AIAA SciTech Forum
6-10 January 2020, Orlando, FL
AIAA Scitech 2020 Forum

10.2514/6.2020-0741

Representative Small UAS Trajectories for Encounter Modeling

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As unmanned aircraft systems (UASs) continue to integrate into the U.S. National Airspace System (NAS), there is a need to quantify the risk of airborne collisions between unmanned and manned aircraft to support regulation and standards development. Both regulators and standards developing organizations have made extensive use of Monte Carlo collision risk analysis simulations using probabilistic models of aircraft flight. We have previously demonstrated a methodology for developing small unmanned aircraft system (sUAS) flight models that leverage open source geospatial information and map datasets to generate representative unmanned operations at low altitudes. This work expands upon previous research by evaluating the scalability and diversity of open source data to support currently needed risk assessments. We also provide considerations for pairing these trajectories with generative manned aircraft models to create encounters for Monte Carlo simulations.

I. Introduction

The U.S. National Airspace System (NAS) is a complex system that supports the safe and efficient operation of air traffic. Both its capacity and ability to maintain safety are stressed by numerous air-carriers, cargo airlines, business jets, general aviation, and most recently, large unmanned aircraft systems (UASs) and small unmanned aircraft systems (sUASs). In order to integrate UASs into the NAS, regulations and standards are required to mitigate collision risks and maintain a sufficient level of safety. Proposed sUAS separation criteria [1–3] have been informed by Monte Carlo simulations, which require the development of UAS specific encounter models.

A. Motivation

Monte Carlo [4] safety simulations have long been a key capability used by the Federal Aviation Administration (FAA) to develop, assess, and certify aircraft conflict avoidance systems that mitigate the risk of airborne collisions [5–7]. Within the simulations, unmanned and manned aircraft behaviors are represented using encounter models, which are statistical models of how aircraft behave during close encounters. They are used to provide a realistic representation of the range of encounter flight dynamics in which an aircraft conflict avoidance system would be likely to alert. Monte Carlo simulations and their associated models are well suited to characterize the performance of surveillance systems, assess the behavior of conflict avoidance algorithms, and estimate overall system collision risk performance [5]. The

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simulations and models are validated through human-in-the-loop simulation and testing or in some cases through flight tests. This analysis approach has been used for standards validation and to support certification, regulatory mandates, and operational approval. For example, the Traffic Alert and Collision Avoidance System (TCAS) 7.1 upgrade [8–10] was validated in part using this approach.

Given the need for Monte Carlo simulations, there is inherently a need for models of sUAS flight. Simulated aircraft should be representative of real-world commercial and civil operations, and it is inappropriate to assume sUAS randomly operate within the airspace. Instead, for instance, railway inspections will be along rail lines, hobbyist operations will tend to cluster over parks and other recreational sites, and golf course surveillance will be over golf courses. To support standards development and performance based requirements, it is advantageous to have a set of realistic reference sUAS encounter models that enables system designers and manufacturers to verify their solutions against the performance standard, while also providing a means for surveillance requirements to be specified by standards developing organizations (SDOs).

B. Scope

The scope of this work was informed by the UAS ExCom Science and Research Panel (SARP), an organization chartered under the ExCom Senior Steering Group, made up of senior managers in eight United States federal agencies – DoD, FAA, NASA, DHS, DOI, DOC, DOJ, and DOE. The SARP's primary goals support UAS integration by focusing on the scientific and technical capabilities of a broad federal technical community and aligning these capabilities with commercial and academic science and research efforts to avoid duplication and reduce cost.

Our research was informed by commercial operational concepts evaluated by the FAA Integration Pilot Program (IPP)* and the UAS test sites. The IPP consists of partnerships between government and private organizations to accelerate safe UAS airspace integration. Across the nine IPP lead participants, a wide range of operational concepts are being evaluated including night operations, flights over people and beyond the pilot's line of sight, package delivery, detect and avoid (DAA), and the reliability and security of data links between pilot and aircraft. While we did not directly participate in the IPPs, we assumed these operational concepts were high priority for industry and regulators. We also assumed routine non-malicious operations (e.g. illegal drug smuggling was not considered). Recreational and amateur UAS operations governed by 14 CFR Part 101, 49 U.S.C. 44809, and AC 91-57B and encounter models representative of these operations [11] were also out of scope.

The scope included United States airspaces with the exception of Classes A and E-above-A. Altitude was restricted to the maximum of 10,000 feet mean sea level (MSL) and 2,500 feet above ground level (AGL). We primarily focused on UAS with wingspans of 25 feet or less, which is similar to or less than the wingspans of general aviation aircraft. This wingspan limit was selected based on the previous separation criteria research by the SARP [2, 3]. We also prioritized sUAS weighing less than 55 lbs maximum gross take-off weight (MGTOW) but did not explicitly exclude heavier UASs. The output of this research could be applicable to aircraft heavier than 55 lbs MGTOW if their operational concepts align with those of current sUASs.

C. Objectives and Contributions

Our overall objective was the development of low altitude unmanned and manned aircraft encounter models to support DAA research. A public, easily accessible corpus of UAS trajectories, however, is not available since beyond visual line of sight (BVLOS) operations are not routine and there is a lack of reporting requirements. Therefore, we seek to generate representative BVLOS UAS trajectories without actual UAS flights as training data. We have previously outlined a sUAS model that takes into account the operational intent of commercial operations and generates trajectories based on open source maps of infrastructure, recreational regions, and other common surveillance targets [12].

