Close proximity and collision risk assessment of drones and urban air mobility

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***Abstract*—For quantitative assessment of close proximity and collision risks of drones and urban air mobility there is a need for simulation approaches that can represent a variety of operations and types of uncertainty and hazards that can affect them. This paper shows that agent-based modelling in combination with Interacting Particle System (IPS) Monte Carlo (MC) simulation and risk decomposition for global failure conditions can be effectively used for assessment of small probabilities of close proximity and collision events. It is demonstrated for a use case with drone and air taxi traffic simulations in an urban area south of Paris.**

Keywords – drones; urban air mobility; safety; collision risk; detect and avoid; Monte Carlo simulation

I. INTRODUCTION

Assuring safe integration of unmanned aircraft (UA) in all airspace classes, including urban areas, is an important element of current research and development (R&D) in air traffic management (ATM). A central element in the European development is U-space [1], which is a set of new services and specific procedures designed to support safe, efficient and secure access to airspace for large numbers of unmanned aircraft systems (UASs). These services rely on a high level of digitalisation and automation of functions, whether they are on board the drone itself, or are part of the ground-based environment. A comprehensive overview of SESAR exploratory research projects on U-space is provided in [2] and a key result is the U-space concept of operations [3].

In ATM changes of operations typically have been achieved in a step-by-step approach and safety risk assessments of such changes have often for a large part relied on safety occurrence data and expert feedback from operators. In UAS traffic management (UTM), drone operations and urban air mobility (UAM) involve drastically new types of aircraft, automation and supporting systems, roles of human operators, and procedures. The lack of experience by operators and the lack of data on safety occurrences imply that safety risk assessment methods that largely depend on expert judgement and safety occurrence data will be limited in achieving valid risk assessment results for such new operations. As a way forward it is recognized in the R&D agenda "Digital European Sky" [4] that for safety assurance of U-Space and UAM: "New safety modelling and assessment methodologies applicable to U-space are needed. Tools are required to analyse and quantify the level of safety of U-space operations involving high levels of automation and autonomy, where multiple actors automatically make complex, interrelated decisions under uncertainty."

Safety risk assessment of new concepts and technologies needs to assess (1) how effective the new concepts and technologies are if they work as intended, as well as (2) what risks are induced if elements in the new concepts and technologies are failing. In the SESAR Safety Reference Material for assessment of changes in ATM [5, 6] these two perspective are referred to as success approach and failure approach, respectively. For new UAS/UAM and U-space supported operations this means that two types of questions need to be answered for the safety assessment:

- *When systems are working as intended in normal conditions.* What is the effectiveness of detect-and-avoid (DAA) systems and how can they be tuned optimally? What is the impact of traffic density and airspace design? What is the impact of normal sensor errors? What is the impact of normal communication delays? What is the impact of normal human reaction times? What is the impact of normal variability in speeds of operations? What is the impact of normal weather variability? Etc.

- *When there are failures or off-nominal conditions.* What is the impact of failures of technical systems, including drone propulsion, communication systems, surveillance systems, navigation systems, DAA systems? What is the effectiveness of mitigating measures for failure conditions? What is the impact of human errors, such as errors in planning and reaction to DAA advisories? What is the impact of unpredicted adverse weather conditions? Etc.

Answering these types of questions in quantitative safety risk assessment of UAS/UAM operations requires modelling and

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simulation approaches that can represent the systems, human operators and environment of relevant operational concepts. The models should represent the performance and uncertainty of normal operations, as well as the impact of off-nominal/failure conditions that may affect the operations. The simulations should effectively represent the interactions of all entities and their variability in normal and off-nominal/failure conditions, such that probabilities of rare safety events can be estimated in reasonable time.

In previous research it has been shown that agent-based dynamic risk modelling for safety risk assessment in ATM is an effective method to assess the risk of complex and novel operations [7]. Such models represent the dynamics and stochastic variability of operations involving complex interactions of technical systems, human operators and environmental conditions, both in normal conditions and in off-nominal/failure conditions. The models are used in rare event Monte Carlo (MC) simulation approaches to assess low probabilities of safety events. Agent-based dynamic risk modelling is included in the SESAR Safety Reference Material [5, 6] and it has been effectively used in various applications, including runway incursions, airborne self-separation, separation minima of conventional operations, ACAS evaluation, and others [8-11].

In this paper we show that agent-based dynamic risk modelling and rare event MC simulation methods can be effectively used for assessment of small probabilities of close proximity and collision events of UAS/UAM operations. Next, Section II explains the scope of the study, Section III presents the development of the agent-based models for the operations, Section IV describes the rare event MC simulation approaches, Section V presents illustrative simulation results, and Section VI discusses the implications of this study.

