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Review of Current State of Artificial Intelligence/Machine Learning and Other Advanced Techniques Related to Air-to-Air Collision Risk Models (CRM) in the Terminal Airspace

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16. Abstract

Collision Risk Models (CRM) are used by regulatory safety agencies to determine the safe separation minima and monitor the air-to-air collision risk level of an airspace. CRMs estimate the expected number of aircraft collisions and "total" risk for a given air traffic concept-of-operation (e.g., parallel approaches). The fidelity of the models, and assumptions used in the models, are determined by the required confidence interval required for the safety analysis, the capabilities of current analytical and simulation methods, availability of empirical data sets, and the capabilities of computational resources.

This paper provides an overview of the state-of-the-art CRMs for terminal area operations. Opportunities to apply recently developed artificial intelligence/machine learning (AI/ML), and data analytics methods such as analytical and rare-event simulation methods, availability of empirical data sets, and leverage available computational resources are identified.

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Acronyms

Acronym	Definition
ACAS	Airborne Collision Avoidance System
ADS-B	Automatic Dependent Surveillance - Broadcast
ATC	Air Traffic Control
BADA	Base of Aircraft Data
CRM	Collision Risk Models
CSPO	Closely Spaced Parallel Operations
DET	Dynamic Event Trees
DP	Departure Procedure
FAA	Federal Aviation Administration
ICAO	International Civil Aviation Organization
IS	Importance Sampling
LoS	Loss of Separation
NLP	Natural Language Processing
NMAC	Near Mid Air Collision
PA	Paired Approach
PBN	Performance Based Navigation
PCA	Principal Component Analysis
ROCD	Rate of Climb/Descent
RNP	Required Navigation Performance
RVSM	Reduced Vertical Separation Minima
STARs	Standard Terminal Arrival Procedures
sUAS	Small Unmanned Air System
TAS	True Airspeed
TLS	Target Level of Safety
TOPAZ	Traffic Organizer and Perturbation AnalyZer
TSS	Terminal Sequencing and Spacing
VOR	Very High Frequency Omni Range Radio

Executive summary

Collision Risk Models (CRM) are used by regulatory safety agencies to determine the safe separation minima and monitor the air-to-air collision risk level of an airspace. CRMs estimate the expected number of aircraft collisions and "total" risk for a given air traffic concept-of-operation (e.g., parallel approaches). The fidelity of the models, and assumptions used in the models, are determined by the required confidence interval required for the safety analysis, the capabilities of current analytical and simulation methods, availability of empirical data sets, and the capabilities of computational resources.

This paper provides an overview of the state-of-the-art CRMs for terminal area operations.

A detailed analysis of over 74 scientific/engineering papers on air-to-air collision risk modelling for the terminal area identified applications of CRMs in terminal airspace was identified for:

1. Parallel runways – straight-in approach
2. Parallel runways – curved path approaches
3. Departures
4. Crossing approach paths for diverging and intersecting runways
5. Intersecting approach and departure trajectories
6. Wake vortex encounters
7. Terminal area sequencing and spacing
8. Missed approaches
9. Low altitude and enroute collision risk

Also, the following super-set of functions required to perform CRM were identified. Note: not every CRM had all the functions.

1. Prescribed navigation procedure
2. Atmospheric model
3. Flight trajectory
4. Surveillance position fixing error model
5. Aircraft/flight-crew conflict detection models

6. Air Traffic Control (ATC) conflict detection model
7. Ground-to-air communications model
8. Aircraft/flight-crew collision avoidance model
9. Collision/conflict model – functional form
10. Collision/conflict model
11. Wake vortex model
12. Wake vortex encounter model

Opportunities to apply recently developed artificial intelligence/machine learning (AI/ML), and data analytics methods such as analytical and rare-event simulation methods, availability of empirical data sets, and leverage available computational resources are identified.

1 Introduction

Airspace operations are defined by navigational procedures that outline the 3-D trajectories that flights transiting the airspace must follow. For terminal area airspace the navigational procedures include Standard Terminal Arrival procedures (STARs), approach procedures, and departure procedures (DP). Each of these categories can be divided into conventional and Performance Based Navigation (PBN) variations.

The sequencing and separation of flights on these navigational procedures is managed by Air Traffic Control (ATC) and their standard operating procedures FAA JO 7110.65, which is the overall air traffic policy. Each air traffic facility has its own standard operating procedure (SOP).

The navigational procedures and the air traffic controllers are obliged to maintain specific horizontal and vertical separation distances between aircraft. The violation of these minimum distances is called loss of separation (LoS) and is considered safety critical.

2 Terminology

To provide assurance that the navigational and ATC procedures achieve the Target Level of Safety (TLS) for the airspace, Collision Risk Models (CRM) are developed. CRMs attempt to accurately estimate the probability of air-to-air collisions to ensure that they are below the TLS. The TLS is set according to the socially accepted level of safety. Some CRM may also evaluate safe separation and other proximity events.

Estimating air-to-air collision risk in an airspace and the mathematical modeling of mid-air collisions have been carried out for more than 60 years (Machol, 1995). During this period, there has been a development of mathematical models, simulations, and data analysis processes for assessment of possible collisions of aircraft with close proximate trajectories, to estimate the risk of collision.

The air-to-air collision risk is defined as the probability of an adverse event in which two aircraft come into contact while both are in the air during a specified time period. The adverse event has a very small probability of occurrence resulting in a catastrophic outcome such as hull loss or fatality. For this reason, they are classified as "rare events."

Applying this definition to airspace operations, the risk is related to those situations in which two aircraft are on conflict course and pass closer than the prescribed horizontal and vertical separation minima, including resulting in a collision.

2.1 Definition of collision and conflict

Each aircraft is defined by a 3-D volume. An example 3-D volume is cylinder defined by lambda xy and lambda z. An air-to-air collision is considered to occur when one volume penetrates the protected volume of another aircraft defined by lambda xy and lambda z. The joint semi-wingspan (lambda_A/2)+(lambda_B/2) of the aircraft is the minimum distance for a collision. An alternate definition of collision with 2 lambda is shown in Figure 1.

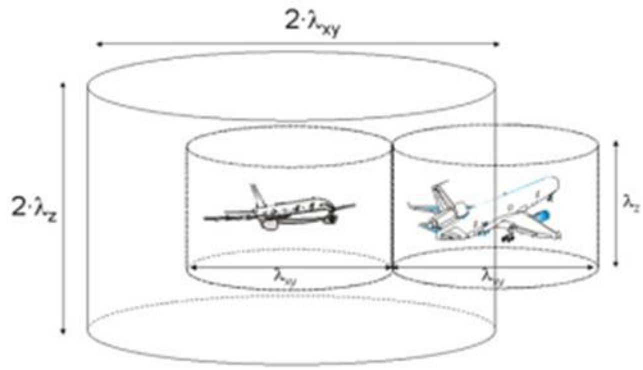

Figure 1. Schematic of collision between two aircraft

A collision occurs when an aircraft, defined by cylinder lambda xy and lambda z, penetrates the protected zone of another aircraft defined by 2 lambda xy and 2 lambda z.

An air-to-air conflict is considered to occur when an aircraft penetrates the separation minima defined by the minimum horizontal (R) and vertical (H) separations (Figure 2). When two aircraft are closer than these distances, the ATC system is considered to have failed.

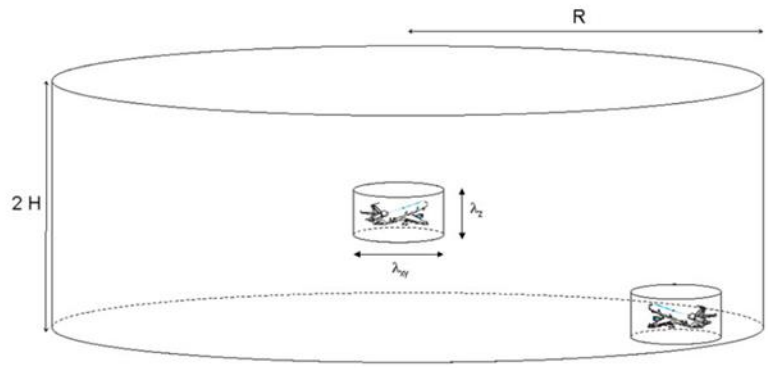

Figure 2. Schematic of separation minima

A conflict occurs when an aircraft penetrates the separation minima (R and H) of another aircraft.

The definitions of collision and conflict are summarized in Table 1.

Table 1 . Definitions of collision and conflict

3-D Volume (e.g., Cylinder)	**Diameter**	**Height**
Aircraft	Lambda x-y	Lambda z
Collision	Lambda x-y	Lambda z
Conflict	2R	2H

2.2 Definition of collision risk metrics

Risk is the composite of predicted severity and likelihood (i.e., probability) of the potential effect of a hazard. With regards to air-to-air collision risk, the hazard is an unexpected deviation of one aircraft toward another aircraft. The effect of the hazard is the potential for an incursion by one aircraft into the collision cylinder of the other aircraft. For air-to-air collisions, risk is typically quantified solely by the likelihood or frequency of a collision, as the predicted severity is assumed to be catastrophic for all such collisions.

The base metric of collision risk is the probability of a collision based on the count of pairwise collisions for a specified set of flights. The collision risk can be quantified in several ways – for example, per-time-unit risk, per-operation risk, or scenario-specific risk for a pair of aircraft.

Examples include:

- expected collisions per flight hour
- expected collisions per flight operation (which is the probability of a collision per operation)
- probability of a collision for a given pair of aircraft (e.g., two approaches on parallel runways)

The first metric has units of events per time. The last two metrics have units of probability. These metrics can also be combined into "total" collision risk by summing overall flights in a given set of flights on specified procedures (e.g., expected number of collisions). Total collision risk is also known as "Airspace Risk."

The probability of a collision can be decomposed into two components:

1. The probability that aircraft are exposed to risk by passing close together.
2. The probability of a collision given two aircraft are close together in the passing.

The latter probability is a conditional probability. From the rules of conditional probability, the overall collision probability can be expressed as:

$$\Pr\{\text{collision}\} = \Pr\{\text{separation violation}\} * \Pr\{\text{collision} \mid \text{separation violation}\} \qquad 1$$

Similar relationships can be obtained by considering a string of successive events leading to a collision, for example:

$$\Pr\{\text{collision}\} = \Pr\{\text{potential separation violation}\} \;* \qquad 2$$

$$\Pr\{\text{potential collision} \mid \text{potential separation violation}\} * \qquad 3$$

$$\Pr\{\text{collision} \mid \text{potential collision}\} \qquad 4$$

Where:

- Pr{separation violation} is the probability that an aircraft would potentially violate the separation standards defined for the particular situation (i.e., potential conflict). As traffic density increases, this probability increases.
- Pr{potential collision | potential separation violation} is the conditional probability of a potential collision between two aircraft that have previously violated the separation standards. This value depends on the encounter kinematics and uncertainties associated to

predicted positions. It represents the intrinsic severity of the encounter and it is independent of the traffic density.

- Pr{collision | potential collision} is the conditional probability of collision among potential collisions having failed all the safety barriers (ATC, TCAS) which are in place to mitigate the risk.

In this example, the first parameter Pr{separation violation} can be expressed as either a per-operation probability (probability of a potential separation violation per operation) or a per-time frequency (potential separation violations per flight hour). The latter two parameters are conditional probabilities. The final collision risk then inherits the units of the first parameter (either units of per-time or per-operation).

A time horizon is established within which all aircraft positions are projected to explore existence of potential conflicts. The relative frequency of potential collisions among potential conflicts F(pot.coll/pot.conf) could be expressed as:

$$F\,(\text{pot coll}\,/\text{pot conf}) = (\#\text{ pot collisions})/(\#\text{ Pot conflicts}) = E\,[Pa] \qquad 5$$

where # pot.collisions is the number of aircraft that are about to collide (and will only collide if all safety barriers fail).

An initial expectation for probability of potential collision among potential conflicts, E(Pa), can be obtained as the relative frequency that two aircraft, on a conflict course, would not only pass closer than the prescribed horizontal and vertical separation minima, but would collide. This expression provides an expected, or global, value and does not assess the severity of each individual potential encounter itself.

3 Applications of Collision Risk Models (CRM) in terminal airspace

Models for analysis of terminal airspace air-to-air collision risk have been developed for analysis of the following concepts of traffic flow in the terminal area (see Figure 3).

The papers referenced for each of the concepts below are based on criteria of recency of publication, foundational importance, and uniqueness of concept of operations described. The goal was not to be exhaustive, but to be representative without excessive duplication.