This paper makes two primary contributions. The first contribution involves improvements to the UAS trajectory model and an assertion that open source datasets have sufficient coverage and diversity to support UAS Monte Carlo simulations. We do not assert that this approach is sufficient to cover every possible encounter that might be of interest but that it is sufficient for current SDO activities. Second, we provide considerations for pairing these UAS trajectories with generative manned aircraft models to create encounters that can directly support development of a broad range of standards. This work is complimented by other efforts to characterize and model low altitude manned aircraft operations [13] and a closed-form analytic means to assess system performance sensitivity to surveillance performance [14].

*https://www.faa.gov/uas/programs_partnerships/integration_pilot_program/

II. Assumptions, Background, and Review

In this section, we overview encounter models and discuss encounter types and considerations. The concepts described in this section will be expanded upon in the discussion in Section IV.

A. Encounter Model Overview

Encounter models represent not only the geometry but also the aircraft behavior (accelerations) during the course of the encounter. These models have evolved significantly over the past four decades [6, 15–17]. The first of these models was developed in the 1980s. They involved aircraft equipped with transponders that cooperatively share information and allowed only two-dimensional (vertical plane) motion. It was built by the MITRE Corporation utilizing data from 12 radar sites and supported the development and certification of TCAS. The 1990s saw the International Civil Aviation Organization (ICAO) and Eurocontrol lead development of simplified models with three-dimensional motion.

The next major encounter model advancement started in 2006, after recognizing the need for three-dimensional models with multiple acceleration points to support manned and unmanned safety analysis. In response, MIT Lincoln Laboratory (MIT LL) started developing more advanced encounter models to represent a wider range of possible scenarios [18]. There have been five generative models developed to characterize manned aircraft behavior:

- **Uncorrelated Encounter Model of the U.S. National Airspace System:** used to evaluate system performance when at least one aircraft is noncooperative or neither aircraft is in contact with air traffic control (ATC) or such that ATC involvement is unlikely [19]; last updated in 2013 [20].
- **Correlated Encounter Model of the U.S. National Airspace System:** used to evaluate the system performance when both aircraft are cooperative and at least one aircraft is receiving ATC services and such that ATC involvement is likely [21]; last updated in 2018 [22].
- **Encounter Models for Unconventional Aircraft:** used to evaluate system performance when encountering unconventional aircraft, which are unlikely to carry a transponder [23].
- **Due Regard Encounter Model:** used to evaluate systems for UASs flying due regard in oceanic airspace [24].
- **Helicopter Air Ambulance Model:** used to evaluate system performance when encountering a helicopter air ambulance (HAA) [3].

These models have supported studies for many different manned aircraft operational contexts, but there are new considerations for sUAS operations including the lower operating altitudes and interactions with service providers and other users. MIT LL has freely and publicly released the trained generative models and associated documentation. However, trajectories sampled from these models have not historically been released into the public domain.

B. Encounter Types

Generally speaking, there are two types of encounter model [18]: correlated and uncorrelated, where correlation is defined as a dependence between conflicting aircraft due to factors before DAA acts, modeling at least 60 seconds prior to closest point of approach (CPA) for collision avoidance encounters [25] and longer prior to CPA when evaluating other separation criteria. If a sufficient correlation exists, then it must be modeled. The main existing correlation in the airspace that must be accounted for in encounter models is that provided by ATC; however, ATC is not directly applicable to the sUASs under consideration by some standards bodies. It is possible that UAS Traffic Management (UTM) [26] separation services may induce a similar correlation, provided the conflict is made aware to UTM. At least one aircraft would need to be an active participant in UTM, in that a correlation may exist if the UTM service is provided to at least one aircraft in the encounter and the service is aware of and acting in response to the other aircraft. Nevertheless, given that there are currently no accepted or operational UTM services, accounting for UTM correlation in the encounter model would have a high degree of uncertainty.

The encounters are therefore assumed to be uncorrelated. This assumption is helpful in that uncorrelated encounter models do not need to represent the relative geometry and correlation between aircraft trajectories in the model itself. Individual aircraft trajectories can be modeled independently and then combined in a separate encounter initialization process. However, this uncorrelated assumption should be validated as more data becomes available on the impact of UTM. For example, if encounters can be extracted from simulations of UTM strategic or tactical separation services, attributes from those encounters can be evaluated against the assumptions of the manned aircraft uncorrelated model [20]. We further elaborate on how to appropriately sample and model trajectories in Section IV.

C. Encounter Considerations

Foremost, encounter models are necessary to demonstrate the relative airborne collision risk reduction of deploying a DAA capability [6], but they can also be used to stress algorithms or evaluate operational suitability [27]. A stressing encounter set is used to test the robustness of the logic. Given that the encounters that stress a given system are dependent on the attributes of that system, it may not be possible to develop a single standard stressing encounter set, but requirements and/or guidance could be provided. Operational suitability captures the effects of the DAA capability on the external environment, on ATC, and on the remote pilot. Encounter models that are designed appropriately can be used to estimate operational suitability metrics, such as alert rate. An alternate approach to estimating operational suitability metrics is identifying and using observed encounters. However, this is likely not possible here because sUAS operations are not prevalent enough in existing observations, and there may be challenges with releasing such data publicly. Additionally, existing observations may not reflect future options with UTM. Therefore, the requirements and reference encounter set must be appropriately developed to estimate these metrics if such metrics are defined in standard.