II. Scoping

A. *Concept of Operation*

In this study an urban area (24 x 16 km) south of Paris has been used, which includes vertical take-off and landing (VTOL) air taxi operations between suburbs, surveillance & loitering VTOL drones, and en-route drones that cross the area at a constant altitude. In the following, often the term 'drone' is used for each aircraft without an onboard pilot, including air taxis. Three airspace design options have been included: (1) free flight, where all operations use the same airspace; (2) mission-dependent altitude layers, where there are dedicated altitude layers for the en-route parts of the various types of operations; (3) mission and heading-dependent altitude layers, where the dedicated altitude layers depend on the type of operation and the direction.

All operations are controlled by pilots-in-command (PICs), who reside in remote pilot stations (RPSs). The PIC sets horizontal and vertical speeds and accelerations for the operations. A command-and-control (C2) link system is used to send mission control data to the drones and to receive flight data from the drones. Navigation data is based on a global navigation satellite system (GNSS) and a pressure altimetry system. Surveillance data is based on transmission of automatic dependent surveillance broadcast (ADS-B) data to/from other drones. Each drone has a DAA system, which uses ownship navigation data and othership surveillance data to provide alerts and guidance to remain well clear of other drones. DAA alerts and guidance are downlinked to the PIC and changes in mission control in response to DAA alerts and guidance can be attained by the PIC only.

A number of aspects have been kept out of the scope. There is no strategic deconfliction of flights. There is no tactical conflict resolution. There is no capacity management. There is no geofencing of particular areas. There are no automatic responses to DAA advisories. There is no manned aviation or interfacing with air traffic control.

B. *Risk Types, Normal Variability and Failure Modes*

Drone operations pose various types of safety risk, including mid-air collision risk with regard to other drones or manned aviation, and ground risk with regard to people, animals, buildings, infrastructure, etc. on the ground. The scope of this study is on the risk of close proximity and mid-air collisions of drones with other drones.

As explained in Section I, safety assessment of drone operations requires to account for normal variability and uncertainty in operations, as well as for off-nominal/failure conditions. The first category refers to variability/uncertainty that exists in every operation, such as normal errors in GNSS-based position estimates, delays in C2 link transmission, delays in response to DAA alerts by a PIC, and variations in speeds and accelerations. The second category refers to failure/off-nominal conditions that may occur during an operation, such as engines failure, C2 link system not working, or PIC not responding to DAA alerts. Such failure conditions typically have low occurrence frequencies and may exist for particular (random) durations. They can be distinguished in local failure conditions affecting a single flight, e.g. a failure of a C2 link system in a drone, and global failure conditions affecting multiple flights, e.g. a failure of C2 link ground infrastructure in a region.

Traditionally in safety assessments there has been most focus on the implications of failure modes. In the agent-based dynamic risk modelling approach followed in this study, the implications of normal variability/uncertainty and (local/global) failure conditions are assessed in union. This allows to evaluate the normal performance of operations, as well as the implications of particular failure conditions in combination with otherwise normal variability in operations.

Types of normal variability/uncertainty that have been included in the scope of this study consider variation in wind speed; normal errors in altitude and vertical speed measurement; normal errors in GNSS-based horizontal position and speed estimates; delays in ADS-B transmission (between drones); delay in C2 link transmission (with RPS); delays in response to DAA alert by PIC; variable rates of turn and climb/descent by PIC in DAA response; variable rates of climb, descent, turn, acceleration, deceleration, cruise speed during nominal flight; and variation in locations and timing of customer demand.

Types of off-nominal/failure modes in the scope of this study are adverse weather not predicted; wrong altitude in flight planning; engines failure; reduced accuracy of pressure altimetry; GNSS-based estimation is not working (aircraft system or in whole region); reduced accuracy of GNSS-based estimation (single aircraft or whole region); C2 link not working (aircraft system, RPS, or whole region); ADS-B system of aircraft is not working; DAA system of aircraft is not working; and no/limited response to DAA alert by PIC.

III. AGENT-BASED MODELLING

A. *Overview of the Agent-based Model*

A high-level overview of the agent-based model is provided in Figure 1. It shows a number of unmanned aircraft that reside in a particular environment and airspace design. The UA movements are influenced by weather conditions and weather is being forecasted by meteorological services. There are customers who pose demand for drone missions. UA operators develop flight plans based on the mission demand, weather forecast and airspace layout. The flight plans are used by PICs as a basis to control the drone missions. The mission control commands by each PIC are uplinked by the C2 link to the flight management system (FMS) of the UA and this determines the flight performance (movements of the drone). The FMS also uses ownship state estimation data, consisting of GNSS-based position and speed estimates and pressure altimetry. This ownship data is shared with other UAs via ADS-B. The ownship and othership states data are used by the DAA system on board of each UA to generate alerts and guidance advisories. The DAA output is downlinked by C2 link and shown on the traffic display in the RPS to the PIC. In response the PIC can adapt the mission to avoid close proximity to another drone. Details on the agents are provided next.