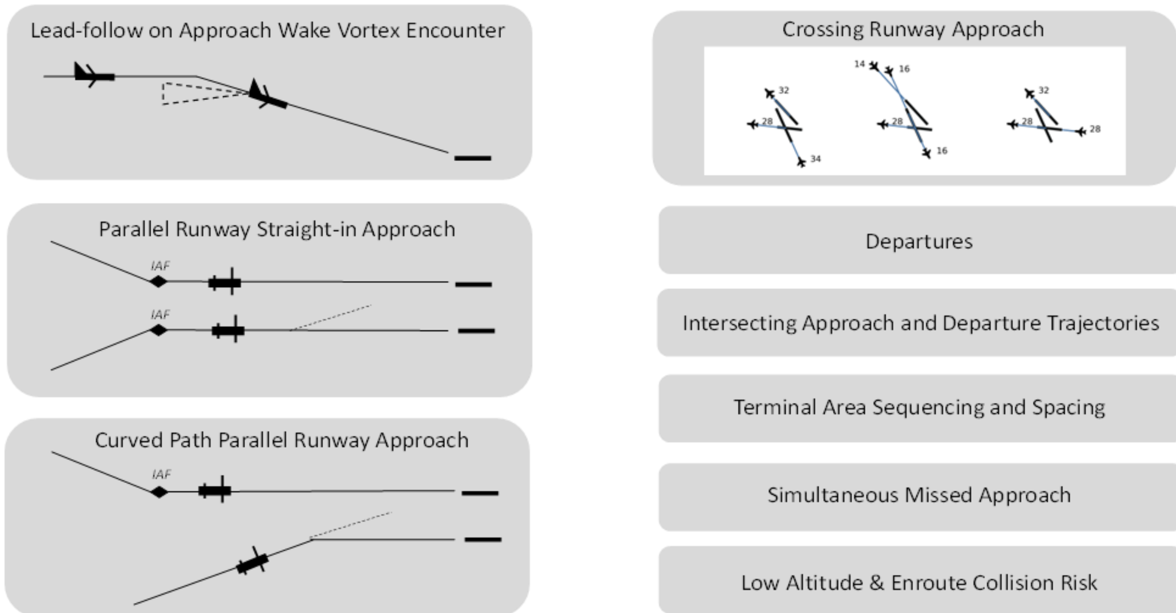

Figure 3. Applications of air-to-air Collision Risk Models (CRM) for terminal area airspace

3.1 Parallel runways – straight-in approach

With increased demand for approach runway slots at airports, there is an opportunity to leverage parallel runways with close spacing (i.e., < 4300 ft). Advances in technologies that have enabled improvements in metering and spacing, navigation error (e.g., Global Positioning System (GPS), Local Area Augmentation System (LAAS)), flight technical error, ground-to-air communication, air-to-air coordination and communication, and metrological forecasting facilitate increased density approach operations.

The paired approach (PA) concept is one that leverages the real-time navigation and communication capabilities of Automatic Dependent Surveillance-Broadcast (ADS-B) equipage initiative to increase airport capacity by performing simultaneous dependent approaches to parallel runways with centerlines spaced at least 700 feet (ft), but less than 2,500 ft apart. Two primary hazards associated with a PA are collision risk and wake encounter risk.

He et al. (2021), Williams, Wood & Nelson (2019), Teng et al. (2019), and Xie et al.(2021) analyzed the collision risk of paired approaches for two aircraft landing on parallel runways with spacing of less than 760 m (2500 ft). This concept also requires a minimum safe separation between the proceeding and following aircraft, while avoiding the wake before the wake of the proceeding aircraft.

Houck & Powell (2000) conducted analysis of collision risk for ultra-closely spaced parallel approaches (<1500 ft) using Monte Carlo trajectory simulations.

Abbott & Elliot (2001) and Lankford et al. (2000) conducted safety analysis to support independent parallel approach operations to runways spaced as close as 2500 ft. This analysis was related to the deployment of the Airborne Information for Lateral Spacing (AILS).

3.2 Parallel runways – curved path approaches

Advances in technology for Required Navigation Performance (RNP) procedures enable closely-spaced parallel runways that include curved approach transitions. Curved path approaches include merging on the final approach segment from downwind-to-base legs as well as from upstream terminal area corner posts. The curved path approaches afford many benefits such as reduced track miles, less fuel burn and emissions, and the potential for routings around noise sensitive areas.

Walls et al. (2016; 2017a; 2017b) conducted a series of safety analysis on simultaneous independent approaches using RNP approaches. These approaches include straight-in approaches (e.g., track-to-[final] fix), and curved-path approaches (e.g., radius-to-fix procedures).

Conway et al. (2016) evaluated safety for Simultaneous Operations on Parallel or near parallel Instrument Runways (SOIR). Independent and dependent approaches were modeled with on straight-in approach and an adjacent curved path approach. Both closed-form (“DLR Method”) and simulation (“Boeing method”) modeling methods were used. This study also evaluated the impact on Airborne Collision Avoidance System (ACAS) performance.

3.3 Departures

Mayer & Swedish (2017) evaluated proposed closely spaced parallel operations (CSPO) departure concepts related to the initial spacing requirement of the 6,000’-and-airborne rule, normally applied to departures from the same runway. The report quantified minimum separation requirements for CSPO dependent departures yielding capacity gains as high as 35%.

3.4 Crossing approach paths for diverging and intersecting runways

Terminal areas can have crossing approach trajectories when runways cross or when the approach trajectories to two or more runways cross.

Krauth et al. (2022; 2021) demonstrate generating trajectories for complex arrival/approach airspace with crossing approach trajectories for two diverging runways. The approach trajectories are also impacted by operational constraints due to the surrounding terrain, noise abatement, or emission mitigation.

Henry et al. (2010) evaluates near midair collision (NMAC) events for intersecting or converging runway pairs. Strategies, such as FAA Order 7110.65Z, Section 3-9-8, define rules for air traffic flow during converging and intersecting runway operations that can establish sufficient aircraft separation to mitigate safety risks. In addition to crossing trajectories, the collision risk analysis must take into account other trajectory scenarios such as an arriving aircraft initiating a missed approach procedure at the same time a departure takes off from a converging runway. The resulting intersecting flight paths create an airborne collision risk. Also, see Eckstein (2010).

Hsu (1981), Anderson & Lin (1996), and Mehadhebi & Lezaud (2003) analyzed collision risk for crossing traffic using a functional-form model. The model allows a small portion of the traffic to operate under direct ATC control. It also includes sensitivity analysis of angles between crossing trajectories. Note: although the example is for enroute airspace, these results are applicable to terminal area operations. These methods have also been enhanced with simulation model, see Liu et al. (2022).

Speijker et al. (2000) describe a risk analysis of simultaneous missed approaches at Schiphol airport for converging runways.

3.5 Intersecting approach and departure trajectories

Fujita (2013) considered collision risk for the case for two aircraft operating in the same terminal area airspace where one aircraft is flying a departure on a Very High Frequency Omni Range Radio (VOR) standard instrument departure (SID) and the other is on RNP standard terminal arrival procedure (STAR).

3.6 Wake vortex encounters

Teng et al. (2019) analyzed the collision risk of paired approaches for two aircraft landing on parallel runways with spacing of less than 760 m (2500 ft). This concept also requires a minimum safe separation between the proceeding and following aircraft, while avoiding the wake before the wake of the proceeding aircraft. In addition to calculating the collision risk, the analysis also determines the safety area that needs to be maintained during the paired approach to avoid the wake vortex encounter.

Many wake vortex encounter studies are also associated with runway throughput capacity studies. Sekine et al. (2021) describe a model for wake encounter risk for alternate wake vortex separations such as “RECAT (wake turbulence category re-categorization).”

3.7 Terminal area sequencing and spacing

Sequencing and spacing of flights that have arrived at the terminal area arrival gate posts present opportunities to maintain separation.

Lankford et al. (2003) developed a model for analysis of risk of collision between aircraft departures with airspeed in excess of 250 knots interacting with transient traffic just outside the Class-B airspace.

Jacquemart & Morio (2016; 2013) describe collision risk modeling in uncontrolled airspace.

Thipphavong et al. (2013) describe a trajectory simulation tool for analyzing NASA’s Terminal Sequencing and Spacing (TSS) system - a suite of arrival management technologies that facilitates sequencing and merging arrivals. Although the model does not calculate CR or NMAC risk, controller workload and flight separation metrics are generated.

3.8 Missed approaches

Speijker et al. (2000) describe a risk analysis of simultaneous missed approaches at Schiphol airport for converging runways.

3.9 Low altitude and enroute collision risk

La Cour et al. (2019) describe a model for collision risk for general aviation aircraft and a small unmanned air system (sUAS) below 500 ft. The model is particularly well suited for beyond visual line-of-sight operations, and is useful for sUAS operators for conducting risk assessment of planned operations as well as for regulators for determining appropriate operational requirements. Also see Zou et al. (2021).

Although not part of the scope of this report – air-to-air collision risk in the terminal area, CR and NMACs models have also been developed for enroute corridor and ATC track systems (Campos & Marques, 2021; Zhang, Shortle, & Sherry, 2015; Tian, Wan, Chen, & Yang , 2015; Brooker, 2003; Brooker, 2006).

Also, collision risk has been modeled for required vertical separation (Moek, Ten Have, & Harrison, 1993; Reich, 1966a; Reich, 1966b; Reich, 1966c).

4 Functions required for air-to-air collision risk modelling for terminal airspace operations

A detailed analysis of over 74 scientific/engineering papers on air-to-air collision risk modelling for the terminal area identified the following super-set of functions (see Figure 4). Note: not every CRM had all the functions.

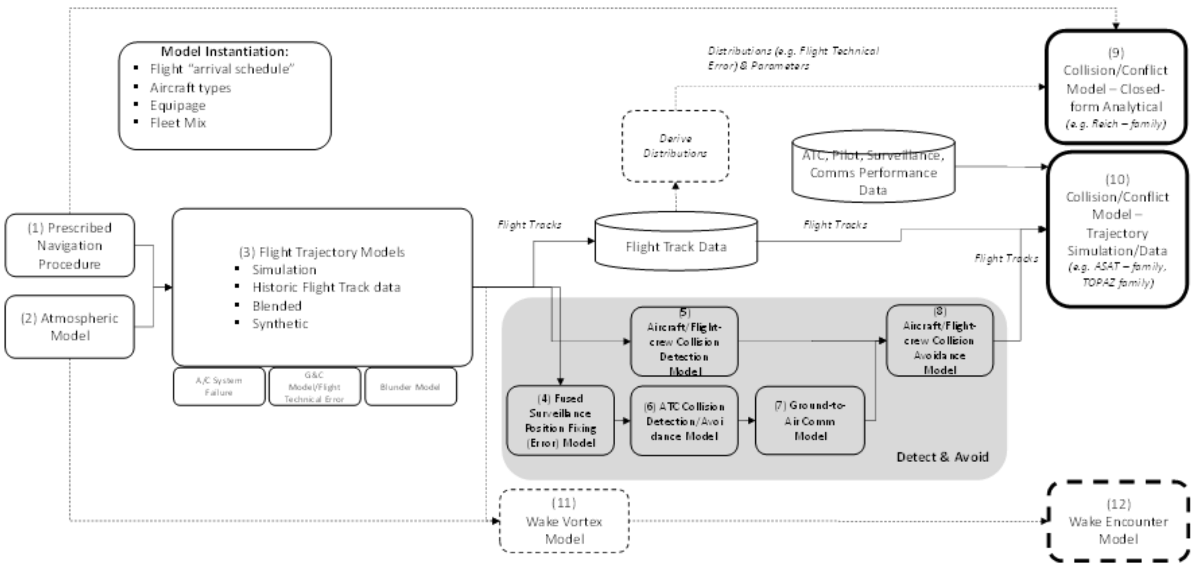

Figure 4. Super-set of all functions deployed in air-to-air terminal area CRM

The papers referenced for each of the functions below are based on criteria of recency of publication, foundational importance, and uniqueness of concept described. The goal was not to be exhaustive, but to be representative without excessive duplication.

The super-set of functions used for air-to-air collision risk modelling for the terminal airspace operations are as follows:

1. Prescribed navigation procedure – defines the 3-D path flown by the aircraft. Includes arrival, approach, missed approach/go-around, and departure procedures.

2. Atmospheric model – defines the atmospheric conditions present (wind, atmospheric density, temperature, and other atmospheric parameters) as the aircraft flies the procedure. All flight trajectories are impacted by the wind model. Flight trajectory models that use lift and drag require atmospheric conditions. Also wake vortex models require atmospheric data.

3. Flight trajectory models – generate the 4-D data that defines the flight of each aircraft on the prescribed navigation procedure. The 4-D data can be generated by simulation models, actual historic flight track data, machine learning generated flight tracks, and by blending all the above. Simulation models can be kinematic models or aircraft performance-based models. The resulting flight track data is used to define distributions used by functional-form Collision Risk Models (see #9 below). The flight track data can also be used directly for the simulation/data driven Collision Risk Models (see #10 below).

4. Fused surveillance position fixing error models – for the purpose of collision detection & avoidance by air traffic control, these models adjust the true position to take into account position errors introduced by "radar" surveillance technologies in the fused position fixing data.

5. Aircraft/flight-crew conflict detection models - for the purpose of collision detection & avoidance by the flight crew and/or the aircraft automation (e.g., ACAS), these models account for time to detect an emerging conflict.

6. Air traffic control (ATC) conflict detection models - for the purpose of collision detection & avoidance by air traffic control (e.g., STCA), these models account for time to detect an emerging conflict.

7. Ground-to-air communications - for the purpose of collision detection & avoidance by air traffic control (e.g., STCA), these models account for time for communication between ATC and flight crew.

8. Aircraft/flight-crew collision avoidance model - for the purpose of collision detection & avoidance by air traffic control or flight-crew or aircraft, these models account for time for and geometry of the flight maneuver. Frequently, CRM do not include collision avoidance models to avoid analysis of the system that is relies on collision avoidance and does not treat it as a barrier (Nichols, 2023).

9. Collision/conflict model – functional form – generates collision risk from a set of equations designed for a specific navigation procedure. The risk is derived from the interaction of distributions of flight track data from the flight trajectory models (see #3).

10. Collision/conflict model – simulation/data/machine learning blended – generates collision risk by pairing trajectories and/or wake vortices for specific navigation procedures to calculate the relative proximity of aircraft.

11. Wake vortex model – generates a 4-D wireframe representing the location of the wake vortex behind the aircraft defined by minimum wake vortex circulation threshold.
12. Wake vortex encounter model – generates the un-commanded-roll from an aircraft entering the 4-D wake vortex wireframe resulting in loss of control (see #11).

4.1 Prescribed navigation procedure

These models define the 3-D path flown by the aircraft for navigation procedures in the terminal area. The navigation procedures include standard arrival procedures (STARs), approach procedures, and departure procedures (DP).

The 3-D path is defined by fixes specified by latitude/longitude, altitude, and velocity. These typically take the form of an "at-or-above" or "at-or-below" limit. Lateral paths may be defined by fly-by and fly-over for the course changes.

4.2 Atmospherics

The atmospheric models define the atmospheric conditions present for the flight trajectory simulation models (see Section 4.3), and the wake vortex models (see Section 4.11).