Scenario specific encounter sets may be used for verification of specific niche operations. This may include formation, coordinated [28], or other closely spaced operations [29]. Also, although multithreat encounters consisting of one sUAS with multiple manned aircraft are expected to be rare, experience with TCAS has shown that an algorithm must be validated in such scenarios. While there are potential approaches to developing a multithreat uncorrelated encounter set, one has yet to be developed and is scoped as potential future work.

The low altitude operations of sUASs, operating in close proximity to terrain and obstacles (e.g., buildings) will constrain the aircraft response. It is important to verify system performance if the sUAS operates in such a manner. Prior manned aircraft encounter models [18] and sets have not considered terrain, obstacles, or FAA Part 77 imaginary surfaces. For large scale Monte Carlo simulation, we do not recommend explicitly modeling these factors due to the computational expense. Future work is required to determine how to appropriately account for terrain and obstacles.

D. Encounter Initialization

Selecting individual aircraft trajectories is not sufficient to define an encounter. The trajectories need to be paired and spatially oriented. This encounter initialization is significantly dependent upon the intent of the Monte Carlo simulation, so we only overview a few important concepts here.

None of the encounter models include a transponder type state and are nominally sensor agnostic. The only exception is one parameter in the correlated manned aircraft model [21, 22] that is based on barometric altitude observations. We assume a manned aircraft equipped with a Mode C transponder behaves the same as an aircraft equipped with automatic dependent surveillance-broadcast (ADS-B). When designing cooperative encounter sets, a mix of Mode C, Mode S, and ADS-B equipped manned aircraft should be simulated and ideally represent the distribution of transponder types across the intended operational environment.

Encounters need to have a representative time period for different evaluations. With the exception of the correlated manned aircraft model [22], the models do not define the length of the encounter nor the relative geometry at the start of the encounter. For example if evaluating a DAA system that uses the UAS ExCom SARP recommended well clear criteria of 2,000 feet horizontal and 250 feet vertical separation [3], encounters should be initialized with aircraft at least 2,000 feet apart laterally. In general, collision avoidance encounters are assumed to start 30–60 seconds prior to CPA and well clear encounters are initialized longer before CPA. Time to CPA will be dependent upon assumed closing speeds between unmanned and manned aircraft. Closing speed is a function of the aircraft's airspeeds and the difference in their headings.

Since sUASs are not routinely operating BVLOS in the NAS, we cannot estimate the relative speed distribution of encounters between an unmanned and manned aircraft. This is important because encounters between manned aircraft are weighted based upon relative speed. For example, the encounter geometry and dynamics of a head-on encounter is different than that of a crossing encounter. For sUASs, there are two approaches to weighting encounters. The first is to use a uniform weighting, such as used by previous well clear research [3]. This is a more simplistic and conservative approach and makes minimal assumptions regarding airspace composition and encounter geometries. The other approach is to pair unmanned and manned aircraft trajectories and estimate the relative speed distribution based on the simulations. The encounter weight can be based either on the relative speed at the CPA or the average relative speed for the entire encounter. As UASs become integrated in to the NAS, this weighting assumption will be revisited.

III. Representative Trajectory Enhancements

While the specifics may vary, the majority of expected unmanned operations can be characterized as airborne reconnaissance and surveillance or transit missions. Thus, it is important to quantify and characterize potential surveillance targets or transit destination locations. For example, if a cargo drone intends to deliver lifesaving supplies from a hospital, it is important to know the locations of the hospitals. Furthermore, for a post-disaster mission such as after a major flood, it is important to know the locations of dams, levees, reservoirs, etc. We have previously outlined a method for using open source data, such as Open Street Maps (OSM), to generate representative trajectories based on these considerations [12]. This section discusses which trajectories and encounter sets to generate based on a selection of geospatial features and data sources.

A. Feature Source

Given identified features, we select a dataset from which to generate the sUAS trajectories. In our initial model, we used solely OSM,"a knowledge collective that provides user-generated street maps [30]." In this work, we consider other federal and state datasets to assess the nationwide scalability and quality of OSM and whether we need to incorporate these other datasets to support SDO activities. This assessment is represented by Fig. 1 showing water features by the New York UAS test site and Fig. 2 showing electric power lines near Gypsum, KS.

Fig. 1 illustrates the GeoFabrik OSM waterways[†] and the New York state hydrography[‡] datasets. The processed OSM waterways lack many of the smaller tertiary features while the New York state features do not include the major canal running across the region. Both datasets provide sufficient diversity of straight line and curving behavior to support SDO activities. The lack of local tertiary features in OSM is an acceptable trade off for OSM's nationwide coverage and ease of use.

