conflict with only one aircraft from another airway.

The objectives and assumptions of this model show that the main difference between this model and models presented in previous subsections [35, 36] is that risk is assumed to be random variable and that consequently the developed conflict risk assessment model should now be able to serve as a decision support tool.

4.4.2 Illustration of the model application

In order to illustrate the developed model, a hypothetic en route sector is used (Figure 4). For each flight the following inputs were used: the entry points into the airspace, entry time, entry flight level, heading, ground, and vertical speed. Values for those inputs were assumed to remain constant during the flight [37, 44].

In real operations, the decision on specific sectorization usage in a certain time period is based solely on the forecasted number of aircraft in the sector. But, other factors exist as well, one of which is the number of potential conflicts. This number indicates an ATCo task-load and conflict risk in the sector. Correct assessment of those indicators is the responsibility of air traffic managers, and it serves them to adjust the existing airspace capacity by changing the sector configuration [37, 44].

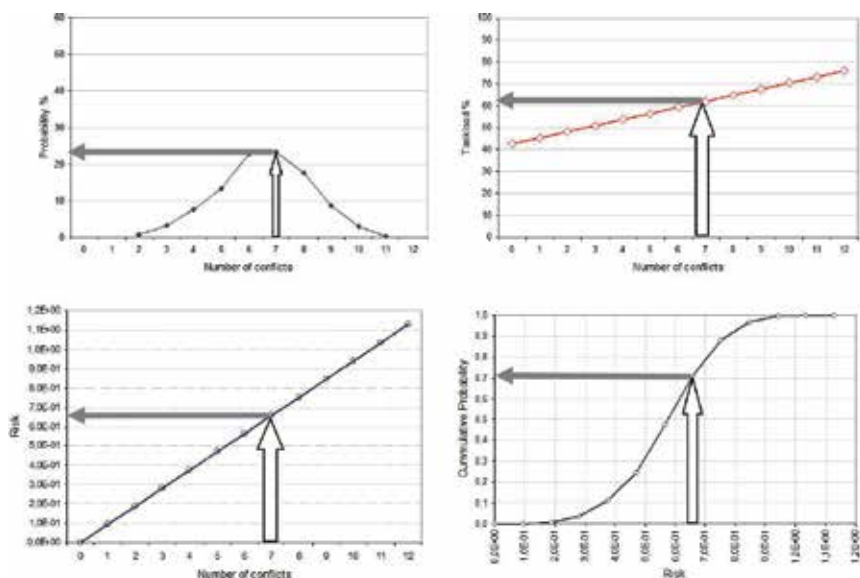


Figure 12. Example showing possible usage of outcomes of developed model by the air traffic managers [37, 44].

Based on the values for the number of conflicts, the risk of conflict, the risk probability, and the task-load determined by the simulation, their possible usage by air traffic managers is explained.

Let the number of conflict $N_c^* = 7$, with a horizontal separation minima of 10 NM and 12 aircraft/hour on AWY₃. **Figure 12** (upper left) enables the determination of a frequency (probability) of seven conflicts (23%), while **Figure 12** (upper right) enables the determination of ATCo task-load of 63%. This task-load value could be compared with critical threshold values which are usually used to define an overload situation [37, 44]. A conflict risk value of $R^* \approx 6.6 \cdot 10^{-1}$ was read from **Figure 12** (lower left) for given N_c^* , while **Figure 12** (lower right), for a risk value $R \leq R^*$, shows a cumulative probability of 0.71.

Figure 12 presents a value which could serve air traffic managers to decide whether or not a specific merging or partitioning of sectors is necessary within a certain time period (e.g., 30–90 minutes), allowing them in such a way to perform real-time analysis on a regular basis (e.g., every half an hour) [37, 44].

5. Conclusion

This chapter presents a framework for airspace planning and design based on conflict risk assessment developed for the purpose of preventing aircraft conflicts and collisions. The proposed framework is hierarchical by nature, containing four planning levels: strategic, tactical, operational, and current day.

During airspace planning and design process, airspace designers are often guided by the need to increase capacity and/or reduce air traffic controller (ATCo) workload. In order to consider safety risks in a systematic way, the proposed framework contains an additional step—safety risk assessment performed by safety analysts guided by the risk reduction need. In such a way, they are providing feedback to airspace designers regarding safety issues of their solutions.

This chapter presents four conflict risk assessment models, each one for different airspace planning level (strategic, tactical, operational, and current day), contained in the proposed framework.

Each of those models defines conflict risk on a different way and also has different objectives. The idea behind every model, i.e., basic development principles, was explained together with specific objectives, assumptions, and conflict risk concepts.

All models are illustrated by the simple numerical examples. The illustration of the model application shows that in addition to airspace geometry (airways length and airways crossing angles), conflict risk in the given airspace also depends on traffic flows/traffic demand, average flow speeds/aircraft speed, average aircraft inter-arrival times, spatial and temporal distribution of aircraft in the airspace, as well as separation minima in horizontal plane.

Experimental results confirmed that conflict risk values are sensitive on traffic demand and airspace volume changes.

A plan for further research considers application of the proposed framework in real-life systems and on large-scale cases. Special attention will be given to investigation of air traffic managers' behavior during decision-making process.

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Section 2

Complexity and Regulation

Air Traffic Complexity as a Source of Risk in ATM

Tomislav Radišić, Petar Andrašić, Doris Novak, Biljana Juričić and Bruno Antulov-Fantulin

Abstract

In this chapter the connection between air traffic complexity and risks in air traffic management system will be explored. Air traffic complexity is often defined as difficulty of controlling a traffic situation, and it is therefore one of the drivers for air traffic controller's workload. With more workload, the probability of air traffic controller committing an error increases, so it is necessary to be able to assess and manage air traffic complexity. Here, we will give a brief overview of air traffic complexity assessment methods, and we will put the traffic complexity assessment problem into a broader context of decision complexity. Human reliability assessment methods relevant to air traffic management will be presented and used to assess the risk of loss of separation in traffic situations with different levels of complexity. To determine the validity of the human reliability assessment method, an analysis of conflict risk will be made based on the real-time human-in-the-loop (HITL) simulations.

Keywords: air traffic complexity, risk, human reliability assessment, air traffic control, simulation

1. Introduction

Humans are at the core of every complex system in the world, and that is true for the air traffic management (ATM) system as well. While extremely resourceful and capable of dealing with unexpected circumstances, humans are also prone to errors. Although significant technological, organizational, operational, and other advances have been made in recent decades, catastrophic accidents driven by human errors are still a regular, albeit increasingly rare, occurrence. Recently, the realization that complete elimination of all human errors will probably never be achievable has taken hold [1]. As with any system that requires high degree of safety, ATM system solves this issue by employing multiple levels of risk and safety management, each providing a layer of the safety net. Nevertheless, methods for reducing the human error are still widely used and being researched. These methods, which consider the effect of human error on risk and reliability, are generally classified under the name of human reliability analysis (HRA). This chapter explores the applicability of HRA as part of the overall risk assessment with a focus on air traffic complexity issues.

There are many motivations for performing a risk or reliability analysis. In most cases it is to reduce the potential for system failure caused by humans. In this case the risk analysis can be used either in the design process or during the operation.

Sometimes it is needed to change or restructure the organizational design in a manner which ensures at least the same level of safety as before. In other cases, risk analysis can be performed as a part of licensing arrangements where the operator is tasked with assuring that a system meets a safety target. Or it can be used during the decision-making process where an operator chooses one of the possible systems to procure. In many of these cases, HRA will be undertaken as part of the more comprehensive risk assessment process.

Air traffic controllers (ATCOs) are at the core of the ATM. They are the central node where most important safety-related tactical decisions are made. Their job is to gather information and process them with the goal of reaching solutions which ensure safe and cost-efficient air traffic. One of their main tasks is prioritization of actions because human mental capacity is limited and it has been shown that ATCOs frequently deal with information overload [2]. Previous research showed that overload usually causes performance decline [3]. Air traffic complexity is one of the main factors driving the increase in the ATCO workload, so it is a reasonable assumption that increased complexity will result in increased errors due to decay in ATCO performance. Therefore, it is important to be able to assess air traffic complexity as a possible source factor of risk.

In this chapter, the connection between air traffic complexity, controller workload, HRA, and risk assessment will be made. For that purpose, in Section 2, a brief overview of complexity will be made, starting with definition and ending with assessment methods. In Section 3, a broader area of decision complexity and inherent difficulty of making the correct decision in a complex system will be presented. In Section 4, a very brief overview of HRA methods relevant to ATM system will be presented, as well as an HRA method developed specifically for use in ATM. In the latter parts of Section 4, an example of how to include the air traffic complexity into the HRA will be shown, and, in comparison, risk analysis based on real-time human-in-the-loop (HITL) simulations will be presented.

2. Air traffic complexity

2.1 Definition and purpose

The Random House dictionary defines complexity as “the state or quality of being complex; intricacy”, and complex as “composed of many interconnected parts; compound; composite”, “characterized by a very complicated or involved arrangement of parts, units”, and “so complicated or intricate as to be hard to understand or deal with” [4]. While this example uses *complicated* to define *complex*, some other sources argue that there is a major difference between the two. Collins English Dictionary states that [5]:

Complex is properly used to say only that something consists of several parts. It should not be used to say that, because something consists of many parts, it is difficult to understand or analyze.

On the other hand, Cilliers, in his seminal book on the topic, claims exactly the opposite [6]:

If a system—despite the fact that it may consist of a huge number of components—can be given a complete description in terms of its individual constituents, such a system is merely complicated. [...] In a complex system, on the other hand, the interaction among constituents of the system, and the interaction between the

system and its environment, are of such a nature that the system as a whole cannot be fully understood simply by analysing its components.

One example of such thinking is presented by Snowden in [7]. He claims that the aircraft can be considered complicated due to many parts. Once disassembled and analyzed, the function of all parts and their relationships can be determined. Human organizations and systems are, on the other hand, complex. They are made up of many interacting agents, with agent being any component of the system with identity. Agents can have multiple identities based on the context, i.e., a person can assume group identity or switch between formal and informal identities based on the environment. As these identities change, the components of the system change, the rules an agent follows change, and interactions between the components change. This makes it impossible to distinguish between the cause and effect because they are intertwined [8].

In the context of air traffic control, complexity was rarely clearly defined, perhaps due to assumed common knowledge. One notable exception is Meckiff (et al.) who stated that the air traffic complexity can be most easily defined as *difficulty of monitoring and managing a specific air traffic situation* [9]. It is intuitively clear that it is easier for the air traffic controller to monitor the airspace sector in which aircraft trajectories do not intersect and there are no level changes than the sector in which there are a lot of merging traffic flows and aircraft often change levels. As such, air traffic complexity could also be defined as a number of potential aircraft-aircraft and aircraft-environment interactions during a given time frame. Not all of these interactions require the same level of attention, urgency, or, ultimately, controller workload to resolve.

Complexity is *not* the same as traffic density. Obviously, the number of aircraft in a sector (also known as density, traffic load, or traffic count) directly influences the air traffic complexity. This number, however, is not the only indicator of the level of complexity, especially if one wishes to compare different sectors of airspace [10–12]. Two traffic situations can have equal density but vastly different complexity. Due to two different types of interactions, some researchers have chosen to make a distinction between **airspace complexity** (also static, structural) and **air traffic complexity** (also dynamic, flow complexity [13]) which is influenced by the airspace complexity. This distinction will be used in this chapter as well. Unless explicitly stated, complexity will from now on refer exclusively to air traffic complexity.

Complexity is *not* a synonym for workload, although it has been proven multiple times that the increase in complexity results in increase in workload which in turn limits the airspace sector capacity [14, 15]. Mogford et al. [11] reviewed numerous research articles in search of complexity and workload relationship. They concluded that the complexity is actually a source factor for controller workload (**Figure 1**). However, complexity and workload are not directly linked. Their relationship is mediated by several other factors, such as equipment quality, individual differences, and controller cognitive strategies [11].

Controller cognitive strategies can be improved through training and experience that is readily seen when comparing experienced and inexperienced controllers. However, if one takes into consideration an average controller with average training, only two avenues to reduced controller workload remain—increasing equipment quality and decreasing complexity.

2.2 Previous research on air traffic complexity

Complexity was a common research topic since the early days of modern ATC operations. First papers that mention complexity were written in the early

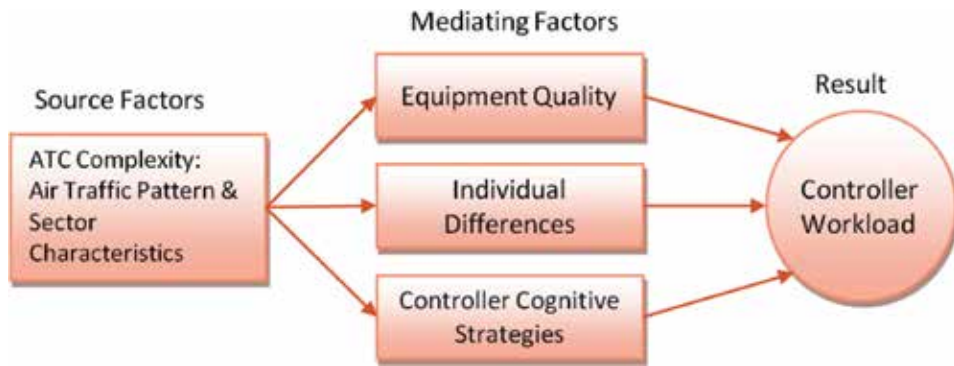


Figure 1.
The relationship between air traffic complexity and workload.

1960s [16]. Since then, dozens of papers and reports were written on the topic of complexity—excellent reviews of those papers were written by Mogford [11] and Hilburn [17]. Instead of writing a completely new literature review, this chapter will present important research paths, ideas, methods, and facts, which are relevant to the present research.

It needs to be noted that most of the early research was conducted in order to better define factors that affect workload. Today, most of those factors, with present understanding and definitions, would probably be called complexity factors. Some studies were nonempirical and lack exact definitions and measurement methods for complexity indicators. Those studies were excluded from this short review to give more room to those studies with experimentally validated complexity factors.

Schmidt [18] approached the problem of modelling controller workload from the angle of observable controller actions. He created the control difficulty index, which can be calculated as a weighted sum of the expected frequency of occurrence of events that affect controller workload. Each event is given a different weight according to the time needed to execute a particular task. Though the author conducted extensive surveys to determine appropriate weights and frequencies for various events, this approach can only handle observable controller actions, which makes it very limiting.

Hurst and Rose [19], while not the first to realize the importance of traffic density, were first to measure the correlation of expert workload ratings with traffic density. They concluded that only 53% of the variance in reported workload ratings can be explained by density.

Stein [20] used Air Traffic Workload Input Technique (ATWIT), in which controllers report workload levels during simulation, to determine which of the workload factors influenced workload the most. Regression analysis proved that out of the five starting factors, four factors (localized traffic density, number of hand-offs outbound, total amount of traffic, number of handoffs inbound) could explain 67% of variance in ATWIT scores. This study showed the importance of localized traffic density which is a measure of traffic clustering. Technique similar to ATWIT will be used throughout the next three decades, including a modified ATWIT scores that will be used in this research.

Laudeman et al. [21] expanded on the notion of the traffic density by introducing dynamic density which they defined as a combination of “both traffic density (a count of aircraft in a volume of airspace) and traffic complexity (a measure of the complexity of the air traffic in a volume of airspace).” Authors used informal interviews with controllers to obtain a list of eight complexity factors to be used in

dynamic density equation. The only criterion was that the factors could be calculated from the radar tracks or their extrapolations. The intention was to obtain an objective measure of controller workload based on the actual traffic. Their results showed that the dynamic density was able to account for 55% of controller activity variation. Three other teams [13, 22, 23] working under the Dynamic Density program developed additional 35 complexity indicators (factors), which were later successfully validated as a group by Kopardekar et al. [24]. Unfortunately, it was later shown that the complexity indicator weights were not universal to all airspace sectors, i.e., they had to be adjusted on a sector-by-sector basis [25]. This shortcoming, while making the dynamic density technique difficult to implement for operational purposes, has no influence if one wishes to compare two concepts of operations under similar conditions (similar sector configuration). Furthermore, same authors [24] suggested that, due to possibly nonlinear interactions between complexity factors, the dynamic density performance could be improved by using nonlinear techniques such as nonlinear regression, genetic algorithms, and neural networks.

Almost the same group of authors will use multiple linear regression method 5 years later to determine which subset of complexity indicators will correlate well with the controller's subjective complexity ratings [26]. After extensive simulator validation, results of this study showed that there are 17 complexity indicators that are statistically significant. Top five complexity indicators were sector count, sector volume, number of aircraft under 8 NM from each other, convergence angle, and standard deviation of ground speed/mean ground speed. Similar work was done by Masalonis et al. [27] who selected a subset of 12 indicators and Klein et al. [28] who selected a subset of only 7 complexity indicators, though with less extensive experimental validation.

In a similar vein, Bloem et al. [29] tried to determine which of the complexity indicators had the greatest predictive power in terms of future complexity. The authors concluded that there is a significant difference in predictive power of different complexity indicators. To complicate the matter further, they concluded that the subset of the complexity indicators that had the best predictive power changed depending on the prediction horizon.

To calculate potential impact of air traffic complexity on workload and costs, in 2000 the EUROCONTROL has given the same set of traffic data to UK National Air Traffic Services (NATS) and the EUROCONTROL Experimental Centre (EEC) with a task of independently devising a method of measuring the level of service [30]. While NATS has estimated ATS output (the service provided), the EEC has estimated the ATS workload needed to deliver the service. Both "were found to produce reasonably consistent results," with an additional note that further analysis should be done before the final parameters for determining ATS provider costs are established. By 2006 EUROCONTROL's Performance Review Commission finalized the complexity indicators to be used for ANSP benchmarking [31]. For this method the European airspace is divided into 20 NM X 20 NM X 3000 ft. cells, and for each cell the duration of potential interactions is calculated. Aircraft are "interacting" if they are in the same cell at the same time. The ratio of the hours of interactions and flight hours is the so-called adjusted density. In addition, the "structural index" is calculated as a sum of potential vertical, horizontal, and speed interactions. The final complexity score is calculated as a product of adjusted density and structural index. All in all, only four complexity indicators are used for this analysis, and no validation of any sort was presented in the report. It was noted, however, that shifting the starting position of the grid by 7 NM caused the ANSP ranking to change dramatically (up to 16 places in an extreme case). Nonetheless, this method is still used for ANSP benchmarking.

First to consider measuring complexity during TBO were Prevot and Lee [32]. They coined the term trajectory-based complexity (TBX) which is a measure of complexity in TBO. The basis of the TBX calculation is a set of nominal conditions—nominal sector size, nominal number of transitioning aircraft, and a nominal equipage mix. Any difference to nominal operations causes a modification to the TBX value. Authors do not explain the method to determine the nominal conditions except that they can “be defined through knowledge elicitation sessions on a sector by sector basis or based upon more generic attributes.” The TBX value is then a number of aircraft that would produce the same workload under the nominal conditions as do aircraft under real conditions (e.g., the TBX of 20 means that the workload is equal to the aircraft count of 20 under nominal conditions even though there are actually only 16 aircraft in the sector). The advantage of this method is that it gives a single complexity value that can be easily related to aircraft count and is thus very user-friendly and self-explanatory (unlike many other complexity metrics). However, this study included only six complexity indicators with weights that were determined in an ad hoc manner and hardly any validation with actual subjective complexity. Only one of those complexity indicators was indirectly related to TBO (number of aircraft with data-link). Many human-in-the-loop simulation runs were performed in which the controllers had to give workload scores which were then compared with TBX value and simple aircraft count. While the authors claim that the subjective workload score correlated better with the TBX value, there was no objective correlation assessment presented. Finally, the authors have not compared the effect of fraction of TBO aircraft on air traffic complexity.

In a subsequent paper by same authors, the relationship between workload and data-link equipage levels was explored [33]. It was concluded that the workload ratings correlated much better with the TBX score than with the aircraft count for varying data-link equipage levels.

Prandini et al. have developed a new method of mapping complexity based exclusively on traffic density [34]. This method is applicable only to the future concept of aircraft self-separation and does not take into account the human factors at all.

Gianazza [35–37] proposed a method for prediction of air traffic complexity using tree search methods and neural networks. This method is based on the assumption that the air traffic complexity in historic flight data increased prior to the splitting of the collapsed sector into two smaller ones and decreased prior to collapsing the sectors into a larger one. The neural network was trained using this historical data, and then it could predict future increase in air traffic complexity. Tree search method was then used to determine the airspace configuration which yields lowest workload and complexity for the given air traffic pattern.

Lee et al. [38] have proposed that airspace complexity can be described in terms of how the airspace (together with the traffic inside it and the traffic control method) responds to disturbances. The effect of disturbances on control activity needed to accommodate that disturbance is what defines complexity in their opinion. The more control activity needed, the more complex the airspace is. They propose a tool, airspace complexity map, which should help to plan the airspace configuration and the future development of ATM.

In Radišić et al. [39], authors used domain-expert assessment to test the effect of the trajectory-based operations (TBO) on air traffic complexity. ATCOs were recruited to perform human-in-the-loop (HITL) simulations during which they were asked to provide real-time assessment of air traffic complexity. Linear regression model was used to select, among 20 most used complexity indicators, those indicators which correlated best with subjective complexity scores. Six indicators were used to generate a predictive linear model that performed well in conventional

operations but less so under TBO. Therefore, the authors defined and experimentally validated two novel TBO-specific complexity indicators. A second correlation model combining these two novel indicators with four already in use generated much better predictions of complexity than the first model. Nonetheless, the best correlation that was achieved was $R = 0.83$ (R^2 -adjusted = 0.691). In subsequent work, the authors attempted to achieve better prediction by using artificial neural networks; however, similar results were obtained. This indicates that there is some variation in subjective complexity scores provided by ATCOs that cannot be explained by traffic properties. Indeed, it might be the case that ATCOs introduce a degree of noise into the complexity scores due to difficulty of maintaining the consistent scoring criteria [40].

Wang et al. [41] in their work used network approach to calculate air traffic complexity based on historical radar data. Their assumption is that air traffic situation is essentially a time-evolving complex system. In that system aircraft are key waypoints; route segments are nodes; aircraft-aircraft, aircraft-keypoint, and aircraft-segment complexity relationships are edges; and the intensities of various complexity relationships are weights. The system was built using a dynamic weighted network model.

Xue et al. [42] in their work analyzed three complexity indicators for simulated UAS traffic: number of potential conflicts, scenario complexity metric, and number of flights. Scenario complexity metric is based on cost of pairwise conflict which is defined as deviation from the original path. To perform analysis on around 1000 scenarios at different density levels, authors had to develop a UAS simulator. Analysis was done using Pearson and ACE statistics methods.

Future concept of operations will involve usage of far wider range of air traffic controller tools; therefore, it is expected that new complexity indicators related to interaction of controllers and equipment will have to be developed. Furthermore, novel complexity assessment methods are needed due to limits of current techniques.

2.3 Complexity estimation methods

In this section, several air traffic complexity estimation methods will be examined in greater detail. All complexity estimation methods are based on the traffic data which describes a traffic situation. Since the complexity is a psychological construct, the most relevant estimator of complexity in a given traffic situation is the air traffic controller. The air traffic controller can look at the traffic data and decide whether a traffic situation is complex or not. All other methods are just attempts at approximating the level of complexity as estimated by the controller. The main problem with expert-based estimation is the inconsistency between controllers, where one controller gives a different complexity estimate than the other. Therefore, most other methods seek ways to make the complexity estimate without human input. Ideally, those other methods would be validated by comparing them to the expert, i.e., controller's estimate; however, this is not always the case.

Three main methods of control-based (i.e., based on ATCOs' experience of complexity as a driver for workload and, subsequently, limiting factor of airspace capacity) air traffic complexity estimation will be presented here:

- Expert-based air traffic complexity estimation—where an expert, in most cases an air traffic controller, gives their estimate of the complexity
- Indicator-based air traffic complexity estimation—where the values of complexity indicators, derived from traffic data, are used to determine the level of complexity

- Interaction-based air traffic complexity estimation—where the complexity is estimated on the basis of the number of aircraft interactions in a given airspace cell (this method could be broadly defined as a very narrow indicator-based complexity estimation method due to a very low number of indicators)
- Others—methods based on other principles, such as counting the number of clearances [43], evaluating proximity based on probabilistic occupancy of airspace [44], measuring sensitivity to initial conditions of the underlying dynamic system called Lyapunov exponents (i.e., assessing predictability of traffic) [45], and many others

3. ATC operations and the decision domains

The decision-making process needs to be adapted to the context in which the operations take place. It is often seen that one kind of decision-making, completely adapted to its environment and therefore useful, cannot be easily transferred to another environment. This is often the case with accomplished engineers being notably less successful after moving into the managerial role.

Classification of such environments and appropriate decision-making modes is sometimes attempted with the goal of making rules about the best ways to manage each context. However, this is not an exact science because there are multiple factors that can change the decision-making context depending on who the person making the decision is, or how experienced they are. Nevertheless, there is still utility in being aware of the environment in terms of decision contexts and learning how to detect when the environment shifts from one domain to another.