Flight trajectory models require: wind vectors (x, y, z) and atmospheric density (for lift and drag calculations).

Wake vortex models require: Eddy Dissipation Rate (turbulence), Brunt Vaisala Frequency, and wind vector (x, y, z).

4.3 Flight trajectory

Flight trajectory data is the core element of collision risk models. This data provides the distributions that are used in the functional-form collision risk models (see Section 4.9) and the flight trajectory proximity measures in proximity collision risk models (see Section 4.10).

Flight trajectory data can be derived from the following methods:

- Simulated flight tracks (Section 4.3.1)
- Historic flight track data (Section 4.3.2)
- Blended simulation and historic flight track data (Section 4.3.3)
- Synthetic track data (Section 4.3.4)

Synthetic track data is a new development that leverages machine learning methods to generate realistic flight tracks.

4.3.1 Simulated flight tracks

At the core of collision risk modelling is the flight trajectory simulation. The simplest form of the simulation is a trajectory model that follows the prescribed navigation procedure. These models do not take into account the performance (i.e., reliability) of the aircraft systems, ATC systems, and airport navigational systems that define aircraft trajectory following.

Advances in technology have enabled simulation that includes aircraft, ATC, and airport systems. In this way, the actual trajectory flown is dictated by "decision logic" representing aircraft and air traffic control automation. This provides significantly more flexibility in the types of procedures that can be evaluated and the behavioral complexity of the flight trajectory. In particular, the reliability of aircraft components can be evaluated.

Section 4.3.1.1 describes the flight trajectory-only simulations.

Section 4.3.1.2 describes the flight trajectory simulation coupled with aircraft, ATC and airport systems.

4.3.1.1 Flight trajectory-only simulation

Flight tracks can be simulated using physics-based models and kinematic equations. The models generate aircraft state variables such as position, altitude, and heading simulated in continuous time (e.g., updated every second). The models can be described as ordinary differential equations or as stochastic differential equations to generate random trajectories.

An example of this type of model is given in Glover and Lygeros (2004). Their model considers a six-dimensional state space and is described by the following system of differential equations:

$$
\begin{aligned}
\dot{X} &= V\cos(\psi)\cos(\gamma) + w_1 \\
\dot{Y} &= V\sin(\psi)\cos(\gamma) + w_2 \\
\dot{h} &= V\sin(\gamma) + w_3 \\
\dot{V} &= \frac{1}{m}\left[(T\cos(\alpha) - D) - mg\sin(\gamma)\right] \\
\dot{\psi} &= \frac{1}{mV}(L\sin(\phi) + T\sin(\alpha)\sin(\phi)) \\
\dot{\gamma} &= \frac{1}{mV}[(L + T\sin(\alpha))\cos(\phi) - mg\cos(\gamma)].
\end{aligned}
$$

6

The state variables of the model are:

- X: Along-track / longitudinal position of the aircraft
- Y: Across-track / lateral position
- h: Altitude of the aircraft
- V: Airspeed
- ψ: Heading
- γ: Flight-path angle
- α: Angle of attack

Other elements of the model include m (mass of aircraft), L (lift), and D (drag). Lift and drag are given by separate functions that depend on airspeed, angle of attack, lift and drag coefficients, air density, and wing surface area.

The inputs to the model are:

- T: Thrust
- γ: Flight-path angle
- ϕ: Bank angle

These can be regarded as control variables. That is, the state-based model can be imbedded within a closed-loop feedback control system with control variables providing the input to the aircraft state model. Roughly, thrust helps to control to a desired airspeed, angle of attack helps to control to a desired altitude, and bank angle helps to control to a desired heading, though the control actions are not completely separable and combine together in a nonlinear way via the state equations.

The variables wx, wy, and wz represent wind velocity in each of the respective dimensions. These can be regarded as external (uncontrolled) inputs or disturbances to the state model. The wind variables can be deterministic or stochastic. For stochastic trajectories, the most common approach is to let wx, wy, and wz be normal random variables with mean of zero and standard deviation proportional to the time step of the simulation.

Aircraft Performance Models

Although realistic flight trajectories can be generated without simulating aerodynamic properties of lift and drag, several models include the aircraft performance models. The standard model that is widely used is the Eurocontrols Base of Aircraft Database (BADA) model, see Tang et al. (2019) and Nuic et al. (2010). The aircraft model applied in BADA version 3.6 is a point-mass model of total energy model. This model balances the rate of work done by forces acting on the aircraft and the rate of increase in potential and kinetic energy with the following equation:

$$(h\ (T-D)\ VTAS) = (mgdh/dt) + (m\ VTAS\ dvTAS/dt) \qquad 7$$

Where:

- T is the thrust
- D is the aerodynamic drag
- m is the aircraft mass
- g is the gravitational acceleration
- vTAS is the true air speed of the aircraft
- h is the altitude of the aircraft

This model is frequently used to derive the inputs to the kinematic model described above for a path segment for a given prescribed navigation procedure (see Section 4.1). For any segment, the thrust and flight path angle required can be calculated as:

$$T = D - W\sin(\gamma) + (m\ dV/dt) \qquad 8$$

Where γ is the required flight path angle to achieve the desired rate of descent.

The BADA model is also useful to obtain two essential aircraft states, TAS and ROCD, for updating aircraft 4D positions. Given an aircraft type and flight phase, the aerodynamics of the aircraft (such as air speed (TAS), rate of climb and descent (ROCD), and thrust) at any time instance can be estimated by using "BADA Performance Tables Files" (BADA PTF). A linear interpolation method is applied between cruise flight levels in our model to estimate the TAS and ROCD at a given flight level (h) by:

$$TASh=TASh1+TASh2-TASh1/h2-h1 \qquad 9$$

$$ROCDh=ROCDh1+ROCDh2-ROCDh1/h2-h1 \qquad 10$$

Where:

- h1 < h < h2

Both TAS and ROCD of a given aircraft can be extracted from BADA PTF if the aircraft's type, mass, flight phases, and flying altitude are known. The aircraft type can be known from flight plan and the proposed simulation model assumes that all aircraft mass are nominal for estimating the ROCD for a climbing aircraft. The altitude of an aircraft can be calculated by its ROCD and flight phase during the simulation.

4.3.1.2 Flight trajectory simulation coupled with aircraft, ATC and airport systems

Advances in technology have enabled Agent-based Simulations. For the purpose of collision risk modelling, these simulations include aircraft, ATC, airport systems. In this way, the actual trajectory flown is dictated by "decision logic" representing aircraft and air traffic control automation. This provides significantly more flexibility in the types of procedures that can be evaluated and the behavioral complexity of the flight trajectory. In particular the reliability of aircraft components can be evaluated. Figure 5, from Shortle et al. (2004) illustrates increased complexity possible with these models. The figure identifies the sequence of navigation procedures (top) and the aircraft, ATC, and airport system models (bottom) that can be simulated.

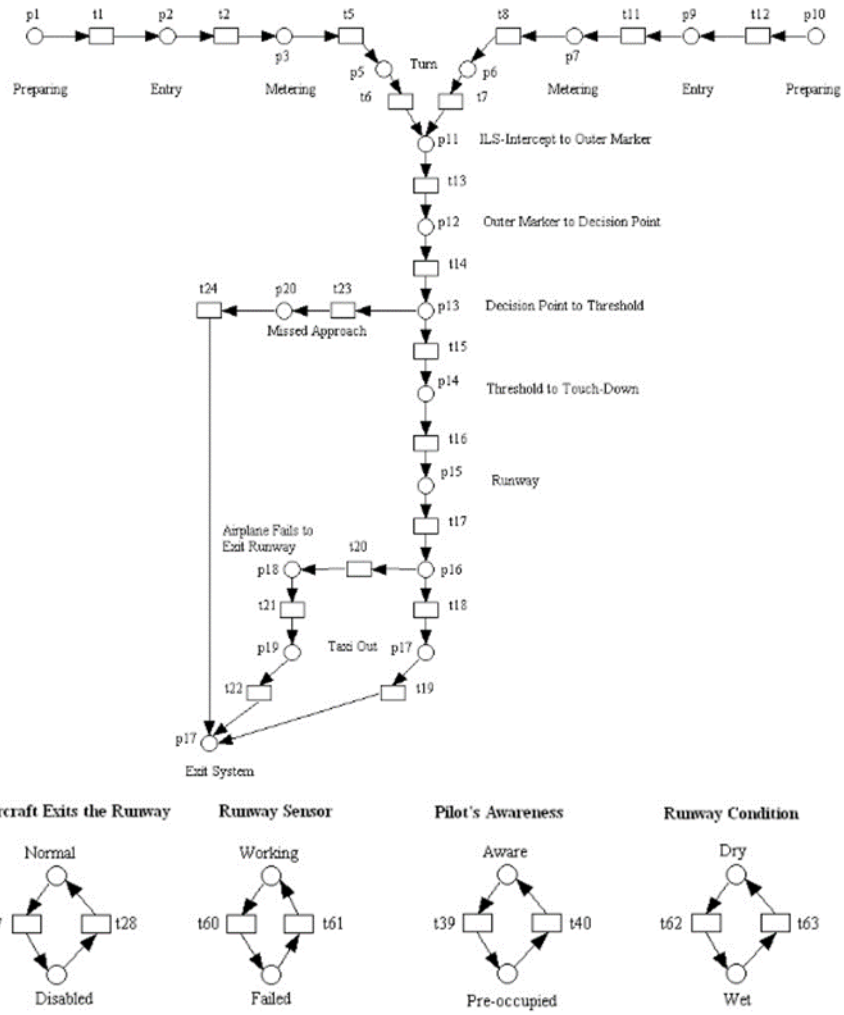

Figure 5. Sequence of navigation procedure segments and maneuvers (top) and aircraft, ATC, and airport system models (bottom) that can be simulated

Simulation of CRM provides significantly more flexibility in the types of procedures that can be evaluated and the behavioral complexity of the flight trajectory (top). In particular, the reliability of aircraft components can be evaluated (bottom).

This class of model is epitomized by the Traffic Organizer and Perturbation AnalyZer (TOPAZ) simulation model developed at the National Aerospace Laboratory (NLR). See Blom & Bakker (2002), Blom, Klompstra, Bakker (2003), Blom et al. (2007a), and Blom et al. (2007b).

An estimation of mid-air collision probability can be derived by running Monte Carlo simulations with a free flight stochastic hybrid model and by counting the fraction of runs for which a collision occurs. The advantage of a Monte Carlo simulation approach is that this does not require specific assumptions or limitations regarding the behavior of the system under consideration.

A Monte Carlo simulator of flight operations performing the prescribed navigation procedure is developed. The simulated trajectories constitute realizations of a hybrid state strong Markov process. A Stochastic and Dynamic Colored Petri Net (SDCPN) formalism is used to model flight operations (Everdij & Blom, 2003; Everdij & Blom, 2006) .

A key problem is that in order to obtain accurate estimates of rare event probabilities, approximately 10−9 per flying hour, it is required to simulate 1011 flying hours or more. Taking into account that an appropriate free flight model is large, this would require an impractically huge simulation time.

TOPAZ overcomes this limitation by using a sequential Monte Carlo simulation approach for estimating small reachability probabilities, including a characterization of convergence behavior (C´erou, Del Moral, Le Gland, & Lezaud, 2002; 2005). The idea behind this approach is to express the small probability to be estimated as the product of a certain number of larger probabilities, which can be efficiently estimated by the Monte Carlo approach. This can be achieved by introducing sets of intermediate states that are visited one set after the other, in an ordered sequence, before reaching the final set of states of interest.

The reachability probability of interest is then given by the product of the conditional probabilities of reaching a set of intermediate states given that the previous set of intermediate states has been reached. Each conditional probability is estimated by simulating in parallel several copies of the system (i.e., each copy is considered as a particle following the trajectory generated through the system dynamics). To ensure unbiased estimation, the simulated process must have the strong Markov property.

Shortle et.al. (2004), use the “TOPAZ” approach to calculate collision probabilities of landing airplanes at nontowered airports. Zhang, Shortle & Sherry (2015) also uses the “TOPAZ” methodology to estimate the collision risk for alternate procedures such as a flow corridor. The methodology is a hybrid collision-risk methodology combining Monte Carlo simulation and dynamic event trees (DET). This implementation specifically includes reliability probabilities for failure of aircraft (avionics) systems.

Another approach that leverages the “TOPAZ” style simulation is the use of dynamic event trees (DET) as framework for collision risk modeling, see Hofer et al. (2002). The Federal Aviation Administration (FAA) has developed the Integrated Safety Assessment Model (ISAM) (Borener, Trajkov, & Balakrishna, 2012). To understand the potential impact of new technologies and procedures on the safety of the system. In ISAM, aviation accidents and incidents are modeled as event sequence diagrams (ESDs). There are 36 different ESD models. Each model starts with a unique initiating event, such as an unstable approach, and follows different scenarios by going through multiple intermediate pivoting events to various end events. In ISAM, several end-events are related to air-to-air collision. Each initiating and pivoting event in an ESD has its own underlying fault tree. Each fault tree at its bottom level consists of many basic events that predict the occurrence of the top event. TOPAZ-style simulations are used to generate the probabilities in the fault trees. See also Roelen et al. (2008) for application of simulations to generate event probabilities.

4.3.1.3 Architectural variants in flight trajectory simulations

There are several architectural variants of these models discussed below:

- open-loop vs closed-loop configuration
- blunders and trajectory deviations
- open architecture simulations and test beds

4.3.1.3.1 Open-loop vs closed-loop configuration

These models can generally be run in either an open-loop or closed-loop configuration (Figure 6).

In the open-loop configuration, the thrust, flight path angle, and heading inputs for each segment of the prescribed navigation procedure are submitted to the model. As the segments are sequenced (i.e., flown), the inputs are updated for the next segment.