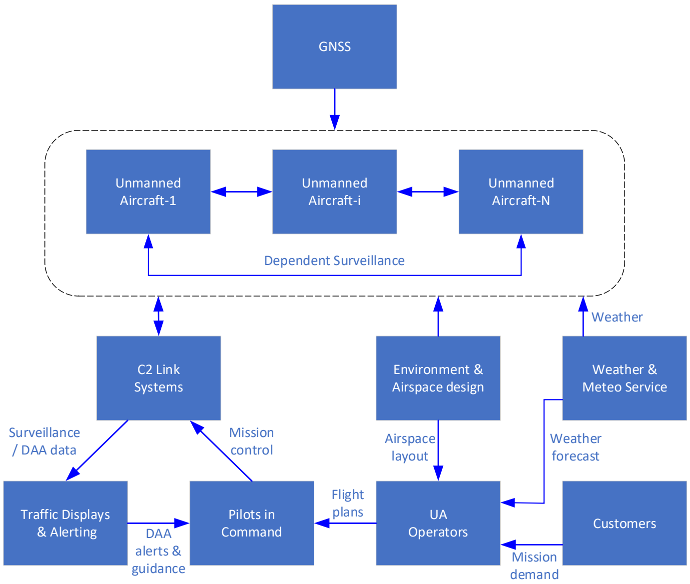

Figure 1: High-level overview of the agent-based model

1) *Weather and meteorological services*

The modelling of weather and meteorological services represents a constant and uniform wind that can be set and it includes a random possibility of an adverse weather condition in the region that is not predicted by the meteorological services. The consequence of adverse weather is that the drone trajectories exhibit oscillatory motion around a nominal flight path, thus representing turbulence.

2) *Customers*

The entity Customers represents the demand for services from the UA operators for the mission types. This demand determines the traffic density in the simulations. The demand for the missions is represented by Poisson processes with mission-type dependent waiting times. It also determines mission-type dependent random departure and arrival positions in the urban areas or at the edges of flight zones.

3) *UA operator*

The UA operator performs the flight planning of the drone flights. The operator uses the airspace design (see Section II.A) and the customer demand as a basis for the flight planning. Flights are planned directly following the customer demand, there is no restriction in the number of available aircraft. The flight planning depends on the type of operation associated with the mission. For air taxi and en-route missions the shortest routes between start and end points are planned, while for surveillance & loitering missions a series of randomly chosen waypoints is used for manoeuvring within an urban area during a particular duration. The planning of flights sets a flight level that is between the altitude bounds of the airspace design for the type of operation considered. This can be done in two modes: (1) *Middle*, planned flight level is exactly in the middle of the altitude bounds; (2) *Random*, planned flight level is uniformly distributed between the altitude bounds. The operator can make an altitude planning error, which implies that a flight is planned at an altitude layer above or below the layer according to the airspace design.

4) *UA flight performance*

A number of aircraft types are defined, which are associated to the operation types (air taxi, surveillance & loitering, and en-route UAS). The flight performance of the aircraft is specified, describing variables like position, heading, speed, and climb speed during manoeuvring. The input for the manoeuvring of the aircraft stems from the flight control system, which uses mission control settings for various flight phases. The flight performance model includes non-nominal modes for uncommanded motion of the drone in adverse weather and for engine failure.

5) *Flight management system*

The FMS of the aircraft contains the flight plan, ownship state estimates, received othership state estimates, output of the DAA system, and input from the PIC via the C2 link. This data is used for mission and flight control, as input of the DAA system, for ADS-B Out transmission to other aircraft, and to inform the PIC. The mission control system uses settings by the PIC to control the various flight phases of nominal operations and to change the trajectories in response to DAA alerts and guidance. Furthermore the mission control system includes autonomous control modes for contingency plans in the case of a lost C2 link or in the case of lost GNSS ownship estimation. The mission control system sends commands to the flight control system for the control of heading, air speed and altitude.

6) Ownship state estimation

The ownship state estimation includes GNSS-based estimation of horizontal position and speed and pressure altimetry for estimates of the altitude and vertical speed.