One such classification attempt is the *Cynefin* framework [7]. It was developed in the early 2000s as a tool for decision-making, and it proposes five decision domains:

- Simple (also, obvious)—In this domain the situation is well known and stable. The cause–effect relations are established and rarely change. Following procedures and best practices is the best course of action to ensure efficient realization of goals. Decision-making process is usually made of the sense-categorize-respond steps. A major issue in this domain is the overreliance on patterns and routine behavior which stifles innovation and precludes any change. This has caused many issues in the past when organizations were not willing to adapt to changes or innovate, but on the other hand, this has also created many opportunities for disruption by newcomers.
- Knowable (also, complicated)—This domain includes environments in which not everything is known but everything can be understood with enough time and effort. In *knowable* domain the experts can work rationally towards solutions by sensing the environment, analyzing the data, and applying the best practices. In contrast with *simple* domain, where the main part of the task is applying the best practices, in *knowable* domain most of the effort is spent analyzing the situation.
- Complex—In this domain are environments or systems which cannot be analyzed by breaking them down into smaller pieces, analyzing them individually, and creating the big picture based on the analysis of individual components. The very act of interacting with the system introduces changes which cannot always be predicted. The main mode of management of complex systems is through observation of patterns, finding ways to sustain those patterns we

desire, and disrupting those we do not. One particular phenomenon that arises in complex systems is the so-called retrospective coherence. The state of the system seems logical and coherent once it is retrospectively analyzed; however, current state of the system could hardly be anticipated in advance because there are many other equally plausible system states.

- Chaotic—Chaotic systems cannot be analyzed for cause and effect relationships. Patterns are not visible, and if one waits for patterns to emerge, the damage could become disastrous. It is in these conditions that the system is most difficult to manage but also most capable of change, for better or for worse.

Air traffic control is all about making decisions, so it is not a novel idea to apply the Cynefin framework to the ATC operations even though Cynefin was originally proposed for business-related decision-making [46]. Air traffic control is a complex system with numerous human and machine agents, organized in deep layers of components glued by multiple communication modes and protocols. This is even more apparent in air traffic management systems. Although someone might look at the routine ATC operations and consider them simple, or even mechanistic, such thinking is a sure way towards probably costly failure. In our opinion, ATC operations can be assigned to all domains depending on the traffic situation or changes in states of the system:

- During the nominal low-traffic ATC operations, the traffic situation is easy enough in terms of workload to be considered as belonging to the *simple* domain. The ATCO needs to sense the traffic situation or a particular part of it, usually by looking at the radar screen and talking to the pilots. Then they need to categorize the task that needs to be performed in order to ensure safe and efficient traffic. The task can be categorized as any of the numerous routine ATC tasks, e.g., conflict resolution, clearing or initiating climbs or descents, managing exit flight level constraints, etc. Then the ATCO acts by issuing a command or a clearance. This process occurs many times an hour, and some parts of it are trained to such a degree that the ATCO is often not even conscious of them.
- In nominal high traffic ATC operations, the number of interactions rises and so does the difficulty of maintaining safe and efficient air traffic. The situation needs to be sensed and then analyzed for all the tasks that need to be performed. Tasks are often prioritized based on the urgency and difficulty. A lot more time is spent on this analysis than in low-traffic situation. The ATCO then solves the issues by applying solutions that are considered to be best practice. There are multiple ways of solving an issue, and all of them are correct if the safety is maintained and flight efficiency is not unreasonably reduced. Unless there is some source of major uncertainty present, such as adverse weather conditions, this type of operations is best described as belonging to the *knowable* domain.
- In off-nominal operations of any traffic level or nominal operations with a major source of uncertainty, such as adverse weather, the decision context often enters the *complex* domain. The traffic situation evolves into unpredictable directions which can be completely explained only post hoc. Systemic complexity management measures, such as regulations, are undertaken to ensure safety because continuing with business as usual could lead, with unacceptable probability, to incidents or accidents. Nonetheless, these measures

are sometimes not enough or are compounded with additional issues which altogether cause the loss of situational awareness for the ATCO or the pilots. Incidents lurk in these conditions.

- Operations in the *chaotic* domain should never happen in ATC. The whole system is designed to prevent such occurrences. However, history has shown us that there are sequences of events that can throw the whole system into a disarray and shift the decision context very quickly from the *simple* into the *chaotic* domain. One example of such a sequence is Croatia Control's area control center (ACC) outage of 2014 when flooding due to unprecedented rainfall combined with human error and organizational deficiencies caused the complete loss of power to all ATC systems for 2 h [47]. When radar screens went blank, quick-thinking ATCOs used their personal mobile phones to contact ACCs of neighboring countries to warn them of potential conflicts, thus preventing midair collisions. This incident clearly illustrates how quickly a situation can go from bad (*complex* domain, operations in adverse weather) to worse (*chaotic* domain, complete loss of power).

It should be noted here that air traffic complexity should not be confused with *complex* domain in the Cynefin framework. Air traffic complexity is present in all decision domains, usually being lower in the *simple* domain and higher at the other end of the spectrum in the *chaotic* domain.

The main purpose of this classification of decision contexts in ATC is to help make ATCOs and supervisors aware of the different environments that are possible behind the seemingly unchanging radar screen. Another purpose, which will be discussed in the next section of this chapter, is to lay down the framework for assessing risks associated with air traffic complexity.

4. Assessing risks associated with air traffic complexity

Complexity in ATM is often split into two parts: airspace complexity (static complexity) and air traffic complexity (dynamic complexity). It is generally agreed that both dynamic and static components of complexity can affect controller workload and influence the probability of occurrence of an ATC (i.e., controller) error. Dynamic complexity relates to the factors describing air traffic complexity, i.e., it can include factors such as traffic volume, climbing/descending traffic, mix of aircraft type, military area activity, and types of aircraft intersection. Static factors, on the other hand, encompass factors related to the airspace, such as airspace structure, proximity of reporting points to sector boundaries, and standing agreements between ANSPs.

In a human factors study, areas rated as some of the biggest contributors to risk in ATM are workload, human error, allocation of function, and situational awareness [48]. As mentioned previously, air traffic complexity is a measure of difficulty of controlling the air traffic in a given sector; therefore, it is a direct contributor to workload. In a sense, ATCO's job is to make correct decisions, whereas air traffic complexity is a factor that makes the search for the right decision more difficult. Therefore, increased complexity can directly increase the probability of a wrong decision being made because the size of the search space increases faster than the set of correct solutions. Here lies the main connection between air traffic complexity and risk. Probability of human error (i.e., human error risk) increases with increased complexity. Thus, it is reasonable to assess the complexity-related risks from the human reliability assessment point of view.

EUROCONTROL investigated the possible relationship between ATM system complexity and safety. They tried to develop a complexity hazard and operability (HAZOP) technique with the main objective being to trial this approach and evaluate its utility for safety assessment and obtain feedback on its acceptability with operations personnel [49]. The attempt at developing complexity HAZOP was unsuccessful due to difficulty of adjusting the HAZOP technique to the complexity issues. Therefore, in this section only HRA methods will be presented.

4.1 Human reliability assessment

This section will provide a brief overview of the HRA methods and their development over the years; however, for a more thorough review of HRA methods, one can find more information in [46, 50]. Only those methods that are in some way relevant to HRA in aviation will be considered.

HRA can be defined as “any method by which human reliability is estimated” [51], and it is generally presented as having three main parts: (1) identifying possible human errors and contributors, (2) modelling human error, and (3) quantifying human error probabilities. These methods were first developed in nuclear power safety systems.

In the early models of HRA, human was often considered as just another part of the system. For example, in [52], a *technique for human error-rate prediction* (THERP) was developed based on the techniques used in nuclear power plant risk management, i.e., a straightforward event tree analysis was performed. Each human action (e.g., reading a display, operating a lever) was given a human error probability (HEP) as a probability with a value from 0 (least probable) to 1 (most probable). Sample of values for different errors can be seen in **Table 1**. The values assigned to each error type came from authors’ experience and from earlier studies performed in the defense sector.

THERP also specified performance shaping factors (PSF) which were used to modify the nominal HEPs based on the context of the action (e.g., time pressure, human-machine interface, etc.). A list of possible PSFs for one error is given in **Table 2**. One can notice that there are no error multipliers associated with each PSF. It is the duty of the assessor to define the maximum affect that each PSF could have on HEPs. Criticism of THERP was mostly that it was too difficult to apply because of quite detailed decomposition of tasks that it relied on a database of HEPs which was never really validated and that it took very broad and casual definitions of human performance factors.

Error	HEP
Failure to perform rule-based actions correctly when written procedures are available and used (with recovery)	0.025
Inadvertent activation of a control; select wrong control on a panel from an array of similar-appearing controls identified by labels only	0.003
Omitting a step or important instruction from a formal or ad hoc procedure	0.003
Omitting an item of instruction when use of written procedures is specified (<10 items)	0.001
Checking the status of equipment if that status affects one’s safety when performing his tasks	0.001
Turn rotary control in the wrong direction when there is no violation of populational stereotypes	0.0005
Errors of commission in check-reading analog meters with easily seen limit marks	0.001

Table 1.
Examples of HEPs given in [52].

1	Stress level of the operator
2	Rate at which the operator must process signals
3	Frequency with which a particular display is scanned
4	Whether a written checklist is used to direct the operator to specific displays
5	Relationship of the displays to annunciators or other attention-getting devices
6	Extent to which the information needed for operator decisions and actions is displayed directly
7	Human factors engineering related to the design and arrangement of the displays

Table 2.
Examples of PSFs for errors related to reading unannunciated displays [52].

Another version of this type of model was done in human error assessment and reduction technique (HEART) [53]. The database of HEPs was much smaller and more generic, so it was more flexible and easier to apply than THERP. Instead of highly detailed errors, the focus is on a handful of generic task types for which probabilities of failure are given (**Table 3**). This simplification has made the HEART technique much more accepted outside the nuclear power industry for which the THERP was designed.

The author has identified the human factors he found relevant by searching the human factors literature and assigned relative weights to them, identified impacts of errors, and suggested a set of human error data which should enable higher reliability of the system. Instead of calling them PSFs, the author called them error-producing condition (EPC) and provided the multipliers for each. Multipliers are used to increase the nominal human unreliability in cases where there are circumstances that increase the probability of human error. Some of the EPCs are shown in **Table 4**.

More generic error types have led to confusion when trying to apply it to a specific industrial application. This problem was addressed by developing specialized versions of HEART for specific industries. One such derivative will be discussed shortly.

These models are characterized by defining two broad categories of errors: errors of omission (when human operator fails to make an action) and errors of commission (when operator makes a wrong action). These simplifications were later put, at least partially, into the context of actual human behavior which knows many other ways of committing an error. For example, [54, 55] included contextual effect such as stress, organizational culture, and tiredness into the model, whereas [56, 57] also included the possible variation in operator's responses and recovery actions undertaken once the errors have been noticed. By taking into account the context of human behavior, these techniques have made a qualitative step forward in comparison to the THERP and HEART, so they are generally called second-generation HRA techniques. This did not, however, improve their adoption in the industry because simpler and more flexible techniques, such as HEART, are more usable and sustainable. For this reason, the first HRA technique developed specifically for ATM was based on HEART technique. It was developed in 2008 and named Controller Action Reliability Assessment (CARA) [58].

4.2 Human reliability assessment in ATC

Compared to HEART, CARA's generic task types were developed to better suit the needs of HRA in ATM (**Table 5**). To make sure that the task types are in line with the commonly used models of ATCO tasks, the basis for task development was

Generic task	Proposed nominal human unreliability	5th–95th percentile bounds
Totally unfamiliar, performed at speed with no real idea of likely consequences	0.55	0.35–0.97
Shift or restore system to a new or original state on a single attempt without supervision or procedures	0.26	0.14–0.42
Complex task requiring high level of comprehension and skill	0.16	0.12–0.28
Fairly simple task performed rapidly or given scant attention	0.09	0.06–0.13
Routine, highly practiced, rapid task involving relatively low level of skill	0.02	0.007–0.045
Completely familiar, well-designed, highly practiced, routine task occurring several times per hour, performed to highest possible standards by highly motivated, highly trained, and experienced person, totally aware of implications of failure, with time to correct potential error but without the benefit of significant job aids	0.0004	0.00008–0.009
Respond correctly to system command even when there is an augmented or automated supervisory system providing accurate interpretation of system state	0.00002	0.000006–0.0009

Table 3.
Generic tasks and proposed human unreliability in HEART technique [53].

Error-producing condition	Maximum predicted increase in unreliability when going from good conditions to bad
Unfamiliarity with a situation which is potentially important but which only occurs infrequently or which is novel	×17
A shortage of time available for error detection and correction	×11
A low signal-to-noise ratio	×10
A means of suppressing or overriding information or features which is too easily accessible	×9
No means of conveying spatial and functional information to operators in a form which they can readily assimilate	×8
A mismatch between an operator's model of the world and that imagined by a designer	×8

Table 4.
EPCs and their multipliers as proposed in the HEART technique [53].

found in EUROCONTROL's studies. Literature and ergonomics database reviews were undertaken to find the data which supports new values of HEPs for each generic task type. Where more than one error probability for a given task was found in the literature or the databases, geometric mean was used to establish a single value. Furthermore, uncertainty bounds of each HEP were determined using the single sample t-test [59].

EPCs used in CARA were, like general task types, developed by adjusting EPCs from HEART and other techniques (most notably SPAR-H [60] and CREAM [61]). To ensure that the CARA EPCs closely follow the well-established contextual structure used in ATC, they were modelled to fit the Human Error in ATM (HERA) [62] classification structure. For initial consideration, CARA EPCs' maximum affect

Task context	Generic task type	HEP	Uncertainty bounds
A. Offline tasks	A. Offline tasks	0.03	—
B. Checking	B1. Active search of radar or FPS, assuming some confusable information on display	0.005	0.002–0.02
	B2. Respond to visual change in display (e.g., aircraft highlighted changes to low-lighted)	0.13	0.05–0.3
	B3. Respond to unique and trusted audible and visual indication	0.0004	—
C. Monitoring for conflicts or unanticipated changes	C1. Identify routine conflict	0.01	Holding value'
	C2. Identify unanticipated change in radar display (e.g., change in digital flight level due to aircraft deviation or corruption of datablock)	0.3	0.2–0.5
D. Solving conflicts	D1. Solve conflict which includes some complexity. Note for very simple conflict resolution consider use of GTT F	0.01	Holding value'
	D2. Complex and time pressured conflict solution (do not use time pressure EPC)	0.19	0.09–0.39
E. Plan aircraft in/out of sector	E. Plan aircraft in/out of sector	0.01	Holding value'
F. Manage routine traffic	F. Routine element of sector management (e.g., rule-based selection of routine plan for an aircraft or omission of clearance)	0.003	Holding value'
G. Issuing instructions	G1. Verbal slips	0.002	0.001–0.003
	G2. Physical slips (two simple choices)	0.002	0.0008–0.004

Holding values are to be updated once more data is available.

Table 5.
Generic task types used in CARA technique [59].

values were taken from HEART, SPAR-H, and CREAM by selecting the most similar EPCs and then picking the one with the highest value (**Table 6**). It is expected that with further refinement of underlying data, the maximum affect values will be adjusted to better suit the actual values in ATC.

For the first time here, one can see that the traffic complexity was taken into account (EPC 17) with maximum affect of 10. CARA User’s Manual provides additional information about this EPC, adding three anchor points for this EPC [63]:

- Higher than normal traffic levels with some non-routine conflicts to solve (EPC multiplier 0.1)
- Higher than normal traffic levels with some non-routine conflicts requiring constrained solutions; possibility of secondary conflicts (conflict resolution can lead to a second conflict) (EPC multiplier 0.5)
- High traffic levels with unusual patterns of traffic requiring problem solving and a number of future conflicts requiring resolution (EPC multiplier 1.0)

EPC multipliers are used to scale the EPC affect from its maximum value to the actual value for the situation that is being assessed, thus getting the actual

HERA element	CARA EPCs	Maximum affect
Documentation/ procedures	1. Shortfalls in the quality of information conveyed by procedures	5
Training and experience	2. Unfamiliarity and adequacy of training/experience	20
	3. On-the-job training	8
Workplace design/HMI	4. A need to unlearn a technique and apply one which requires the application of an opposing philosophy—stereotype violation	24
	5. Time pressure due to inadequate time to complete the task	11
	6. Cognitive overload, particularly one caused by simultaneous presentation of non-redundant information	6
	7. Poor, ambiguous, or ill-matched system feedback—general adequacy of the human-machine interface	5
	8. Trust in system	—
	9. Little or no independent checking	3
	10. Unreliable instrumentation	1.6
Environment	11. Environment—controller workplace noise/lighting issues, cockpit smoke	8
Personal factor issues	12. High emotional stress and effects of ill health	5
	13. Low vigilance	3
Team factor issues	14. Difficulties caused by team coordination problems or friction between team members	10
	15. Difficulties caused by poor shift hand-over practices	10
Pilot-controller communication	16. Communications quality	—
Traffic and airspace issues	17. Traffic complexity	10
	18. Unavailable equipment/degraded mode—weather issues	—
Weather	19. Weather	—
Non-HERA: organizational culture	20. Low workforce morale or adverse organizational environment	2
Non-HERA: cognitive style	21. Shift from anticipatory to reactive mode	10
	22. Risk taking	4

Table 6.
 CARA EPCs and values of their maximum affect [59].

effect (AE). As is the case with many HRA techniques, some expert opinion is needed here to determine where the assessed scenario falls on the scale of 0.1–1.0. An example of human error risk calculation is given in the next section.

4.3 Using CARA to assess the effect of complexity on ATCO error risk

To better show how CARA is used to assess the effect of complexity on ATCO error risk, a simple example will be used. In this example, we suppose that the ATCO is working on an en route sector with moderately high air traffic complexity. Weather is calm and there are no failures in any of the air or ground equipment. In these conditions, we might want to assess the probability that the ATCO will not notice a conflict.

To do this, we select a generic task type (GTT) that best suits our situation. Here, it is *C1. Identify routine conflict* with HEP of 0.01. Appropriate EPC to select in this case is the *EPC 17: traffic complexity* with maximum affect of 10. Also, we use our expertise to determine that the current traffic situation is moderately complex, so we use EPC multiplier to determine the assessed effect (AE) equal to 0.4. Calculating the probability (P) of ATCO's failure to detect the conflict is then calculated using Eqs. 1–3.

$$P = GTT \times ((EPC - 1) \times AE + 1) \quad (1)$$

$$P = 0.01 \times ((10 - 1) \times 0.4 + 1) \quad (2)$$

$$P = 0.046 \quad (3)$$

The result shows that the probability of ATCO failing to notice a conflict in a moderately complex situation is 0.046 or 4.6%. The -1 and $+1$ in Eq. 1 are added to ensure that the resulting EPC is more than 1 without needlessly increasing the EPC (e.g., if only the final $+1$ was added). Conversely, the probability of ATCO identifying a conflict is equal to 95.4%. These probabilities are valid for a situation with only one ATCO; however, en route ATC operations are usually performed with two ATCOs handling a sector (planning and executive ATCOs). The probability that both ATCOs will fail to notice the conflict is equal to $0.046 \times 0.046 = 0.0021$ which is to say that approximately 1 in 500 conflicts in moderately complex traffic situations will not be identified (step 1 in **Figure 2**). Fortunately, ATC tools, such as short-term conflict alert (STCA), will sound the alarm in that case, and the ATCO will have the opportunity for a timely recovery.

This calculation showed how to use CARA to determine probability of a single event. Events can be chained into probability trees to calculate the probability of a sequence of events. Building on the previous example, we can calculate the probabilities of further events after the conflict was identified or after a conflict was missed. First possibility, and a more probable one, is that the conflict was identified. Next step for ATCOs is to solve it. Let us assume that this task can be assigned to the *D1. Solve conflict which includes some complexity* GTT which is assigned HEP of 0.01. Using a GTT with the same HEP as in previous example, in combination with same EPC for traffic complexity, will yield the same error probability of 0.046 (step 2 in **Figure 2**). If ATCO notices that the conflict is not solved, they will make another attempt to solve it (step 3 in **Figure 2**). This can be considered a recovery action for the previous error (not solving the conflict). It is up to the assessor to analyze the traffic situation and operational procedures to determine how many attempts an ATCO could have before the STCA alarm rings. Modelling of additional tools, such as separation tool which helps ATCO to determine whether the conflict resolution action was successful or not, can assist the assessor in determining the most accurate sequence of events.

If the conflict was missed or the ATCO could not solve it in time, STCA will sound the alarm. This usually occurs 2 min before the loss of separation. ATCOs' response to the STCA can be modelled using the *B3. Respond to unique and trusted audible and visual indication* GTT which is assigned HEP of 0.0004. Due to short time until loss of separation, it is reasonable to use EPC number 5: *time pressure due to inadequate time to complete the task* which is assigned maximum affect value of 11. Since this GTT only relates to noticing and responding to the STCA, the

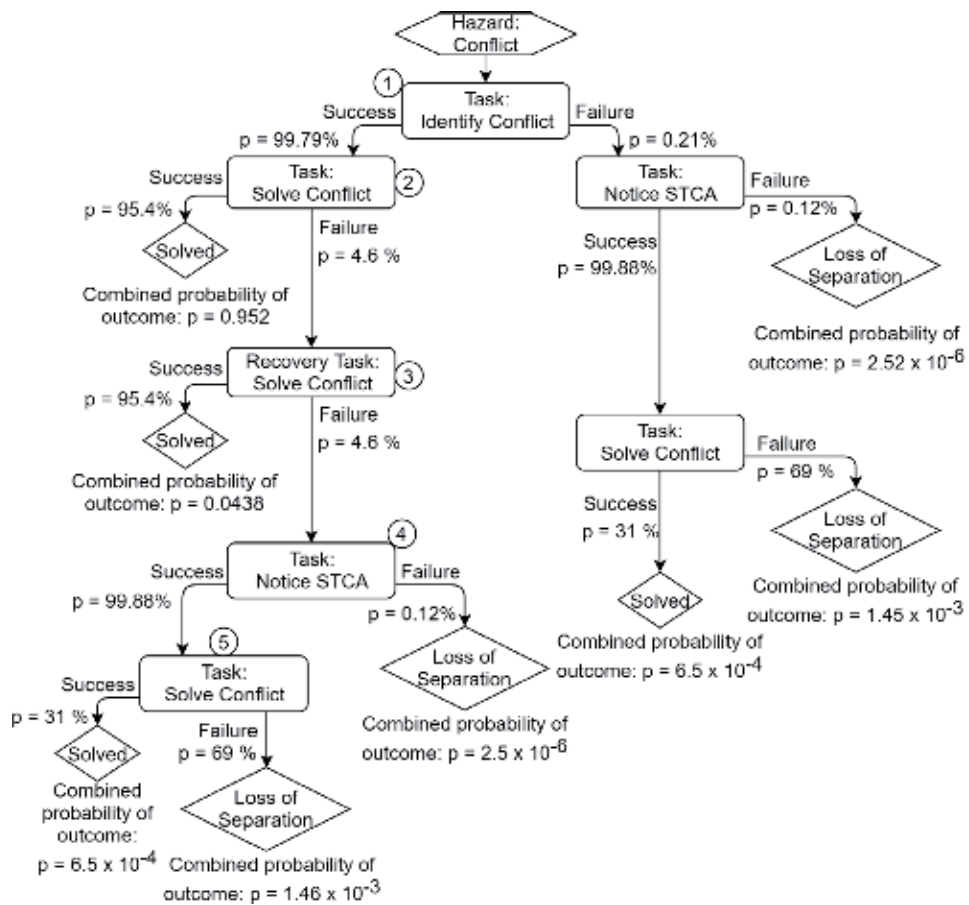


Figure 2.
 Probability tree for conflict resolution in moderately complex traffic according to CARA.

actual effect of this EPC will be on the lower side, so the multiplier is set to 0.2. Calculation of the error probability is then made with Eqs. 4–6.

$$P = GTT \times ((EPC - 1) \times AE + 1) \quad (4)$$

$$P = 0.0004 \times ((11 - 1) \times 0.2 + 1) \quad (5)$$

$$P = 0.0012 \quad (6)$$

This calculation shows that the probability of not noticing the STCA alarm will be 0.12% (step 4 in **Figure 2**). Once the ATCO notices the STCA, they will make another effort to solve the conflict. This time, the appropriate GTT is *D2: complex and time pressured conflict solution* which is assigned HEP value of 0.19 with confidence interval between 0.09 and 0.39. The assessor should use expert guidance to determine which value should actually be used; in this example, 0.15 will be used. In addition, assessor could add two EPCs, one for time pressure (*(5) time pressure due to inadequate time to complete the task*) and one for complexity (*(17) traffic complexity*); however, CARA User Manual states that the EPC 5 should not be

combined with GTT D2 and neither should EPC 5 and 17 be used together [63]. This prevents overly pessimistic results. Therefore, only EPC 17 will be included in the assessment. Like in previous steps of this example, we will use 0.4 as EPC multiplier to determine the assessed effect. The calculation is given by Eqs. 7–9.

$$P = GTT \times ((EPC - 1) \times AE + 1) \quad (7)$$

$$P = 0.15 \times ((10 - 1) \times 0.4 + 1) \quad (8)$$

$$P = 0.69 \quad (9)$$

This calculation shows that, in complex traffic situation, the probability of a conflict not being solved under time pressure (STCA alarm) will be 69% (step 5 in **Figure 2**). In comparison, if the traffic is not complex, the probability of failure will be only 15%. Obviously, assessor should adjust the values of GTTs and EPCs to better suit the situation being assessed, so these probabilities are in no way final.