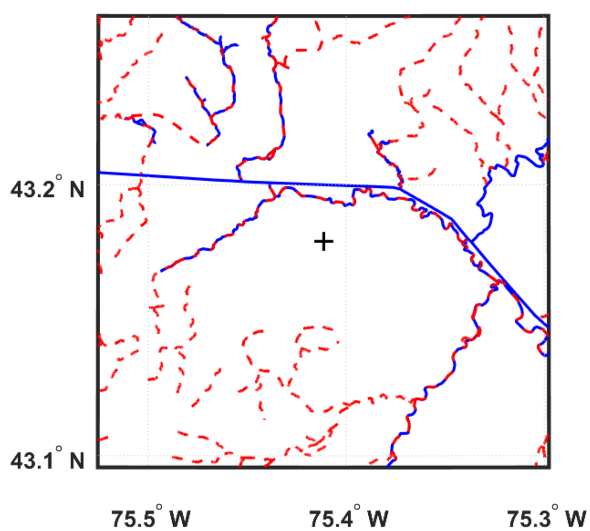

Fig. 1 OSM water ways (solid blue) and state hydrography (dashed red) near the New York UAS test site.

Since OSM does not have sufficient data for all expected sUAS operations, we also assessed the Homeland Infrastructure Foundation-Level Data (HIFLD), which has U.S. nationwide coverage for many critical infrastructure features and use cases [31]. Fig. 2 illustrates the DHS HIFLD electric power transmission lines[§] and Kansas state electric power lines[¶] near Gypsum, KS. The federal dataset includes only transmission power lines operating at relatively high voltages varying from 69–765 kV, whereas the state dataset also includes distribution lines operating at 34.5 kV. As in Fig. 1, while the state features have greater coverage, the underlying behavior of the features is sufficiently similar

[†]https://download.geofabrik.de/north-america/us/new-york.html
[‡]http://gis.ny.gov/gisdata/inventories/details.cfm?DSID=928
[§]https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-power-transmission-lines
[¶]http://www.kansasgis.org/catalog/index.cfm?data_id=276&show_cat=6

between the nationwide and state datasets. This comparison also demonstrates the importance of clearly defining the commercial intent of the simulated UAS; simply asserting that Fig. 2 illustrates power lines can be misleading.

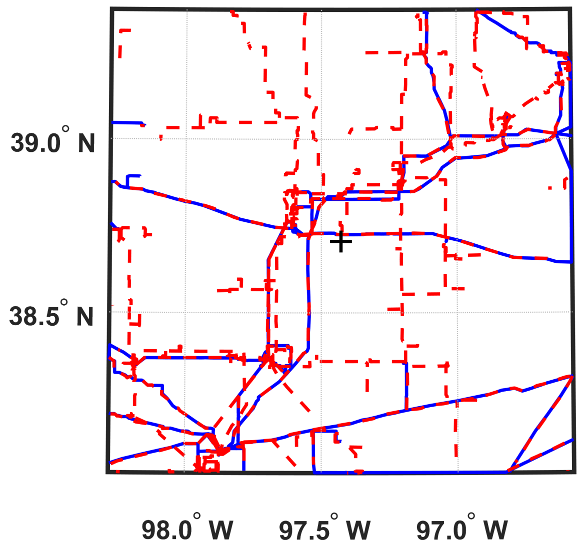

Fig. 2 HIFLD electric transmission lines (solid blue) and state electric lines (dashed red) near Gypsum, KS.

Based on a heuristic comparison of similar features between these datasets, we believe OSM and federal datasets have sufficient coverage and diversity to support encounter model development. A key advantage of OSM is a singular map projection. For the majority of state data, we had to convert from a local state projection, hindering scalability. We also have not yet attempted to merge features from different datasets; this is scoped as potential future work.

B. Trajectory Behavior

Each trajectory is formatted as a set of waypoints, and each waypoint has associated with it the time into the trajectory it should be traversed by the aircraft (assuming a fixed airspeed). Unlike the generative manned aircraft models, these waypoints do not take into account airspeed acceleration and turn rate.

The trajectories seek to maintain a constant MSL altitude and will command a vertical change if the difference between the intended altitude and waypoint altitude is greater than 25 feet in magnitude. This basic terrain following functionality is based on either the NOAA Global Land One-km Base Elevation Project (GLOBE) [32] or NASA Shuttle Radar Topography Mission (SRTM) [33] global digital elevation models. Additionally, physical vectors from Natural Earth Data [34] are used to identify oceanic regions to improve computational efficiency. As noted in Section II.D, we do not assume any transponder equipage and the waypoint altitude should be assumed as truth. We do not estimate geometric or barometric altimeter reports.

For these feature-based trajectories, the aircraft is intended to operate directly over the feature of interest. For example, these trajectories would not be representative of sUAS inspecting well to the side of a higher voltage transmission lines at a oblique angle or below the lines themselves. However, for Monte Carlo simulations to estimate airborne collision risk, these trajectories will be sufficient. A small lateral offset will not fundamentally change the behavior of the trajectory. If such an offset was desired, Maki et al. describes time and space-time offset estimation approaches for estimating airborne collision risk [35].