- The model for GNSS-based state estimation includes availability modes, representing working or not, and accuracy modes, representing the state estimation being in normal accuracy or reduced accuracy ranges. These modes are determined by modes at the GNSS receiver in each UA and modes representing the GNSS in the region. Errors in the position and speed estimates are chosen from Gaussian distributions with mode-dependent standard deviations.
- A model for the pressure altimetry system is used, which includes modes for the altitude and vertical speed estimation in normal accuracy ranges and for reduced accuracy ranges. Altitude and vertical speed measurement errors are chosen from Gaussian distributions with mode-dependent standard deviations.

7) Othership state data

Position and speed estimation data is exchanged with other UAs by ADS-B, thus providing the basis for dependent surveillance at each UAS. A model for the availability of the ADS-B system at each UAS is included, which represents the possibility of the system not being available. Transmission between a pair of UASs requires the ADS-B at both UASs to be working. The duration of ADS-B transmission is chosen from a uniform distribution.

8) C2 link

The C2 link is the logical connection used for the exchange of information between the PIC in the RPS and the UA. A model for the availability of the C2 link system represents the possibility of the system not being available. It consists of three components, representing availability of C2 link systems in the UA and RPS, and availability of the C2 link infrastructure in the whole region. The latter component represents a global failure mode, affecting all UAs in the region. If C2 link transmission is possible, durations for the uplink and the downlink of information are chosen from uniform distributions.

9) DAA system

In the scope of the agent-based model, the DAA system is the prime means for detecting conflicts and providing guidance and alerts for remaining well clear. In the current study, we have integrated DAIDALUS (Detect and Avoid Alerting Logic for Unmanned Systems), which has been developed by NASA as a DAA reference system [12]. DAIDALUS is a rule-based system that uses constant-velocity projections over a lookahead time to determine the level of threat of a well-clear volume and to compute horizontal and vertical guidance to remain or regain well-clear. Its parameters have been tuned for the various types of UAS operations in our study. Since DAIDALUS was not designed for VTOL operations, it has been deactivated during VTOL phases. Other UAS may however detect and avoid a UAS during its VTOL phases.

10) Remote pilot station

The Remote Pilot Station receives aircraft data and DAA data via the C2 Link and shows this data to the PIC by traffic display and alerting.

11) Pilot in command

The PIC is the agent who sets the control of the various types of aircraft operations in nominal conditions and who is informed by the DAA system about conflicting aircraft and guidance to avoid close encounters. The situation awareness model of the PIC includes information of the ownship for nominal flight control actions, such as the flight plan, airspeed, altitude and heading, as well as the downlinked DAA data. Based on the situation awareness components, the PIC implements actions in response to the DAA alert and guidance information. PIC action models include: (1) PIC response mode, describing probabilities of response to horizontal and vertical guidance; (2) delay in the response to DAA alert and guidance information, chosen from a log-normal distribution; and (3) PIC mission control actions, which describe the manoeuvring to selected directions/altitudes and returning back to the planned trajectory if there is no DAA alert remaining.

B. Modelling of Nominal and Off-nominal conditions

For simulation-based safety risk assessment of operations it is needed to represent variability in performance both in nominal conditions and in off-nominal conditions. For this purpose the agent-based model includes a range of discrete states that describe nominal and off-nominal modes that influence particular characteristics of system performance. The system performance at a particular aircraft *i* may be influenced by local systems at the aircraft as well as by global systems outside of the aircraft (which also influence systems of other aircraft).

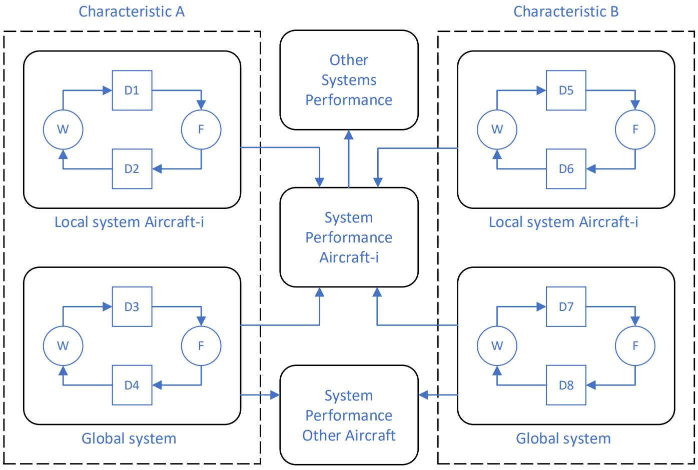

Figure 2. Schematic diagram of Working and Failing modes of local and global system characteristics A and B influencing system performance of aircraft i. D1 to D8 are transitions with exponentially distributed delays.