Finally, the probability of each outcome can be calculated by multiplying the probabilities of each event that led to that outcome. For example, if one wishes to calculate the probability that the conflict will be solved only after two failed attempts and an STCA alarm, step 5 in **Figure 2**, they should multiply probabilities of all events leading to that outcome as seen in Eqs. 10–12.

$$P_{outcome} = P_{event1} \times P_{event2} \times \dots \times P_{eventN} \quad (10)$$

$$P_{outcome} = 0.9979 \times 0.046 \times 0.046 \times 0.9988 \times 0.31 \quad (11)$$

$$P_{outcome} = 6.5 \times 10^{-4} \quad (12)$$

The last step in this process is to sum up all the probabilities of a favorable outcome (conflict solved) versus all the probabilities of an unfavorable outcome (loss of separation). In this example, the probability of the favorable outcome is 99.71% versus the probability of an unfavorable outcome which is 0.29%.

To better appreciate the effect of traffic complexity on the risk of human error, comparison with the traffic situation which is not complex can be made by excluding the traffic complexity EPC from the calculation. This calculation is omitted here for brevity, but the same method without the traffic complexity EPCs yields probability of a loss of separation below 3.5×10^{-5} per conflict (approximately 1 in 28,600 conflicts). That is two orders of magnitude less probable than in the case with moderate complexity (0.29% or 1 in 345). On the other hand, if the traffic is highly complex, the assessor might use higher EPC multiplier for complexity, all the way up to 1. In that case, the probability of an unfavorable outcome, i.e., loss of separation, is 2% (1 in 50) which is 7 times more probable than in the example above (**Table 7**).

4.4 Using simulations to assess the effect of traffic complexity on risk

In addition to CARA, another method for assessing risks related to air traffic complexity is by conducting simulations. Simulation is a core method for ATM research and training, with different purposes requiring different levels of fidelity

	Low complexity	Moderate complexity	High complexity
$p(\text{solved})$	0.999965	0.9971	0.98
$p(\text{loss of separation})$	0.000035	0.0029	0.02

Table 7.
 Comparison of probabilities to solve the conflict in traffic situations with different levels of complexity.

and simulation scope. Fidelity refers to the level of similarity between the simulated environment and the actual operations. Simulation scope can be broadly divided into strategic and tactical simulations. Strategic simulation tools (e.g., EUROCONTROL's NEST) are used to analyze current and forecast future ATM situation on a global level. On the other hand, tactical simulation tools are used to accurately simulate ATC operations on a sector level (e.g., ATCoach by UFA or Micronav's BEST Radar Simulator) [64]. For studies involving human factors, tactical real-time human-in-the-loop simulations provide the most reliable results.

Most representative results are produced when the simulator satisfies these requirements:

- Realistic working environment
- Accurate and versatile aircraft models
- Representative ATC tool operation
- Built-in stochasticity
- Human voice communication
- Research-level data logging
- Suitable meteorological model
- Suitable system and sub-system failure modelling

We used HITL simulations to assess the effect of trajectory-based operations (TBO) on air traffic complexity; for more information about that study, see [39]. Here we will provide a brief description of the methodology used and additional analysis of human errors made during that experiment. This will enable comparison of the simulation with the results obtained from CARA.

4.4.1 Example of an HITL simulation methodology

Simulation scenarios were developed based on the actual flight data. To measure complexity in conventional and trajectory-based operations, each simulation scenario had to be developed in three versions: conventional operations, 30% aircraft flying TBO, and 70% aircraft flying TBO.

Ten suitably experienced air traffic controllers were recruited to perform simulations. They all held professional air traffic controller licenses and had operational experience in Zagreb CTA Upper North sector (where the simulated traffic situations would take place). Before the actual experiment began, each controller received training in order to get accustomed with the simulator interface and operational procedures (though they were designed to closely resemble

their actual working environment). The training consisted of an introductory lecture, pre-simulator briefing, simulator runs, and post-simulator briefing. One pseudo-pilot was used for all simulation runs. The controller could communicate with the pseudo-pilot only via voice communication (through headset) or data-link.

Each controller performed three scenarios for each of the three types of the operations, each corresponding to different traffic loads—low, medium, and high (9 runs in total). *Low* scenarios were modelled to represent off-peak traffic, *medium* scenarios to represent peak traffic, and *high* scenarios to represent future peak traffic loads with 15% higher peak traffic. To prevent order of simulation scenarios affecting results, each controller was randomly assigned order in which he or she will perform different versions of the scenario (conventional, 30% TBO, 70% TBO). The order in which scenarios with different traffic loads (low, medium, high) were performed was, however, fixed and known to ATCOs. This enabled controllers to assess complexity more consistently.

During each simulation run, a subjective complexity measurement (SCM) tool opened every 2 min, accompanied by nonintrusive aural notification. The tool consisted of seven buttons (1–7), and the controller had to click on the one which was closest to the perceived level of air traffic complexity. The controller's complexity assessment was time-stamped and stored.

In addition to the subjective complexity measurement scores, objective complexity indicators were also calculated in real time, time-stamped, and stored. For the purpose of calculating new complexity indicators post-simulation, all aircraft states were stored for each time step of the simulation (1 s). Aircraft state included all data that pertained to the specific flight at that point in time (e.g., position, velocity, heading, mass, pitch, bank, throttle, drag, climb mode, acceleration mode, assigned flight level/speed/heading, route, etc.).

All other available information was also stored. Human-machine interactions were recorded in-application, while an additional application was used to record radar screen and voice communication.

4.4.2 Simulation results and comparison with CARA

Overall, 88 simulator runs were performed, each lasting for approximately 50 min. Though it is very difficult to ascertain the number of potential and actual conflicts, the frequency of STCA alarms and loss of separation occurrences can be used to assess the risk that air traffic complexity introduces. Before going into further details, it must be noted that the probabilities presented herein are accurate only for this particular set of scenarios in this particular airspace controlled by these particular ATCOs, even if the sample size issues are disregarded. These probabilities should not be used for making real-life operational decisions and are presented here as an example of the human reliability analysis that can be produced from real-time HITL simulations.

In **Figure 3**, all 88 simulation runs are plotted, showing scenario complexity and number of STCA alarms for each. Blue dots represent simulation runs which had only STCAs, whereas red dots show those runs in which loss of separation also occurred. ATCOs were not allowed to give additional complexity scores once the loss of separation occurred, thus preventing that event from influencing their opinion. Separation minima were 5 NM horizontally and 1000 ft. vertically. Complexity scores were calculated as an average of the ATCO's subjective complexity scores made during the peak 20 min of the simulation run [39]. Correlation coefficient between these two variables, complexity and number of STCAs, is 0.71, which indicates a somewhat strong correlation.

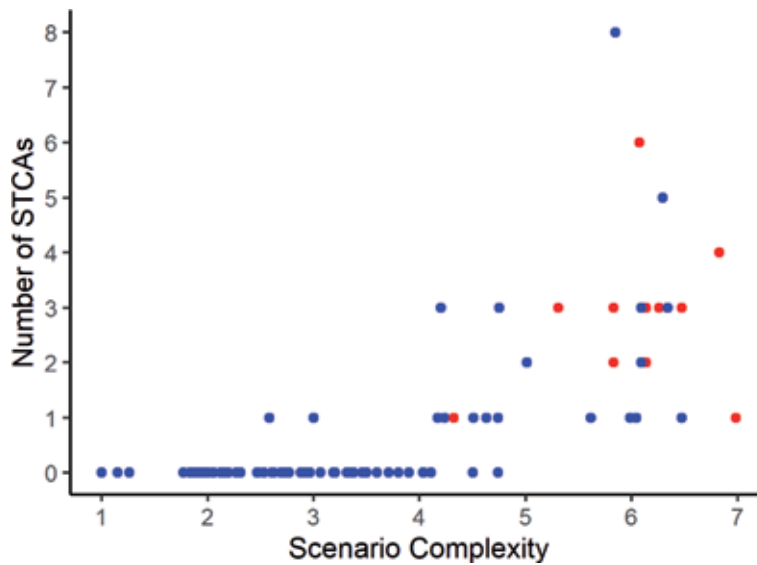


Figure 3. Number of STCA alarms vs. scenario complexity (red dots represent loss of separation).

First thing to notice is that most of the simulator runs, 58 out of 88, finished with zero STCAs. Of the remaining 30, only 5 were in *medium* traffic load scenarios, i.e., scenarios with traffic loads equal to current peak traffic. The remaining 25 were all in *high* traffic load scenarios which were designed with 15% higher peak traffic loads.

Next thing to notice is that, even though the complexity scores are highly subjective, it is very rare to have scenarios with complexity higher than 4 and no STCAs (only 4 out of 33 or 12%). This indicates that the ATCOs are bunching most of the scenarios into the lower half of the scale, perhaps underestimating the actual difficulty of managing the traffic situations.

In terms of HRA, it is interesting to calculate the probability that the STCAs will be resolved before the loss of separation occurs. Overall probability of human error in this case is only 0.155 (11 out of 71) compared to the figure calculated by CARA in the example presented in the previous section, which was 0.69. Surprisingly, this probability will not change much even if the scenarios were filtered by complexity. For example, for scenarios with complexity above 5, the probability of an STCA turning into a loss of separation is 0.175 (10 out of 57). For scenarios with complexity above 6, the probability is only slightly higher at 0.189 (7 out of 37). Here, ATCOs obviously show significant compensatory effects which should be included into CARA or modelled more precisely by assessors using the existing GTTs and EPCs.

On the other hand, the probability that the simulation run will contain at least one loss of separation rises sharply with complexity. For the lower half of the complexity scale, this probability is zero. If we consider all scenarios with complexity score equal to or above 4, the probability of loss of separation is 0.33 (11 out of 33). For scenarios with the score equal to or above 5, the probability is 0.5 (10 out of 20), and for scenarios with the complexity score above 6, the probability is 0.538 (7 of 13). This shows that even though the probability of an STCA turning into loss of separation is lower than expected by CARA, the number of conflicts rises to the level at which the loss of separation becomes extremely probable.

As for the *Cynefin* framework, it could be applied here only in broad brushes. One could argue that the first quarter of the complexity scale in these simulations

maps to the *simple* domain because there are no STCAs. Second quarter, with only a couple of STCAs which were quickly resolved, perhaps maps to the *complicated* domain. The third quarter could be mapped to the *complex* domain because there are many STCAs, but only two were not resolved in time. Finally, the last quarter of the scale arguably maps to the *chaotic* domain due to high probability of loss of separation which indicates that the ATCOs had lost the immediate control of the situation. Notwithstanding the *Cynefin* framework, it is clear that the ATM system should be designed to keep the complexity in the lower half of the scale and serious efforts are needed to achieve this in the face of the rising traffic demand.

5. Conclusion

In this chapter we have shown how the air traffic complexity, through increasing the difficulty of finding the correct solution to the traffic conflict, influences human error probability and, consequently, risk in ATM as well. CARA HRA technique was used to show an example of calculation that can be used to assess the probability of a loss of separation in traffic situations with low, moderate, and high complexity.

Like other HRA techniques, CARA also relies on an expert assessor who must be able to correctly model the ATC operations by choosing the appropriate GTTs and EPCs. This process is very sensitive to small changes in the initial conditions because adding or omitting a single probability calculation often results in an order of magnitude different final probabilities. This problem is further exacerbated by uncertainty in modelling the ATC operations. For example, it is nearly impossible to determine beforehand how many opportunities to resolve a conflict will an ATCO have before a loss of separation occurs. In the example shown in Section 4.3, we used two attempts before an STCA sounded the alarm and one attempt afterwards. If any of those attempts were omitted, the probability of a loss of separation would have increased by a significant amount (up to 10 times). Furthermore, different ATCOs will use different strategies to solve a conflict, especially if the conflict solution implies secondary potential conflicts, which makes modelling of ATC operations in CARA even more difficult. This is not to say that CARA should not be used for HRA or as a part of broader risk assessment. It just means that CARA should be used with caution and that the results should be considered more as an indication of a risk instead of as an exact quantification of risk.

To better illustrate the accuracy of CARA and to show an additional method for risk assessment, we have presented a brief analysis of a simulation-based risk modelling. During the HITL simulations, which included complexity assessment, STCA alarms and loss of separation occurrences were identified and recorded. Expectedly, it was shown that the number of STCAs quite strongly correlates with the perceived level of air traffic complexity. More interesting was the fact that the probability of STCA turning into loss of separation was much smaller than the one predicted by CARA. Also, it almost did not change with the increase of complexity which indicates presence of strong compensatory effects.

On the other hand, the human error probability for a conflict, defined as a probability of a failure to solve the conflict resulting in a loss of separation, increases with the increase in complexity. Of all 88 simulation runs, zero losses of separation occurred in scenarios with complexity below 4 (55 simulation runs). However, for simulation scenarios with score above 6, loss of separation occurred in 54% of simulation runs. This increase can somewhat be explained by higher traffic loads, leading to more conflicts which then led to more occurrences of loss of separation. The truth is, however, that the increase in traffic was not such that the number of

conflicts should rise to the levels achieved in the simulations. Simulation scenarios with high traffic load had only 15% more flights than scenarios with medium traffic load. It is the complexity of the traffic situation that precluded the ATCOs from being aware of all possible interactions and from solving the conflicts before it was too late. Though the sample size in the simulation study was quite small, it is clear that the model developed by the assessor in the CARA technique should be adjusted to reduce the probability of failing to solve the STCA.


In conclusion, both CARA and simulator study have a place in risk analysis in ATM. Best results are achieved when the simulations are performed to gather the probabilities of human error in a specific environment and when CARA is used to integrate the individual probabilities into a big picture assessment of ATM risks. The simulation study showed that the air traffic complexity is not only a large source of uncertainty but that it correlates nonlinearly with probability of loss of separation. This makes it difficult to model in common HRA techniques, with results having large error margins, but the greatest error would be to not model it at all.

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ICAO Risk Tolerability Solution via Complex Indicators of Air Traffic Control Students' Attitude to Risk

Serhii Borsuk and Oleksii Reva

Abstract

The solution of the ICAO risk tolerability is proposed via complex indicators of air traffic control students' attitude to risk. Physically tangible rates and characteristics are used to determine air traffic control students' attitude to risk levels during flight separation minima violation. The following features of human factors expression are taken as corresponding indicators: main decision-making dominants, aspiration levels, and parameters of the fuzzy risk estimates. The final solution is received with the help of a multiplicative approach. Indicators developed in the paper are proposed to be received with special survey procedure and further results processing and normalization. The explained method is applicable for both acting air traffic controllers and students of the corresponding educational majors.

Keywords: human factor, risk estimation, air traffic control, separation minima, aspiration level, main-decision making dominant, fuzzy estimates, risk tolerability solution

1. Introduction

Professional activity of “frontline” air operators (flight crew and air traffic controllers) can be considered a continuous decision-making chain in risk circumstances. This activity is part of the human factor, which is the main reason for air accidents for the last decades according to the statistics [1, 2]. Detrimental impact of the risk perception on flight safety is relevant for civil aviation. This is especially urgent for a complex system “flight crew—aircraft—environment—air traffic control authority” [3–5].

Results of researches dedicated to the development and operation of air transport management (ATM) system show that sufficient flight safety level support is impossible without efficient, proactive risk management activities. In turn, these activities are an integral component of the system and entirely correspond to the International Civil Aviation Organization (ICAO) safety paradigm.

According to the ICAO definition, flight safety is “the state, in which risks associated with aviation activities, related to, or in direct support of the operation of aircraft, are reduced and controlled to an acceptable level.” Thus, it is necessary to take into account risk estimates for the proper support of flight safety. Considering

the definitions by Eurocontrol, International Civil Aviation Organization (ICAO), and other sources [6–10], let us regard risk as a probability of undesirable situation with harmful consequences. Its “severity” part can be determined using various methods, including the qualimetric ones. They allow forecasting hazardous situations and performing necessary activities by the management and operator of the air transport system. It contributes to accident prevention and risk reduction.

Risk management-related tasks should be resolved. In order to do this, some necessary qualimetric steps should be carried out. They should include the evaluation of quality–quantity indicators of the control process. This issue is relevant and complex for civil aviation. Indeed, hazards tend to accumulate during air transport system operation. Taking into account numerous objective and subjective factors, this might result in the so-called “factor resonance” phenomenon [11].

2. Risk tolerability

Generalizing worldwide experience of flight safety management, ICAO proposed to estimate civil aviation threats with special risk tolerability distribution [7]. It is composed of two aviation accidents parameters: likelihood and severity. All their possible combinations were considered. ICAO divided obtained results into three groups: Intolerable, tolerable, and acceptable (**Figure 1**).

There are five qualitative levels of the air accident likelihood and severity proposed by ICAO. They are recommended for risk estimation and combined into the safety risk matrix. These levels can be described using the terms of fuzzy mathematics taken as corresponding fuzzy variables $T(S)$ and $T(L)$ [12, 13]:

$$T(S) = R_C + R_H + R_{Mj} + R_{Mn} + R_N; \quad (1)$$

$$T(L) = R_F + R_O + R_R + R_I + R_{EI}; \quad (2)$$

where fuzzy variables’ terms are R_C —catastrophic, R_H —hazardous, R_{Mj} —major, R_{Mn} —minor, R_N —negligible, R_F —frequent, R_O —occasional, R_R —remote, R_I —improbable, and R_{EI} —extremely improbable. Risk cases distribution across all possible likelihood and severity combinations is shown in **Table 1**.

Using the ICAO flight safety management recommendations, the US Federal Aviation Administration published circular with their own safety risk matrix. Combinations of severity and likelihood explained there have 62.5% of partially or totally acceptable levels [14]. However, they use four levels for both severity and likelihood. Moreover, the “acceptable risk level” is determined as a flexible value, which depends on the pilot’s particular opinion.

Risk estimation proposed by Eurocontrol is partial and concerns severity only [6]. Also, their recommendations delegate calculation of risk distribution

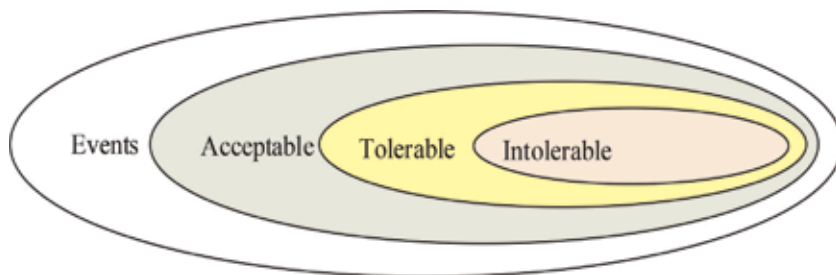


Figure 1.
Risk cases distribution.

combinations to the national authorities. Another risk matrix is proposed by the Korea Advanced Institute of Science (KAIS), Hongneung Campus, Seoul [15]. Some of these examples use four and five risk levels, while ICAO sticks to the three ones mentioned earlier. To keep up with ICAO, its definitions are used; and, therefore, 4-rate and 5-rate cases falls out of the analysis scope.

Providing general comments on risk tolerability, ICAO unfortunately gives no exact values. That is why various methods should be used to resolve risk tolerability distribution. Results of this kind can be implemented to enhance ATC learning process, to influence aircraft separation minima changes, to improve rules and instructions, etc.

The priority arrangement method (PRM) is the first one. It applies the normalized significance coefficient for each term of both fuzzy variables. Unfortunately, this led to a significant decrease in the number of generally acceptable cases that is unacceptable from the common-sense point of view [16]. Another method used for the same purpose is Harrington desirability function [17]. The results for all the mentioned approaches are shown in **Table 2**.

Another crucial point is that risk tolerability distribution solution should be performed with tangible and clear indicators and parameters. The “frontline” air operators should be primarily familiar with them. Such clarification problem is resolved with application of such ICAO safety concept components as the use of sound SOPs, hazard sources determination, risk factors control, personnel attitude to hazardous actions and conditions, etc. [18]. Considering the “attitude to risky actions or conditions” as the leading inbound marker to the problem, it is regarded as an explanatory link for flight safety within the human factor.

Risk cases indicators	Risk level description
5A, 5B, 5C, 4A, 4B, 3A	Intolerable
5D, 5E, 4C, 4D, 4E, 3B, 3C, 3D, 2A, 2B, 2C, 1A	Tolerable
3E, 2D, 2E, 1B, 1C, 1D, 1E	Acceptable

Table 1.
 ICAO risks cases [7].

Approach	Risk level (%)		
	Intolerable	Tolerable	Acceptable
ICAO proposal	24	44	32
FAA proposal	18.75	18.75	62.5
Harrington coefficients	40	36	24
PRM iteration 1	28	40	32
PRM iteration 2	68	20	12
PRM iteration 3	76	12	12
PRM iteration 4	76	20	4
PRM iteration 5	84	12	4
PRM iteration 6	88	8	4
PRM iteration 10	88	8	4

Table 2.
 Risk tolerability distributions.

“Frontline” air operators’ professional activity is a continuous chain of decisions generated and implemented in apparent and latent forms. It is also influenced by multiple factors of stochastic and deterministic nature. Thus, it is possible to research the mentioned above attitude through the human factor indicators that influence decision making under risk circumstances:

- Main decision-making dominants;
- Aspiration levels;
- Fuzzy risk estimates.

Typical values of these indicators should be used to resolve risk tolerability distribution. It is worth mentioning that there are no similar studies of risk tolerability distribution resolution for presented rates.

Let us examine these indicators and their roles in more details. Researches performed so far deal with the risk of flight separation minima violation set by ICAO for the horizontal plane as at 2014.

3. Case study conditions

All methods proposed later on were implemented in the case study, which includes survey and data processing. In the performed survey, 132 air traffic controller students of fourth to fifth years of study from National Aviation University (Kyiv, Ukraine) and Kirovohrad Flight Academy (Kropyvnytskyi, Ukraine) were involved. By the time of the survey, all of them had completed at least 1 year of learning with more than 100 hours at ATC simulation facilities. In the survey, 11 flight separation minima were proposed including 8 km (1 minimum), 10 km (4 minima), 12 km (1 minimum), 20 km (4 minima), and 30 km (1 minimum). All minima were proposed to the students one by one during the survey.

4. Main decision-making dominants

Main decision-making dominants [19–30] are parameters of human factor influence on decision making. They describe the attitude of “frontline” air operators to risk: whether the operator is inclined, not inclined, or indifferent to risky behavior. They also characterize motivation to achieve success or avoid failure. Dominants are found from utility estimation functions $f_{UF}(L)$ received from the distances between two aircraft within violated separation minimum.

In the simplest cases, the form of the utility function chart can be used to define the main decision-making dominant. However, for more detailed analysis, risk premium (RP) concept is introduced [31]. Risk premium is the difference between expected lottery reward, and it is determined equivalent.

The classical approach uses only one point $L_{0.5}$ for dominant determination:

$$RP = \bar{L} - L_{0.5} \begin{cases} < 0 & - \text{inclined to risk} \\ > 0 & - \text{not inclined to risk,} \\ = 0 & - \text{indifferent to risk} \end{cases} \quad (3)$$

where \bar{L} is an expected lottery point:

$$\bar{L} = 0.5 \cdot (L_0 + L_1) = 0.5 \cdot (0 + L_{norm}) = 0.5 \cdot L_{norm}. \quad (4)$$

Use of Eq. (4) for dominant determination makes results a bit rough. It can be shown by the example, when $\bar{L} = L_{0.5}$ (Figure 2, blue line). In this case, the respondent demonstrates an indifferent attitude to risk. But an example when this conclusion is wrong can be easily proposed (Figure 2, red line). It is achieved with introducing of two more points in the dominant analysis.

Five points are used instead of three to increase accuracy. The analysis of the points can be performed using coordinates proportion method [20]. According to this method, the sum of coordinates $\sum y$, which is equal to $2.5L$, corresponds to the linear utility function of the respondent who is indifferent to risk. Thus, it is enough to compare coordinates of the sum of five points with $2.5L$. Risk-indifferent participants have $\sum y = 2.5L$, the risk inclined ones have $\sum y > 2.5L$, and the risk non-inclined respondents have $\sum y < 2.5L$.

