Uncertainty in avionics analytics ontology for decision-making support

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With the growing congestion in the airspace, Air Traffic Management (ATM) requires advances in massive data processing, sophisticated avionics techniques, coordination with weather updates, and assessment of multiple types of uncertainty. The complex situation overwhelms pilots and ATM controllers. To provide dependable artificial decision-making support for ATM and Unmanned Aerial System Traffic Management (UTM) systems, ontologies are an attractive knowledge technology. This paper proposes an Avionics Analytics Ontology (AAO) to bring together different types of uncertainties including semantic from operators, sensing from navigation, and situation from weather modeling updates. The approach is aligned with the Uncertainty Representation and Reasoning Evaluation Framework (URREF), that develops an uncertainty ontology. The degree of uncertainty to improve effectiveness in ATM/UTM decision-making processes quantifies information veracity; in addition to accuracy, timeliness, and confidence. Application examples are presented that involves two ATM/UTM operation scenarios where Unmanned Aerial Vehicles (UAVs) fly nearby commercial aircraft and/or airports which requires situation awareness safety response. As compared to a baseline approach without Automatic Dependent Surveillance-Broadcast (ADS-B), results from recorded ADS-B data demonstrate a over 0.75 veracity improvement) from Newark Liberty International Airport.

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1. INTRODUCTION

There has been a growth in the use of ontologies for communities such as medical diagnostics, target assessment, and chemical composition. An area that can benefit from an unified ontology is that of avionics; with only limited reporting for groups interested in supporting the the Federal Aviation Administration (FAA) Next Generation Air Transportation System (NextGen) and the Single European Sky ATM Research (SESAR) systems. The use of ontologies would enhance the coordination between physics-based sensing (e.g., positing and navigation), human-derived communications (e.g., call sign and Notice to Airmen—NOTAMS), and situation reporting (e.g., weather map updates on the cockpit displays). The ontologies support a common taxonomy for reporting to help pilots and Air Traffic Controllers (ATC) make difficult decisions in the context of data, feature, and information uncertainty.

Air Traffic Management (ATM) is growing in complexity as avionics systems are getting sophisticated, airspaces are densely occupied, and air transport is flying in more adverse weather conditions. Overwhelmed aviators, air traffic controllers, and air transport businesses have to prioritize dependability (safety, security, reliability, etc.) in aviation procedures while sharing the airspace with other types of aircraft such as unmanned aerial vehicles (UAVs). Due to the emergence of inexpensive UAVs, accessible from a diverse set of users from the scientific, recreational, commercial, civil and military aviation communities, there is need for a common set of rules (or procedures) for Unmanned aerial system Traffic Management (UTM). ATM/UTM aerospace information management systems need be (1) *efficient* with larger amounts of data, (2) *effective* with combining information from different sources such as weather forecasts, flight profiles, airports, and UAVs, and (3) *relevant* through reducing uncertainty in decision support systems (DSS).

An attractive approach to support decision making in advanced ATM/UTM systems is the implementation of *Ontologies for NextGen Avionics Systems* (ONAS). Ontologies are meant to model cognitive processes by representing and reasoning on knowledge. Following this direction, a proof of concept for an ONAS solution was proposed [1], which has a knowledge-based ATM/UTM architecture for avionics analytics. In this *Avionics Analytics Ontology* (AAO), an ontological database captures information (data along with meaning) as to concepts, entities, and relations in order to build knowledge related to weather, flights, and airspace. The ontology enables artificial reasoning to make decisions based on the knowledge stored and the current situation estimates.

The AAO supports Decision-Support System (DSS) for ATM/UTM to dependably minimize human intervention by making decisions simultaneously based on multiple information inputs. A key issue when designing DSSs is the credibility, reliability, and veracity of the

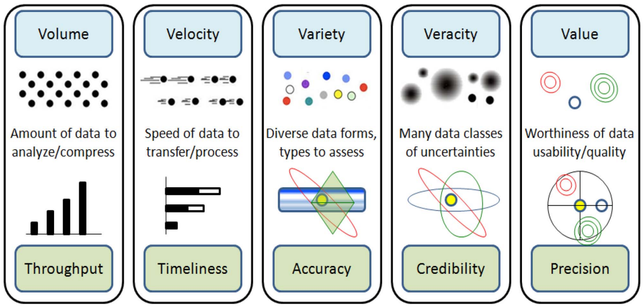

Fig. 1. Big Data Constructs and Uncertainty Metrics

gathered information. Veracity is an element of big data that assesses the truthful of the data and is include in the 4 V's of big data: volume, variety, velocity, and veracity; while other options include value, volatility, and visualization. Veracity can be used to assess the truth of data for such cases are aircraft sensor failures [2]. The alignment of the big data V's and the Uncertainty Representation and Reasoning Evaluation Framework (URREF) are shown in Fig. 1.

This paper proposes to endow the above AAO with semantic uncertainty for input information to improve DSS effectiveness in the decisions taken. The proposed approach is based on the Uncertainty Representation and Reasoning Evaluation Framework (URREF). It deals with the URREF input criterion (i.e., weight of evidence, relevance to problem, and credibility). The ontology development presents *veracity* as part of information *credibility*. The AAO construct captures not only information on concepts, entities, and relations; but also uncertainty of the input information as to its veracity for metadata information. The AAO considers the degree of uncertainty by means of quantitative metrics of throughput, timeliness, confidence, and accuracy. Veracity then includes qualitative metrics such as reliability, credibility, and quality mapped to precision and recall. The URREF assessment enhances avionics DDS analytics when considering semantic and physical data sources. Ultimately, it will enhance Situation AWareness (SAW) as well as Situation Assessment (SA) in information fusion [3].