A schematic diagram of these elements of an agent-based model is shown in Figure 2. It shows two characteristics for local and global systems, which all have a nominal mode Working and an off-nominal mode Failing. Transitions between the modes are via delay gates, where the delays are chosen from exponential distributions. For instance, this model structure can describe the performance of GNSS-based state estimation at an aircraft. Here, characteristic A may represent availability for a local system (GNSS receiver at aircraft *i*) and for a global system (GNSS performance in the region). Both the local and the global systems need to be in the Working mode for GNSS-based state estimation at aircraft *i*. Lack of GNSS-based state estimation implies that position estimates are not available for navigation and surveillance functions. Characteristic B in Figure 2 may represent the level of accuracy of GNSS-based state estimation as achieved by the local and global systems. Here the Working mode may represent a normal accuracy level, where state estimates are affected by normal errors, and the Failure mode may represent a reduced accuracy mode with enlarged errors in the state estimates. The achieved accuracy affects the navigation and surveillance performance of the affected aircraft.

IV. RARE EVENT MONTE CARLO SIMULATION

Straightforward MC simulation of the dynamic and stochastic behaviour of the interacting agents only allows to assess probabilities of close proximities and collisions up to a certain level in a given time. In this study we use two techniques to accelerate the MC simulation: Interacting Particle System (IPS) method and risk decomposition for global failures.

A. IPS MC simulation

In [11, 13] acceleration of MC simulation has been achieved for air traffic scenarios using the IPS method of [14]. It makes use of a series of decreasing miss distances $d_{c+1} < d_c$ $(c = 1 \ldots M)$. Each miss distance d_c is composed of a horizontal miss distance (HMD) and a vertical miss distance (VMD). In IPS MC simulation, N runs of the agent-based model are conducted over a finite time interval in M miss distance cycles plus an additional collision cycle.

Next we explain key features of the IPS approach for two miss distance cycles and a collision cycle as illustrated in Figure 3. Here a circle represents a simulation object or particle, which describes the simulation of the complete agent-based model (the total state space of all flights, systems, humans). In each cycle, N particles are simulated. In miss distance cycle c, the simulation of a particle is ended either if it has reached a simulation end time T (green circles in Figure 3), or if the miss distance boundary d_c has been reached by a pair of aircraft (circles ending on miss distance line in Figure 3). We denote the number of particles that have hit boundary d_c as N_c^h and the associated fraction of particles as $\gamma_c = N_c^h / N$. If no particle has hit d_c (i.e. if $N_c^h = 0$) then the MC IPS simulation stops at that boundary. The particles that have hit a miss distance boundary are stored.

At the start of each following cycle, resampling of the stored particles is used (illustrated by copying of particles in Figure 3). This means that the complete state space is copied, including all continuous states (e.g. aircraft positions and speeds, surveillance estimates, flight plans) and all discrete states (e.g. system modes, weather conditions, failure conditions). Next the simulation of each particle is continued independently, including its unique stochastic variations as defined in the agent-based model.

In the last simulation cycle (collision cycle), the simulation of each particle is proceeded until the simulation end time T. Here all collisions between aircraft pairs are counted as N^{coll}. Following a collision, the involved aircraft are removed from a particle, since the consequences of collision and potential ground impact are out of the scope of this study.

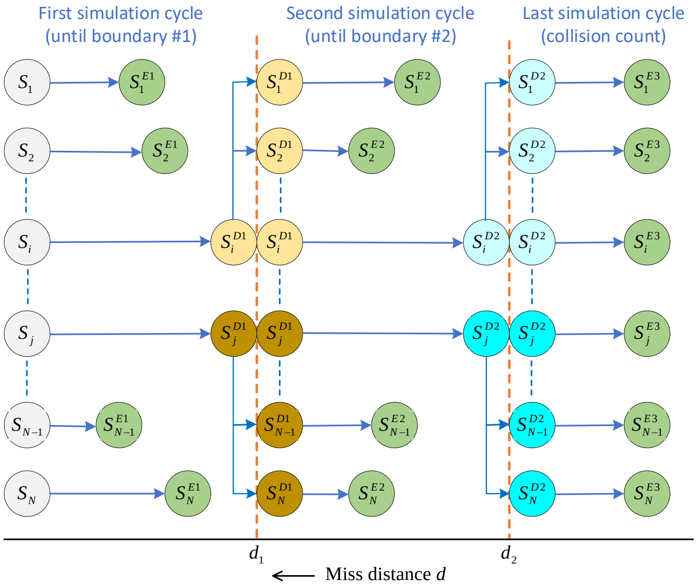

Figure 3. Illustration of IPS MC simulation for estimation of rare miss distances and collisions