To generate a trajectory, a path must be computed via interpolation of the waypoints. We let the trajectory implementers decide how to interpolate or smooth between waypoints. To facilitate reasonable interpolations, the maximum allowable spacing between waypoints is 3000 ft. One interpolation method used in previous work is solving an unconstrained optimization problem to interpolate aircraft trajectory data in the terminal airspace [36]. The problem is formulated as:

$$\underset{P}{\text{minimize}} \quad \|AP - \hat{P}\|_F^2 + \lambda_1\|D_2P\|_F^2 + \lambda_2\|D_3P\|_F^2, \tag{1}$$

where P is a matrix containing the position at each timestep and D_1 and D_2 are the second- and third-order difference matrices respectively. A is a diagonal matrix that simply encodes whether or not the position at a particular time was given. This formulation seeks to choose a position at each time step that fits the data while minimizing the overall acceleration and jerk (second and third derivative of position with respect to time). Notably, this interpolation method is different than the piecewise cubic Hermite interpolating polynomial (PCHIP) used for processing data for manned aircraft encounter model development.

C. Example Trajectories

Fig. 3 illustrates a set of trajectories generated for long line linear infrastructure inspection in Nevada HIFLD. Fig. 4 and Fig. 5 illustrate the vertical behavior for these two sets of waypoints. The railway trajectory was based on OSM while the electric power line transmission trajectory was based on HIFLD data. The trajectory shape, distance between waypoints, and total distance varies. Note that the waypoints for the railway inspection are closer during the curves. The electric power transmission inspection travels 36 nm and flies along a low mountainside, necessitating vertical maneuvers to maintain MSL altitude. Conversely the railway inspection runs along the curving yet flat Truckee River and requires only minor vertical maneuvers to maintain altitude.

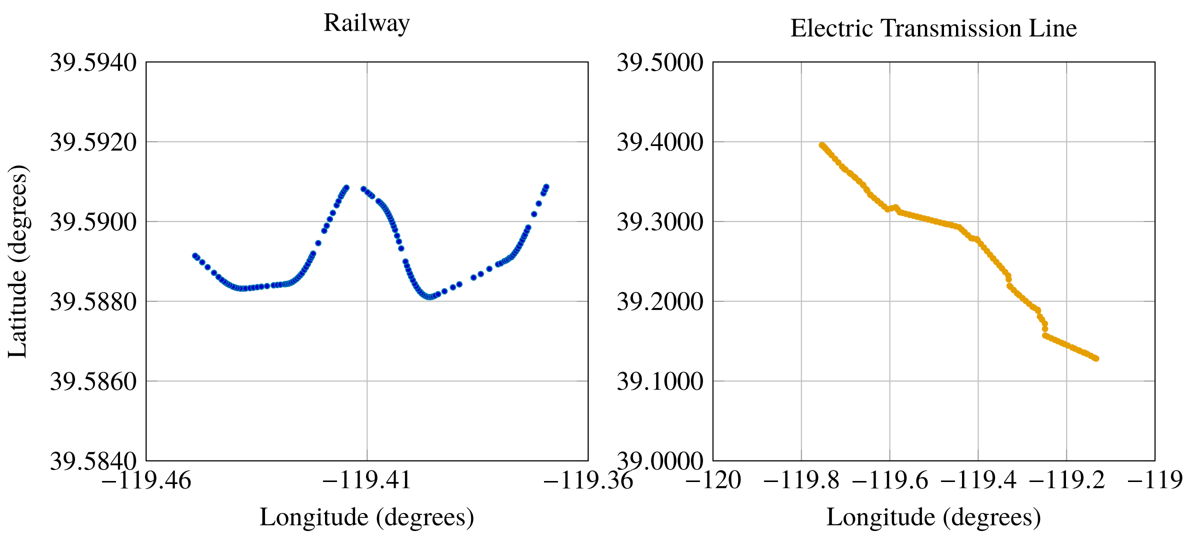

Fig. 3 Example trajectory waypoints for long linear infrastructure inspections in Nevada.

D. Quantity of Avaiable Waypoints Examples

To evaluate the scale of this discriminative model, we generated all potential trajectories across sixteen states and territories of the United States for three long linear infrastructure use cases: the inspection of electric power transmission lines [37], railway inspection based on the UAS Focus Area Pathfinder Program [38], and oil pipeline maintenance [39]. These use cases and locations of Alaska, California, Florida, Kansas, Massachusetts, North Carolina, North Dakota, New Hampshire, Nevada, New York, Oklahoma, Puerto Rico, Rhode Island, Tennessee, Texas, and Virginia were selected primarily based on the FAA IPP and FAA Pathfinder programs. With a maximum spacing of 0.5 nautical miles between waypoints during trajectory generation, Table 1 reports the total waypoints for each use case. The quantities are dependent on both the complexity of the features (e.g. curves are represented by many closely spaced waypoints while straight line segments require less waypoints) and the total mileage of these use cases vary.

As a reference for scale, we can compare the total UAS waypoints to the actual observations (Table 2) used to train the generative manned aircraft models. The scale of just the long linear infrastructure waypoints compares favorably and highlights one of the advantages of identifying the majority of potential trajectories for specific use cases. If UAS flight data became available, it is possible to validate the trajectories with thousands of flight hours.