The key distances, taken as the points, are 0 km, distance for $\frac{1}{4}$ of utility, distance for half of the utility, distance for $\frac{3}{4}$ of utility, and full separation minimum ($L_0, L_{0.25}, L_{0.5}, L_{0.75}, L_{norm}$). Such distances are chosen to support utility lotteries solution. Each distance possesses a particular utility $u(L)$. Border points obviously have utilities equal to 0 and 1. Intermediate points have utility values equal to 0.25, 0.5, and 0.75, correspondingly:

$$\begin{aligned} u(L=0) &= f_{UF}(L=0) = 0; & u(L_{0.25}) &= f_{UF}(L_{0.25}) = 0.25; \\ u(L_{0.5}) &= f_{UF}(L_{0.5}) = 0.5; & u(L_{0.75}) &= f_{UF}(L_{0.75}) = 0.75; \\ u(L_1 = L_{norm}) &= f_{UF}(L_1 = L_{norm}) = 1. \end{aligned} \quad (5)$$

All intermediate distances are found with the help of lotteries. These lotteries are commonly implemented in economic proceedings [32]. However, they were applied for hardware performance as well [19], what makes them applicable for aviation risks assessment. The method of two-level lotteries application in aviation risk evaluation is already explained in details earlier [20–30].

Lottery method is applied three times to get three lottery equivalents. Here, a lottery equivalent is a result that represents the distance between two aircraft. This distance is such that operator does not care whether to get it with 100% probability or to participate in the lottery. In other words, it is used to find the distance of lottery equivalent $L_{0.5}$ with the utility of 0.5. The lottery has 50% of receiving any

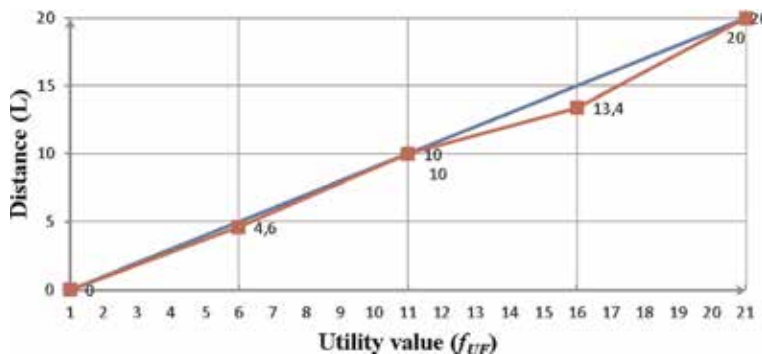


Figure 2. Rough estimation example leading to wrong conclusion for $L = 20$ km. Blue line—rough estimate; red line—improved estimate.

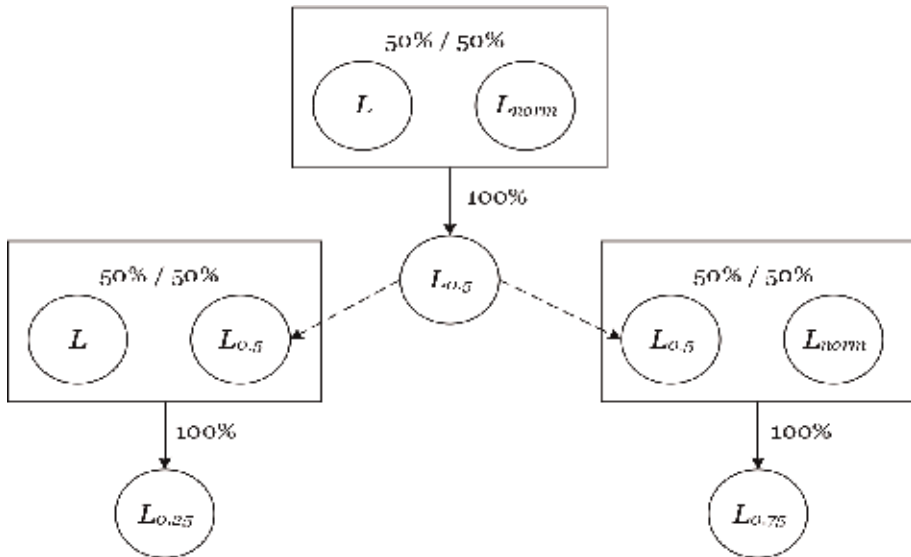


Figure 3. Lotteries used to determine utility function points for flight separation minima.

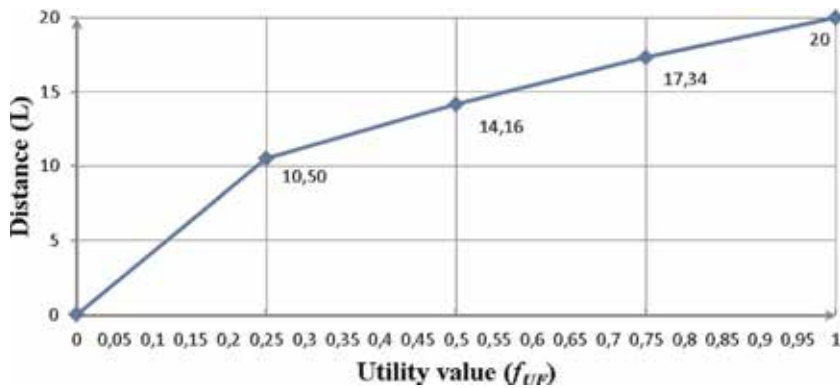


Figure 4. Generalized utility estimate function for all participants with the flight separation minimum $L = 20$ km.

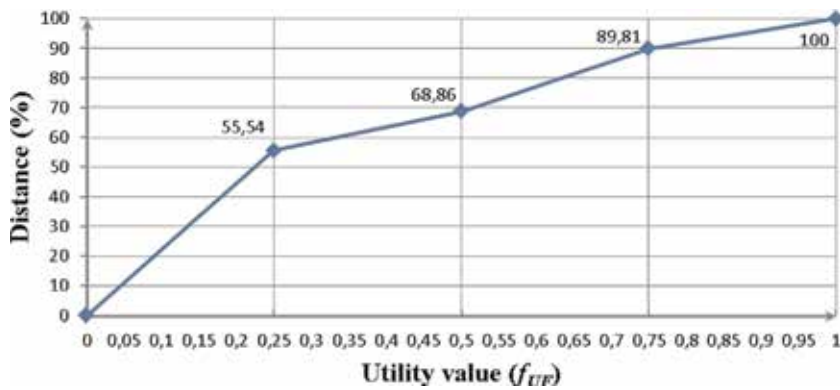


Figure 5. Normalized utility estimate function for all participants and all flight separation minima.

marginal results. For the lottery of the first level, these results are 0 km and full flight separation minimum.

The first received lottery equivalent is used to find two more lottery equivalents for $L_{0.75}$ and $L_{0.25}$ (Figure 3). Considering two initial points and three point received from lotteries, it is possible to build the desired utility estimate function.

The example of generalized utility estimate function for all participants plotted for $L = 20$ km is given in Figure 4.

Normalized utility estimate function for all participants concerning all proposed minima is given in Figure 5.

Figures 4 and 5 show that utility rise in a non-linear way. Utility function data are taken from case study survey. In both graphs, a fundamental understanding of risk for all involved ATC students concerning single $L = 20$ km separation minimum (Figure 4) and all mentioned minima taken together (Figure 5) is presented. According to the graph points, it can be stated that, in general, ATC students possesses non-inclined to risk behavior.

5. Aspiration level

Aspiration level is one of the main psychological features and participants' typical peculiarities, fundamental for personality. It is recommended to be determined during the medical investigation of air accident [33]. Basically, aspiration level is the stable characteristic of an identity, which is used: (a) for defining the complexity level of tasks wanted to be resolved, (b) for the target selection of further actions depending on the previous success/failure, and (c) for determining the desired self-image. Aspiration level demonstrates the correspondence between personal goals and capabilities. Thus, aviation operators with high aspiration level are characterized by high confidence level, persistence, high productivity, and healthy criticism in achievements estimation [34, 35].

Given researches are related to the of human factor expression qualimetry during flight separation minima violation. Considering recommendations of the proceedings [5], hereafter, the aspiration level is defined as a point of distance L^* on the flight separation minimum. The L^* point corresponds to the highest utility increase from the air traffic controller's point of view. In other words, it corresponds to ATC operator's highest performance during support of proper flight safety level at given distance between two aircraft. The proceedings [16, 36, 37] allow plotting and analyzing utility chart by a formally unlimited number of points for open decision-making task.

Since the aspiration level L_{AL} is the relatively stable indicator of personal air traffic controller commitments [16, 38–41], then $L_{AL} = L$ if and only if.

$$\begin{cases} \Delta f_{UF}(L) = f_{UF}(L_r) - f_{UF}(L_{r-1}) > f_{UF}(L_i) - f_{UF}(L_{i-1}); \\ i = \overline{2, (r-1)}, \end{cases} \quad (6)$$

or if

$$\begin{cases} \Delta f_{UF}(L) = f_{UF}(L_r) - f_{UF}(L_{r-1}) \Rightarrow \max; \\ f_{UF}(L_r) > 0. \end{cases} \quad (7)$$

The overall contribution from this utility function includes three more reference points. They are L^- , which corresponds to maximum utility increase in lower semi plane $(-100; 0)$, L^0 , which corresponds to distance with 0 utility for $(-100; 100)$

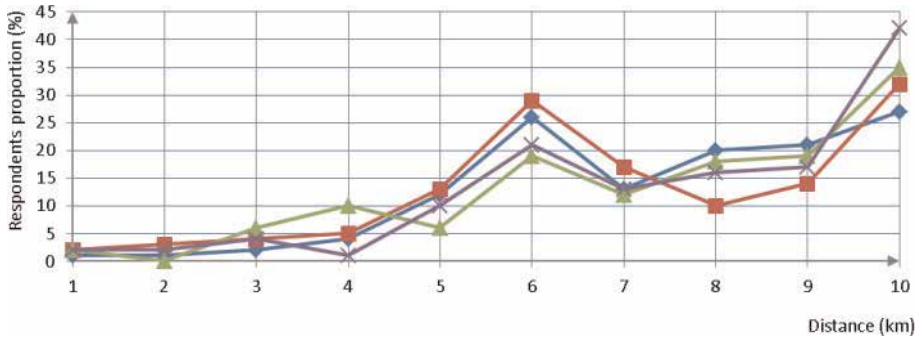


Figure 6. The aspiration levels distribution of the respondents for four flight separation minima of the cross-aircraft aircraft $L = 10$ km. Distances as at 2014. Red line—under IFR (instrument flight rules) procedure with continuous radar monitoring in the approach area APP (local ATC) (TMA (terminal control area)) using ATC automated system except approach segment; Blue line—at take-off phase (within control zone (CTR (control zone) at altitudes 1700 m and below) when medium aircraft follows heavy; Green line—for lateral separation for the IFR flights under continuous radar monitoring when crossing the level occupied by the same direction traffic in ACC (general ATC) (CTA (control area)) and APP (TMA) at the moment of crossing on conditions that no tracks converging; Purple line—under IFR procedure with continuous radar monitoring when crossing the same direction level occupied by another aircraft in approach area APP (TMA) using ATC automated system at the moment of crossing on conditions that no tracks converging.

scale, and L^+ , which corresponds to the maximum utility increase in top semi plane (0; 100).

After data analysis, a series of charts for all 11 separation minima were plotted. The examples of these charts are presented in **Figure 6**. Each chart here represents a single aspiration indicator distribution for one of four $L = 10$ km minima. Each of the presented four plots shows how many participants consider each particular distance between 0 km and separation minimum as delivering maximum utility. In other words, every plot shows aspiration level distribution for all respondents. For all the taken minima, the distance chosen most often is 10 km, which is the separation minimum itself. However, many ATC students choose other distances to provide maximum utility growth.

Interestingly, all the taken minima have peak point close to the middle of the separation minimum range. In **Figure 6**, such middle peaks coincide for all $L = 10$ km separation minima. The same effect is observed for the group of $L = 20$ km separation minima as well.

6. Fuzzy estimates

Main decision-making dominants and aspiration levels do not cover the whole totality of human factors expression during flight separation minima violation. The experience of earlier researches witnesses that the human factor qualimetry can be significantly improved by fuzzy models of risk level estimation [42–50]. These models implementation conforms to the human mental process property of providing qualitative estimates rather than quantitative.

Considering all mentioned above and applying Miller’s “magic number” [51], the following risk severity scale can be presented as the fuzzy variable T :

$$T = \tilde{R}_C + \tilde{R}_{VB} + \tilde{R}_B + \tilde{R}_{AV} + \tilde{R}_S + \tilde{R}_{VS} + \tilde{R}_D. \quad (8)$$

where \tilde{R}_C —critical, \tilde{R}_{VB} —very big, \tilde{R}_B —big, \tilde{R}_{AV} —average, \tilde{R}_S —small, \tilde{R}_{VS} —very small, and \tilde{R}_D —disappearing.

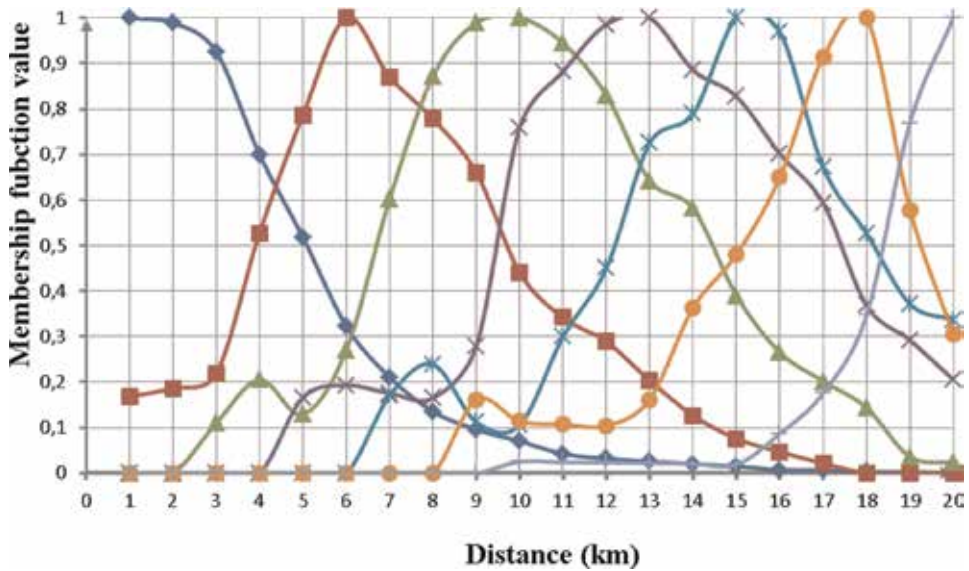


Figure 7. The values of the membership function for “risk severity” fuzzy variable terms: Blue—“Critical,” red—“Very big,” green—“Big,” purple—“Average,” light blue—“Small,” orange—“Very small,” and teal —“Disappearing.”

Using the proposed scale (Eq. (8)), air traffic control students as respondents expressed their opinions about hazard severity for all distances between two aircraft during flight separation minima violation [45, 52]. Their answers gave data for the fuzzy variable membership function of “risk severity” [53, 54]. After the initial data are collected, they are normalized using the “supportive matrix” method [55]. The final values are used to plot the family of membership functions charts for all terms of “risk severity” fuzzy variable (**Figure 7**).

Starting from the left side, each line represents a separate fuzzy variable term of the membership function value (catastrophic, very big, big, average, small, very small, and negligible) concerning every possible distance between two aircraft.

Every line in **Figure 7** shows the integral opinion of cross-aircraft distance categorized as one of the seven severity levels. For example, the distance of 6 km is considered to have a “very big” severity level with the membership value of 1. At the same time, the nature of fuzzy values also possesses the severity of “catastrophic,” “big,” and “average” levels with the correspondent membership values. Such plot allows finding aggregated ATC students’ opinion about the distances belonging to the particular severity levels.

Since one of the main requirements is to be as close as possible to the ICAO terms, the number of given terms should be reduced. It is performed by the removal of the modifier “very” [9, 51, 55]. After all, the seven use terms were reduced to five in the following way:

$$\begin{array}{ccccc}
 \tilde{R}_C & \tilde{R}_{VB} \cup \tilde{R}_B & \tilde{R}_{AV} & \tilde{R}_S \cup \tilde{R}_{VS} & \tilde{R}_D \\
 \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \\
 \tilde{R}_C & \tilde{R}_B & \tilde{R}_{AV} & \tilde{R}_S & \tilde{R}_D
 \end{array} \quad (9)$$

7. Aggregation

Since three different parameters are used to define the opinions of ATC students about risk, it would be convenient to combine them into one single indicator. Such

an indicator should include all three parameters with reasonable proportions. In current research, the widely applicable aggregation function is taken [9]:

$$f = \left(\frac{1}{k} \sum_{i=1}^k \alpha_i \times R_i^p \right)^{\frac{1}{p}}, \quad (10)$$

where p is conditional compromise coefficient which is used to define the acceptable compensation rate of small values with big ones, k is number of risk indicators (in current case $k = 3$), R_i is an indicator, determined by risk level, and α is a weight coefficient. For main decision-making dominant, R_D is used, R_{AL} is used for aspiration level, and R_F for fuzzy estimates. Since there is no preliminary information about their significance, they are considered to be equally important. Taking into account the same assumption, $p \rightarrow 0$ for the “careful” aggregation policy and thus:

$$\phi = \prod_{i=1}^k R_i. \quad (11)$$

The multiplicative approach is clear, applied with ease, and has an extensive application history among technical and humanistic systems research [51, 55–59]. However, since data should be normalized to the $[0, 1]$ range, it should be changed in the following way:

$$\phi = \sqrt[k]{\prod_{i=1}^k R_i}. \quad (12)$$

Thus, for a single flight separation minimum, aggregated estimate takes the following form:

$$R = \sqrt[3]{R_D \cdot R_{AL} \cdot R_F} = \sqrt[3]{\frac{L_D}{L_{norm}} \cdot \frac{L_{AL}}{L_{norm}} \cdot \frac{L_F}{L_{norm}}}. \quad (13)$$

Here, (L_D, L_{AL}, L_F) are generalized and normalized distances found for main decision-making dominant, aspiration level, and fuzzy estimates, correspondingly. The L_{norm} distance stands for the separation minimum distance taken for reference.

The last thing to do is to select the proper key points of all three methods. During the detailed analysis, the following rules were reached:

- All 11 flight separation minima should be taken into account;
- Dominants should be used for all risk inclination categories;
- Lottery equivalent in use is 0.75 as it strongly correlates with the aspiration level;
- The aspiration level itself is taken for all minima;
- A fuzzy estimate is considered as the severity level changing from minor to major in the ICAO concept (from average to small in authors’ terms).

These rules allowed to receive separate formulas for each risk level indicator and the general formula for integral calculations. The correspondent results of

No	Separation minimum	Particular methods indicators			Integral indicator R
		R_D	R_{AL}	R_F	
1	$L = 8$ km	0.74	0.77	0.74	0.75
2	$L = 10$ km	0.78	0.75	0.66	0.73
3		0.78	0.72	0.66	0.72
4		0.79	0.75	0.70	0.75
5		0.80	0.77	0.69	0.75
Generalize within distance		0.79	0.75	0.68	0.74
6	$L = 12$ km	0.75	0.72	0.76	0.74
7	$L = 20$ km	0.70	0.68	0.60	0.66
8		0.65	0.75	0.73	0.71
9		0.72	0.73	0.62	0.69
10		0.70	0.71	0.69	0.70
Generalize within distance		0.69	0.71	0.66	0.69
11	$L = 30$ km	0.68	0.73	0.71	0.71
Final estimate		0.73	0.74	0.71	0.73

Table 3. Aggregated indicators for risk level estimation (yellow cells designate final value for a single separation minimum or generalized minima with the same distances).

generalized and aggregated indicators overall calculations are presented in **Table 3**. Given results show that air traffic controllers, in general, consider distances more than 0.73 of flight separation minima as acceptable.

Table 3 shows the final point, which may be called severity separator. It can be found in the right bottom cell. In the opinion of ATC students, all distances to the left from this point are more likely to be risky, and vice versa, all distances to the right from this point are more likely to be riskless. Such a result can be also considered as an integral reserved value for flight separation minima.

8. Risk tolerability distribution solution

To resolve the ICAO risk tolerability distribution, the following approach was applied. Since there are five levels of severity, four key points are required.

- Concerning main decision-making dominants, three lottery key points were considered as an intermediary between the severity levels. The last fourth point was taken as flight separation minimum distance.
- Concerning aspiration levels, three key utility points were used with the flight separation minimum distance as well.
- Concerning fuzzy estimates, the reduced intersection points were used, as shown in Eq. (9).

The final results with all three presented methods are presented in **Table 4**. Here, R_C —catastrophic risk level, R_H —hazardous risk level, R_{Mj} —major risk level, R_{Mn} —minor risk level, R_N —negligible risk level, L_C —distance equivalent to catastrophic risk level, L_H —distance equivalent to hazardous risk level, L_{Mj} —distance

Risk levels		Models in use		
		Dominants	Aspiration levels	Fuzzy estimates
Unacceptable	R_C	$L_C < L_{0.25} \Leftrightarrow$ $\Leftrightarrow L_C < 0.31$	$L_C < L^- \Leftrightarrow$ $\Leftrightarrow L_C < 0.46$	$0 < L_C < \tilde{L}_C \Leftrightarrow$ $\Leftrightarrow 0 < L_C < 0.42$
	R_H	$L_{0.25} < L_H < L_{0.5} \Leftrightarrow$ $\Leftrightarrow 0.31 < L_H < 0.53$	$L^- < L_H < L^0 \Leftrightarrow$ $\Leftrightarrow 0.46 < L_H < 0.65$	$\tilde{L}_C < L_H < \tilde{L}_B \Leftrightarrow$ $\Leftrightarrow 0.42 < L_H < 0.56$
	R_{Mj}	$L_{0.5} < L_{Mj} < L_{0.75} \Leftrightarrow$ $\Leftrightarrow 0.53 < L_{Mj} < 0.73$	$L^0 < L_{Mj} < L^* \Leftrightarrow$ $\Leftrightarrow 0.65 < L_{Mj} < 0.74$	$\tilde{L}_B < L_{Mj} < \tilde{L}_{AV} \Leftrightarrow$ $\Leftrightarrow 0.56 < L_{Mj} < 0.71$
Acceptable	R_{Mn}	$L_{0.75} \leq L_{Mn} < L_{norm} \Leftrightarrow$ $\Leftrightarrow 0.73 < L_{Mn} < L_{norm}$	$L^* < L_{Mn} < L_{norm} \Leftrightarrow$ $\Leftrightarrow 0.74 < L_{Mn} < L_{norm}$	$\tilde{L}_{AV} < L_{Mn} < \tilde{L}_S \Leftrightarrow$ $\Leftrightarrow 0.71 < L_{Mn} < 0.83$
	R_N	$L_N \geq L_{norm}$	$L_N \geq L_{norm}$	$L_N \geq 0.83$

Table 4.
Partial solutions of ICAO risk tolerability distribution for flight separation minima.

Risk levels	Integral estimates	
Unacceptable	Catastrophic	$L_C < 0.39$
	Hazardous	$0.39 \leq L_H < 0.58$
	Major	$0.58 \leq L_{Mj} < 0.73$
Acceptable	Minor	$0.73 \leq L_{Mn} < 0.94$
	Negligible	$L_N \geq 0.94$

Table 5.
The integral solution of ICAO risk tolerability distribution with risk estimates.

equivalent to major risk level, L_{Mn} —distance equivalent to minor risk level, L_N —distance equivalent to negligible risk level, $L_{0.25}$ —distance equivalent to 0.25 lottery determinant, $L_{0.5}$ —distance equivalent to 0.5 lottery determinant, $L_{0.75}$ —distance equivalent to 0.75 lottery determinant, L^- , L^0 , and L^+ were explained earlier, \tilde{L}_C —distance where “critical” term ends, \tilde{L}_B —distance where “big” term ends, \tilde{L}_{AV} —distance where “average” term ends, and \tilde{L}_S —distance where “small” term ends.

Finally, the application of a multiplicative approach allows to resolve the ICAO risk tolerability distribution (Table 5) with integral estimates.

9. Conclusions

It is possible to make general conclusions based on the presented scientific results. These conclusions concern the development of a new methodology. It is dedicated to the qualimetry of human factor regularities expression during the decision making in aeronautical systems. The ICAO recommendations were taken into account during the correspondent indicators development. They were implemented by the composition of fuzzy models applied to air traffic control students’ attitude to flight separation minima violation in a horizontal plane. Other components of such attitude include well-grounded key points of utility estimate functions for the mentioned minima continuum plotted within formally closed and open decision-making tasks. The first group of points is used to find respondents’ main decision-making dominants (inclination, indifference, and non-inclination to

risk). The second group of points is used to find aspiration levels that correctly characterize respondents' self-image.

Important scientific results include:

1. For the first time, the multiplicative approach is grounded and implemented to determine the integral estimate of air traffic control students' attitude both to sole flight separation minimum and minima totality. The correspondent cent is equal to 0.73 of flight separation minima.
2. The new method of main decision-making dominant determination is proposed. It differs from the widely known one by more key points being used and a novel algorithm submitted for their analysis.
3. The results of the main decision-making dominants analysis show that non-inclination is a major attitude among air traffic control students. It allows changing the professional education programs, taking into account the received results.
4. Especially important feature of the received results is their proactivity. It will enable preventing potentially harmful consequences of air traffic controllers' work by implementing personalized training on various simulators.