Based on the IPS MC simulation results, the probability that any aircraft pair reaches a miss distance boundary d_c in the time frame $(0, T)$ is estimated as

$$P(d_c) = \prod_{k=1}^{c} \gamma_k$$

and the expected number of aircraft pair collisions in the time frame $(0, T)$ is estimated as

$$m^{coll} = \frac{N^{coll}}{N} \prod_{k=1}^{M} \gamma_k \, .$$

By accounting for the number of flights and flight hours, above statistics can be extended to risk estimates per flight and per flight hour, as is customary in aviation. In this scheme setting

$M = 0$ implies that no miss distance cycles are used, such that ordinary MC simulation for collision events remains.

B. Risk decomposition for global failure conditions

Risk decomposition for global failure conditions supports the assessment of rare global failures that would be encountered only very seldomly in IPS MC runs. For each global condition a simulation setting is defined as Working, Failing, or Stochastic.

- If the simulation mode is set as Working then the related system mode in the agent-based model is set as Working during a total simulation run. This is used to evaluate the conditional risk given that the mode is in the nominal condition.
- If the simulation mode is set as Failing then the related system mode in the agent-based model is switched from working to failing at a random time during a simulation run. Next, Bernoulli sampling is used to switch back from failing to working after a mean time of the global failure mode. This scheme is used to evaluate the conditional risk given that the mode is in the failure condition during a simulation run.
- If the simulation mode is set as Stochastic then the system mode in the agent-based model is updated at each time step in the simulations according to Bernoulli sampling. As such in this simulation mode no risk decomposition is used, but rather the system mode is switched between working and failing. This simulation mode can be used if the failure mode occurs sufficiently often.

In the simulations with risk decomposition, IPS MC simulation is performed for all possible combinations of working and failing global modes. For instance, a risk decomposition for two conditions leads to conditional risks for four cases (Working-Working, Working-Failing, Failing-Working, and Failing-Failing), which are multiplied with the probability of each case, and next the risk contributions of the four cases are summed to attain the overall risk.

C. D(emo)-CRAT

Based on above agent-based models and rare event MC simulation approaches a software tool was developed in C++, called D(emo)-CRAT (Demonstrator Drone Collision Risk Assessment Tool) [15]. This tool allows to configure all parameters of the agent-based model (224 parameters in case of 3 urban areas, including 58 for DAIDALUS), to configure the MC simulations (12 parameters in case of 3 miss distance boundaries), to run the MC simulations on multiple threads, and to visualize statistics of close proximity and collision events obtained by the MC simulations.

V. Illustrative Simulation Results

Next some illustrative MC simulation results are shown for a use case in an urban area south of Paris. A broader set of results is available in [15].

A. Impact of DAA for Air Taxi Operations

Figure 4 shows the locations of close proximity events (HMD≤50m, VMD≤15m) for air taxi operations between Orsay and Brétigny-sur-Orge flying at random levels between 400 and 2000 ft, with a mean time between the flights of 600 s. The duration of each simulated period is 12 hours and 1000 simulation particles are used. This implies that the total number of expected flights in the simulation is 72,000. Without DAA, the traffic leads to a close proximity probability of P=6.7e-3 per flight or P=2.2e-2 per flight-hour. With DAA, the close proximity probability is reduced by a factor 4.5 to P=1.5e-3 per flight or P=4.8e-3 per flight-hour. It can be recognised in the bottom pane of Figure 4 that in this simulation all of the remaining close proximity events are in the urban areas. Several factors contribute to this phenomenon: (1) during VTOL the DAA system is not active, since it was not designed for VTOL operations; (2) aircraft approaching an urban area can suddenly encounter air taxies that are in VTOL without sufficient time to react; (3) air taxies may use nearby arrival or departure positions and thus come in close proximity.