In the closed-loop configuration, actual aircraft state data is fed-back to closed-loop control law (Glover & Lygeros, 2004; Zhang, Shortle, & Sherry, 2015). The control law calculates an error term based on the actual aircraft state and the “target” state required by the active segment of the prescribed navigation procedure.

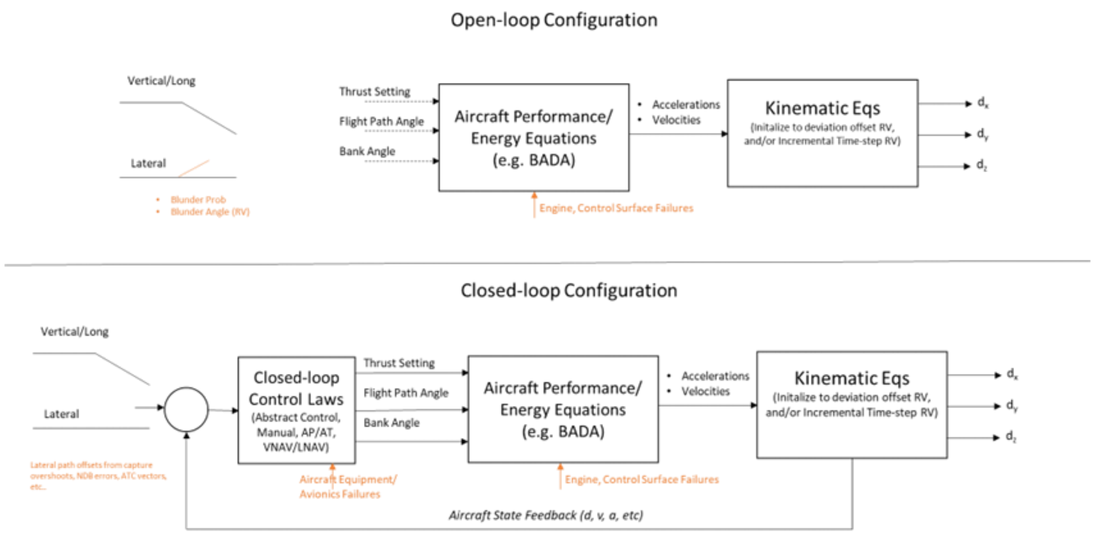

Figure 6. Open-loop and closed-loop configurations for flight trajectory simulation

4.3.1.3.2 Blunders and trajectory deviations

Blunders and trajectory deviations are introduced into open-loop configuration simulations as intentional deviations at a specified location with a specified trajectory. See Lankford et al. (2003) and Glover & Lygeros (2004).

It is also technically feasible to simulate "failures" in aircraft performance by adjusting parameters in the aircraft performance model such as engine thrust, lift, and drag. This paper review did not identify examples in the literature where this was implemented.

Closed-loop simulation configurations introduce intentional deviations as described above. Closed-loop configuration simulations provide additional opportunities to introduce blunders and trajectory deviations through "failures" in the avionics (e.g., (Bakker & Blom, 1993; Blom & Bakker, 2002; Zhang, Shortle, & Sherry, 2015)).

4.3.1.3.3 Open architecture simulations and test beds

BlueSky air traffic simulator is a Python 2.x (using the numpy and pygame libraries). It includes open-source data on navaids, and performance data of aircraft and geography. In addition, to simulations of aircraft performance, the simulator includes flight management system (Lateral Navigation (LNAV), Vertical Navigation (VNAV)), autopilot, conflict detection and resolutions, and airborne separation assurance systems. The aircraft performance is compatible with BADA 3.x data (http://homepage.tudelft.nl/7p97s/bluesky/).

OpenAP: Open Aircraft Performance (and Emission) Model is a simple, open-source model, built from open data (see https://openap.dev/).

JSBSim,an open-source flight dynamics model (FDM), is a physics/math model that defines the movement of an aircraft under the forces and moments applied to it using the various control mechanisms and from the forces of nature (Berndt, 2001). The model can be run by itself as a standalone program, taking input from a script file and various vehicle configuration files.

Advanced Air Mobility (AAM) -Gym (Brittain, Yang, & Wei, 2021), a first simulation testbed based on the community-standard OpenAI gym interface for reinforcement learning, enables building an extensible set of use-cases and algorithms around a standardized interface.

4.3.2 Historic data

With increased availability of “radar” flight track data (including ADS-B data), historic flight track data is frequently used.

Mayer & Swedish (2017) merged Airport Surface Detection Equipment, Model X (ASDE-X) and STARs data. Each departure track was paired with the other departure tracks for the same day. This ensures the same air traffic procedures (e.g., noise abatement) and atmospheric conditions (e.g., wind) for the paired flight tracks.

Historic flight track data is also used to generate statistical distributions for flight technical error and flight tracks that are used as the basis for the simulations described in Section 4.3.1. See Lankford (2003), Nelson et al. (2019), Mayer & Swedish (2017).

Historic flight track data is also used to supplement simulated flight track data (see Section 4.3.3 below)

4.3.3 Blended

To obtain reliable simulation results, simulated aircraft behavior must reflect actual aircraft behavior. One approach to ensure accuracy of simulated behavior would be to have the simulation randomly sample from these available historical trajectories. However, the number of available observations is insufficient for the large number of repeated trials required by the Monte Carlo simulation.

Henry et al. (2010) and Eckstein (2010) blend historic flight data with physics-based model flight trajectory data by using Principal Component Analysis (PCA). The advantage of using PCA in this way: the full amount of variability exhibited in observed trajectories can be captured, and the trajectories can be generated in a computationally efficient manner.

Mayer & Swedish (2017) use historical flight track data for the speed and altitude components of the trajectory. The lateral component of the trajectory is synthetic trajectories generated by sampling a cross-track error from a distribution and generating a 'wings-level' or 'blunder turn' flight trajectory.

4.3.4 Synthetic track data

Synthetic track data seeks to overcome challenges related to historic track data and simulated track data.

The main problem with historic data is that there is often a limited number of tracks, insufficient to observe the rare events of interest. For example, to estimate collision risk associated with simultaneous missed approaches, track data must be obtained in which many missed approaches are observed. Missed approaches themselves are uncommon, so basing a model on a handful of such events may be challenging. Of course, the number of observed tracks can be expanded in a variety of ways – e.g., by going further back in time or obtaining track data in another environment (say, at other airports). The problem with expanding the data sets in this way is that old tracks may not be representative of the current flight environment and trajectories at other airports may not be representative of trajectories at the airport in question.

The goal in generating synthetic trajectories is to obtain a large number of "realistic" tracks using only a limited number of observed tracks. The generated tracks should be realistic based on the laws of physics and flight procedures. They should follow similar distributions as real trajectories. And they should include a wide diversity of tracks, including ones that have never been seen before.

Krauth et al. (2022) use a variational autoencoder to generate synthetic tracks based on existing tracks near an airport. Figure 7 shows an example of the original tracks and the synthetic tracks. Variational autoencoders are a deep learning technique used to generate synthetic data. This approach has been used, for example, to generate realistic images of faces of people who do not exist.

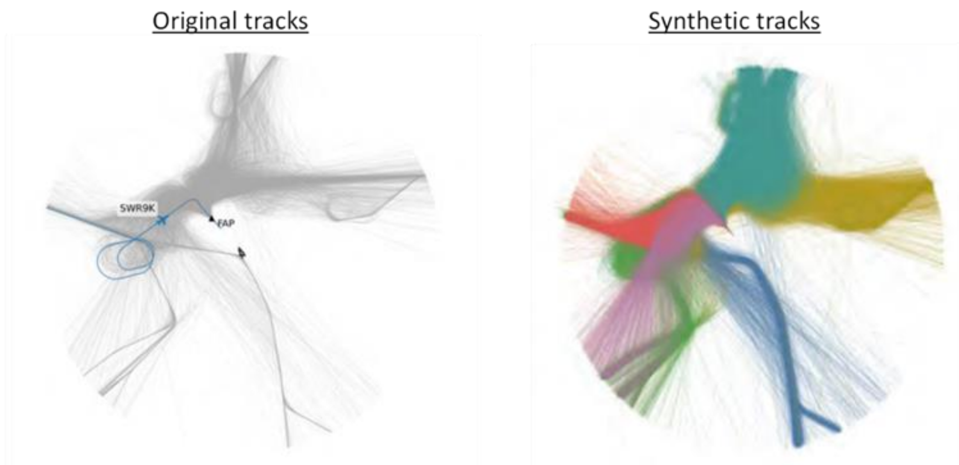

Figure 7. Example of the original tracks (left) and the synthetic tracks (right)

A variational autoencoder is an extension of a deterministic autoencoder. A deterministic autoencoder reduces the dimensionality of the input space, in order to represent the input data more compactly, similar to data compression. The goal is to create an encoder (compression algorithm) and decoder (decompression algorithm) such that the decoded tracks are as close as possible to original tracks.

In a variational autoencoder, an additional step is created in which random draws are made from the encoded space. When these are decoded, they generate tracks that are similar to, but not exactly the same, as the original track data. The basic trade-off is designing a variational autoencoder not to overfit the data. The decoded tracks should be as close as possible to original tracks, which can be accomplished by making the encoded space larger, which can tend to overfit the data. The encoded space should provide meaningful information.

This approach is new and there are still open research questions, particularly regarding the suitability of using synthetic techniques in a safety analysis. The authors note that the method has trouble generating trajectories based on uncommon events (e.g., go-arounds). For example, the method can generate realistic tracks based on events like holding patterns, which are common enough in the original data, but not go-arounds. In theory, synthetic tracks follow the "same distribution" as the real track data, but it is not clear if the tails of the distributions match, and the tails are typically what drive the results of a safety analysis.

4.4 Fused surveillance position fixing (Error) model

For the purpose of collision detection and avoidance by air traffic control, these models adjust the true position to take into account position errors introduced by "radar" surveillance technologies in the fused position fixing data. In modern automation platforms, the surveillance sources are fused in a ‘tracker’ and painted on the screen with a given update rate. Note: These elements can be included in the collision risk model described below (Nelson, Williams, & Wood , 2019).

Brooker et al. (2004a; 2004b) and Teng et al. (2019) describe models for radar inaccuracies for mid-air collision risk modeling.

4.5 Aircraft/pilot collision detection model

Lankford (2003) defines the time for detection based on a distribution for collision detection.

Kochenderfer et al. (2010) provide an overview of collision avoidance models and evaluation of the robustness of collision avoidance optimization to modeling errors.

Collision avoidance is also modelled in the TOPAZ-family of models (see Section 4.3.1.2)

4.6 Air traffic control (ATC) collision detection model

Lankford (2003) defines the time for detection based on a distribution for collision detection. Hawley & Bharadwaj (2018; 2019) developed a machine learning model to identify anomalous traffic behaviors that can lead to loss of separation (LoS) events. Specifically, the model applies reinforcement learning to detect and mitigate impending airspace loss of separation events.

This interaction is also modelled in the TOPAZ-family of models (see Section 4.3.1.2)

4.7 Ground-to-air communications model

Lankford (2003) define the time for delay in ground-to-air communications. This interaction is also modelled in the TOPAZ-family of models (see Section 4.3.1.2)

4.8 Aircraft/pilot collision avoidance model

Bai et al. (2012) give a method for collision avoidance for unmanned aircraft using partially observable Markov decision processes (POMDPs). The idea of this approach is to automatically generate the collision resolution logic using POMDP models. The models can be trained by running many encounter scenarios via simulations and updating the collision logic to maximize a reward function. Once trained, the models provide suggested resolution maneuvers given the current state of the aircraft and encounter geometry. One challenge with discrete-state POMDP models is the high dimensionality of the state space, making them difficult to train. In this paper, the authors develop a continuous-state model that they are able to solve directly.

Mueller et al. (2016) present a similar algorithm for collision avoidance of rotor aircraft using POMDPs. The algorithm uses horizontal plane accelerations in two dimensions to resolve conflicts. The algorithm balances the trade-off between alert rate and safety.

This model is used for the purpose of collision detection and avoidance by air traffic control or flight-crew or aircraft. These models account for time and geometry of the flight maneuver.

Billheimer et al. (2016) conducted a pilot human in the loop (HITL) feasibility study of the paired approach concept in a motion simulator. One of the objectives of the study was to evaluate subject flight crew performance when confronted with nominal and off-nominal situations.

Lankford (2003) limit aircraft performance by using data from distributions for bank angle rate, band angle limit, and true airspeed.

Brittain et al. (2021) describe a deep multi-agent reinforcement learning simulation framework to identify and resolve conflicts among a variable number of aircraft in a high-density, stochastic, and dynamic enroute sector. The simulation allows the agents to have access to variable aircraft information in the sector in a scalable, efficient approach to achieve high traffic throughput under uncertainty. Agents are trained using a centralized learning, decentralized execution scheme where one neural network is learned and shared by all agents.

Frequently, CRM do not include collision avoidance models to avoid analysis of the system that relies on collision avoidance.

4.9 Collision risk (functional form analysis)

Functional-form collision risk models are a set of equations that calculate the collision risk. The equations include parameters that represent the variations that can occur in the physical system that would, with some probability, generate a collision.

Traditional functional-form collision risk models were used by defining a fixed value to each parameter (see Section 4.9.1).

Subsequent applications of functional-form collision risk models are run in a Monte Carlo simulation setting whereby the parameters are selected from a distribution for each run of the simulation (see Section 4.9.2). The resulting calculations themselves form a distribution that is used to determine the collision risk.

These two applications of the functional-form collision risk are described below.

4.9.1 Stand-alone functional-form Collision Risk Models

The Reich CRM was introduced to calculate collision risk for Reduced Vertical Separation Minima (RVSM) (Reich, 1966a; 1966b; 1966c). The model accounts for errors in navigation and piloting that could result in two aircraft colliding with minimum separation standard.

A number of extensions have been developed based on the Reich CRM. Table 2 summarizes some of these extensions and their variations.