All the results form strong premises for further researches, which should be performed in the following areas:

- a. The study of decision-making indicators, taking into account age, academic performance, and other factors;
- b. The analysis of the mentioned indicators dynamics during the whole professional activity period of air traffic control personnel;
- c. The complex research of the proposed indicators for three dimensions with space utility functions plot and integral indicators estimation for such conditions.

It should be mentioned that further research areas are not limited to the proposed ones but merely demonstrate opinion on primaries.

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Risk Assessment under Uncertainty

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Abstract

System safety assessment (SSA) has become a standard practice in air traffic management (ATM). System safety assessment aims, through a systematic and formal process, to detect, quantify, and diminish the derived risks and to guarantee that critical safety systems achieve the level of safety approved by the regulatory authorities. Verification of compliance with the established safety levels becomes the last but an essential part of the safety assurance process. This chapter provides a Bayesian inference methodology to assess and evaluate the compliance with the established safety levels under the presence of uncertainty in the assessment of systems performances.

Keywords: risk assessment, Bayesian inference, uncertainty, safety compliance

1. Introduction

Safety in aviation, and particularly in air traffic management (ATM), has evolved to the concepts of safety management and risk management. To achieve and guarantee safety, operators and providers develop and implement safety management system (SMS). SMS is a methodical and explicit approach for handling safety that comprises the required organisational arrangements and accountabilities, as well as the applicable safety policies and safety procedures. Hazard identification, risk assessment and risk mitigation have become essential processes within the framework of the SMS. Manufacturers, air navigation service providers (ANSPs) and operators shall implement a formal risk management process within their SMS.

This process, known as safety assessment (SA), has become a standard practice in the aviation industry. The global aim of SA is to ensure (by means of formal and systematic identification, evaluation and management of risks connected with hazards) that the design, production and operation of a system attain the safety levels settled by the safety regulatory authorities. Safety assessment has become a standard practice in the aviation industry [1–8].

SA typically implies three major phases that advance alongside the whole lifespan of the system [9, 10]:

- FHA—Functional hazard assessment
- PSSA—Preliminary system safety assessment
- SSA—System safety assessment

Figure 1 illustrates the liaisons between these three phases and the system life cycle.

System definition is the first stage of the system lifecycle. Its purposes are as follows:

- i. To establish initial objectives for the system operating within its pertinent operational environment
- ii. To define the functions to support these objectives
- iii. To agree on high-level system requirements and interfaces

From the safety perspective, the first phase in the SA is referred to as functional hazard assessment (FHA). FHA aims to specify the safety level to be attained by the system in terms of safety objectives. A safety objective is a qualitative or quantitative statement that outlines the maximum acceptable frequency or probability of occurrence for a specific hazard or failure condition. If the hazard is a system failure, the safety objective will be the maximum allowed rate of failure. FHA is executed at the start of system design and development before the functions of the system have been deployed into procedures, equipment, or people components.

To determined system safety objectives, each function and combination of functions is assessed by safety analysts to:

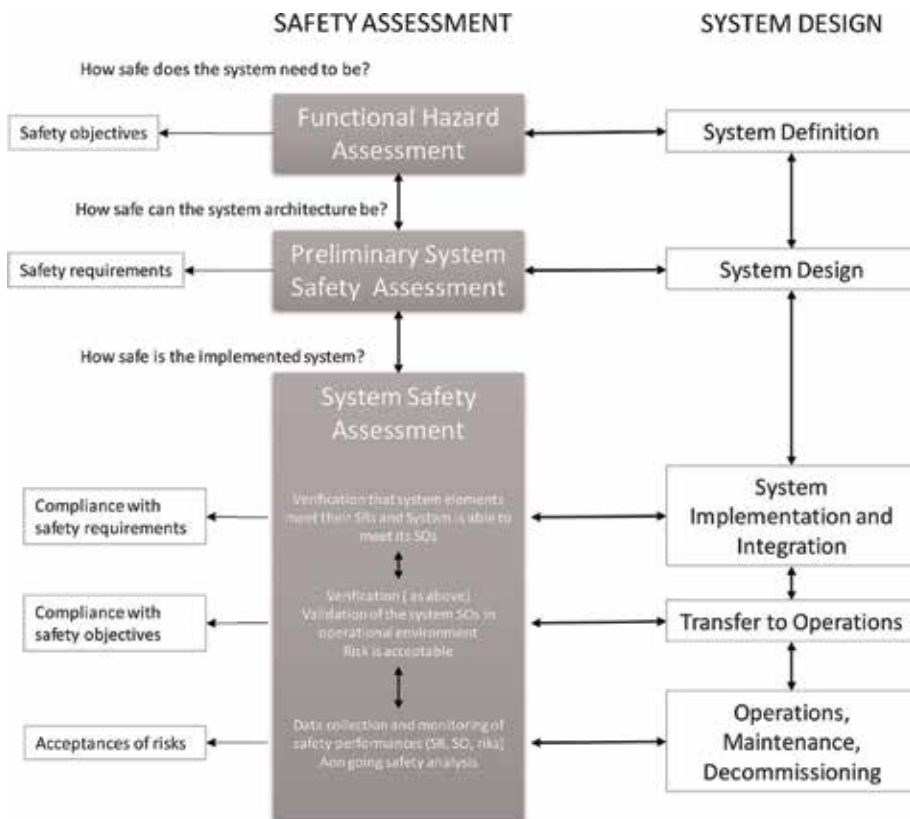


Figure 1. Safety assessment phases alongside and system life cycle.

- Identify possible hazards and failures modes derived from the system definition.
- Identify hazard consequences or effects on operations.
- Evaluate the severity of each hazard consequences.
- Determine safety objectives, i.e. the maximum acceptable frequency for each hazard's occurrence.
- Assess intended aggregated risk.

The main step in this phase is the identification and classification of failures by their severity [11, 12] and the definition of safety objectives.

The following lifecycle stage is a system design. At this stage, the system operation and functions are defined in detail, describing the new system as an assortment of subsystems or components. In parallel, the risk assessment process develops a preliminary system safety assessment (PSSA). The objective of the PSSA is to prove that the designed system architecture can soundly attain the safety objectives stated during the FHA.

PSSA inspects the system architecture and concludes how failures could cause the hazards acknowledged in the FHA, it identifies required mitigations to minimise the risk or even eradicate them, and it specifies these measures in the form of safety requirements. A safety requirement is a risk measure, which may cover several different aspects such as operational, human, functional, organisational, procedural and performance, among others. Therefore, the PSSA process apportions safety objectives to the system elements and generates safety requirements, and then it stipulates the level of risk of each system element. The system architecture will meet the safety objectives established at the system level at the FHA, only if the architecture components satisfy their safety requirements.

After design, the next steps in the system lifecycle are implementation and integration. System implementation includes the production of the individual components, and integration refers to their amalgamation into the system. The next step, known as transfer into operations, refers to the system deployment, its on-site installation, its integration as part of an operational environment and the validation of its performances. During the system operation, maintenance actions, preventive and corrective, are accomplished in order to preserve the required safety and service level. Finally, once the system has reached the end of its operational life, decommissioning stands for the system withdrawal from the operation.

The last stage of the safety process, the system safety assessment (SSA), is developed in parallel to system implementation to verify whether the system, as implemented, achieve an acceptable risk. This means that the envisage mitigations have been put in place; all safety goals, objectives and requirements have been satisfied; and the expected level of safety has been successfully attained during the system operation [13, 14].

SSA monitors the safety performances of the system through its lifetime. It collects evidence and arguments to confirm that each implemented system component satisfies its safety requirements and safety objectives. It is, in the end, a continuous safety compliance assessment [15].

The SA process, although extended and widely accepted in aviation, is affected by a series of limitations. The main limitation neither resides in the fact that the process does not sufficiently considers nor widely capture the inherent uncertainty

in every step of the safety assessment. The process has also shown limitations in dealing with lacking data if when the system is brand new or when there is few measurable information about its performance. These limitations severely affect the effectiveness of the last step in the process, the system safety assessment. Additionally, many times, decision-makers cannot support their safety compliance decision on objective tools. As a consequence, the process has not enough objectivity or transparency.

This chapter illustrates that a systematic approach for dealing with uncertainties in safety compliance evaluation is possible through Bayesian reasoning. Bayesian inference is a systematic method that helps decision-makers to select a suitable path in relation to the acceptance of a system against its safety results. It is particularly useful if under the presence of uncertainty about the actual failure rates of a system and/or about the consequences of the decision-making process. It could also take into consideration the predilections of the decision-makers, experts' understanding and the consequences of the decisions to be made.

2. System safety assessment limitations

Most safety assessment decisions are taken under the assumption that the magnitudes of the variables and parameters describing the system performance are equal to their estimates. But, this postulation is valid as long as there is enough data or precise expertise for an accurate estimation of the system parameters [16]. This does not happen in many situations, particularly for new systems where only tiny information is accessible about its performance. Uncertainty also comes from partial or imprecise models or deficient data gathering.

There are several approaches to the concept of uncertainty [17–19]. Uncertainty is often understood as a “state of knowledge” [20]. Ayyub [21] describes it in terms of knowledge imperfection due to intrinsic shortages of knowledge acquisition. Walker [22] expresses uncertainty as “any departure from the unachievable ideal of complete determinism”. Aven [23] defines it as “...lack of understanding about the behaviour and outcomes of a system, and discernible magnitudes”.

Although there is a wide variety of definition for the concept of uncertainty, the common element in all of them is the notion of deficient or partial knowledge of a system and its performances because of shortages in apparent information and noticeable data [24, 25].

Uncertainty denotes the nondeterministic conduct of a system and the ambiguous magnitudes of the parameters that define how the systems behave or perform. It might have an epistemic or aleatory nature. Aleatory uncertainty accounts for the usual disparity of the physical phenomena. Epistemic uncertainty accounts for the limited knowledge of the parameters used to describe and explain the system [26, 27].

Both types of uncertainties are an essential component of any safety assessment. Uncertainty is introduced through the SA process at several stages. During FHA uncertainty is related to the modes of failure and the consequences of such failures. There are also uncertainties related to the extent of the consequences and consequently to the severity assigned of every failure condition. All these uncertainties are also translated into the assignment of SO—safety objective (the lower frequency of occurrence admissible for each failure circumstance), and into the derivation of safety requirements during the PSSA. During the SSA, uncertainties will come from inaccurate or incomplete medialization or data gathering.

The current safety compliance process acknowledges that multiple potential failure situations are possible, i.e. a single failure condition or hazard might lead to

several failure modes and, accordingly, to diverse effects and consequences. This uncertainty has been traditionally mitigated with the definition of the worst-case scenario. This way to proceed appears to be too biased and over-conservative, which lead to excessively conservative safety requirements. The consideration of worst-case scenario incorporates a sort of guard band to reduce the chance of accepting a system that does not perform safely enough. This guard band implies a cost to the system. This could only be evaded if the decision-maker has truthful (i.e. not conservative neither optimistic) guesses of the uncertainties in the magnitudes backing up the decisions.

As can be seen, most decision-making processes in safety compliance assessment during SSA imply judgement of safety performance in a context with uncertainty [28, 29]. However, the existing SSA process does not comprise a methodical process to cope with all those uncertainties. Today, SSA is reduced to gathering evidence and a simple binary comparison of those evidence towards safety goals and requirements.

3. System acceptance decision under uncertainty

Let us consider that the outcome of the SSA process is a dual pronouncement by the safety regulator to authorise, or not, the operation of a system. To help decision-makers in such a judgement, six uncertainties should be computed: two related to the acceptance of the system, two linked with the nonacceptance of the system and two linked with the consideration of insufficient information.

An essential step is also to evaluate the decision-maker's utilities. Decision-maker's utilities reflect the consequences, expressed typically as costs, connected to each of the former listed uncertainties. Determining an individual's utilities typically comprises expressing preferences among different options [30–33].

Figure 2 shows a decision diagram for safety assessment. Rectangles stand for decision node. The decision-maker choices a_i are as follows:

- a_1 —Judge the system compliant.
- a_2 —Judge the system as noncompliant.
- a_3 —Judge the information insufficient.

Circles are random nodes representing the “states of nature”, where: S_1 represents that the system is actually compliant.

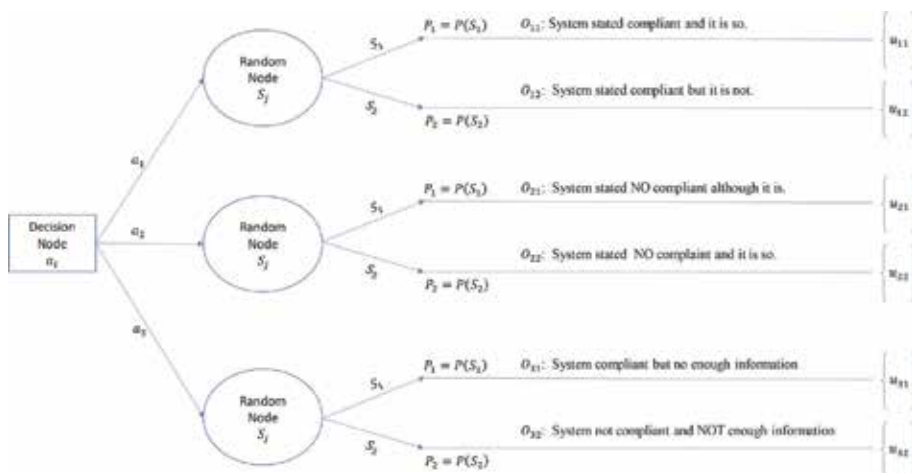


Figure 2.
 Safety assessment decision tree.

S_2 represents a NOT compliant system.

The uncertainties about the system states P_j are dependent on the data “Data” and information “Inf” available and will be calculated in subsequent sections of the chapter.

$$\begin{aligned} P_1 &= P(S_1) = P(S_1|Data, Inf); \\ P_2 &= P(S_2) = P(S_2|Data, Inf) = 1 - P_1 \end{aligned} \quad (1)$$

The paths in the tree correspond to the likely outcomes O_{ij} following the actions by the decision-maker. Six outcomes are considered:

- O_{11} : The system is affirmed compliant and it is so.
- O_{12} : The system is affirmed compliant though it is not.
- O_{21} : The system is affirmed NO compliant while it is truly trustable.
- O_{22} : The system is affirmed NO compliant and it actually is so.
- O_{31} : Although the system is truly compliant, it is not enough to make a decision.
- O_{32} : It is not enough to make a decision.

The rightmost end of the tree indicates the decision-maker’s utilities u_{ij} for each of the six branches. Each pair $(a_i, S_i) \in C = A \times N$ determines a consequence of decision-making. The utility $u_{ij}(c)$ which is defined on $C = A \times N$ can be expressed as $u_{ij}(c) = u(a_i, S_j)$ and defines the preferences of the decision-maker.

If action a_1 is taken, larger compliance is preferred over a smaller one:

$$u(a_1, S_1(a_1, S_2)) \text{ if and only if } S_1 \geq S_2 \quad (2)$$

If action a_2 is taken, diverse preferences can be outlined.

- a. After a nonacceptance decision, the actual state of the system becomes irrelevant. This situation is equivalent to a constant utility for each value of S_j , i.e. $u(a_2, S_j) = cte \quad \forall S_j \in N$.
- b. The combination of a nonacceptance decision and low system compliance is perceived as an opportunity loss. With a_2 decision-maker loses the occasion to admit a trustworthy system. The utility function $u(a_2, S_j)$ would not be constant any more, and smaller values of the actual system compliance would be preferred over larger opportunity loss). $u(a_1, S_1) \geq u(a_1, S_2)$ if and only of $S_1 \leq S_2$.

Despite the precise forms of $u(a_1, S_1)$ and $u(a_1, S_2)$, there is an “equilibrium” value S_0 such as

$$u(a_1, S_0) = u(a_2, S_0) \quad \forall Ns_j \in [0, 1] \quad (3)$$

Therefore, the utility functions must follow the following relations:

$$\begin{aligned} u(a_1, S_j) &> u(a_2, S_j) \text{ if } S_j > S_{j0} \\ u(a_1, S_j) &< u(a_2, S_j) \text{ if } S_j < S_{j0} \end{aligned} \quad (4)$$

A decision-maker should choose the action that maximises the predictable utility $P(S_j) = P(S_j|Data, Inf)$. He should choose the action a^* such that satisfy the following expression:

$$E_N[u(a^*, S)] = \max_{a_i \in A} E_N[u(a_i, S_j) * P(S_j)] \quad (5)$$

4. Quantification of the uncertainties

Safety compliance has been allocated a probability of truth or falsity. This probability corresponds to the decision-maker uncertainty (or state of knowledge), about safety compliance being true.

This probability is, namely, the uncertainty on the state of nature of the system compliance considering previous knowledge and information which is expressed as $P(S_j) = P(S_j|Data, Inf)$, where a proposition “Data” stands for data, while “Inf” stands for background information. This section details how $P(S_j) = P(S_j|Data, Inf)$ are calculated.

The proposed structure subscribes the concept that probability is not a frequency, rather a measure of uncertainty, belief or a state of knowledge. That is, probability allows doing credible thinking in situations where reasoning with certainty is not possible.

The result is the predictive probability that the system meets the safety objectives for what it has been designed, considering the envelope of data, knowledge and information gathered about the system during its design, production and operation.

To that aim, compliance assessment is redefined as the calculation of the degree of belief in the fulfilment of the applicable SO by the candidate system. The system is considered compliance if all the rate of failures λ_n satisfy their pertinent safety objective O_n .

Here the basis of Bayesian theory is applied to obtain an improved estimation of the system’s components rate of failure λ_n .

Let us define a set of propositions, each one with a probability stating the grade of confidence in its states, being these states either TRUE if λ_n is lower than its safety objective, O_n , or FALSE otherwise.

$$S = \{S_n : n \in Q\} \text{ where } S_n = \begin{cases} TRUE \text{ if } |\lambda_n| \leq O_n \\ FALSE \text{ otherwise} \end{cases} \quad (6)$$

This grade of confidence $P(S_n|Data, Inf)$ is denoted as a conditional probability. Each conditional probability $P(S_n|Data, Inf)$ mirrors our grade of assurance in λ_n satisfying its mandatory safety objective, O_n .

The grade of assurance in the system compliance $P(C_s|Data, Inf)$ will be evaluated as the intersection of the belief of compliance of all particular failure conditions:

$$\begin{aligned} P(S_j|Data, Inf) &= \bigcap_{n=1}^N P(S_j|Data, Inf) \\ &= P(S_1|Data, Inf) \cap P(S_2|Data, Inf) \cap \dots \cap P(S_n|Data, Inf) \end{aligned} \quad (7)$$

Uncertainties about the magnitude of the variables that govern the stochastic performance of the system are random variables which follow particular probability functions (pdfs). Consequently, rates of failure λ_n become, therefore, also random variables. Therefore, safety assessments are reduced to the determination of the failure rate pdfs.

For straightforwardness, we adopt probability function for the failure rate of a component, λ_n , conditional upon one or more unknown parameters θ . Other indicators could be selected instead, for example, the delay time between defect and failure or the number of failures in a period of time, but the theory hereafter applies equally.

The corresponding probability function is indicated as $(\lambda_n|\theta)$. To some extent previous knowledge about the expected values of λ_n should impact decisions about the system acceptability. However, θ is commonly unknown, and $f(\lambda_n|\theta)$ is not known unambiguously, so it cannot be used directly in making such decisions about system acceptance. $f(\lambda_n|\theta)$ is usually approximated by estimating θ over data and supposing the parameters are equal to estimates.

Maximum likelihood method is applied [34, 35]. Eq. (24) expresses the likelihood function:

$$L(\theta; D) \propto \prod_{i=1}^n p(\lambda_i|\theta) \propto \prod_{i=1}^n f(\lambda_i|\theta) \quad (8)$$

The Maximum likelihood estimate (MLE) is

$$L(\hat{\theta}; \text{Data}) \geq L(\theta; \text{Data}) \quad \forall \theta \neq \hat{\theta} \quad (9)$$

In practical applications, previous inequality is usually strict, and a single maximum exists. The classical approach to inference now substitutes θ by the first-order approach. In this case, as few data are available; this approximation would be very poor:

$$f(\lambda_n|\theta) \approx f(\lambda_n|\hat{\theta}) \quad (10)$$

Decisions concerning compliance assessment, which seek for unknown values of λ_n , might alternatively be resolved conditional upon the observation, information, data or available knowledge, rather than on the unknown parameters. This allows to base decisions upon $f(\lambda_n|\text{Data}, \text{Inf})$ instead on $f(\lambda_n|\theta)$, provided that Data and Inf are known.

The conditional probability distribution $P(\lambda_n|\text{Data}, \text{Inf})$ describes then the uncertainty in the parameter under study (λ_n) considering observed data “Data” and the prior understanding of the system Inf. It denotes the sample of the rate of failure distribution, conditional upon the observed data, and it is exactly the magnitude required for the decision-making process, with no approximation. $P(\lambda_n|\text{Data}, \text{Inf})$ is calculated using the Bayes’ theorem:

$$P(\lambda_n|\text{Data}, \text{Inf}) = \frac{P(\text{Data}|\lambda_n, \text{Inf}) \times P(\lambda_n|\text{Inf})}{P(\text{Data}|\text{Inf})} \quad (11)$$

where:

$P(\lambda_n|\text{Data}, \text{Inf})$ is referred to the posterior distribution. All inference regarding λ_n will be derived from the posterior distribution.

$P(\text{Data}|\lambda_n, \text{Inf})$ corresponds to the likelihood distribution, at times mentioned as sampling.

$P(\lambda_n|\text{Inf})$ is the prior distribution.

$P(\text{Data}|\text{Inf})$ is the marginal probability.

Epistemic uncertainty is incorporated through the prior distribution $P(\lambda_n|\text{Inf})$. It synthesises the level of confidence in our model parameters λ_n , and it expresses experts’ preliminary state of information or knowledge. The prior distribution might be informative or non-informative.

The first ones deliver important information about the unquantified parameters. They are the way to capture past data and expert knowledge into a probability distribution and incorporate them into the model. Conjugate priors streamline the assessment of the preceding equation and permit analytical resolutions. However,

prior can follow any distribution, and the preceding equation can be solved using numerical integration.

Non-informative priors are sometimes named as flat priors, vague priors, diffuse priors or reference priors. They are used when there is just very little background information about the parameters.

Most of the times, the Bayesian method requires numerical simulation because of the complexity of the distributions involved. That implies that the solution of Eq. (27) has to be obtained by numerically Markov chain Monte Carlo (MCMC) simulation [36, 37].

The resulting posterior distribution, $P(\lambda_n|Data, Inf)$, stands for updated knowledge about λ_n and, as stated before, will be the foundation for all inferential conclusions regarding λ_n .

The distribution $P(Data|\lambda_n, Inf)$ signifies the aleatory uncertainties or change naturally included in data and models. It also accounts for inefficiencies in the data assembly as well as inadequacies in the models. Likelihood function most commonly employed in system safety assessment are binomial, Poisson or exponential ones [38–40].

And finally $P(Data|Inf)$ is just a normalisation factor.

$P(S_n|Data, Inf)$ can be obtained from the posterior distributions $P(\lambda_n|Data, Inf)$ through the marginalisation of the parameter λ_n , as shown in the next equation:

$$\begin{aligned}
 P(C_{sn}|Data, Inf) &= \int_{\Lambda} P(O_n, \lambda_n|Data, Inf) \cdot d\lambda = \int_0^{O_n} P(O_n|\lambda_n)P(\lambda_n|Data, Inf) \cdot d\lambda \\
 &= \int_0^{O_n} P(O_n|\lambda_n) \frac{P(Data|\lambda_n, Inf) \times P(\lambda_n|Inf)}{P(Data|Inf)} \cdot d\lambda
 \end{aligned}
 \tag{12}$$

Eq. (12) calculates an average of the model uncertainty through the integration of the sampling $P(O_n|\lambda_n)$ through the posterior distribution $P(\lambda_n|Inf)$ [36]. The outcome is a predictive probability of a failure rate λ_n meeting its safety objective.

5. Conclusions

The safety assessment is a methodical and prescribed procedure applied by ANSP to find, quantify and diminish risks in ATM systems and ensure that new services or systems reach assurance levels required by the aviation authorities. The assessment of safety compliance against approved safety levels becomes the last but essential part of the safety assurance process.

Nevertheless, this method is still exhibiting a series of limitations, the most important being its failure to cope with the uncertainty intrinsic in each step of the assessment and its lack of ability to deal with the lack of data in early stages of operation, and only small measurable information about its performance can be accessed. While most choices in the safety assessment involve a trial under uncertainty, the present system safety assessment process does not embrace any organised process or help to address all these uncertainties. So, the process misses the simplicity and impartiality essential for regulatory decision-making.