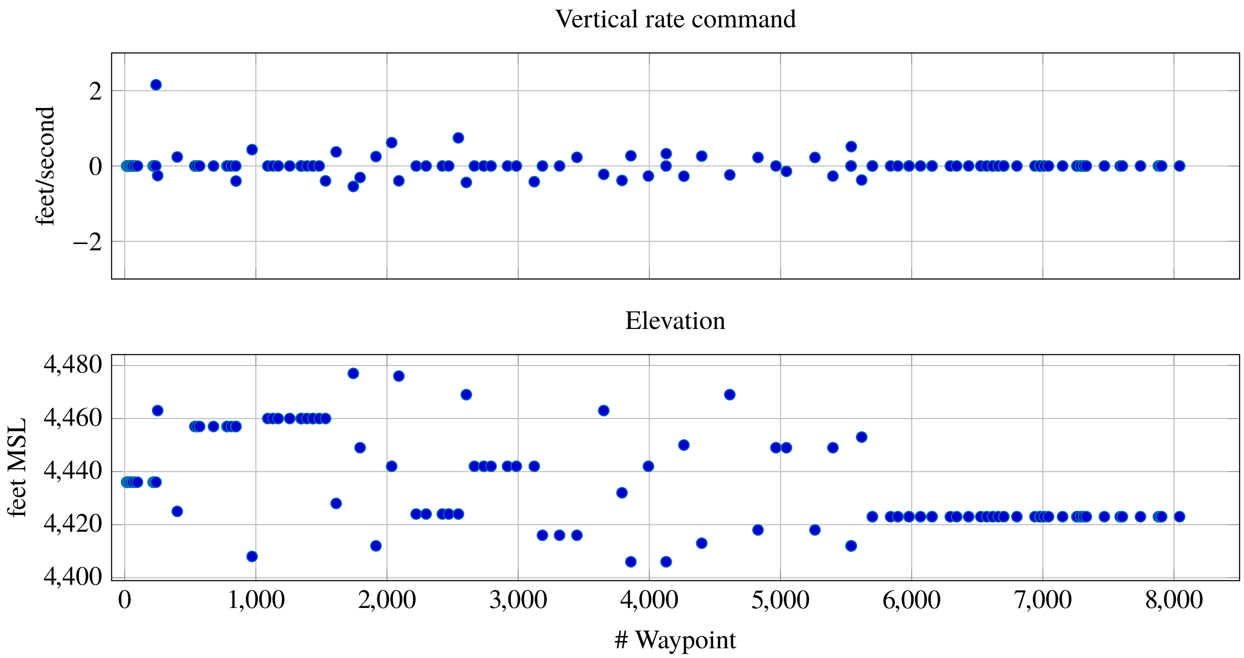

Fig. 4 Example railway inspection vertical trajectory in Nevada.

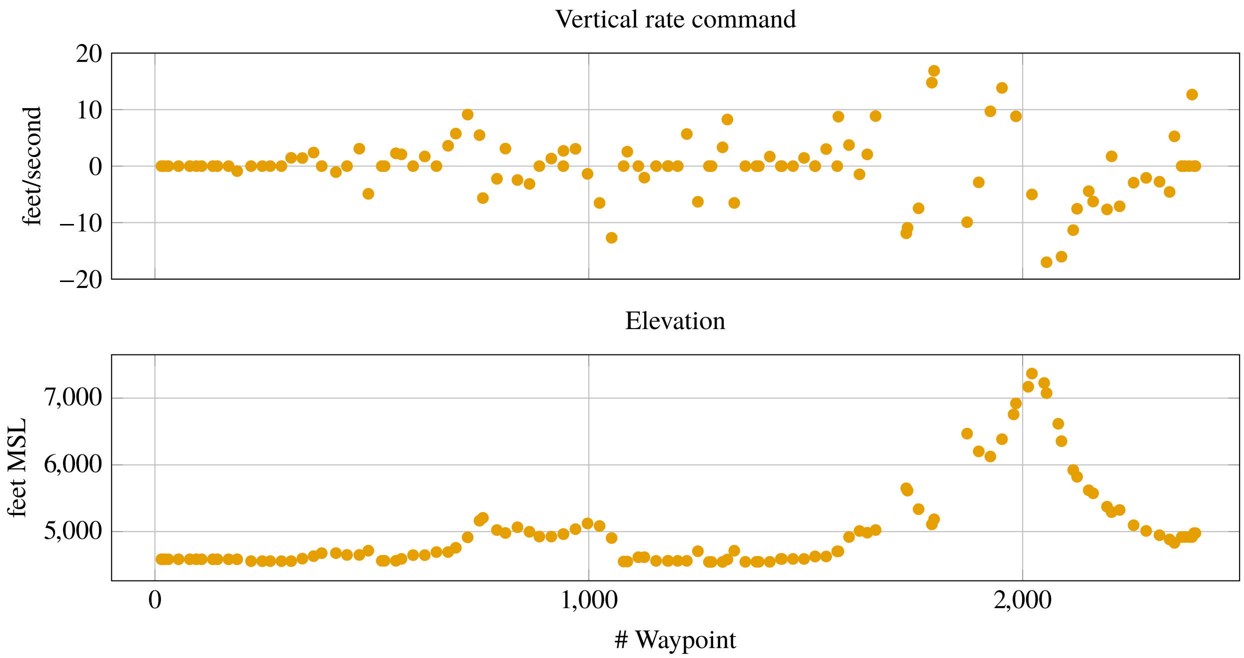

Fig. 5 Example electric transmission line inspection vertical trajectory in Nevada.