Table 2. Summary of Reich-model extensions

Model	**Time-dependent position error**	**Curved trajectories?**	**"Total" risk**	**Note**
Reich (1966)	no	no	yes	
Hsu (1981)	yes	no	no	Intersecting routes
Anderson and Lin (1996)	yes	no	yes	Intersecting routes
Mehadhebi and Lezaud (2003) (Rice)	yes	yes	no	
Fujita (2013)	yes	yes	yes	

4.9.1.1 Reich model

The original Reich model (Reich, 1966a; 1966b; 1966c) was developed for the estimation of collision risk of long-range air traffic systems such as trans-ocean traffic. Although the Reich CRM has been applied in many operational scenarios, its application is mainly limited to the risk estimation of parallel route separation and longitudinal/vertical separation of aircraft flying straight. The model accounts for variation in trajectories from target straight-line centerlines and as well as variation in airspeeds in each dimension.

The Reich model determines the total collision risk in an enroute airspace environment by determining the transient risk to each aircraft. For each aircraft, a predicted location (A) for each time is established based on the flight plan, and a box is then constructed about the aircraft with dimensions based on the separation minima established for the airspace (Figure 8). Figure 8 is reproduced from Reich (1966a) and shows a schematic of this proximity shell around an aircraft.

Risk of collision is high when a second aircraft has a predicted position (B) inside the box or just outside it. As the predicted position (B) moves away from the box, the collision risk becomes negligible.

A second box, the proximity shell, is constructed outside the separation minima box that depicts where the collision risk for two adjacent aircraft becomes negligible

Total risk for the airspace is determined by considering each aircraft pair that will become proximate, the length of time that they are proximate, and the path that an aircraft takes through the proximity shell of the other.

Additionally, flying errors may cause the actual aircraft positions (A', B') to vary from the predicted positions determined from the flight plans (A,B). As depicted in Figure 9 reproduced from Reich (1966a), the risk of collision is determined by the likelihood of the vector A'B' becomes sufficiently small such that the aircraft come into contact. This likelihood depends on the predicted vector AB, as well as the probability and magnitude of the flying errors that cause the variations in the aircraft positions.

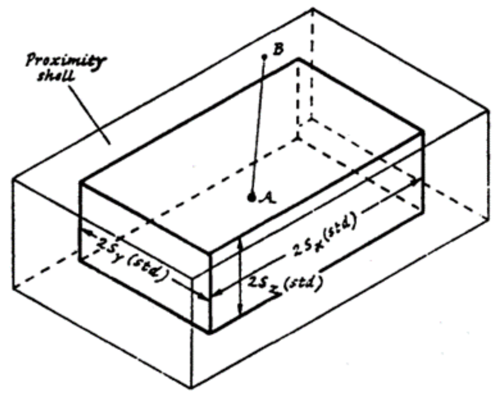

Figure 8. Proximity shell around aircraft

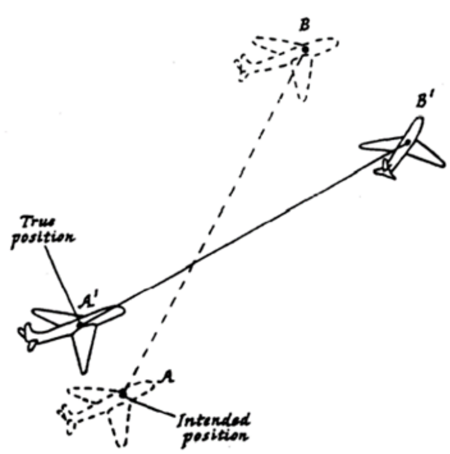

Figure 9. Predicted and actual collision risk

The Reich CRM makes the following assumptions:

- Aircraft are modeled as three-dimensional boxes. Collisions occur whenever the boxes associated with two aircraft overlap each other.
- Aircraft intend to fly along straight, level, parallel centerlines.
- Position errors from the centerlines are random.
- Position errors in the vertical dimension and lateral dimension are independent.
- Airspeeds are random.
- Position errors and velocities are independent (that is, the speed of an aircraft does not impact the distribution of position error).
- Variations in position and speed are time-independent, meaning that the random distributions are the same at all points along the intended path.
- No collision avoidance maneuvers are taken.

The last assumption is critical and is not always mentioned. In the Reich model, there is no consideration for conflict detection and avoidance. For example, in enroute airspace, if two aircraft are deviating from the centerline and a collision is imminent, the model does not account for TCAS which might alert the pilots to take evasive actions. Aircraft deviations are corrected only in the sense to return the aircraft to the centerline, but not in response to the locations of any nearby aircraft. These assumptions are articulated more precisely in the Hsu (1981) model described later.

The Reich model requires several parameters as input:

- λ_x is the average length of an aircraft.
- λ_y is the average width of an aircraft.
- λ_z is the average height of an aircraft.
- Sy is the lateral separation of the track centerlines.
- Py(Sy) is the probability of lateral overlap of aircraft flying on adjacent lateral paths at the same flight level. (This is typically a low probability, as the lateral separation of the track centerlines makes it unlikely that two aircraft would deviate a sufficient distance to overlap in the lateral dimension.)

- Pz(0) is the probability of vertical overlap of aircraft flying at the same flight level. (This is typically a high probability as aircraft flying at the same flight level are intended to fly at the same vertical position.)
- |v_r | is the average relative along-track speed of two aircraft flying at the same flight level in the same direction.
- |v_x | is the average ground speed of an aircraft.
- |v_y | is the average relative lateral cross-track speed between two aircraft.
- |v_z | is the average relative vertical speed between two aircraft flying at the same flight level.
- Esame is the same direction lateral occupancy, i.e., the average number of same direction aircraft flying on adjacent tracks within segments of length 2 Sx of each other. This measures how often aircraft on one track "pass" aircraft on the other track.
- Eopposite is the opposite direction lateral occupancy (i.e., the average number of opposite direction aircraft flying on adjacent tracks within segments of length 2 Sx, centered on the typical aircraft). This measures how often aircraft pass each other in the opposite direction.
- S-x is the length of the longitudinal window used in the calculation of occupancies.

Based on these parameters, the collision risk is given via the following equation:

$$N_{\mathrm{ay}} = P_y(S_y)P_z(0)\frac{\lambda_x}{S_x}\left\{\mathrm{E}_{\mathrm{same}}\left[\frac{|v_r|}{2\lambda_x}+\frac{|v_y|}{2\lambda_y}+\frac{|v_z|}{2\lambda_z}\right]+\mathrm{E}_{\mathrm{opposite}}\left[\frac{2|v_x|}{2\lambda_x}+\frac{\left|\overline{v_y}\right|}{2\lambda_y}+\frac{|v_z|}{2\lambda_z}\right]\right\} \qquad 11$$

Ny is the expected number of collisions per flight hour due to the loss of lateral separation between aircraft flying on laterally adjacent tracks. Analogous equations can be developed for the collision risk due to separation loss between vertically separated tracks.

The Reich CRM estimates total risk, which is defined as the collision risk considering all aircraft in a flow. This is in contrast to pairwise risk, which considers risk associated with a single pair of aircraft. In the Reich model, total risk is accounted for by the factors E_{same} and E_{opposite}, which quantify how often aircraft pass each other on parallel tracks either with same-direction flow or opposite-direction flow.

The Reich model has been used extensively in the industry. The model has been used in the formulation of the Reduced Vertical Separation Minima (RVSM) and route spacing for

Performance Based Navigation (PBN) (Fujita, 2013). A slightly modified version of the Reich CRM was used by the International Civil Aviation Organization (ICAO) to determine minimum separation standards for the North Atlantic Organized Tracks system, depicted in Figure 3 below (Sáez Nieto, Arnaldo Valdés, Garcia, McAuley, & Izquierdo, 2010).

The original Reich model is limited only to straight-line trajectories and does not account for curbed paths and converging/diverging traffic flows (Fujita, 2013). Further, it assumes procedural control only and does not account for the ability of ATC to intervene if a potential conflict is recognized (Sáez Nieto, Arnaldo Valdés, Garcia, McAuley, & Izquierdo, 2010).

4.9.1.2 Hsu Model

One extension to the Reich model is to consider time-dependent position errors developed by Hsu (1981). This extension might be appropriate for landing aircraft where the position errors at the start of the approach are greater than at the runway threshold.

The Hsu model considers intersecting routes, also assuming straight-line level paths. A concept of "critical volume of collision" is developed which is the smallest volume of airspace surrounding an aircraft, outside which the circumcenter of another aircraft must stay in order to be clear of any potential or actual body contact.

The Hsu model makes a number of assumptions following the spirit of Reich Model:

- Each aircraft occupies a space in the shape of a circular cylinder.
- The number of aircraft involved in any one mid-air collision is two and only two, that is, there is no single-aircraft collision or collisions involving three or more aircraft.
- Along-track, across-track, and vertical position deviations are independent.
- The altitude assigned to an aircraft is not altered enroute.
- Navigational errors between aircraft pairs are independent.
- Navigational position errors can be adequately described by distribution models with symmetry and unimodality.
- All aircraft in the regions investigated are operating in a non-radar environment, and thus are not monitored by a controller.
- No external information concerning position errors of the aircraft can be obtained to prompt the pilot's corrective action.

- No collision avoidance maneuvers are taken as a result of visual or instrument detection between aircraft.
- Within the segment of flight-path under consideration, the navigation performance of an aircraft is homogeneous and does not depend upon the flight-time or the distance travelled (i.e., time-independent errors).

The Hsu model considers pairwise risk, not total risk.

In the Hsu framework, different distributions for positional errors can be used in the calculations. For example, a mixture of two double exponential distributions (DDE) is used to illustrate the calculation of collision probabilities at intersecting air routes. Both the bivariate gaussian and bivariate DDE model are used to illustrate the computation of the aircraft overlap density function.

4.9.1.3 Anderson and Lin Model

Anderson and Lin (1996) extended the Hsu model for crossing routes to include a total risk calculation (instead of pairwise risk). The model considers the total risk in a similar way as the Reich CRM.

The idea is as follows. While, technically, all aircraft pairs in a flow must be considered for the total risk, in practice, aircraft pairs that are far away from each other have negligible collision risk and can be ignored in the calculation. They take into account the possibility that two crossing aircrafts are proximate (judging from information available to air traffic controllers) and include only those pairs in the calculation. The risk of collision is the product of the proximity probability with the collision risk of proximate pairs. Probability distributions with parameters derived from actual operational data are used.

Being distance based, it allows the controller the flexibility of an alternate separation standard and can result in greater efficiencies and better use of the airway in some instances.

The model assumes straight-line paths. This assumption is not restrictive for oceanic and enroute airspaces. However, it is not the case for flights in terminal airspaces. Aircraft make turns frequently in terminal airspaces. Drift caused by unexpected wind during the turns should also be modeled.

4.9.1.4 Blom and Bakker Model

Blom and Bakker extended the Reich model by relaxing assumptions that (a) the probability distributions for velocity and position across dimensions are independent, and (b) the probability distributions for velocity and position in each dimension are independent (Bakker & Blom, 1993;

Blom & Bakker, 2002). These assumptions can be restrictive. In particular, regarding the former assumption, velocity in one direction usually depends on velocity in another direction (e.g., the ascent rate generally depends on the along-track rate).

As an example, the assumption that velocity and position in the along-track dimension are independent amounts to the following relationship among the respective densities:

$$f_x(r_x, v_x) = f_{r,x}(r_x) f_{v,x}(v_x) \qquad 12$$

Similar assumptions are made for the other dimensions. The extended model does not assume this independence, so the joint distribution of position and velocity across all three dimensions is described by a single joint density function:

$$f(r_x, r_y, r_z, v_x, v_y, v_z) \qquad 13$$

The joint density function is not assumed to be broken up as products of individual independent marginal densities.

Their extended framework is like the original Reich model in that the overall collision rate is the sum of the collision rates in each of three dimensions. Each aircraft is modeled geometrically as a box, so the collision rate is the sum of the rates that another aircraft enters through each dimension of the box. As an example, the following formula gives the rate at which a collision occurs in the along-track / longitudinal direction.

$$\begin{aligned} \varphi_x(t) = & \int_{-s_y}^{s_y} \int_{-s_z}^{s_z} \int_{-\infty}^{0} -v_x f(v_x, r_x = s_x, r_y, r_z) dv_x dr_z dr_y \\ & + \int_{-s_y}^{s_y} \int_{-s_z}^{s_z} \int_{0}^{\infty} v_x f(v_x, r_x = -s_x, r_y, r_z) dv_x dr_z dr_y, \end{aligned} \qquad 14$$

An example of the application of the Reich Model with a full set of parameters is available from the ICAO (ICAO, 2012).

4.9.2 Functional-form collision risk embedded in a Monte Carlo simulation

Monte Carlo simulations are able to quantify the probability of risk associated with a flight operation. The fast-time simulation is carefully constructed to accurately determine the probability of collision.

Blom et al. (2003) and Shortle et al. (2004) embed the functional-form collision risk model in a flight trajectory simulation (Figure 10). First, an aircraft trajectory simulator generates stochastic flight tracks for a scenario of interest (e.g., simultaneous missed approaches). Dynamically colored Petri nets (DCPNs) provide the mathematical framework for generating the stochastic tracks in continuous time. DCPNs combine the concept of stochastic differential equations with discrete-state Markov chains. The differential equations provide the continuous dynamics of the aircraft and the Markov chains provide the discrete mode shifts due to system failures, control system mode changes, and so forth. Second, the resulting flight tracks are fit to statistic distributions, which become the input to a functional-form collision model, such as the Reich model or generalized Reich model (Bakker & Blom, 1993).

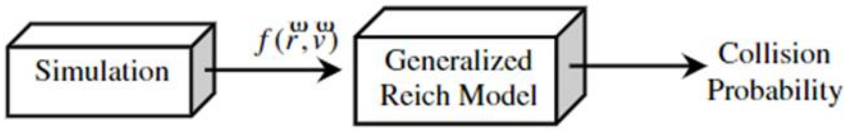

Figure 10. Functional-form collision risk model embedded in a simulation

4.10 Collision risk (simulation)

Advances in simulation technology have enabled the development of simulations to model the occurrence of overlap of airspace between aircraft (Figure 11). A collision occurs when two aircraft trajectory's results in an overlap of airspace.