This chapter discussed the mathematical grounds for a cohesive Bayesian inference methodology, to assess and evaluate compliance with system safety goals and requirements, taking into account the uncertainty in performances. This work proposes a Bayesian structure that assesses safety compliance as a decision-making issue taken place under the presence of uncertainty.

Bayesian approach enables more comprehensive management of the uncertainties inherent to all system safety assessments and improves impartiality and accepting of compliance decisions and judgements, particularly in the cases where uncertainty is a limitation. This method might be applied to any safety or regulatory compliance process. It might be directly implemented by either operator or manufacturers, as well as by safety oversight authorities.

This work aims to increase the use of statistical Bayesian methods in the ground of aviation safety compliance assessment, up to a level equivalent to the one achieved so far in other critical industries, such space or nuclear power industries. The method offers a significant improvement to how ANSP presently take on regulatory safety compliance. Whereas the theoretical grounds are not new, their application to aviation signifies a noteworthy progression over current practices.

Conflict of interest


The authors declare no conflict of interest.

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Section 3

New Airspace Users

Trajectory-Based, Probabilistic Risk Model for UAS Operations

Hector Usach, Juan A. Vila and Áurea Gallego

Abstract

To enable the safe integration of Unmanned Aircraft System (UAS) into the civil airspace, the European Aviation Safety Agency (EASA) has elaborated a new regulatory framework that is operation-centric and risk-based. Based on this principle, gaining authorization to conduct certain types of operations depends on a safety risk assessment. To harmonize this process, the Joint Authorities for Rulemaking on Unmanned Systems (JARUS) released a qualitative methodology called Specific Operation Risk Assessment (SORA). However, SORA is not a complete safety assessment tool since, in some cases, a quantitative risk analysis is still required. This work develops a probabilistic risk model that extends SORA to evaluate the ground risk and the air risk components along a specified UAS trajectory quantitatively. The proposed model is supplied with illustrative data and is validated in a representative UAS mission. In the future, the risk model will be exploited to develop a decision tool for determining the minimum-risk trajectory when multiple, alternative routes are available.

Keywords: risk assessment, UAS, SORA, Bayesian networks, contingency management

1. Introduction

In order to harmonize the regulation of Unmanned Aircraft System (UAS) across the European Union and to foster the development of the UAS market, the European Aviation Safety Agency (EASA) is elaborating a new regulatory framework that relies on the Concept of Operation (ConOps) for drones [1]. According to this concept, UAS operations can be classified into three categories, named “open,” “specific,” and “certified,” as summarized in **Table 1**. Each of these categories has an associated regulatory regime that is proportionate to the risk of the operation. Operations within the open category do not require prior authorization by the competent authority. Operations within the specific category require authorization by the competent authority based on an operational risk assessment performed by the operator. Finally, operations within the certified category are subject to a full certification process based on the safety objectives in [2].

The task of performing an operational risk assessment to obtain authorization for operating a UAS is sensitive and complex. To facilitate and harmonize this process, the Working Group 6 of the Joint Authorities for Rulemaking on Unmanned Systems (JARUS) initiative developed the Specific Operation Risk Assessment (SORA) methodology [3]. The SORA is a qualitative process that basically particularizes the risk assessment steps in [4] to evaluate the risks involved

Open category	Specific category	Certified category
MTOW ^a < 25 kg; and height < 120 m; and in VLOS ^b ; and Outside reserved areas	MTOW ^a < 25; or height ≥ 120 m; or BVLOS ^c	Risks like manned aviation (size, complexity, kinetic energy)
No certification	SORA	Full certification

^aMaximum take-off weight.
^bVisual line of sight.
^cBeyond visual line of sight.

Table 1.
EASA's concept of operation for drones.

with the operation of UASs of any class and size and for any type of operation; and ultimately to determine the corresponding mitigation measures. Although it is specially intended for UASs operating within the specific category, it may be used as an acceptable means of compliance with safety objectives for the certified category as well [3].

It is to be noted, however, that although the SORA analysis is qualitative in nature, a quantitative risk analysis is still required in some circumstances. For instance, Annex C to the SORA document encourages the use of quantitative data to support the qualitative assumptions and decisions regarding the strategic mitigations for the air risk. Even so, SORA does not prescribe any quantitative model from which these data should be obtained. There exist other shortcomings regarding the qualitative approach of the SORA process. As an example, the work in [5] identifies a number of inconsistencies that ought to be resolved.

Given all the above, this work proposes to complement the SORA process with a probabilistic risk model that evaluates the ground risk and the air risk components along a specified UAS trajectory quantitatively. The quantitative data provided by the model can be used to validate whether a particular operation (either specific or certified) reaches the Target Level of Safety (TLS) required by regulation. Moreover, the quantitative model can be exploited not only for risk assessment purposes, but also as a decision tool for determining the optimal trajectory in case of mission replanning.

Several works have already proposed quantitative models to assess the risk of UAS operations. A review of some of these models can be found in [6]. Other examples include the work in [7]. It provides both a qualitative and a quantitative risk analysis of UAS operations in integrated airspace: the qualitative analysis is actually a Failure Mode and Effect Analysis (FMEA), while the quantitative analysis is based on a Fault Tree Analysis (FTA). However, none of the previous approaches is consistent with the SORA framework. Conversely, the aforementioned work in [5] follows a similar approach than the one in this work: it identifies the inconsistencies of SORA and proposes to close these gaps through a complementary, mathematically based approach to risk assessment. In particular, it provides a simple, probabilistic formulation of a barrier-based safety model. The difference between [5] and the work in this chapter is that we exploit the Bayesian formulation to model how a threat can develop into a hazard (rather than a bow-tie representation); and, especially, that we are focused on estimating the risk along a specified flight trajectory (rather than on evaluating the effectiveness of the safety barriers). Other risk models in the literature will also be referenced along this work conveniently.

An important consideration is that risk models for UASs are in general highly dependent on the ConOps under consideration, and especially on the type of airspace where the operation takes places (e.g., airspace type and class, operating

altitude, encounter rate, conflict management layers available, etc.). Due to the wide variety of ConOps that can be envisaged, it is difficult to develop a model that captures the characteristics of all the possible operating environments. So considering the research interests of the authors, this work is focused on UASs operating in the Air Traffic Management (ATM) environment. This implies that the UAS must comply with existing rules and procedures for manned aviation (e.g., rules of the air or airspace structure). UASs operating in the UAS Traffic Management (UTM) environment (e.g., ConOps proposed by the CORUS project [8]) are therefore out of the scope of this work.

The rest of the chapter is organized as follows. Section 2 details the ConOps considered in this work, as well as the demonstration mission that will be used to validate the proposed risk model. Section 3 develops the probabilistic risk model for the proposed ConOps. Section 4 provides the validation results. Finally, Section 5 concludes the chapter and outlines future lines of research.

2. Proposed concept of operation

In order to provide a broad vision of the problem under study, this work is not focused on a particular type of operation. Rather, the proposed ConOps describes a wide range of flight profiles with the following general common features:

- The UAS operation is to be performed Beyond Visual Line of Sight (BVLOS) of the operator.
- The UAS operation is to be performed under Instrument Flight Rules (IFR). When airspace requirements impose compliance with Visual Flight Rules (VFR), airspace segregation will be necessary.
- The UAS operation may enter in controlled airspace. The operation may also take-off or land at a controlled airport. Therefore, coordination with the corresponding Air Traffic Control (ATC) authority is compulsory. Additionally, the UAS can fly under non-conventional ATC services not included in controlled areas; for example, an ATC unit that acts specifically at the operations area, similar to the one used to coordinate the operations in a firefighting.
- The UAS operation is to take place out of urban areas.

Due to the inherent complexity of the proposed ConOps, it is assumed that Unmanned Aircraft (UA) models capable of flying these missions will be comparable to manned aircraft in terms of size and complexity. A representative UA that will be used for demonstration purposes is the IAI Super Heron model. Furthermore, the UAS will be remotely piloted by an operator (called remote pilot); and the communication between the remote pilot and the UA will be conducted using a Command and Control (C2) data link. So, the UAS will actually be a Remotely Piloted Aircraft System (RPAS), which includes the Remotely Piloted Aircraft (RPA), the remote pilot station(s), and the C2 link.

2.1 Demonstration mission description

One among all the possible missions described by this, ConOps will be used to validate the probabilistic risk model discussed below. The proposed mission consists

of a route from a departure airport to an operations area; a series of maneuvers within this area; and finally a route toward the destination airport. In particular, in the proposed demonstration mission, represented in **Figure 1**, the UAS must depart from the uncontrolled airport of Teruel (International Civil Aviation Organization

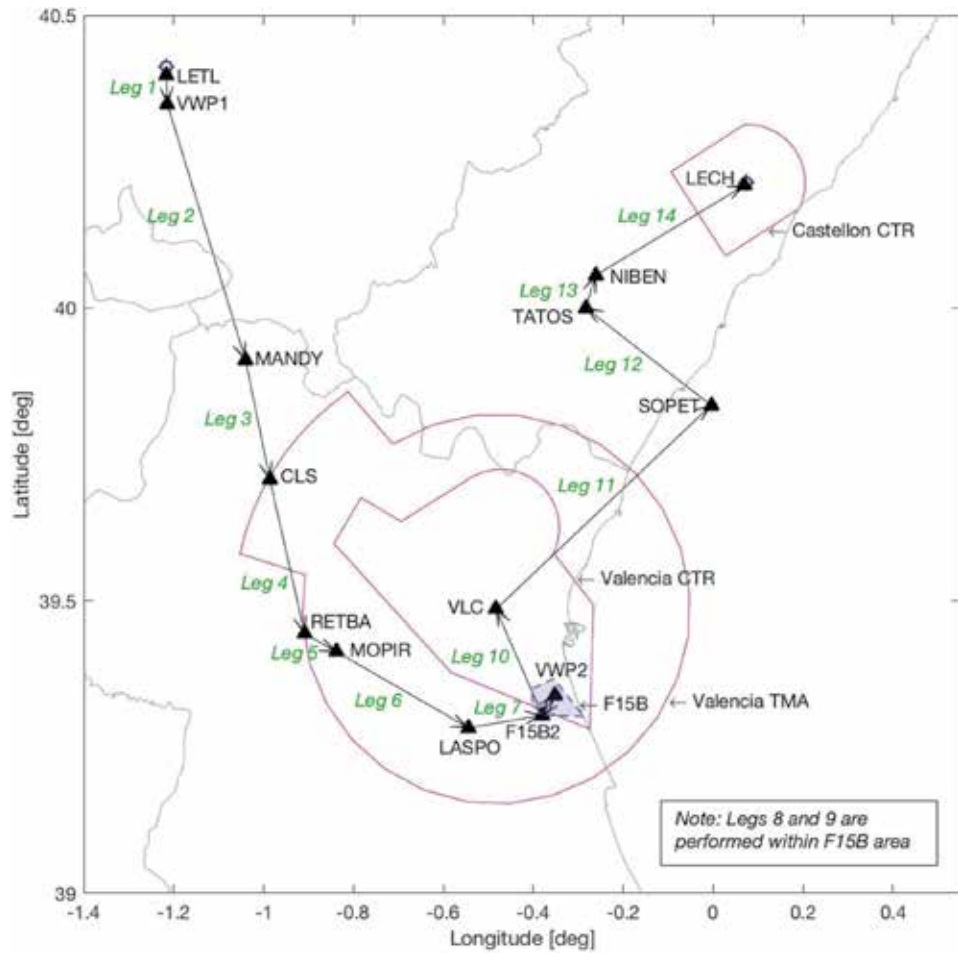


Figure 1.
Demonstration mission.

Segment #	Segment type	Waypoint sequence	Remark
1	Departure	LETL → VWP1 → MANDY	Uncontrolled airspace
2	En-route	MANDY → CLS → RETBA → MOPIR → LASPO	Controlled airways R29 and M871
3	Ingress	LASPO → F15B2	Uncontrolled airspace
4	Operations	F15B2 → VWP2 → F15B2	Uncontrolled airspace
5	Egress	F15B2 → VLC	VFR corridor
6	En-route	VLC → SOPET	Controlled airway B26
7	Arrival	SOPET → TATOS → NIBEN → LECH	Standard arrival SOPET1S

Table 2.
Route specification for the demonstration mission.

(ICAO) code LETL) to perform some direct observations over the Albufera’s natural park in Spain; and then land at the controlled airport of Castellón (LECH). The operations area has well-specified limits (defined by perimeter F15B in **Figure 1**) which must be enforced using a geo-awareness system. In addition, given that this area is located within the Controlled Traffic Region (CTR) of the València Airport (ICAO code LEVC), the mission will require special permission from Air Traffic Service (ATS) authorities. To perform this mission, a route connecting the departure site, the operations area, and the arrival site must be specified. The proposed route is composed of 14 flight legs, which are structured into seven flight segments (described in **Table 2**), and which have been constructed in compliance with the Spanish Aeronautical Information Service (AIS) [9]. The risk assessment results of this mission will be presented in Section 4.

3. Probabilistic risk model compliant with the SORA framework

In order to develop a probabilistic risk model that is consistent with the SORA framework, it is necessary to account with the Holistic Risk Model (HRM) behind the SORA methodology. In short, the HRM is focused on the occurrence of a single, generic *hazard*, named “UAS operation out of control,”¹ an emergency condition with the potential to provoke three possible *harms*: fatal injuries to third parties on the ground, fatal injuries to third parties in the air or damage to critical infrastructures. At the same time, the out of control condition can originate from different *threats*, like a technical error, a human error, etc. Further details can be found on Version 1 of the SORA document [3].

To estimate the likelihood of occurrence of each of the previous harm categories (here expressed as P_{harm}), the Version 1 of the SORA document mentions a mathematical model that depends on three factors: the probability of being out of control (P_{ooc}), the conditional probability of striking the entity of value (i.e., third parties on the ground or in the air, or critical infrastructures) once the operation is out of control ($P_{strike/ooc}$), and the conditional probability of causing the given harm if the strike has actually occurred ($P_{harm/strike}$):

$$P_{harm} = P_{ooc} P_{strike/ooc} P_{harm/strike} \quad (1)$$

However, SORA does not further detail this model since SORA is a risk assessment methodology of a qualitative nature. This work will use Eq. (1) as the basis to develop a quantitative, probabilistic risk model for UAS operations. To do so, Eq. (1) will first be rearranged for convenience so that it is expressed as a function of the probability of impact (P_{impact}) rather than the probability of being out of control. In the sequence of events of a UAS mishap, the “impact” event is an intermediate condition between the out of control event and the event of striking a third party, see **Figure 2**. Having this in mind, P_{impact} can be expressed as:

$$P_{impact} = P_{ooc} P_{impact/ooc} \quad (2)$$

where $P_{impact/ooc}$ is the conditional probability of having an impact given the out of control condition. Eq. (1) can thus be rewritten as follows with minor effort:

¹ In Version 2 of the SORA document, the SORA hazard was renamed as “loss of control.” However, this work retains the original name of the hazard to better differentiate it from the “loss of control in-flight” condition, which refers to the aircraft stall.

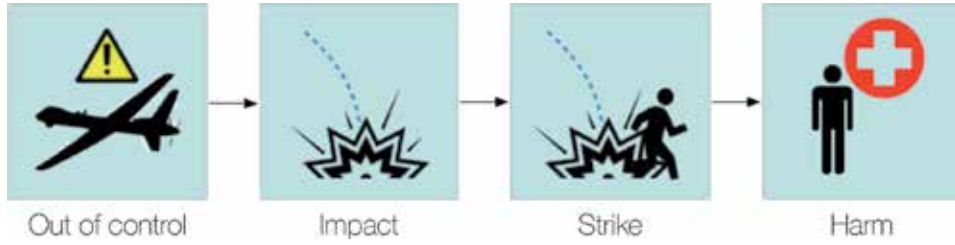


Figure 2.
Sequence of events of a UAS mishap.

$$P_{harm} = P_{impact} P_{strike/impact} P_{harm/strike} \quad (3)$$

Note, however, that the likelihood of occurrence of an aircraft accident is usually expressed as the number of occurrences per flight hour, not as a probability. Therefore, Eq. (3) can be rewritten in terms of rate of occurrence as follows:

$$\lambda_{harm} = \lambda_{impact} P_{strike/impact} P_{harm/strike} \quad (4)$$

where λ_{harm} is the rate at which the harm under analysis occurs (per flight hour), and λ_{impact} is the rate at which the impact event is expected to occur (also per flight hour). In general, Eq. (4) expresses an instant risk as the different terms involved in this equation can vary along space and time. For example, the probability of striking a third party on the ground depends on the population density in the vicinity of the impact area. The aim of this work is to assess the risk posed by a UAS flying a given trajectory $r = r(t), t \in [a, b]$, $a < b$, where $r(t)$ is a curve C between two points $r(a)$ and $r(b)$. Therefore, in order to compute the overall risk along a defined flight path, it is necessary to perform the line integral of Eq. (4) along the curve C between $r(a)$ and $r(b)$:

$$\Lambda_{harm} = \oint_C \lambda_{harm}(r) ds = \int_a^b \lambda_{harm}(r(t)) \|r'(t)\| dt \quad (5)$$

where ds is an elementary arc length. Note that Eq. (5) is expressed in terms of occurrences per hour of operation along a specified distance ($[s^{-1} \cdot m]$ using the International System of Units). Then, the average risk along this trajectory in terms of occurrences per flight hour is given by:

$$\bar{\lambda}_{harm} = \frac{\Lambda_{harm}}{L(C)} \quad (6)$$

where $L(C) = \oint_C ds$ is the length of the curve C between $r(a)$ and $r(b)$ (i.e., the length of the planned trajectory). Next, Eq. (5) will be particularized to assess the risk of causing fatal injuries to third parties on the ground (hereinafter *ground risk*), and to third parties in the air (hereinafter *air risk*). Due to lack of data and time constraints, the risk of causing damage to critical infrastructures will not be assessed in this work.

3.1 Ground risk model

In order to derive the ground risk component (denoted as Λ_G) from Eq. (5), it is necessary to develop an impact model (term λ_{impact} in Eq. (4)), a strike model (term

$P_{strike/impact}$), and a harm model ($P_{harm/strike}$). The proposed models for these terms are discussed next.

3.1.1 Impact model

The ground impact model provides the rate at which a ground impact occurs (λ_{impact}). In the literature, this term is often assumed to be constant and is either estimated based on historical accident data, component failure data, and expert judgment [10, 11], or deduced from the TLS required by regulation [12–14]. By contrast, this work suggests modeling λ_{impact} using Bayesian Belief Networks (BBNs), which provides two major advantages:

1. The model can be supplied with both qualitative and quantitative data simultaneously [15]. This is specially useful in models with high degree of uncertainty, like in the problem under study.
2. Probabilistic inference can be used to replace an initial assumption regarding one model variable by a perceived *evidence* regarding this variable and then, the model automatically updates the remaining probabilities based on the presence of such evidence [16]. In practice, this capability can be used to update the probability of a ground impact given the real-time state of the system (for instance, depending on whether the C2 link is loss or alive).

The proposed BBN describing the ground impact model is represented in **Figure 3**. As it can be observed, the model is described by a directed, acyclic graph where nodes represent variables and edges represent the conditional dependencies between these variables. Each node variable is associated with a Bayesian probability that is expressed with a Conditional Probability Table (CPT). In this case, the sink node represents the probability of a ground impact (P_{impact}), and the remaining nodes describe the sequence of events between the initiating factors and the expected outcome. Therefore, the probability of a “ground impact” depends on the combined likelihood of experiencing a “loss of control in-flight” and a “boundary violation” condition (i.e., exceeding the operational limits approved for the operation), see **Figure 3**. At the same time, these abnormal flight conditions can be caused by an “inappropriate guidance,” i.e., a guidance command that is not suitable for the current state of the aircraft (because it exceeds the flight envelope limits, because it is not consistent with the approved Mission Plan, etc.). In addition, the “boundary violation” can also result from a “navigation error” like the loss of the Global Navigation Satellite System (GNSS) signal. The “inappropriate guidance” is based on the combined effect of an “autopilot malfunction” (including loss of function and malfunction) and “pilot ineffectiveness.” The human pilot is considered to be “ineffective” when she or he takes a wrong guidance decision, or when a correct decision is badly executed (e.g., selection of an inappropriate control mode, poor piloting skills, etc.). The source of an “autopilot malfunction” or a “pilot ineffectiveness” condition may be the use of incorrect navigation information caused by a “navigation error.” Finally, the pilot may also be “ineffective” when she or he is not in the control loop due to the “C2 link loss.”

In order to obtain the output probability P_{impact} , it is necessary to define the CPTs of each of the events of the previous BBN. As it can be observed, these events basically include technical errors (e.g., “navigation error,” “autopilot malfunction,” etc.) and human errors (e.g., “pilot ineffective”). The CPT of an event cataloged as a technical error can be obtained from the technical specifications or can be

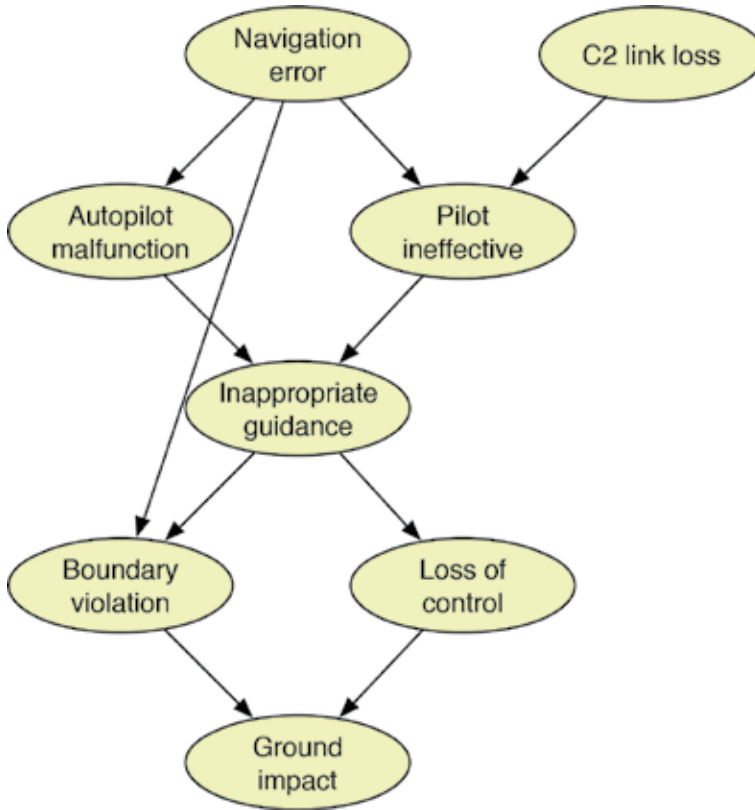


Figure 3.
Ground impact BBN model.

deduced from system tests. By contrast, the CPT of an event cataloged as a human error depends on human factors like type of activity being carried out, workload, etc. Some authors have already attempted to develop human performance models for specific activities (e.g., ATC controllers [17] or pilots of manned aircraft [18]). However, the development of a detailed human performance model is a vast task that exceeds the scope of this work. For this reason, we will calibrate the proposed model using technical data when possible, and illustrative data from experts' judgment otherwise, see the Appendix. The output data will be assumed to be representative of the case study, although it should be validated in a future stage using some of the approaches proposed in the literature (e.g., see [19, 20]).

Another important remark regarding the previous model is that it provides the probability of the occurrence of the ground impact event (P_{impact}), not the failure rate (λ_{impact}). In order to derive λ_{impact} from P_{impact} , it is necessary to assume a given probability distribution function. As in similar approaches in the literature (e.g., see [15, 21]), this work assumes that P_{impact} follows a Poisson distribution, so λ_{impact} is given by:

$$\lambda_{impact} = -\ln(1 - P_{impact}) \quad (7)$$

3.1.2 Strike model

The strike model represents the conditional probability that an impact at a specific location strikes a person. To model this term, this work will use a widely accepted model in the literature [10–13, 16, 22]:

$$P_{strike/impact}(r) = \rho_G(r) LA \quad (8)$$

where $\rho_G(r)$ is the population density at the impact point, and LA is the lethal area of the airborne platform. Census data are often used to estimate $\rho_G(r)$ [10, 14, 16, 23]. With respect to the lethal area, two crash modes are often considered in the literature: vertical free fall [10, 22, 23] and unpremeditated, gliding descent [10, 11, 13, 16]. For simplicity, this work assumes that the ground impact occurs following a vertical free fall so that the impact location is close to the point where the initiating failure has occurred. Therefore:

$$LA = \pi \left(\frac{\max(w_{ua}, L_{ua})}{2} + R_p \right)^2 \quad (9)$$

where w_{ua} is the UA wingspan, L_{ua} is the UA length, and R_p is the radius of an average person. Note that LA is thus a constant parameter because none of these terms vary with the aircraft trajectory.