IV. Sampling Considerations

For an uncorrelated encounter, a single aircraft trajectory is sampled from an encounter model and paired with a different, separately sampled trajectory. A collection of encounters, often used for Monte Carlo simulations, is referred to as an encounter set. For these encounter sets, there are several considerations relating to SDOs, systems development, and certification processes. These considerations include the intent of the encounter set, quantity of modeled aircraft, and environmental features.

Table 1 Total waypoints for long linear infrastructure trajectories for sixteen states and territories.

Use Case	Total Waypoints
Electric Power Transmission Lines	12,418,028
Regular Railways	4,807,270
Oil Pipelines	947,972

Table 2 Training data for manned aircraft encounter models.

Model	Flight Hours	Update Rate	Observations (Estimated)
Due Regard [24]	10,759	60 s	645,540
OpenSky Low Altitude [13]	310,000	≥ 1 s	241,000,000
Unconventional - Weather Balloons [23]	650	6 s	40,200
Uncorrelated 2.0 - 1200 code [20]	295,000	5 or 12 s	212,400,000

For the encounter to be representative and valid, we pair trajectories with common initial states. For example, an encounter that has a sUAS initialized at 500 feet AGL and another at 5,000 feet AGL would not be appropriate to evaluate a DAA system, as the aircraft are too far apart to ever trigger the DAA system. Commonly used initial variables for the manned aircraft models are:

- **Geographic location** G**:** Different environments in which aircraft operate,
- **Airspace class** A**:** The airspace class in which aircraft operate,
- **Altitude layer** L**:** Airspace is divided into altitude layers.

We also need to account for variables, such as speed (v), that are dependent or implicit in the generative manned aircraft models but explicitly defined for the UAS trajectories. Regardless if a model is generative or discriminative, encounter models should be built using using operational data. Unlike the generative manned aircraft models, there is no inherent probabilistic distribution of these variables when generating representative sUAS trajectories. As noted in Section III.D, we generated potential trajectories based on the available open source features for three use cases in different locations. The set of trajectories represents where sUASs may operate but does not contain values for the frequency or likelihood of specific trajectories within the set.

In response, this section discusses each of the variables outlined above, describing how to sample the unmanned and manned models to generate valid encounters. We base the discussion on generation of an uncorrelated encounter between a sUAS and manned aircraft operating under visual flight rules (VFR), yet the discussion applies to other models as well. Refer to the uncorrelated manned aircraft model documentation [19, 20] for sampling techniques.

A. Geographic Location

The majority of the MIT LL manned aircraft encounter models do not include a geographic variable, as it was shown that there was a negligible sensitivity of the model to location. However, the widely used uncorrelated manned aircraft model [20] does include a sensitivity to location. Uncorrelated aircraft behavior may vary across different geographic regions due to varying weather patterns, fleet mix, navigation equipage, regulations, mission types, and other factors. The geographic variable has four coarse possible states:

- Contiguous United States (CONUS), Alaska, Canada, and Mexico,
- Hawaiian and Caribbean islands,
- CONUS offshore, and
- Offshore from the Hawaiian and Caribbean islands.

For SDO activities, manned aircraft trajectories should be sampled from all geographic states. The manned aircraft airspeed distribution is dependent on the geographic variable, thus the relative airspeed during an encounter will also be dependent. It would be inappropriate to pair a sUAS trajectory representative of remote sensing of Hawaiian coral reefs [40] with a manned aircraft sampled with a CONUS geographic state. However while there are four geographic states, any analysis specific to the FAA IPP should only sample trajectories using the mainland CONUS geographic state.

Generating representative encounters between a sUAS and manned aircraft is straightforward. Simply sample the manned aircraft model and pair the resulting manned aircraft trajectory with a UAS trajectory based on its geographic state. For example, UAS trajectories based on Hawaiian infrastructure should be paired with manned aircraft trajectories sampled with the island's geographic variable. It would inappropriate to pair a UAS trajectory based on Kansas features with the same manned aircraft trajectories. UAS trajectories should be sampled uniformly.

Suppose UAS trajectories were available for all 48 states in the CONUS and Alaska. When sampling this trajectory set, the specific location, such as Kansas or Nevada, should not be taken into account. This is analogous to how the uncorrelated manned aircraft model was trained; it simply matters that the trajectories are within CONUS or Alaska. By effectively sampling over the CONUS, we produce a set of trajectories with a representative distribution of vertical and turn rates. We would expect more vertical rate changes to maintain altitude over the mountains than over the flat plains; and straighter features long the flat plains. The encounter set should reflect this distribution as DAA system performance could be sensitive to vertical rate changes. By considering all CONUS and Alaskan trajectories, the distribution of vertical rate changes is implicitly representative.

Additionally, a short review of island-based sUAS operations [40–43] indicates that using our representative UAS trajectories of structured search patterns based on open source data [12] is sufficient for many island-based use cases. We currently assume a lack of sensitivity to coarse geographic location for uncorrelated UAS trajectories; this assumption maybe revisited in future work.

B. Airspace Class

The uncorrelated manned aircraft model has four potential initial states. Three states represent the FAA airspace classes B, C, and D. The fourth state, O, represents "other airspace," and includes airspace class E and G. When sampling this model, the manned aircraft is initialized to an airspace class and cannot transition into a different airspace class state. The manned aircraft model is then sampled accordingly to the desired distribution of airspace classes.