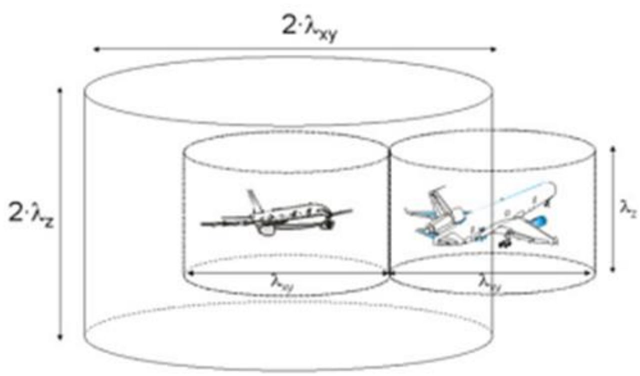

Figure 11. Overlap of airspace between aircrafts

For the purpose of air-to-air collision risk modelling, the simulations have been developed with increasing complexity.

Airspace Simulation and Analysis Tool – Next Generation (ASATng) is Monte Carlo simulation (McCartor & Ladecky , 2005). Figure 12 shows the Overview of ASAT Model (Nichols, 2023). ASAT uses statistical inputs for aircraft flight trajectories (flight dynamics, propulsion/performance, wake turbulence, on board avionics), geographical/geodetic constraints (digital terrain elevation data, obstacles), environmental data (standards atmosphere, nonstandards atmosphere, measured wind and temperature gradients data), navigation ground systems, surveillance performance (e,g, PRM, ASR-9, ARSR, TCAS, ADS-B), and human factors (pilot, ATC).

ASATng has a continuous time simulation with a straight-forward set of flight dynamics limited to straight lines, constant acceleration, constant turn radius, etc... ASATng randomizes certain parameters in the Monte Carlo Simulation such as bank angle or start/end points on a segment. It uses Monte-Carlo simulation embedded with a simple flight dynamics model, a range of surveillance models, and other airspace features to tally the number of proximity events.

The main unique feature of this model is a two-phase simulation to ensure that aircraft are aligned in the time dimension to ensure the closest point of approach is achieved for any two flight trajectories.

ASAT generates collision risk in a deterministic or a probabilistic form. The probabilistic results are the result of running the ASAT tool as a Monte Carlo simulation. The ASAT Monte Carlo simulation runs millions of simulations for a scenario by repeatedly sampling values from probability distributions for input variables. This produces a wide range of output results that encompass possible outcomes associated with the varied inputs. Note: In a real-time simulation, only a small number of variables can be simulated; hence the advantage of fast-time simulation.

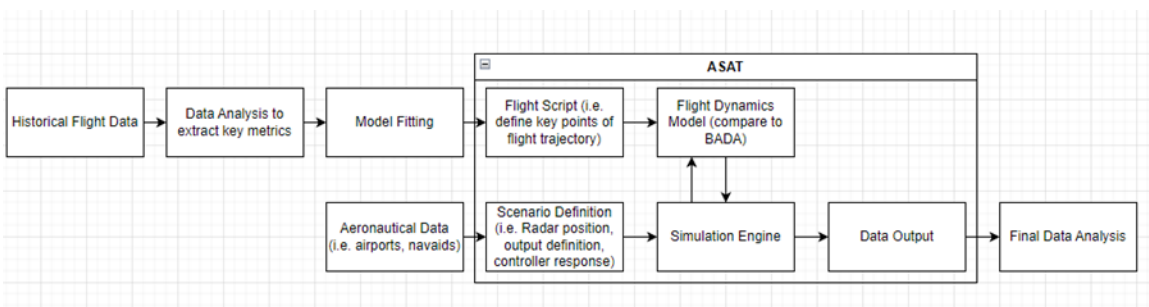

Figure 12. Overview of ASAT model

At the core of these simulations is a flight trajectory model. The actual trajectory flown is dictated by “decision logic” representing aircraft and air traffic control automation. This provides significantly more flexibility in the types of procedures that can be evaluated and the behavioral complexity of the flight trajectory. In particular, the reliability of aircraft components can be evaluated. Figure 13, from Shortle et al. (2004) illustrates the sequence of navigation procedures (top) and the aircraft, ATC, and airport system models (bottom) that can be simulated.

These models are described in more detail in Section 4.3 above.

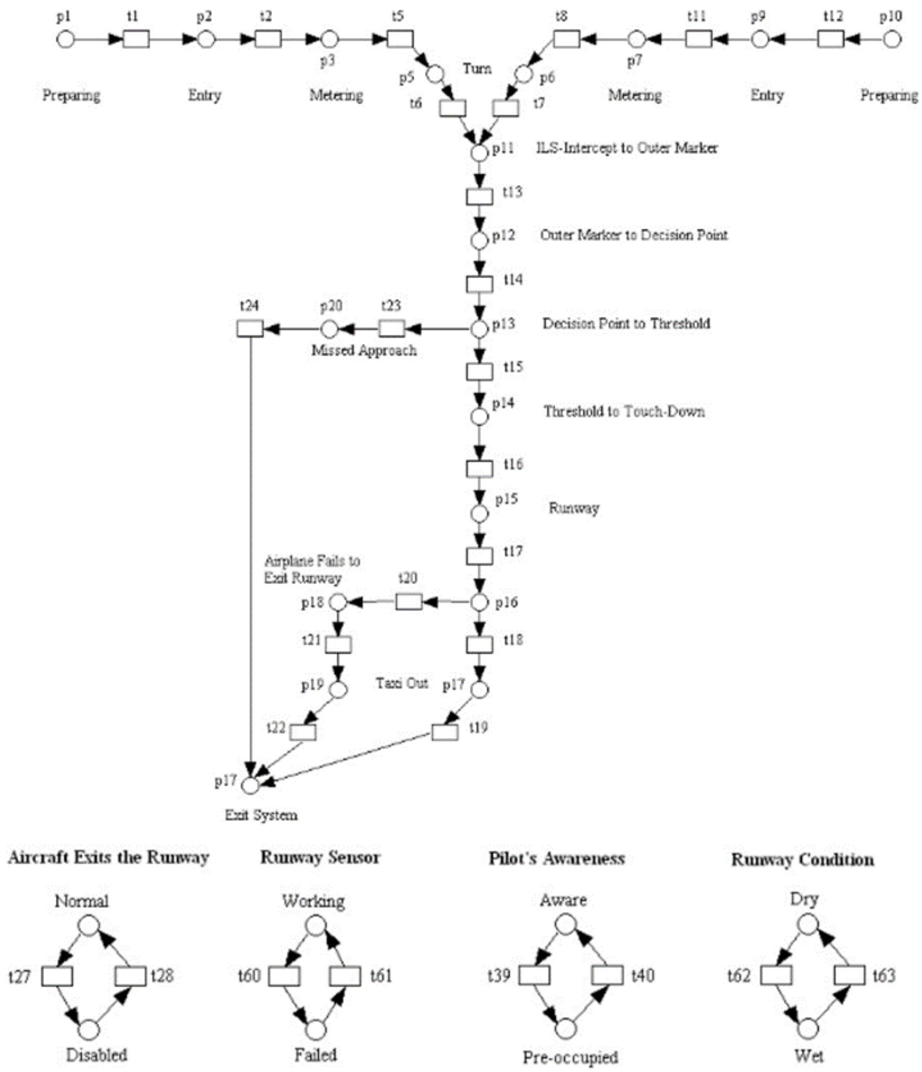

Figure 13. Navigation procedures (top) and aircraft, ATC, and airport system models (bottom) that can be simulated

Simulation of CRM provides significantly more flexibility in the types of procedures that can be evaluated and the behavioral complexity of the flight trajectory (top). In particular, the reliability of aircraft components can be evaluated (bottom).

This type of simulation allows for a tradeoff between safety and throughput to be conducted, and a sensitivity analysis identifies the most critical parameters in the model. See section 4.3.1.2 (above).

4.11 Wake vortex model

The Wake Vortex Model generates a 4-D wireframe representing the location of the wake vortex behind the aircraft defined by minimum wake vortex circulation threshold.

In an analysis of a reduced separation distance for parallel approaches during crosswind operations, Lankford (2003) defines the strength of the Wake Vortex at a fixed distance behind the Wake Vortex generating aircraft based on crosswind and temperature as a function of altitude. A critical parameter is the Eddy Dissipation Rate (EDR), which is the cube root of the dissipation rate of turbulent kinetic energy, and the standard measure for the strength of the wake vortex.

4.12 Wake vortex encounter model

Wake Vortex Encounter Model generates the un-commanded roll from an aircraft entering the 4-D wake vortex wireframe (see Section 4.11) leading to loss of control.

5 Opportunities for data analytics and AI/ML in CRM

This section describes the opportunities for applications for data analytics and artificial intelligence/machine learning (AI/ML) for air-to-air collision risk modelling.

5.1 Enabling methodologies

With the advances in technology, specifically super-computing and cloud computing and storage, it is now feasible to use simulations to evaluate more complex navigation procedure concepts. The following ideas could be used to better interpret the results of the simulation, and to better use the computing power to focus the simulation on the rare events.

5.1.1 Sensitivity and uncertainty assessment

Simulation models of risk produce outputs with inherent uncertainty. There are several sources of uncertainty. One is probabilistic uncertainty, sometimes called aleatory uncertainty. This uncertainty arises from the fact that a finite amount of simulation time is applied to evaluate an event which is randomly sampled. As more samples are collected, the uncertainty goes down. This type of uncertainty could be theoretically reduced to zero with an infinite computer budget.

The second type of uncertainty is epistemic uncertainty, which has to do with uncertainty about the system itself.

One example is input uncertainty. This arises from the fact that the input parameters of the model are not known exactly. For example, a collision model might include a pilot response time modeled by some probability distribution, say, a gamma distribution. The parameters of the distribution (e.g., mean and shape parameters) need to be quantified. This might be done via a separate data collection effort focused on measuring response times to ATC commands in real flights and finding the parameters of the gamma distribution that give the closest fit to the data. If an infinite amount of data could be collected, then the "true" parameters for the response time-distribution would be known. But since the collected data is finite, representing a limited picture of the true distribution, the estimated parameters will deviate from the true values. That is, there is some error or uncertainty in the input parameters. In some cases, there may be no data at all, so numerical values must be assumed based on expert judgment.

Approaches to deal with this include sensitivity and uncertainty analysis. In a sensitivity analysis, the goal is to determine which parameters have the greatest impact on the output of a model. This can help to focus data collection efforts. For example, if collision risk has very low sensitivity to a parameter, then it does not matter much if the parameter is not known accurately. But if the collision risk is highly sensitive to a parameter, then further data should be collected. Alternately, an uncertainty analysis attempts to quantify the uncertainty of the final collision risk metric based on the uncertainty in the input parameters. This is important since rare events often have significant uncertainty ranges, because the input parameters may not be known very accurately. An uncertainty assessment provides important information to aid decision makers in deciding if a system is safe enough. (This is similar in principle to hurricane predictions that provide an uncertainty range for the path of a hurricane. Knowing the uncertainty range is better for making evacuation decisions compared to a single projected path.) A number of studies have been conducted evaluating the uncertainty and sensitivity of collision and wake risk as a function of uncertainty in the input parameters. Examples include Ye et al. (2019), Noh and Shortle (2015), Wang and Shortle (2012), Shortle et al. (2012), Noh and Shortle (2020), and Zare and Shortle (2017a; 2017b).

In addition to input uncertainty, the model itself has uncertainty in terms of the assumptions made. For example, the Reich model assumes that pilots are not directed to make resolution maneuvers in response to a detected conflict. This assumption is conservative in the sense that it makes the risk higher compared to the real situation. Some assumptions may lower the risk and some increase the risk. And in some cases, there may be an unknown relationship between an assumption. Also, many modeling assumptions are implicit and not explicitly documented in the model description. Everdij et al. (2006) have developed a framework for assessing bias and uncertainty in aviation risk models. Their framework attempts to quantify the total bias due to all model assumptions (some assumptions may increase the estimated risk, some may decrease it, some may have a neutral effect) and total uncertainty.

5.1.2 Rare-event simulation

Evaluating risk via Monte-Carlo simulation can be prohibitive when the events of interest are rare. This is because a large number of replications may be needed to observe the events in simulation. For example, if a collision event occurs with probability 10-9, then 109 replications are needed to observe one simulated collision, on average. But even more replications are required to generate a tight confidence interval on the rare-event estimate. For example, if one could generate 1,000 simulation replications per second on a computer, it would still take about 3 years to generate an estimate with a relative error of 10% for a 10-9 event (Shortle, J.; L'Ecuyer, P., 2011). Rare-event simulation techniques can be used to "accelerate" the computer simulation to arrive at accurate estimates in a reasonable computation time.

There are two main approaches to rare-event simulation – important sampling (IS) and splitting (Shortle, J.; L'Ecuyer, P., 2011). Importance sampling seeks to change the underlying probability distributions in the model to make the rare-event more likely. This alters the chance of observing the event in the simulation, so a corrective factor must be applied so that the final estimate of the event probability is unbiased. The main challenge with importance sampling is how to choose the adjusted probability distributions in the model. If the rare event is favored too heavily, then it can make the variance of the simulation estimate larger. The optimal change of measure depends on the structure of the model, and so effective use of importance sampling often relies on detailed knowledge of the problem and may not translate well if the original model is changed.

The second approach is splitting. The idea of splitting is to interrupt the simulation whenever it gets "close" to the rare event and then restart the simulation multiple times from this starting point. This helps to use the computation time more efficiently by concentrating computer effort on runs that are more likely to hit the rare event. Splitting tends to work well when the system takes many "small steps" to get to the rare event, rather than a few "large jumps". For example, if an aircraft blunder onto the wrong approach path is a key part of the model, this is a case where the risk goes up significantly because of this one event. Importance sampling may be a better approach for such a problem rather than splitting.