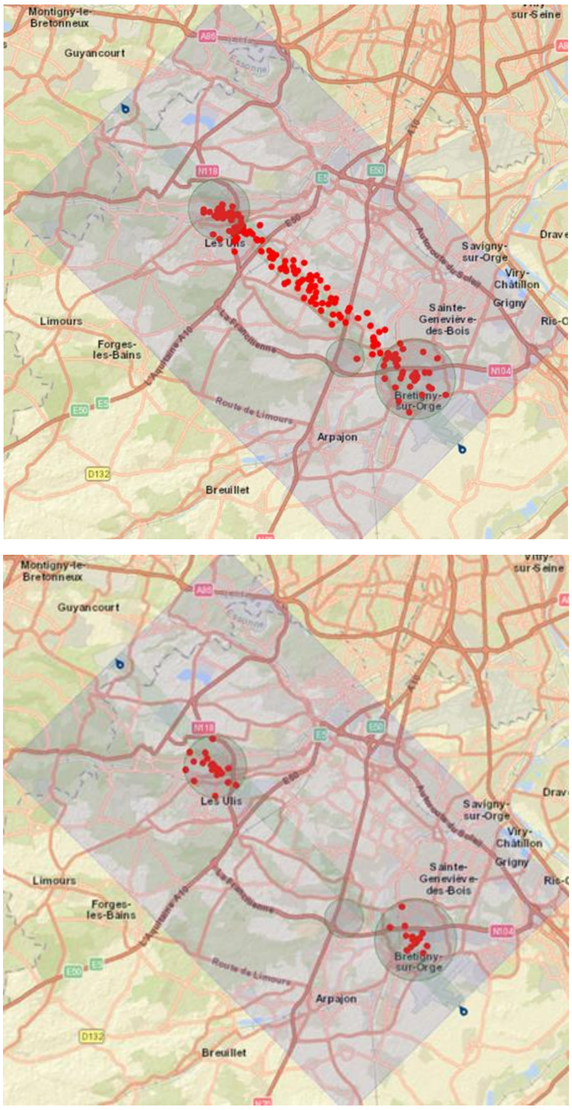

Figure 4: Close proximity events (HMD≤50m, VMD≤15m) for air taxi operations between Orsay and Brétigny-sur-Orge. Top figure: without DAA. Bottom figure: with DAA.

B. IPS Cycles

Figure 5 illustrate results of an IPS MC simulation for a scenario with air taxi operations between Orsay and Brétigny-sur-Orge with a mean time between flights of 600 s. The duration of each simulated period is 12 hours and 5000 simulation particles are used, implying a total of 360,000 flights. Four IPS cycle were used with the following limits:

- Cycle 1: HMD≤100m, VMD≤30m,
- Cycle 2: HMD≤50m, VMD≤15m,
- Cycle 3: HMD≤25m, VMD≤10m,
- Cycle 4: Collision, implying HMD≤11.3m, VMD≤2.5m being the size of the air taxi.

Figure 5 shows the decrease in event probability over these cycles. These probabilities decrease effectively from 1.0e-2 to 1.0e-4 events per flight.

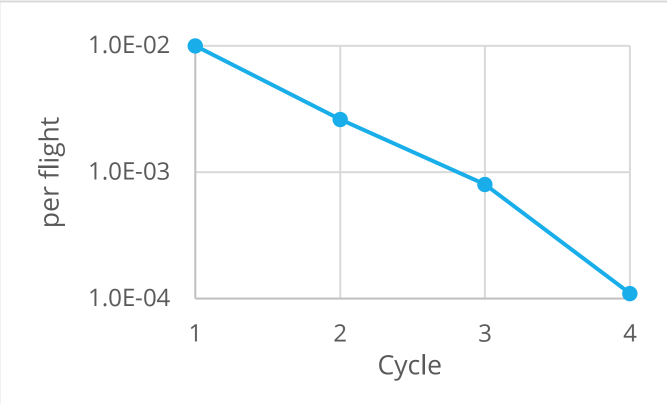

Figure 5: Probabilities of close proximity and collision events in four subsequent IPS cycles

C. PIC Response to DAA

The performance of the PIC in responding to the downlinked DAA advisories is an important factor in the effectiveness of the joint cognitive system consisting of the DAA system and the PIC. The model of the PIC performance includes models for the delay in response and for the response mode. The response delay is chosen from a lognormal distribution. For a sensitivity analysis two settings are used:

- *Slow*: mean delay is 9 s and standard deviation is 3 s (in line with human-in-the-loop simulations of [16]);
- *Quick*: mean delay is 3 s and standard deviation is 1 s.

The response mode distinguishes between a mode where the PIC responds and a mode where the PIC does not respond to a DAA advisory. Given that the PIC responds, there can be three types of PIC response, which are studied in a sensitivity analysis:

- *Altitude Response*: The PIC responds to DAA altitude guidance only;
- *Direction Response*: The PIC responds to DAA direction guidance only;
- *Both*: The PIC responds both to direction and altitude guidance.

Figure 6 shows risk reduction factors for close proximity events (HMD≤50m, VMD≤15m) for the PIC response options in UAS en-route crossing operations at an altitude of 2500 ft and mean time between the flights of 900 s. The risk reduction factor is the close proximity probability for a scenario without DAA divided by the close proximity probability for a scenario with DAA and a PIC response option. It follows that the largest risk reduction is attained if the PIC responds both to the direction and altitude guidance with a small delay. If the PIC would only respond to one of the guidance dimensions, it is more effective to only change altitude than to only change direction.