For the UAS trajectory, instead of sampling a generative model conditioned on an airspace class, each trajectory waypoint needs to be assigned an airspace class. This can be completed using data from FAA National Airspace System Resources‖. Representative trajectories must be filtered such that a sufficient number of consecutive waypoints are within the desired airspace class. For each filtered trajectory, each subset of consecutive waypoints that are within the desired airspace class must be identified. A single trajectory may have multiple sets of appropriate waypoints.

When pairing with the manned aircraft trajectory, the set of all appropriate UAS waypoint tracks should be sampled. We do not recommend selecting a trajectory first and then sampling from its track segments, as doing so will potentially bias the encounter set towards specific trajectories rather than an aggregate behavior. Sampling the complete set of track segments is more analogous to the training of the uncorrelated manned aircraft model.

C. Altitude Layer

All previous manned aircraft generative models divide airspace into altitude layers, similar to the prior models developed by Eurocontrol, which in 2001, had a lowest altitude layer of 1,000–5,000 feet AGL [17]. Specifically, for the uncorrelated [20] and the majority of the unconventional models [23], airspace is divided into four altitude layers. The lowest layer spans 500–1,200 feet AGL and is intended to capture aircraft in the traffic pattern or performing low-altitude maneuvers. The second layer of 1,200–3,000 feet AGL is a transition zone up to where the hemispheric rule begins. The next layer covers 3,000–5,000 feet AGL, where a mix of low altitude enroute and maneuvering aircraft operate. Lastly, the highest altitude is 5,000 feet AGL and above and primarily composed of enroute VFR traffic. Only the recently developed HAA model has a discrete altitude layer below 500 feet AGL, where sUASs operate. In the absence of a fully developed low altitude encounter model (one is in development [13]), the existing manned aircraft models should be leveraged and paired with UASs based on their intended altitude.

D. Airspeed

The encounters should reflect realistic aircraft flight dynamics. For the manned aircraft generative models, airspeed is dependent upon other variables, such as altitude layer; it is not directly controlled or sampled. Since the UAS trajectories are represented as waypoints, intended airspeed must be explicitly defined. As previously demonstrated [3],

‖ `https://www.faa.gov/air_traffic/flight_info/aeronav/aero_data/NASR_Subscription/`

the Association for Unmanned Vehicle Systems International (AUVSI) Unmanned Systems and Robotics Database** can be used to identify and generate distributions of advertised UAS speeds; however this distribution would not be weighted based on actual fleet composition or specific aircraft usage.

Moreover, the uncorrelated manned aircraft model uses true airspeed while the UAS trajectories use ground speed. Due to the scope and emphasis on low altitude airspeed, we assume that true and ground airspeed are sufficiently equivalent for a sUAS. The correlated and uncorrelated manned aircraft models have the same assumption. Additionally, these airspeeds can be used to estimate representative closing speeds when initializing encounters, as discussed in Section II.D.

E. Operational Intent

A key function of Monte Carlo simulations is the exploration of parameter trade spaces by varying, for example, the heading, frequency of heading change, and frequency of vertical rate change. Instead of random heading changes to induce maneuvering trajectories, we generated trajectories across a range of geospatial features relevant to commercial operations to generate realistic maneuvers. Consider that railways are typically straighter than rivers which are generally more meandering. An encounter may evolve differently and result in different performance metrics depending on the operational intent of the trajectory, as illustrated in Section III.C.

An important case would be the assessment of a forward facing radar with a limited field of regard on an aircraft, where the ability to detect and track other aircraft is dependent on the aircraft's relative heading. Therefore a complete Monte Carlo simulation should include trajectories representative a variety of operational intents.

V. Conclusion and Encounter Model Access

This paper describes the further development of a scalable and extendable methodology for generating representative sUAS trajectories operating BVLOS to support fast-time Monte Carlo collision risk simulations. These trajectories can be paired with trajectories sampled from manned aircraft encounter models and enable both operational and safety research efforts. Potential future work consists of finalizing encounter models with SDOs, estimating relative speed distributions across encounters, consideration of terrain, developing representative parcel delivery trajectories, evaluation of encounter geometry dependence on UTM, and assessing the difference between true and observed airspeed. Specifically these future efforts can address needs of the ASTM Committee F38 on UASs†† or RTCA SC-147 on TCAS‡‡.

We are pursuing an open source transition of the encounter models to GitHub.com. GitHub is a service for software development version control and widely used across industries. The GitHub transition aligns with the intended previous technology transition of the encounter models but takes advantage of modern software practices, promotes traceability, and reduces barriers to coordination across organizations. Specifically, the software can be found at `https://github.com/Airspace-Encounter-Models`.

Acknowledgments

We greatly appreciate the support and assistance provided by Sabrina Saunders-Hodge, Karl Garman, Adam Hendrickson, and William Oehlschlager from the Federal Aviation Administration. We also like to thank fellow MIT Lincoln Laboratory staff Dr. Rodney Cole, Randal Guendel, Ian Jensen, Ngaire Underhill and Mykel Kochenderfer of Stanford University.

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**`http://roboticsdatabase.auvsi.org/`

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‡‡`https://www.rtca.org/content/sc-147`

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