5.1.2.1 Importance sampling

Importance sampling works as follows. First, consider a random variable X and suppose that it represents the output of a Monte-Carlo collision simulation, where X = 1 if a collision occurs, and X = 0 otherwise. The standard way to estimate the probability of a collision is to run n simulation replications, count up the total number of collisions, and then divide by n. That is, if Xj represents the output of simulation j , then the probability of a collision is estimated as the sum of Xj divided by n. The basic problem is that if the true probability of a collision γ is very small, then the relative error of the estimate, which is $(\gamma n)^{-½}$, becomes very large. (The relative error is the standard deviation of the estimate divided by its mean, a measure of the “noise-to-signal" ratio.) For example, if γ = 10-9, then the number of runs n required to achieve a relative error of 10% is 1011.

In importance sampling, samples are taken using a new density function g for the underlying probabilistic mechanics of the simulation, rather than the original density function f. Intuitively, the new density g is chosen so that the rare event is more likely. The method works by doing Monte-Carlo simulation runs Y1, Y2, …, Yn, using the new density function. Since the new simulation runs are biased, a correction factor must be applied to get an unbiased estimate of the rare event. The specific correction that is needed is the likelihood ratio L(y) = f(y) / g(y), which is the ratio of the original density function divided by the new density function.

One example of an importance sampling approach is using conditional probability for initial blunders. For example, a blunder might be an aircraft overshooting the approach path and veering into a parallel approach. The collision risk is evaluated using a simulation in which the aircraft is assumed to commit a blunder. This makes the collision more likely and hence more computationally tractable to estimate via simulation. Of course, the simulation is not estimating the true probability of a collision, but rather the probability of a collision conditional on the blunder, namely:

$$\Pr\{\text{collision} \mid \text{blunder}\} \tag{15}$$

To obtain the probability of a collision, a correction factor must be applied, namely the probability of a blunder in the first place (which might be estimated using historical data). The laws of conditional probability give the corrected probability of a collision, namely:

$$\Pr\{\text{collision}\} = \Pr\{\text{collision} \mid \text{blunder}\} \times \Pr\{\text{blunder}\} \tag{16}$$

This approach can be described within the framework of importance sampling. The simulated outputs Y1, Y2, …, Yn of the “modified” simulation are binary values (1 = collision, 0 = no-collision), sampled from a simulation in which a blunder is assumed to occur. Each value must be weighted by Pr{blunder}, which is the likelihood ratio, to get the true probability of a collision.

Now, more complex applications of importance sampling to collision risk problems are possible. In the blunder example, one is essentially changing the initial conditions of the simulation so that an aircraft starts with a blunder. But internal probability density functions within the simulation can also be changed. For example, if the model has a stochastic differential equation that controls the lateral position of an aircraft in the presence of wind or noise, the control values could be changed so that it the aircraft is more likely to drift into the parallel path over time. Importance sampling provides a framework for making these internal adjustments to the simulation and then determining the appropriate correction factor so that the simulation samples are un-biased.

5.1.2.2 Splitting

The splitting idea is to interrupt the simulation whenever it gets "close" to the rare event. Figure 14 shows an example of the approach applied to wake risk (Zare, A.; Shortle, J., 2017a). The triangle shows an approximate zone for the location of the wake. The objective is to simulate how often a trailing aircraft enters this zone. In the simulation, the aircraft dynamics are modeled as stochastic differential equations. In each simulation, the position of the trailing aircraft relative to the leading aircraft might look something like one of the sample paths shown in the figure. The aircraft starts in a location that is safely away from the leading aircraft. It might drift a little bit downward or closer to the leading aircraft, but will likely drift back to a position that is safely separated from the leading aircraft in an effort to maintain safe separation standards. The challenge from a simulation perspective is that very few sample paths reach the wake zone. Millions of simulation replications might be evaluated without seeing a single path hit the rare-event zone.

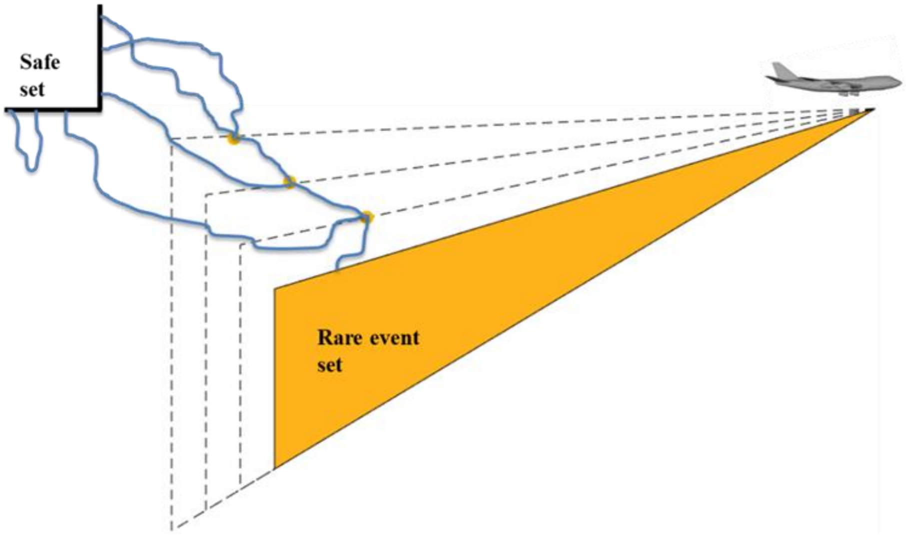

Figure 14. Example of Splitting Simulation method applied to wake risk

Visualization of how "splitting" can focus simulation processing on generating data for rare events.

In splitting, the simulation is restarted or "split" into multiple simulations from intermediate interruption points. The dashed lines represent possible restart points, called "levels". While it may be extremely rare for the simulation to reach the rare-event set, it may be only slightly unlikely to reach the first level set, and thus possible to observe with a limited computational budget. When the simulation reaches the first level set, the simulation is interrupted and multiple separate simulation runs are generated from this interruption point. Most simulated sample paths from this starting point will drift back to the safe zone, but a few might drift to the next level. If a path hits the next level, a similar process is repeated. The simulation is stopped and multiple separate simulations are restarted from this point. The idea is that by splitting the simulation in this way, more computational effort is expended on the runs that are closer to the rare event. An unbiased estimate of the rare event is achieved by observing that each time the simulation splits, each downstream simulation gets weighted by a factor of 1/n, where n is the splitting factor at a level. (Simulation runs that have split twice get weighted by a factor of 1/n2, etc.)

Examples of this approach applied to aviation safety include Blom et al. (2007a) (collision risk) and Zare and Shortle (2017a) (wake encounter risk).

There are many variations on this splitting idea. For example, the number of intermediate levels can be varied. The locations or shape of the levels can be varied. The number of replications at each interruption, or the splitting factor, can be varied. (The figure shows a replication factor of two, but other factors could be chosen). There are also variations of the implementation scheme. In the example, each simulation is split into a fixed number of replications. This is called fixed splitting. But one could also specify a fixed total number of runs that are started at each level among all simulations. This is called fixed-effort splitting.

The main challenge for splitting is defining a function that accurately measures how “close” a system is to the rare event given its current state. Such a function is called the importance function. The main challenge with splitting is how to choose a good importance function. As an example, for enroute collision risk, one might define the importance function based on the distance between two aircraft – aircraft that are closer together are more likely to collide. In other words, the levels would be concentric circles around an aircraft. However, the situation is more complicated. Two aircraft, one nautical mile apart, heading straight towards each other represent a more dangerous situation compared to two aircraft, one nautical mile apart, heading away from each other. Thus, the best choice for an importance function may not be concentric circles, but rather ovals that stretch out in front of an aircraft.

5.2 Data analytics and AI opportunities

This section discussed opportunities to enhance the functions in Section 4 using data analytics and AI.

5.2.1 Data analytics

Preliminary review of the superset of functions for CRM has identified the opportunities for applying data analytics and AI/ML as summarized in Table 3.

Table 3. Data analytics and AI/ML foreach of the CRM super-set functions

Function	Model Description	Data Analytics Opportunities (Additional Data for Existing Model/New Model)	AI/ML Opportunities
Prescribed Nav Procedure	3-D Trajectory (Fixed)	Not Applicable	Not Applicable
Atmospheric Model	Wind Direction/Magnitude Distribution Atmospheric properties	X	
Flight Trajectory Model		X	X
Fused Surveillance Error Model	Position distributions	X	
ATC Detection Model	Time distributions	X	X
Ground-to-Air Model	Time distributions	X	X
Pilot/Aircraft Detection Model	Time distributions	X	X
Pilot/Aircraft Avoidance Model	Time distributions	X	X
Wake Vortex Model		X	X
Wake Vortex Encounter Models		Not Applicable	X
Collision/Conflict Model		Not Applicable	Not Applicable

5.2.2 Generating synthetic flight tracks using variational auto-encoders

Safety analyses require a sufficiently large numbers of simulated or historical tracks to adequately capture rare events (e.g., those that occur on the order of one in 10^9 operations). The statistical "rule of 3" says that if N data points are observed with zero fatalities, then the 95% upper bound on the fatality estimate is 3/N. Collecting operational data and/or generating simulated flight tracks for any complex navigation procedures may be cost and time prohibitive (even on super computers). Synthetic flight tracks generated using variational auto encoders may provide a solution to generate additional flight tracks that represent the complex combinatorics of the underlying navigation procedure. Note: this approach is not a “distribution filling” approach but relies on the combinations of alternate behaviors that generate realistic but unique flight tracks.

Krauth et al. (2022) describe a method for using variational autoencoders to generate synthetic flight tracks (described earlier in this report). The method uses deep learning to generate realistic flight tracks that appropriately reflect the laws of physics and flight procedures specific to an airport.

From a safety analysis perspective, there is a potential for tremendous benefit, since safety analyses require large numbers of simulated or historical tracks to adequately capture rare events (e.g., those that occur on the order of one in 109 operations). The authors claim that the method can generate “realistic” flight tracks from a relatively small sample of actual flight tracks and that the synthetic tracks follow the same distribution as the original tracks.

However, there are several limitations and open research questions associated with this approach:

- The method has difficulty generating trajectories based on uncommon events. For example, events like go-arounds, that are seldom observed in the initial flight track data, are not well captured in the synthetic tracks.
- In theory, synthetic tracks follow the same distribution as the real track data. But do the synthetic tracks accurately capture the tails of the distributions (i.e., the extreme events)? In a safety analysis, estimates of collision risk are typically driven by the tails of the distributions, so it is important that the synthetic tracks accurately reflect the tails that would be observed with real data.

In summary, the core research question is:

Can synthetic flight tracks, which are generated by variational autoencoders, lead to accurate estimations of risk when fed into a collision risk model, as if they came from real flight-track data? Figure 15 shows a proposed research framework to help address this question.

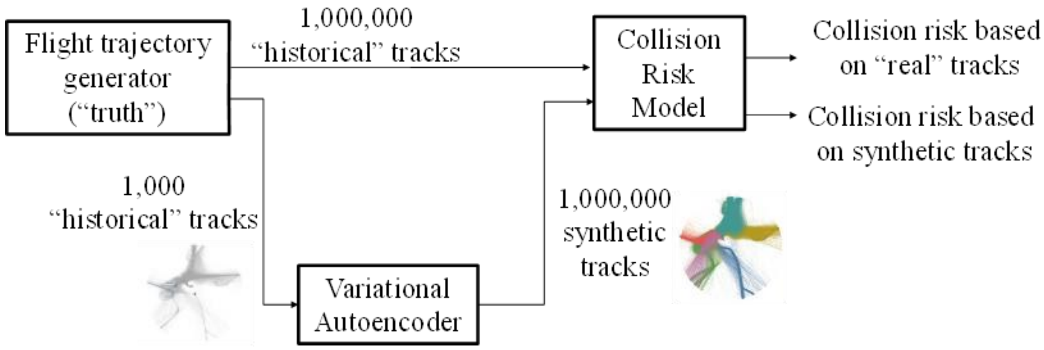

Figure 15. Framework for analyzing characteristics of synthetic flight tracks

Can the synthetic flight tracks, which are generated by variational autoencoders, lead to accurate estimations of risk when fed into a collision risk model, as if they came from real flight-track data?

The idea is to first construct a flight trajectory simulator for some scenario of interest (e.g., parallel approaches). The trajectory generator should model anomalous behavior that would be important in a collision-risk analysis (e.g., go-arounds, missed approaches, blunders, airport specific procedures, etc.). The model is assumed to represent “truth” – that is, trajectories generated by the model are assumed to represent historical trajectories.

The first step is to generate a baseline estimate of collision risk. This is done by generating a large number (say, one million or one billion) simulated tracks, and running them through a collision risk model. Since the tracks are assumed to be equivalent to historical tracks, this provides the ground-truth estimate for collision risk.

The next step is to suppose that only a subset of these tracks is available to the analyst, say, 1,000 tracks. These tracks are fed into a variational autoencoder to produce an equivalent number of synthetic tracks, similar to the method described by Krauth et al. (2022). These tracks are also fed into the collision risk model.

The collision-risk estimates for both approaches are compared. If they yield similar results, then the variational autoencoder approach may be an accurate method for doing collision-risk analysis using only a limited number of historical tracks. Such an experiment should be conducted over a variety of operational scenarios and trajectory models.

5.2.2 Natural Language Processing (NLP) for better inputs

Significant quantities of data are "buried" in narrative text in the form of operational logs, audits reports, accident/incident reports, and other reports. NLP techniques could be applied to extract quantitative measures from these narrative texts (e.g., ASRS, audio-text). One example is the use of ASRS reports to estimate the probability of a downstream event, given an accident event.