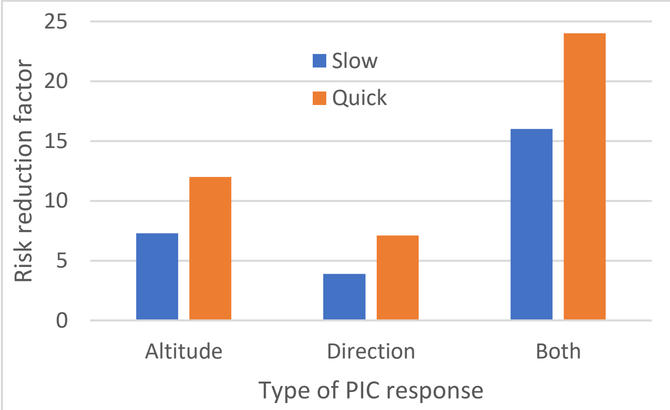

Figure 6: Close proximity risk reduction factors for types of PIC responses to DAA advisories in UAS en-route crossing operations: altitude response only, direction response only, both altitude & direction response, slow and quick response.

VI. Discussion

UAS/UAM operations involve many interacting systems, humans and environmental conditions, including various types of drones and operations, various communication, navigation and surveillance systems, both air- and ground-based, various levels of automation, various levels of human interactions and oversight, and diverse operating environments. The performance, resilience and safety of such complex sociotechnical systems depend on their dynamic interdependencies and their performance variability both in normal conditions (e.g. sensor errors, human reaction time, normal weather) and in off-nominal/failure conditions (system failures, human errors, adverse weather). UAS/UAM operations are based on radically new operational concepts for which there are no or only little data and experience. It has been rightly identified that there is a need for new modelling and assessment methods to analyse and quantify their safety [4].

In this paper we have shown that agent-based dynamic risk modelling and rare event MC simulation approaches can be effectively applied to quantify close proximity safety events of UAS/UAM operations up the level of collision. The models describe various types of operations, airspace designs, customer demand, navigation and dependent surveillance systems, C2 link systems, and PIC behaviour, and they have an interface with the reference DAA system DAIDALUS. The models describe dynamics and stochastic variability of the agents in normal conditions as well as in off-nominal/failure conditions, which can affect the performance of a single agent (local system) or many associated agents (for a global system).

The objective of this study has been to demonstrate the risk assessment methods for UAS/UAM operations and the scope has been limited on purpose. Examples of possible extensions of the scope are: strategic deconfliction of flight plans (thus avoiding peculiar conflicts); tactical conflict resolution by UTM; interaction between UTM and ATM; geofencing systems. This study focused on assessment of the risk of close proximities and collisions between drones. The scope may be extended to other types of risks, such as ground risk, airspace infringement risk, and collision risk with manned aircraft. Also other (e.g. flight-efficiency) indicators may be employed such that the agent-based modelling can be used for studying resilience of drone operations for performance variability in nominal and off-nominal conditions. Other DAA systems may be incorporated, such as ACAS sXu that is being developed for small UAS with hovering functionalities [17]. If the scope is broadened, related agent-based models would have to be extended, e.g. incorporating more complex routes, geospatial models of buildings and obstacles, or population density models.

A limited number of illustrative simulation results have been provided in this paper (chosen from a broader set in [15]), mostly showing the impact on close proximity events by the DAA system and by the type of PIC response. These types of results provide valuable insights in the safety of the UAS/UAM operations, but clearly the particular quantitative results depend on the scope (e.g. excluding strategic deconfliction), on the modelling assumptions, and on the large set of parameter values in the agent-based model. In a quantitative safety assessment of a particular operational concept, appropriate choices have to be made for all these aspects. Nevertheless, at this stage of the development of UAS and UAM concepts, the most important contribution of the agent-based dynamic risk modelling is to provide structured understanding in the safety impact of different choices and settings in a range of operational concepts. Comparison of simulation results for different scopes and sensitivity analysis for variations in parameter settings provide such safety feedback to design and they can provide a basis for the development of operational performance standards.

In conclusion, this paper has shown that agent-based dynamic risk modelling and rare-event Monte Carlo simulation are effective methods for quantifying and analysing levels of safety of UAS and UAM operations. We expect that application and continued development of the models and the D(emo)-CRAT software tool can effectively support understanding and improving the safety of this new era of air transport.

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