3.1.3 Harm model

The harm caused to a person after a strike depends on multiple factors, including type of UA (e.g., size, fragility, etc.), conditions at the point of impact (e.g., speed, position), or secondary effects like explosions, etc. [24]. However, in compliance with the SORA approach, this work assumes the worst-case condition where: (1) there are no sheltering structures that mitigate the effect of a ground impact, and (2) any direct impact of a UA causes the instant death of the people involved in the accident. Therefore:

$$P_{casualty/strike}(r) = 1 \quad (10)$$

So, in summary, the proposed ground risk model is given by:

$$\Lambda_G = LA \int_a^b \lambda_{impact}(r(t)) \rho_G(r(t)) \|r'(t)\| dt \quad (11)$$

3.2 Air risk model

As in the case of the ground risk, deriving the air risk component (denoted as Λ_A) from Eq. (5) requires to develop an impact model (term λ_{impact} in Eq. (4)), a strike model (term $P_{strike/impact}$), and a harm model ($P_{harm/strike}$). The proposed approach to develop these terms is discussed next.

3.2.1 Impact model

The air impact model provides the rate at which a Mid-Air Collision (MAC) between two aircraft occurs (λ_{impact}). In the literature, this term is often modeled using the Maxwell molecule formulation [21, 23, 25], which assumes that the air traffic behaves randomly in airspace, and thus that the rate at which a MAC occurs is proportional to the traffic density in the operational volume. However, this theory does not contemplate the conflict management layers available in the air-space [26], schematized in **Figure 4**; and, for this reason, it does not adequately represent traffics operating in the ATM framework. To overcome this, this work proposes to develop the air impact model following the same approach than in the

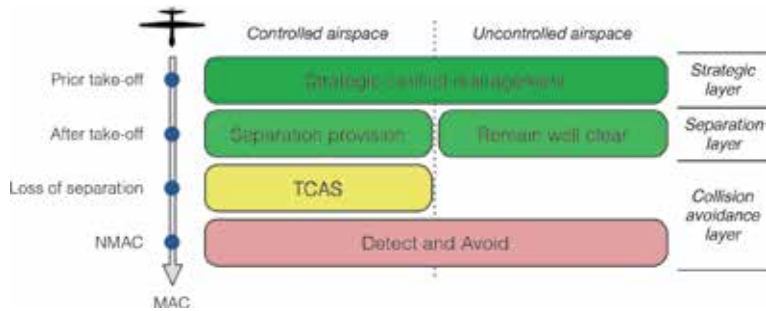


Figure 4. Conflict management layers in UAS. Credit: Drone icon by Anthony Lui from the Noun Project.

ground impact: using BBNs. In particular, two BBNs will be developed: one for segments performed in controlled airspace and other for uncontrolled airspace.

3.2.1.1 Mid-air collision model for segments performed in controlled airspace

The proposed mid-air collision BBN model for flight segments performed in controlled airspace is represented in **Figure 5**. The output node of this model is the “MAC” node which has an associated probability P_{impact} . The sequence of events leading to this flight condition depends on two major events: the “separation error” and the “collision avoidance error.” As it is shown in **Figure 4**, the “separation error” occurs when both “strategic separation” and “tactical separation” fail. “Strategic separation error” basically refers to the failure of the procedural separation mechanism, while “tactical separation error” involves the ATC surveillance capability. The “tactical separation error” node probability depends on the combined likelihood of the corresponding ATC unit being “ineffective” and the remote pilot performing an “inappropriate guidance.” ATC is ineffective when a possible conflict is not detected, or when ATC provides an incorrect clearance. This node probability certainly depends on the “traffic density”² in the area. “Inappropriate guidance” refers to conditions where the ATC clearance is not correctly executed by the remote pilot. Note that the probability of experiencing an “inappropriate guidance” depends on the same sequence of events than in the ground impact BBN model described in Section 3.1.1.

Once the “separation error” occurs, collision avoidance layers can still prevent the MAC from occurring. In controlled airspace, it is assumed that aircraft will be equipped with a transponder. Therefore, collision avoidance can be performed at two levels with a different time horizon. At a first level, Traffic alert and Collision Avoidance System (TCAS) can trigger a traffic alert/resolution advisory. The effectiveness of this layer depends on the remote pilot because it is assumed that she or he must still approve or reject the resolution advisory. If the TCAS alert results “ineffective,” then the Near Mid-Air Collision (NMAC) condition will occur. After this happens, a second collision avoidance mechanism can still reduce the probability of a MAC impact by performing an evasion maneuver seconds after the point of closest approach. This maneuver may be either a See and Avoid (SAA)-based maneuver performed by the remote pilot, or a Detect and Avoid (DAA)-based

² Note that, in **Figure 5**, the “traffic density” node has a rectangular shape instead of an ellipse. This notation emphasizes that this node is not a probabilistic node, but a decision node, i.e., a node representing an input variable of the model. In other words, the traffic density is considered to be known at a given airspace volume.



Figure 5.
 Mid-air collision BBN model in controlled airspace.

maneuver performed by the automatic system (if a DAA system is equipped onboard the UAS). A “DAA error” may occur if the onboard sensors are unable to detect the conflicting traffic. SAA may be “ineffective” when the remote pilot has a reduced situational awareness, or when the pilot is not in the control loop due to the “C2 link loss.” Finally, as in the ground impact model, this work assumes that the MAC event follows a Poisson distribution so λ_{impact} can be deduced from P_{impact} using Eq. (7).

3.2.1.2 Mid-air collision model for segments performed in uncontrolled airspace

The proposed mid-air collision BBN model for flight segments performed in uncontrolled airspace is represented in **Figure 6**. As in the BBN model for controlled airspace, the output node is the “MAC” node which has an associated probability P_{impact} . However, as it can be observed in the figure, the sequence of events leading to this flight condition differs when flying in uncontrolled airspace. To start with, separation provision is independent of the ATC service. In this case, the main separation mechanism is the definition of the mission boundaries and the use of



Figure 6.
Mid-air collision BBN model for uncontrolled airspace.

geofencing to enforce these boundaries. However, a “boundary violation” may occur due to “inappropriate guidance” or because of a “navigation error.” Once the “boundary violation” occurs, the likelihood of experiencing a “separation error” increases with the “traffic density” in the area.

Even if the UAS flies within the specified boundaries, other traffics may also be encountered in the same operational volume. For this reason, the remote pilot is required to “remain well clear” of other aircraft at all times. However, the remote pilot may fail at remaining well clear because she or he performs an “inappropriate guidance.” The proposed model assumes that the likelihood of the remote pilot failing at remaining well clear increases with the “traffic density” because of the increased pilot workload.

The other key difference when operating in uncontrolled airspace is that aircraft are not required to be equipped with a transponder. Therefore, one cannot assume that an intruder aircraft will be a cooperative traffic, what makes the TCAS layer inoperative. As a result, after a “separation error” occurs, the “NMAC” condition is assumed to happen, and the only feasible collision avoidance mechanism is the SAA or DAA maneuver. This is one of the factors that certainly increases the operational risk when flying in uncontrolled airspace.

3.2.2 Strike model

The strike model represents the conditional probability that an impact between two aircraft strikes a person in the air. In the case of a UAS operation, an impact is expected to cause a strike only if the transient aircraft is a manned aircraft. Therefore, the strike model should account for the ratio between manned and unmanned aircraft in the vicinity of the operating area. For simplicity, this work assumes that all mid-air collisions involve a manned aircraft as long as the UAS is not performing a formation flight with other UAs. This way, all impacts are supposed to result in a strike:

$$P_{strike/impact} = \rho_A(r) \quad (12)$$

where $\rho_A(r)$ is the number of people onboard the collided aircraft. In order to estimate this term, it is necessary to characterize the aircraft flying in the airspace volume where the operation takes place. For example, it is possible to assume that most aircraft flying a controlled airway will be airliners, while most aircraft flying in uncontrolled airspace will be general aviation aircraft.

3.2.3 Harm model

The harm model determines the likelihood of causing fatal injuries to people onboard the collided aircraft once the strike between the UAS and the manned aircraft has occurred. As in the case of the ground risk model, this work assumes the worst-case condition where all strikes result in a casualty:

$$P_{casualty/strike} = 1 \quad (13)$$

So, in summary, the proposed air risk model is given by:

$$\Lambda_A = \int_a^b \lambda_{impact}(r(t)) \rho_A(r(t)) \|r'(t)\| dt \quad (14)$$

4. Validation results

The probabilistic risk model in Section 3 has been implemented in Matlab and has been supplied with the illustrative data in the Appendix. To validate this model, a risk assessment will be performed for the demonstration mission in Section 2.1. In particular, the risk assessment will be performed considering six different operational conditions of the UAS (named as **OC1** to **OC6**), described in **Table 3**. The

ID	Operational condition	DAA equipped
OC1	Nominal condition	None
OC2	Autonomous condition (C2 link loss)	None
OC3	Degraded navigation condition (GNSS signal loss)	None
OC4	Nominal condition	RTCA SC-228 compliant
OC5	Autonomous condition (C2 link loss)	RTCA SC-228 compliant
OC6	Degraded navigation condition (GNSS signal loss)	RTCA SC-228 compliant

Table 3.
 Operational conditions evaluated in the risk assessment.

results obtained are shown in **Figure 7**, where each subfigure shows the ground risk component and the air risk component along each flight leg of the demonstration mission, considering a specific operational condition.

As it can be observed, the air risk component is the main contribution to the total risk whenever a DAA system is not equipped onboard the UAS (**Figure 7a–c**). However, this risk component can be almost entirely removed if a DAA system is equipped and it complies with the Minimum Operational Performance Standards (MOPS) of RTCA SC-228 [27] (the most stringent requirements required by SORA, almost an ideal DAA). When it comes to the ground risk component, it becomes a determining factor specially when overflying high population density areas like the metropolitan area of València (corresponding to flight legs 8 to 11, see **Figure 1**).

Another interesting result that can be deduced from **Figure 7** is that the loss of the C2 link has a greater impact on the air risk than on the ground risk (what is in

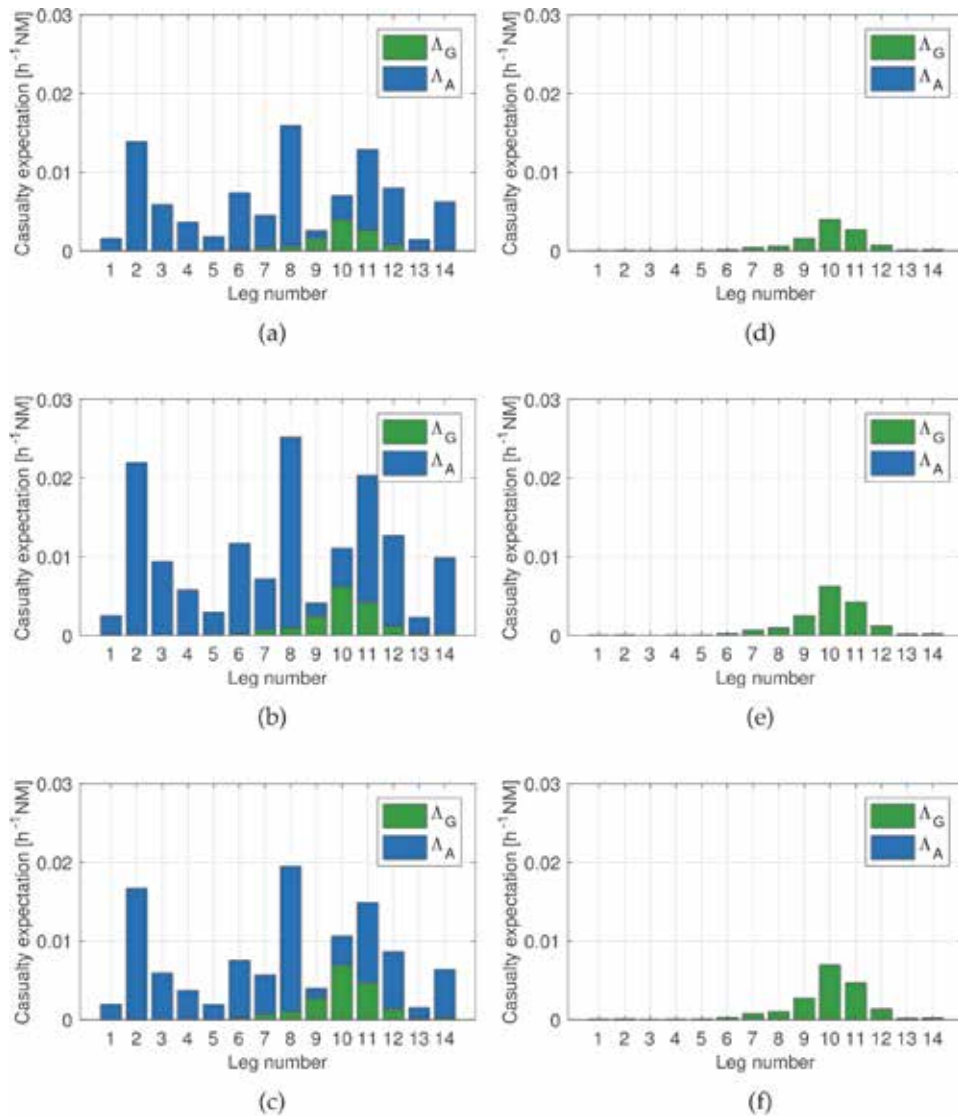


Figure 7. Risk assessment results: Ground risk and air risk components in each flight leg of the demonstration mission. (a) Operational condition OC1. (b) Operational condition OC2. (c) Operational condition OC3. (d) Operational condition OC4. (e) Operational condition OC5. (f) Operational condition OC6.

Operational condition	Λ [h^{-1}NM]	$\bar{\lambda}$ [h^{-1}]
OC1	9.29e-02	4.67e-04
OC2	1.47e-01	7.39e-04
OC3	1.09e-01	5.48e-04
OC4	1.04e-02	5.23e-05
OC5	1.64e-02	8.24e-05
OC6	1.82e-02	9.15e-05

Table 4. Cumulative risk and average risk when the UAS flies the demonstration mission in different operational conditions.

line with the results in [7]). This is due to the fact that, during this abnormal flight condition, the remote pilot is unable to intervene in the operation; and consequently tactical separation, TCAS and SAA conflict management layers are not effective. Conversely, the results obtained indicate that the loss of the GNSS signal is slightly more critical when it comes to the ground risk than to the air risk.

Finally, **Table 4** shows the cumulative risk when considering the entire demonstration mission. Note that the cumulative risk Λ is computed by adding the ground risk component and the air risk component along all the flight legs of the planned trajectory; while the average risk $\bar{\lambda}$ is computed from Λ using Eq. (6). As an example, the cumulative risk when the UAS operates in **OC1** is $\Lambda = 9.29 \cdot 10^{-2} \text{ h}^{-1}\text{NM}$; although it can be reduced down to $\Lambda = 1.04 \cdot 10^{-2} \text{ h}^{-1}\text{NM}$ by means of the DAA capability (**OC4**). Considering that the estimated path length for this route is $L = 199 \text{ NM}$, the average risk in these conditions is $\bar{\lambda} = 4.67 \cdot 10^{-4} \text{ h}^{-1}$ and $\bar{\lambda} = 5.23 \cdot 10^{-5} \text{ h}^{-1}$, respectively.

5. Conclusions

Current regulatory framework for the operation of UAS in Europe is operation-centric and risk-based. Based on this framework, the authorization for conducting a specific mission is given on the basis of an operational risk assessment performed by the operator. In order to facilitate and harmonize this process, EASA established a qualitative risk assessment methodology called SORA. However, SORA is not a complete safety assessment tool because quantitative results are still required to demonstrate that a specific operation can be conducted safely.

In this chapter, a probabilistic risk model for UAS operations is proposed. The proposed model estimates the likelihood of occurrence of a catastrophic accident when a UAS flies a specified trajectory. One of the main novelties of the proposed model is that it is consistent with the HRM of SORA. Therefore, the probabilistic model can be used to support the qualitative assumptions and decisions taken by the SORA applicant.

The risk model must be supplied with a number of input parameters such as aircraft model, population density or traffic density, among others. The degree of uncertainty about these parameters will determine the trustworthiness of the results obtained. In this work, illustrative data is used to validate the model in a demonstration mission for different operational conditions. Results show that the C2 link loss event is more critical to the air risk than to the ground risk. Conversely, the loss of the GNSS signal has a greater impact on the probability of experiencing a ground impact than a MAC, according to the results.

Future work is to make use of Bayesian inference to update the state of knowledge about the system parameters and provide confidence in the approach. Another line of research is to adapt or extend the risk model to account for future Very Low Level (VLL), high density airspace like the UTM/U-space, where an encounter between two UA is more likely to occur than one with a manned aircraft. Finally, the risk model will be used to determine the minimum-risk trajectory when multiple, alternative routes are available (e.g., after an in-flight contingency occurs).

Conflict of interest

The authors declare no conflict of interest.

Appendix: model data

This appendix provides the illustrative data used to estimate the ground risk and the air risk from Eqs. (11) and (14), respectively.

A.1. Ground risk model data

The model parameters of Eq. (11) are LA , λ_{impact} , and ρ_G . To estimate the lethal area LA , it is necessary to specify the UA dimensions and the average person model. In this case, it is assumed that the intended mission will be performed using the IAI Super Heron model, which has a wingspan and length of 16.6 and 8.5 m, respectively [28]. An average person is usually modeled as a cylinder of height $H_p = 1.75$ m and radius $R_p = 0.25$ m [23]. To estimate the ground impact event rate λ_{impact} from the BBN model, it is necessary to specify the CPT for all the nodes in **Figure 3**. As an example, the CPT used for the “C2 link loss” node is shown in **Table 5** (which assumes that the corresponding Mean Time Between Failure (MTBF) is 1 h); while the CPT for the “Inappropriate guidance” node is shown in **Table 6**. The remaining tables can be found in [29], but are here omitted for

C2 link loss	
F	T
3.6788e-01	6.3212e-01

Table 5.
CPT for “C2 link loss” node.

Autopilot malfunc.	Pilot ineffective	Inappropriate guidance	
		F	T
F	F	1	0
F	T	0	1
T	F	0	1
T	T	0	1

Table 6.
CPT for “inappropriate guidance” node.



Figure 8.
Population density in Spain (excluding the Canary Islands) based on census data from INE.

brevity. Finally, to compute the population distribution ρ_G , we have accessed the Spanish census data provided by Instituto Nacional de Estadística (Spanish Statistics Institute) (INE) in [30], and we have processed it using the ArcGis software. The resulting data has been converted to a raster image with a cell size of 1×1 km (represented in **Figure 8**) and has been exported to Matlab.

A.2. Air risk model data

The model parameters of Eq. (14) are λ_{impact} and ρ_A . In this proposal, λ_{impact} varies along the aircraft trajectory $r(t)$ as a function of the airspace class where the operation takes place (basically on whether it is controlled or not) and the aircraft density in each operational volume. The airspace class is an evidence for this model, since it is implicit in the route specification (see **Table 2**). To obtain the traffic density, this work has exploited the Network Strategic Modeling Tool (NEST) software by European Organization for the Safety of Air Navigation (Eurocontrol), which provides a dataset comprising 31.626 real cooperative flights operated in Europe during AIRAC cycle 1307, see **Figure 9**. Then, the CPTs for all the event

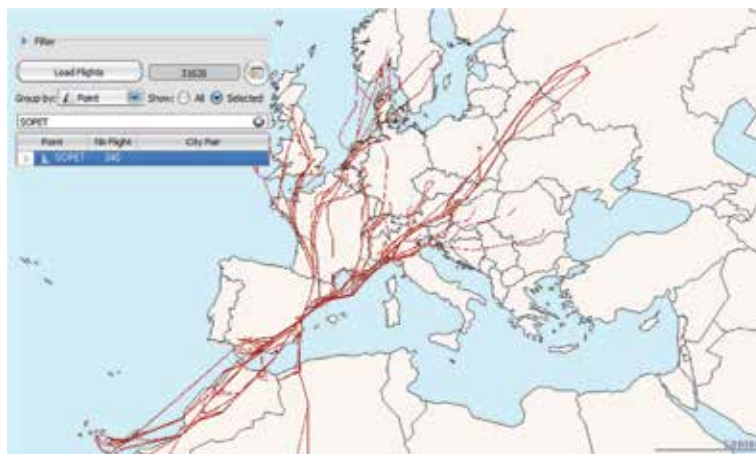


Figure 9.
NEST screenshot showing traffics flying over waypoint SOPET on July 18, 2013.

nodes in **Figures 5 and 6** are specified considering the possible traffic densities in the mission; see [29] for further details. Finally, to estimate the number of people onboard the manned aircraft involved in the MAC (ρ_A), this work assumes that the most probable intruder aircraft when flying in controlled airspace is a short-to-medium-range airliner like a Boeing 737 or an Airbus A320 (two of the world's most successful commercial airliners), with an estimated capacity of $\rho_A = 180$ passengers. When flying in uncontrolled airspace, the intruder aircraft is assumed to be a general aviation aircraft like a Cessna 172 or a Piper PA-28 Cherokee, with an estimated capacity of $\rho_A = 4$ passengers.

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Risk-Based Framework for the Integration of RPAS in Non-Segregated Airspace

Javier Alberto Pérez-Castán and Alvaro Rodríguez-Sanz

Abstract

Remotely Piloted Aircraft Systems (RPAS) are new airspace users that require to be safely integrated into the non-segregated airspace. Currently, their integration is planned for the horizon 2025, but there is a lot of pressure by RPAS operators to fly as soon as possible. This research focuses on the development of a risk-based framework for the integration of RPAS in non-segregated airspace. The risk-based framework relies on a hierarchical methodology that is split into two time horizons: design and operation. Different operational and geometrical factors characterise each stage. Then, a set of risk and operational indicators are defined for each stage. These indicators evaluate the operational airspace state and provide information about how the integration of RPAS should be. Primary results provide information about geographical and temporary restrictions. Geographical restrictions refer to the airways that favour or inhibit the integration of RPAS, and temporary restrictions denote the time span when the RPAS can pierce into the airspace.

Keywords: air traffic management, risk assessment, risk-based framework, RPAS, RPAS integration

1. Introduction

The integration of Remotely Piloted Aircraft System (RPAS) in non-segregated airspace is one of the most complex and demanding challenges for the aviation community in the years ahead. The beginning of RPAS integration in non-segregated airspace is expected to be reached by the time frame 2025, according to European RPAS Steering Group [1]. This aim requires broad and structured analysis of the current situation as well as the potential solutions to be implemented. In this way, the development of a risk-based framework to ensure the safe integration of RPAS is crucial for its achievement.

RPAS operation in upper airspace does not require higher technological developments, but it demands detailed analysis about the safety of their integration with conventional aircraft. European Aviation Safety Agency (EASA) and Federal Aviation Administration (FAA) require that the integration of RPAS must not imply a diminish on current safety levels [2, 3]. This requirement means that further research is required to accomplish this goal. A new framework will be compulsory in the future to take the operational features of RPAS into account. One of the goals

of this framework is to allow setting out the safety of the RPAS operation jointly with conventional aircraft [4–6].

Could RPAS fly safely in non-segregated aircraft? The complexity of the answer does not fall into a yes or not issue, because it must be yes, but instead we must focus on how. Currently, conventional aircraft fly according to prefixed routes that are modelled according to air traffic flow patterns, although there are several airspaces based on free-route [7]. Then, RPAS must adapt to the current airway network and current air traffic patterns. One of the main concerns is that RPAS operational patterns can differ from conventional aircraft ones [8, 9]. Although RPAS could be assumed to be modelled as slow conventional aircraft, there are uncertainties about communications, navigation and surveillance issues that must be analysed in advance [10].

Due to this lack of operational and technical knowledge about RPAS operation, regulators and Airspace Navigation Service Providers (ANSPs) seek to introduce RPAS based on a minimum interaction with conventional aircraft [11, 12]. The problem arises when both airspace users operate jointly in the same scenario where the interaction between them cannot be avoided. The first solution to his problem is the segregation of specific air traffic volumes for the different airspace users. However, this segregation should only focus on specific flight levels (FLs) or airways, as airspace cannot be completely segregated in different air traffic volumes for PRAS and conventional aircraft. One of the expected outcomes of this work is to appraise airways or FLs segregation for RPAS.

The most complex assessments about RPAS integration focus on three research areas. The first deals with the global problem of risk management. Clothier et al. [13] developed a framework for structuring the safety case of the RPAS operation. Moreover, various regulators assessed the primary difficulties that must be solved before RPAS operation [14, 15]. The second research area analyses the risk imposed by the single flight for one RPAS in terms of the number of casualties. Several authors developed different risk models to calculate what kind of populated areas are riskier for on-ground pedestrians [16–18]. The third research area involves the development of collision/conflict-risk models for the integration of RPAS. There are several studies about RPAS collision avoidance [9, 19, 20] (similar to conventional aircraft situations) but few of them focus on conflict risk [21, 22]. Conflict risk is a prior indicator of collision risk. However, none of those studies responds either how the RPAS integration should be or where RPAS could fly in non-segregated airspace.

With the goal of responding to the above research questions, it is required to assess the safety level of the airspace and to develop one specific methodology. Manual 9689 of International Civil Aviation Organisation (ICAO) [23] sets out that airspace planning requires a thorough analysis of every factor that could affect safety. In [24, 25], authors claimed the need for airspace design fulfilling levels of safety under different operational features. Different models were developed to evaluate the collision risk based on airspace geometry [26, 27]. A step further, Netjasov [28] developed a conflict-risk model to assess the level of safety, including air traffic flows. However, there is not a unique methodology that allows analysing the airspace risk-state for the integration of RPAS.