6 Conclusions

This report provides an overview of the state-of-the-art CRMs for terminal area operations through a detailed analysis of over 74 scientific/engineering papers on air-to-air collision risk modelling for the terminal area.

The report identified the categories of operational scenarios that have been analyzed in the CRM analyses:

1. Parallel runways – straight-in approach
2. Parallel runways – curved Path Approaches
3. Departures
4. Crossing approach paths for diverging and intersecting runways
5. Intersecting approach and departure trajectories
6. Wake vortex encounters
7. Terminal area sequencing and spacing
8. Missed approaches
9. Low altitude and enroute collision risk

Also, the following super-set of functions required to perform CRM were identified. Note: not every CRM had all the functions.

1. Prescribed navigation procedure
2. Atmospheric model.
3. Flight trajectory
4. Surveillance position fixing error model
5. Aircraft/flight-crew conflict detection models

6. Air Traffic Control (ATC) conflict detection model
7. Ground-to-air communications model
8. Aircraft/flight-crew collision avoidance model
9. Collision/conflict model – functional form
10. Collision/conflict model
11. Wake vortex model
12. Wake vortex encounter model

The key to safety analyses is the ability to get a sufficiently large numbers of simulated or historical tracks to adequately capture rare events (e.g., one in 10^9 operations). The statistical "rule of 3" says that if N data points are observed with zero fatalities, then the 95% upper bound on the fatality estimate is 3/N. Collecting operational data and/or generating simulated flight tracks for any complex navigation procedures may be cost and time prohibitive (even on super computers). The following data analytics methods and AI/ML approaches showed promise to address this challenge:

1. Sensitivity and uncertainty assessment
2. Rare-event simulation – importance sampling
3. Rare-event simulation – splitting
4. Generating synthetic flight tracks using variational auto-encoders

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A Applications of AI/ML in collision avoidance

AI/ML: has been widely applied to collision avoidance.

This section provides an overview of AI/ML applications.

A-1 Deep neural network compression applicable to aircraft collision avoidance systems

The development of advanced decision-making formulation allows its implementation in complex decision-making processes, such as in collision avoidance systems. In the last years, researchers have classified aviation collision avoidance models as observable Markov decision processes. This perspective allowed them to use dynamic programming to develop more robust and reliable collision systems, like the Airborne Collision Avoidance System X (ACAS X) family. However, ACAS X models, like the ACAS Xu, produce large numeric lookup tables (usually in the range of hundreds of Giga Bytes of floating points) that contain the scores of the different maneuvers related to millions of discrete states. This is a challenge for their implementation given a required target of less than 120 MB for gloating point storage (Kuchar & Yang, 2000).

Different methodologies have been studied to reduce the score tables' storage capacity. Downsampling is a technique that minimizes the degradation in decision quality by removing states in the table whose values' difference is smooth; this showed reductions up to a factor of 180. Nevertheless, this compression is not enough yet. Since score tables still need over 2 GB in storage (Youn & Yi, 2014). Researchers have also studied block compression (Kochenderfer & Monath, 2013), score table natural symmetry (Julian, Lopez, Bush, Owen, & Kochenderfer, 2016), decision trees, and support vector machines (SVM) regressions. Nonetheless, the same outcome is still present. Despite the advantages and reductions of each of these methods, the target reduction has not been achieved.

Recent developments in neural networks have demonstrated that deeper neural networks can represent more information than shallow networks (Montufar, Pascanu, Cho, & Bengio, 2014). One previous limit in the depth of the networks was the saturation of the activation functions. However, the creation of piecewise-linear activation functions (rectified linear units, ReLUs) has diminished this constraint and permitted the representation of larger data sets with deep neural networks. Therefore, this methodology explores the application of deep neural networks for the compression of score tables, keeping their corresponding performance.

In the case of the ACAS Xu, the actions in the score table are the horizontal resolution advisories to the ownship. The first five state variables represent the geometry of the 2D encounter between two aircraft. The last three variables allow the addition of three dimensions, the previous advisory, and the current acceleration to the vector.

A-2 Machine learning aided trajectory prediction and conflict detection

With the development of more advanced wireless connections, sixth-generation wireless networks attempt to amalgamate space, air, ground, and underwater communications (Sun et al., 2020). To accomplish this goal, a more complete understanding of the internet of aerial vehicles is required; this is especially true in air-ground integrated vehicular networks (AGIVNs), which operate low-altitude airspace. As low and medium-altitude aerial vehicles, such as drones and helicopters, become more operational, low-medium-altitude airspace is getting populous. This has drastically increased the number of accidents in this low altitude range. As a result, safety commissions and entities are requiring higher requirements for AGIVN to reduce the probability of aerial collisions.

Current surveillance methods expose constraints to future denser air traffic management (ATM). To counteract these challenges, different surveillance architectures have been proposed. One of them is the automatic-dependent surveillance broadcast (ADS-B) (Jheng, Jan, Chen, & Lo, 2020) and (Strohmeier, Schafer, Lenders, & Martinovic, 2014). This technique suggests more intelligent air management; this is due to the abundance of aerial vehicle information attributed to the spread geographic distribution of the ADS-B stations.

A normal way to determine conflict alarms between aerial vehicles is to segment the airspace into areas or sections. However, this approach does not permit one to account for the time-varying and dynamic nature of the real conflict detection process. To solve this problem, this paper proposes a grouping strategy using ADS-B stations. The process starts by converting the route conflict problem into a 3-D coordinate conflict problem. Then, the conflict area is uniformly mapped onto the time axis. The interceptions of the x, y, and z-axes at similar time intervals determine if collisions are present. Subsequently, the grouping method divides the vehicles' multidimensional data (Leonardi, 2019) into several smaller groups. The creation of these small groups reduces the complexity and execution time of the conflict detection process.

Another big challenge with conflict detection is delayed flights. It is not strange to have errors as big as 7 km between actual flights and planned flights. These differences commonly require onboard trajectory predictions to avoid incidents. Hence, this paper also recommends a combination of a long short-term memory (LSTM)-based trajectory prediction methodology along the conflict prediction algorithm (Shi, Xu, Pan, & Zhang, 2018; Palangi et al., 2016). Therefore, this section of the report exposes three contributions to alleviate the collision dilemma. The first one is a geometric model to determine conflict flags based on a grouping-based algorithm. The second contribution includes a machine learning-based (LSTM) algorithm to predict short and long-term trajectories. Finally, the team addressed the effect of trajectory prediction accuracy on the conflict detection approach.

A-3 Machine learning aided air traffic flow analysis

The last decade's developments in the aeronautic industry have created a revival in the demand for air travel. Despite the great benefit of this revitalization, this has also caused a boost in air space density. This growth in the saturation of the air space has opened experts' eyes to the need for more intelligent and high-precision air traffic flow management (ATFM). To achieve these goals, different aerial surveillance technology has emerged. Automatic dependent surveillance-broadcast (ADS-B) is one of them. This technology provides a ground/air data link that permits real-time communication between the ATM systems. However, this is not enough. Professionals have pointed out that to obtain the best performance of these new broadcasting technologies, the inclusion of machine learning methods is imperative. Previously studied machine learning methods applied to traditional traffic flow predictions base their performance on historical trajectories and fixed flight plans. These static approaches are acceptable; nonetheless, big-volume real ADS-B messages could assist better in reflecting the true air traffic situation in real airspace. Therefore, this team of scientists proposed a new flow prediction method using two machine learning approaches based on big-volume real ADS-B messages. The machine learning methods are support vector regression (SVR) algorithms (Liu & Chen, 2017) and LSTM (Palangi et al., 2016)

A-4 Two-layer machine learning obstacle collision avoidance system for energy-trajectories optimization

Given the economical and target-oriented benefits of unmanned vehicles, organizations and governmental entities are becoming more interested in the automatization of such systems. Current autonomous aerial vehicles, such as drones, operate in multiple mission types, becoming strategic equipment. Nonetheless, despite their versatility, technology barriers and emerging regulations still limit autonomous aerial vehicles. To overcome these challenges, the Federal Aviation Administration (FAA) has determined two aspects for improvement, detection, and avoidance of obstacles (U. S. Department of Transportation, 2014).

Current separations guidelines for unmanned vehicles are like those for manned aerial vehicles. Thus, they must restrict themselves to a multilayer framework, and its corresponding implications. Collision avoidance systems, as well as conflict resolution modules, and other subsystems, are integrated into the vehicle's onboard system to detect and avoid possible conflict scenarios, within seconds. However, response improvements are critical for unmanned assets to help reduce uncertainty and so the safety of the vehicles, their cargo, and their surroundings.

In the last years, research in the collision avoidance field has focused its attention on stochastic methods and rod maps to develop better 3D-path planning algorithms. Some of them are the theta* and A* algorithms. These models use artificial potential field methods, which is a methodology that assigns attractive and repulsive forces (for obstacles) to the purpose of an optimal collision-free path (Khatib, 1986). Despite its advantages, artificial potential field methods still encounter challenges, such as local minima. To resolve these problems, some researchers have suggested the implementation of geometric methods and mixed-integer linear programming (MILP).

This research takes these concepts and proposes a two-layer obstacle collision avoidance algorithm whose aim is to create an optimized path based on energy minimization. The algorithm comprises two phases. The first one is a global-path optimization phase. In this stage, the algorithm takes data from an airborne sensor and identifies the obstacles using a cluster approach. The clustering process minimizes the separation between pairs of nearby obstacles based on a distance-based constraint. The second phase is a local-path optimization module; this uses a multi-phase optimal obstacle avoidance criterion.

The clustering technique is essential for the global optimizer; hence, the research team evaluated several clustering algorithms. The primary ones were the k-means algorithm, which is one of the most popular despite its need for the number of clusters a priori; the NJW algorithm, which uses a spectral approach to determine the number of clusters (not always correct though); and the DBSCAN algorithm, which is a density-based spatial clustering model that does not rely on a priory knowledge. To compare and validate performance, the team selected the DBSCAN and the spectral clustering techniques to compare clustering accuracy and computational efficiency.

To account for the online trajectory optimization, the team used a model predictive control (MPC) scheme. The scheme specializes in solving nonlinear constrained dynamic trajectory optimization. This allows them to provide proved tractable solutions (Moon & Prasad, 2009; Kang & Prasad, 2013).

A-5 Hybrid machine learning model for incident risk prediction

For the past years, researchers across the world have studied and developed qualitative and quantitative ways to measure dangerous behaviors. Some results of this research are namely causal models, collision risk models, human error models, third-party risk models, automatic dependent surveillance-broadcast (ADS-B) systems, target windows, etc.

This research proposes a hybrid machine learning model to quantify the risk related to the consequences of dangerous events. The investigators expect that these results will help to create a decision support system to examine incidents/accident scenarios methodologically, increasing proactive safety.

The research team exploring this method used the Aviation Safety Reporting System (ASRS), which is an aircraft database covering most of the domains and operations that could generate an accident. The proposed task is a complex endeavor since the heterogenous data in ASRS creates problems, such as high-dimensional data, primarily categorical data, unstructured data, and imbalanced class distribution. To deal with some of these issues, the investigators proposed a splitting strategy. They divided the data into two categories, structured data, and unstructured data. For the unstructured data, the investigators suggested an SVM technique. On the other hand, they proposed a deep learning technique that allows the processing of the high-dimensional feature space of the structured data. The advantage of this approach is a better use of the strengths of each type of data. In general, the contributions of this research are a machine learning methodology to determine the relationship between anomalies and their consequences by grouping events into five categories, as well as the development of a probabilistic fusion rule to combine the predictions of the different models.

A-6 Machine learning approach for conflict resolution in dense traffic scenarios with uncertainties

Another challenge of the growing density in the airspace is the mathematical complexity embedded in predicting highly populated environments. Investigators have tried multiple approaches to mathematically model conflict resolution in Air Traffic Controller scenarios. Some of those models include probability reach sets with second-order cone programming to represent aircraft deconfliction (Kuchar & Yang, 2000), aircraft reachable space (Hao, Cheng, & Zhang, 2018), model predictive control (MPC) (Yokoyama, 2018), large-scale conflict resolution models (Allignol, Barnier, Durand, Gondran, & Wang (n.d.)), etc. However, the problem with them is their scalability for an increasing number of aircraft and their high mathematical complexity. Most of these methods also present constraints such as a required complete knowledge of the relationship conflict scenarios-maneuvers and low quality under high uncertainty.

To solve these problems, scientists have implemented machine learning methods to deal with the complexity of mathematical models. However, despite their improvements, machine learning algorithms still struggle to manage large and continuous state and action spaces. As a solution, researchers have considered Reinforce Learning (RL) techniques. RL models have shown superior performance in conflict resolution problems. Additionally, RL has proved its capacity to deal with continuous action spaces by using a general-purpose continuous Deep Reinforce Learning (DRL) framework (Lillicrap et al., 2015). Therefore, in this research, the research team proposed the development of an AI agent capable of resolving conflicts in lateral dimensions and the presence of surrounding traffic and uncertainty. The idea is to present a highly dense learning environment to the AI agent, and let it learn how to solve the conflict by rewarding positive maneuvers that increase the separations and negatively otherwise.

A-7 Optimizing collision avoidance in dense airspace using deep reinforcement learning

This is another methodology to deal with the increasing demand for eVTOL and its corresponding increase in air traffic density in the near future. This specific methodology uses a mathematical framework for collision avoidance of aerial autonomous vehicles using the Markov decision process (MDP) (Bellman & Dreyfus, 2015).

Researchers have defined an MDP by the input parameters S, A, T, R, and γ, where S is the state space, A is the action space, T is the state transition function, R is the reward function, and γ is the discount factor. In a Markov process, the algorithm takes action A, through a state space S, and assigns a reward based on the performance of the action. The objective of this process is to maximize the accumulative total reward. For this proposed methodology, the researchers used a sigma-point sampling and a generative model to create the transition function. This allows them to generate a generic form of the Bellman equation to denote the expected discounted reward for the next state, S.

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