Therefore, the main goal of this research is to develop a risk-based framework to provide geographical and temporary restrictions for the safe integration of RPAS. The risk-based framework is split into two different temporal horizons: design and operation. The risk-based framework evaluates the state of the scenario regarding different risk-based indicators. The risk-based indicators relies on geometrical and operational features of airspace. The risk-based indicators sort airways and crossing points to detect airways (or flight levels): (1) where RPAS can operate because their integration is safe, and (2) when should be planned the operation of RPAS

depending on a particular schedule of conventional aircraft. A further aim is to set out the pillars of a future decision-making process for ANSPs.

The rest of the article is structured as follows. Section 2 presents the structure of the risk-based framework and defines the different types of variables and indicators that must be considered. The risk-based indicators constitute the main outputs of the methodology that permit to assess the viability of the RPAS integration. It also describes the methodology for the design phase and the operational phase. Section 3 presents the case study and the application to one Spanish airspace volume and discusses the results. Lastly, Section 4 summarises the main contributions and further works.

2. Risk-based framework

The risk-based framework aims to analyse the safe integration of RPAS in non-segregated airspace. In non-segregated airspace, both conventional aircraft and RPAS must operate together. The problem arises when RPAS operate with different technical and operational features than conventional aircraft. Then, the integration of RPAS focuses on reducing their impact on conventional aircraft; in other words, RPAS must adapt themselves to current operations reducing their impact on current aviation. The risk-based framework is split into two phases depending on the operational information available:

- design phase: this phase aims to appraise the impact of RPAS in non-segregated airspace for strategic phase. It can be applied both for design purposes and for analysing the operation of one particular scenario. This phase works with basic information of an airspace volume: airway structure and air traffic flow; and
- operational phase: this phase addresses a temporal horizon where 1-hour schedule of conventional aircraft is evaluated. The goal is to analyse how the introduction of RPAS affects one specific schedule.

2.1 Design phase

This phase evaluates the way the integration of RPAS affects the airspace in a design or strategic phase. Thus, this analysis covers different input variables as the morphology or geometry and the main characteristics of the air traffic flow that operates at the airspace. The main results of this phase are:

- thorough knowledge of the current airspace state, where it is intended to integrate RPAS jointly with conventional aircraft; and
- identification of the airways and FLs that allows their segregated use for RPAS. The segregated use implies that the RPAS can fly without any affection to the conventional aircraft.

Design-phase indicators provide information about the state of the airways and the crossing points. They are the most elementary components to analyse the current operational situation of the airspace. These indicators separately evaluate the morphological and geometrical features of the airspace (static indicators) and their operation (dynamic indicators).

2.1.1 Static indicators

Static indicators provide information to analyse the current state of the airspace based on its morphology and geometry. The goal is to perform a prior analysis setting out the airspace design. Static indicators focus on the basic airspace components: airways and crossing points.

2.1.1.1 Static indicator of airway complexity

The complexity of an airway is characterised by the sections that are exposed to risk. The risk in an airway is modelled by the locations of the airway that are exposed to conflict with aircraft of other airways. These sections are denoted as critical sections ($d_{i,j}$) around the crossing point. The static indicator of airway complexity relates to the ratio of the airway that is exposed to conflict in regards to the whole length of the airway (L_i).

$$\beta_i = \frac{\sum_{j \neq i} d_{i,j}}{L_i} \quad (1)$$

$$d_{ij} = \frac{2S_{min}}{\sin \alpha_{ij}}$$

where i and j are the airways that intersect at the crossing point, $\alpha_{i,j}$ is the angle between both airways, and S_{min} is the separation minima (typically 5 Nautical Miles—NM).

2.1.1.2 Static indicator of crossing-point complexity

The complexity of a crossing point depends on the number of intersections between the airway pairs that coincides at it and the angle between the airway pairs. In this way, combining both factors, it can be calculated the static indicator of crossing-point complexity:

$$\gamma_n = \frac{\sum_{WP_n} d_{i,j}}{d_{elem}} \quad (2)$$

where $\sum_{WP_n} d_{i,j}$ is the sum of all critical sections in a crossing point (WP_n) and d_{elem} represents the elementary critical section. The elementary critical section is calculated for the crossing angle of 90° , which provides the minimum critical section.

2.1.2 Dynamic indicators

Dynamic indicators focus on the operational features of the airspace. This allows analysing the operational characteristics of the air traffic flows to select the airway that favour or inhibit the RPAS integration.

2.1.2.1 Dynamic indicator of airway density

This indicator provides information about the number of aircraft that operates an airway. It relates the real airway density (Q_i) and the theoretical maximum air traffic flow through it (Q_i^{max}).

$$\delta_i = \frac{Q_i}{Q_i^{max}} \quad (3)$$

$$Q_i^{max} = \frac{(\bar{v}_i)}{S_{min}}$$

where (\bar{v}_i) is the average speed of aircraft in airway i .

2.1.2.2 Dynamic indicator of crossing-point density

Taking into account the operational characteristics of the airspace, the dynamic indicator of crossing-point density provide an indicator of the number of aircraft that pass through it.

$$\epsilon_n = \sum_{\substack{i, j \in WP_n \\ i \neq j}} \delta_i \quad (4)$$

2.1.2.3 Dynamic indicator of airway conflict

This indicator evolves from the previous dynamic indicators with a different goal. δ and ϵ are relative counters of the air traffic through the airways and crossing points, while ζ is the dynamic indicator of airway conflict. This indicator provides information about the possibility of conflict depending on the airspace operational features.

$$\zeta_i = \sum_{\forall n \in i} \sum_{\substack{i, j \in WP_n \\ i \neq j}} \delta_i \delta_j \quad (5)$$

Moreover, this indicator also works as a reference value to analyse the air traffic segregation by airways and FLs. Therefore, it is needed to calculate the total value for the whole airspace based on the sum of every airway conflict indicator:

$$\zeta_{tot} = \sum \zeta_i \quad (6)$$

2.2 Operational phase

The operational phase focuses on a different temporal horizon than the design phase. The operational phase is characterised by the disappearance of generic air traffic flows (modelled by airway density and average ground speed), and it entails a one-hour schedule. This schedule of air traffic fulfils the operational characteristics of the scenario, but each aircraft has its own characteristics (speed and entry time). Besides, this concept will rely on further work based on 4D trajectories. The operational phase allows the introduction of RPAS in specific schedules. Apart from analysing how this introduction affects the risk indicators, this phase provides the following results:

- in-depth knowledge of the path evolution from the conventional aircraft schedule;

- safety assessment for the RPAS integration for different schedules based on the risk indicators; and
- identification of airways and FLs that favour or inhibit the introduction of RPAS based on the airway availability.

Operational-phase indicators provide information about the whole airspace. In this way, they permit to appraise the airspace situation by the RPAS integration. These indicators conclude if the integration of RPAS is feasible and the temporary restrictions.

2.2.1 Number of conflict

N_c is the number of times that the separation minima are infringed (5 NM in European en-route airspace).

$$N_c = \text{Number of times } \min(\text{sep}(t)) < S_{min} \quad (7)$$

where $\min(s(t))$ is the minimum distance between an aircraft pair.

2.2.2 Conflict severity

Conflict severity (θ) is an indicator of the seriousness of the conflict, as not every conflict implies the same severity. Conflict severity is calculated by the combination of the conflict time span (τ) and the minimum distance reached by an aircraft pair:

$$\theta = \min(\text{sep}(t))\tau \quad (8)$$

2.2.3 Airway availability

This indicator aims to calculate the risk exposition of an aircraft flying an airway. This indicator is called airway availability because it links the time span the aircraft can safely fly an airway with the time span the aircraft can suffer a conflict. Knowing the airways that present higher availability (the time span the aircraft can safely fly without suffering a conflict), it can be extracted the airways that favour or inhibit the integration of RPAS.

λ_i indicator is based on the Temporary-Blocking Windows (TBWs) concept [29, 30]. The TBWs are calculated for every aircraft pair, i.e. the time span that the airways are blocked because a separation minima infringement will occur. The primary features of the TBWs are:

- the time duration of the TBWs depends on the crossing angle of the airways and the ground speed of the aircraft involved; and
- the time location of the TBWs depends on the entry time of the conventional aircraft and RPAS, length of the airways, the ground speed and the distance between the airway entry-point and the crossing point.

λ_i is calculated by the size of overall TBW (d_{BW}) that affect the airway i . Therefore, the risk exposition of an aircraft relates the non-available time ($t_{NA,i}$) and the exposition time (t_{exp}):

$$\lambda_i = 1 - \frac{t_{NA_i}}{t_{exp}} \text{ where } 0 \leq \lambda_i \leq 1 \quad (9)$$

Herein, the exposition time relates to a one-hour schedule. A minor TBW implies a bigger airway availability, which reduces the risk exposition. Moreover, airway availability is a novel indicator defined in this work. There is no previous knowledge about the threshold that this indicator should acquire. Then, the authors propose a division into four stretches (0–25%, 25–50%, 50–75% and 75–100%). Airways with airway availability greater than 50% are airways where RPAS could be included.

3. Risk-based framework application

The risk-based framework was applied to the air traffic volume LECMPAU (Pamplona) in Spain. This airspace is constituted by 24 airways and 55 crossing points. The period of study was July and August 2016, and the operational data was obtained from NEST [31].

3.1 Design phase

This section introduces the results of the design phase in the strategical horizon. This is the most valuable innovation of this work, and a further motivation is related to the fact that this methodology could also be applied to a pre-tactical phase. The design phase focused on a fix air traffic distribution for the whole day while in the pre-tactical phase, a temporary variation of the air traffic flow for a specific day could be considered. However, the application for a pre-tactical phase was out of the scope of this work. The process was as follows:

1. airways and crossing point were characterised based on the geometric information (length, angle and critical section) and operational information (air traffic flow and average speed); and
2. static and dynamic indicators were calculated for each airway and crossing point. With this information, we ordered and analysed which of them had a greater impact on safety.

3.1.1 Design-phase indicators

Firstly, design-phase indicators are calculated for LECMPAU both for airways and for crossing points. However, for the sake of clarity, we only present the results for the airway due to the high number of crossing points. **Table 1** shows the results for the design-phase indicators of the LECMPAU airways.

β_i indicator was constituted by the number of crossing points, the number of intersecting airways, their crossing angles and their lengths. The primary conclusions were:

- most of the values of β_i were, in general, very high because LECMPAU presented 55 crossing points and 24 airways;
- the lowest values referred to the airway UM190 ($\beta_{UM190} = 0,7518$) because there were only two intersections. This airway presented 75% of complexity

Airway	β_i	δ_i
UN858	1.00	0.0037
UM190	0.75	0
UP181	3.18	0.0090
UL176	4.40	0.0267
UQ262	5.42	0
UQ148	2.07	0
UN10	3.25	0.0267
UN857	3.92	0.0046
UL866	7.17	0.0005
UN995	7.03	0.0043
UN976	3.14	0.0275
UM601	2.84	0.0478
UM176	4.00	0
UQ57	3.04	0
UQ73	3.94	0
UT430	2.09	0
UP152	4.03	0.0034
UN725	1.21	0.0385
UQ400	1.18	0
UQ88	1.46	0
UL184	1.93	0
UQ424	1.45	0
UQ300	1.52	0
UQ268	2.10	0

Table 1.
Design-phase indicators for LECMPAU airways.

that was very high, although this was the lowest value. This meant that throughout the 75% of the airway length, an aircraft could suffer conflict with other air traffic flows; and

- the highest values were referred to as airways UQ262 ($\beta_{UQ262} = 5,4207$ with 6 intersections), UL866 ($\beta_{UL866} = 7.1743$ with 9 intersections) and UN995 ($\beta_{UN995} = 7,0303$ with 9 intersections). It was obvious that the number of intersections implied higher values of complexity, but it was also remarkable that the length of the airways was a crucial factor for complexity. Therefore, the crossing point PPN was the most concurred and provided the highest value of complexity.

Therefore, the highest values of the airway complexity static indicator were referred to the airways that concurred at crossing point PPN. **Figure 1** shows a representation of the static indicators of the airway and crossing-point complexity.

Regarding the dynamic indicator of airway density (δ_i), see **Table 1**, there were 13 airways without air traffic (54%) and 25 crossing points without air traffic (45%)

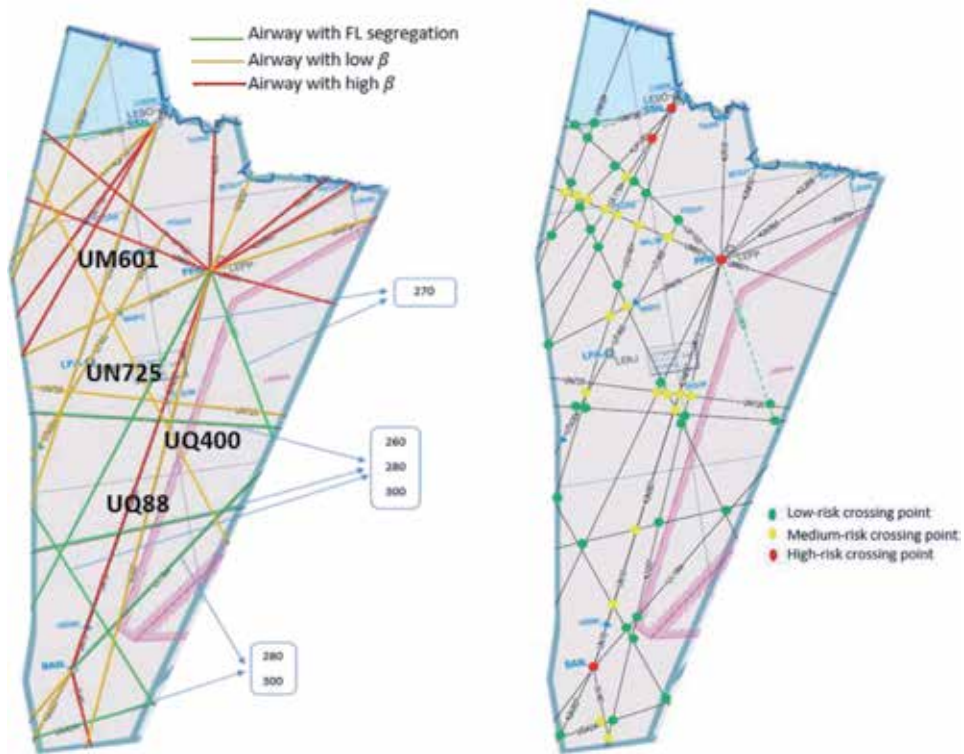


Figure 1.
Results of the design-phase analysis.

in this airspace. This implied that the air traffic flow distribution was rather concentrated in specific airways and crossing points.

3.1.2 Airway segregation

The airway segregation aimed to identify the airways (or geographical restrictions) that allowed the safe integration of RPAS because they did not generate conflicts with conventional aircraft. First, the total value for the whole airspace of the dynamic indicator of airway conflict ($\zeta_{tot} = 0.0037$) was calculated. Second, the airways without air traffic were individually evaluated by the introduction of RPAS through them ($\delta_i = 0 \rightarrow \delta_i = 1$). Then, ζ_{tot} was recalculated to check if the new ζ_{tot} exceeded the base-scenario value. In this case, the airway could not be segregated because the introduction of RPAS increased current risk levels; otherwise, RPAS could be introduced because they did not cross with other air traffic flows. **Table 2** presents the results of the indicator ζ_i .

As can be seen in **Table 2**, no airway was identified for its segregation.

3.1.3 FL segregation

The primary conclusion of the previous section was that no airway could be segregated at LECMPAU. In spite of this limitation, this work evaluated the existence of specific FLs that allowed the safe integration of RPAS. The process was similar to airway segregation but focusing on the FLs of interest: from FL250 to FL300.

Airway	ζ_{tot}
UM190	0.0108
UQ262	0.1449
UQ148	0.1567
UM176	0.0422
UQ57	0.0689
UQ73	0.0422
UT430	0.1210
UQ400	0.0304
UQ88	0.0304
UL184	0.0350
UQ424	0.0350
UQ300	0.0304
UQ268	0.1837
Base-scenario ζ_{tot}	0.0037

Table 2.
Results of ζ_{tot} for LECMPAU airway segregation.

There are five airways that could be segregated at different FLs for the integration of RPAS, see **Figure 1**. UQ400, UQ88 and UQ300 presented three FLs (260, 280 and 300) where RPAS could be integrated without any interaction with conventional aircraft. UM176 and UQ74 could be segregated at FL270 (see **Table 3**). ζ_{tot}^{FL} varied for each FL their value, which implied that it would be required to estimate a specific and independent value for ζ_{tot} . This independent value would remove inefficiencies for the integration of RPAS.

3.2 Operational phase

3.2.1 Base schedule with RPAS

To study the operational phase, a real one-hour schedule was selected from the rush hour of LECMPAU at FL290. **Table 4** shows the operational information of the schedule composed of four conventional aircraft and one RPAS. In this schedule, one RPAS is introduced by UM176 with a typical speed of 250 kts.

3.2.2 Temporary-blocking windows (TBWs)

The first step was to calculate the TBWs that will underline the airway indicator and conflict detection. **Table 5** provides the length or time span of the TBWs for the different aircraft that could interact between them.

The length of the TBWs increased with the RPAS due to its lower speed. The TBWs (i.e. the time exposed to conflict) almost doubled the value for conventional aircraft. **Table 6** provides the temporary limits (initial and final) for the TBWs between aircraft pairs.

3.2.3 Operational-phase indicators

According to the TBWs, aircraft with an entry time located inside the TBWs entailed a conflict between those aircraft pairs. In this example, there was no

Airway	ζ_{tot}^{250}	ζ_{tot}^{260}	ζ_{tot}^{270}	ζ_{tot}^{280}	ζ_{tot}^{290}	ζ_{tot}^{300}
UN858	0	0	0	0	0	0
UM190	0.4903	0.5911	1.0445	1.7939	2.3628	1.1805
UP181	0.5528	0	0	0	0	0
UL176	0.2512	0	0	0	0	0
UQ262	0.4382	1.0439	1.5495	3.0551	2.7039	2.5510
UQ148	0.5058	0.9344	1.4552	2.7312	2.8154	2.9160
UN10	0	0.7542	0	1.1512	0	1.6451
UN857	0	0	0	1.0887	0	0.9156
UL866	0.9234	0.4331	1.1965	1.0887	0	0.9156
UN995	0	0	0	0	0	0
UN976	0	0	0	0	0	0
UM601	0	0	0	0	0	0
UM176	0.2564	0.2888	0.4519	0.9624	2.2068	1.4878
UQ57	0.3028	0.2888	0.5137	0.9624	2.4138	1.4878
UQ73	0.2564	0.2888	0.4519	0.9624	2.2068	1.4878
UT430	0.5058	0.4726	1.0935	1.9611	2.4653	2.5284
UP152	0.4903	1.0529	0	0	2.7128	1.5682
UN725	0	0	0.5137	0	0	0
UQ400	0.2351	0.1690	0.5137	0.8999	2.2080	0.7584
UQ88	0.2351	0.1690	0.5137	0.8999	2.2080	0.7584
UL184	0.6088	0.3702	0.9449	0.8999	2.6966	0.7584
UQ424	0.6088	0.3702	0.9449	0.8999	2.6966	0.7584
UQ300	0.2351	0.1690	0.5137	0.8999	2.2080	0.7584
UQ268	0.8537	1.3565	1.0451	2.5607	3.3841	3.3381

Table 3.
 Values of ζ_{tot}^{FL} for each airway and FL.

Aircraft	Airway	Entry time	FL	V(kts)
1	UL176	12:13:56	290	310.13
2	UM601	12:20:31	290	416.67
3	UN10	12:25:00	290	420.11
4	UL176	12:57:28	290	351.75
RPAS	UM176	12:30:00	290	250

Table 4.
 Schedule of LECMPAU with one RPAS.

conflict between any aircraft. In the same way, there was no conflict; the indicator of conflict severity was zero.

However, airway availability was calculated for all airways taking into account base schedule, see **Table 7**.

The airway availability indicator decreased with the introduction of RPAS. In the case $\lambda_i = 0$ (UQ262 and UN857), it meant that there was no availability of this airway because the introduction of an RPAS through the airways could imply one

Aircraft	1	2	3	4	RPAS
1	—	206	—	—	—
2	206	—	177	192	310
3	—	177	—	—	641
4	—	192	—	—	—
RPAS	—	310	641	—	—

Table 5.
Temporary-blocking windows (sec) for the base schedule.

Aircraft	1	2	3	4	RPAS
1	—	[12:15:18, 12:18:44]	—	—	—
2	[12:15:43, 12:19:08]	—	[12:20:19, 12:23:16]	[12:16:25, 12:19:37]	[12:14:12, 12:19:22]
3	—	[12:22:15, 12:25:12]	—	—	[12:14:40, 12:25:21]
4	—	[12:58:22, 13:01:34]	—	—	—
RPAS	—	[12:51:09, 12:56:19]	[12:49:39, 13:00:20]	—	—
Entry time	12:13:56	12:20:31	12:25:00	12:57:28	12:30:00

Table 6.
Initial and final time of the TBWs.

Airway	λ_{AWYj}
UN858	0.8932
UM190	1
UP181	0.1488
UL176	0.8917
UQ262	0
UQ148	0.2907
UN10	0.8901
UN857	0
UL866	0.6741
UN995	0.7024
UN976	0.7093
UM601	0.7007
UM176	0.5572
UQ57	0.3298
UQ73	0.6176
UT430	0.8931
UP152	0.4501

Airway	λ_{AWVj}
UN725	0.8911
UQ400	0.8890
UQ88	0.8736
UL184	1
UQ424	1
UQ300	1
UQ268	0.6802

Table 7.
Airway availability indicator for FL290.

conflict during the 1 hour. On the contrary, in the case $\lambda_i = 1$ (UM190, UL184, UQ424 and UQ300) there was full availability for the safe introduction of RPAS. In other words, those airways allowed the introduction of RPAS because no interaction with conventional aircraft would occur. Results of this indicator should provide similar results to the dynamic indicator of airway conflict. However, air traffic flows of the operational phase are not the same as the design phase because of the specific rush hour characteristics.

4. Conclusions

This research developed a new risk-based framework to evaluate the safe introduction of RPAS in non-segregated airspace. The risk-based framework tackled two temporal horizons for the introduction of RPAS based on a design phase (strategical horizon) and an operational phase (tactical horizon). This innovative approach allowed considering the different variables that affected the aircraft operation at both temporal horizons, which ensured a hierarchical assessment. The design phase covered different input variables as the morphology or geometry, and the main characteristics of the air traffic flow. Meanwhile, the operational phase was characterised by the disappearance of generic air traffic flows (modelled by airway density and average ground speed) and focused on a one-hour schedule (constituted by conventional aircraft and RPAS). Different indicators were modelled depending on the temporal horizon. The design phase considered static and dynamic indicators (based on the airspace structure and generic air traffic flows). The operational phase considered three indicators: number of conflicts, conflict severity and airway availability. The application of the methodology was to detect geographical restrictions (airways that favour or inhibit the integration of RPAS) and temporary restrictions (when the RPAS can pierce into the airspace without generating any conflict).

This methodology was applied to Spanish airspace LECMPAU at different FLs from FL250 to FL300, which were the most favourable for RPAS integration due to their low density. The different static indicators ordered airways considering their complexity. LECMPAU was a complex scenario because of the high number of airways and crossing points. The airway segregation analysis concluded that no full airway could be segregated for RPAS; however, different FLs could be used considering their segregation for RPAS. The segregation of FLs for RPAS implied that they could operate these FLs without being exposed to conflict with conventional aircraft. A one-hour schedule of conventional aircraft was analysed for the

introduction of one RPAS. Operational-phase indicators were assessed and based on the temporary-blocking windows, no conflict arose. The temporary-blocking windows provided the temporary restrictions for the integration of RPAS. Moreover, the airway availability indicator ordered the airway providing information about the airways that favoured (or inhibited) the introduction of RPAS with the operational-phase specific schedule. Regarding future research lines, the calculation of an independent and fixed value for conflict probability is crucial for the assessment of different airspaces and FLs. A further goal will be the analysis of the whole process to introduce flight plans of RPAS in non-segregated airspace ensuring safe scenarios.

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Conflict of interest


The authors declare no conflict of interest.

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One of the most complex challenges for the future of aviation is to ensure a safe integration of the expected air traffic demand. Air traffic is expected to almost double its current value in 20 years, which cannot be managed without the development and implementation of a safe air traffic management (ATM) system. In ATM, risk assessment is a crucial cornerstone to validate the operation of air traffic flows, airport processes, or navigation accuracy. This book tries to be a focal point and motivate further research by encompassing crosswise and widespread knowledge about this critical and exciting issue by bringing to light the different purposes and methods developed for risk assessment in ATM.

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