This paper presents application examples that involve two ATM/UTM operation scenarios where UAVs are flying nearby commercial aircraft and/or airports. The closeness of UAV proximity has an impact on the ATM/UTM decisions taken by the DSS. The DSS provided by the URREF-based AAO takes into account semantics from updates of weather maps, airport maps, and route maps as well as information uncertainty (veracity of the above updates, in particular from flights). The scenarios are meant to represent realistic flight situations since they make use of real-time airspace information provided by a flight tracking service (Flightradar24 [4]).

The rest of the paper is organized as follows. Section 2 recalls existing approaches for ATM. Section 3 reviews supporting and existing technologies and concepts regarding SAW and SA. Section 4 introduces the URREF. Section 5 discusses the AAO foundations for ontological decision-making support in avionics, and the uncertainty scope and considerations for veracity metrics. Section 6 presents applications examples by means of three application examples. The final section presents the conclusions and future research steps.

2. EXISTING APPROACHES FOR AIR TRAFFIC MANAGEMENT

Air Traffic Management evolved with air services and current incorporates three methods: Air Traffic Control (ATC), Air Traffic flow Management (ATFM), and aeronautical information services (AIS).

The approaches to decision support improved with technology, collaboration, visualization, and mandates. For example, in 1982, Pararas developed a modular system using Mixed Integer Linear Programming Language (MILP) modular automation approach for ATM/C that afforded aircraft dynamics, a flexible controller interface, and a real-time terminal area simulation [5]. Many approaches in the 90s sought to use automation for optimization of airspace data to support visualization. In 2000, Ball et al [6] reported on efforts for collaborative decision making using the distribution of the National Airspace System (NAS) status information and the management of en-route traffic flow through optimization with a ground delay program, convective weather forecast, and LAADR (Low Altitude Arrival and Departure Routes) for congestion avoidance. The FAA methods were documented to include decision making, capacity performance, traffic flow, and weather support [7]. Access to the information services in a unified display assists controllers, pilots and dispatchers for a flight management system, as demonstrated by the NASA Multi Aircraft Control System (MACS) [8]. A key element for ATM is the International Civil Aviation Organization (ICAO) air traffic management [9] information that includes traffic flow requirements, separation rules, flight information, coordination routines, message format, phraseology, ADS services, and Controller/pilot Data Link Communications (CPDLC).

ATM decision support systems design sought advances in airspace dynamics developed for monitoring, capacity flow, and scheduling for system wide information management (SWIM), that did not focus on the information services. In 2008, the Sky-Scanner project sought to develop LIDAR sensing for monitoring as an improved decision support system for ATM [9]. The data was utilized with a risk-based approach from the airspace rules to augment capacity flow [10]. Further, the Next Generation Air Traffic Management (NGATM) operational concepts were sought for the Single European Sky Air Traffic Management Research (SESAR) and the United States' Next Generation of Air Transportation System (NextGen) programs which included a 4-Dimensional Trajectory Negotiation and Validation System [11]. The system was to support safety, capacity, efficiency, and the environment. An optimization method for spatial-temporal airspace use was developed to assist in scheduling for intent negotiation. Efforts continue to provide techniques for ATM including: performance based operations, capacity and flow control, efficiency and environmental impact, departure and arrival management, Terminal area (TMA) and surface operation interactions, complexity management, and planning quality.

An analysis of text messages was conducted using a Conflict Probe which predicts potential airspace impending separation violations and a Trajectory Predictor suggesting a more accurate aircraft position [12] The Common Message Set (CMS) relays flight plan, altitude, radar tracking and other data. The message data includes: Flight Plan Information (FH), Flight Plan Amendment (AH), Cancellation Information (CL), Interim Altitude Information (LH), Departure Information (DH), and Converted Route Information (HX). A Java En Route Development Initiative (JEDI) software was used to translate the message types for separation error prediction [13]. However, researchers have yet to focus on the semantic analysis of the meaning of the messages as an information service. The need for an ontology was highlighted by Koelle and Strijland [14]. NASA sought to development an otology as evidenced in the slides [15] and the current version is released as the NASA Air Traffic Management Ontology (atmonto) [16]. To the best of our knowledge, no reports can be found of a literature publication using the NASA ATM ontology.

3. DECISION-MAKING SUPPORT IN AVIONICS ANALYTICS

This section reviews supporting and existing technologies and concepts regarding SAW and SA in support of the analysis towards the URREF.

A. Situation Awareness

The decision-making process is based on the four-stage loop called Observe-Orient-Decision-Act (OODA) [17]. The OODA loop is essential for situation aawareness assessment in information fusion [18]. Fig. 2 shows a SAW model.

SAW allows systems to understand dynamic and complex environments, and operate with them. Cognitive SAW can be divided into three separate levels: perception of the elements in the environment, comprehension of the current situation, and projection of future status [18].

The concepts of the OODA loop enable a processing of information. The Observation stage is the SAW perception level. The Orientation stage takes into account the information acquired from the Observation stage and the knowledge represented by the ontology, to understand the situation (SAW comprehension level).

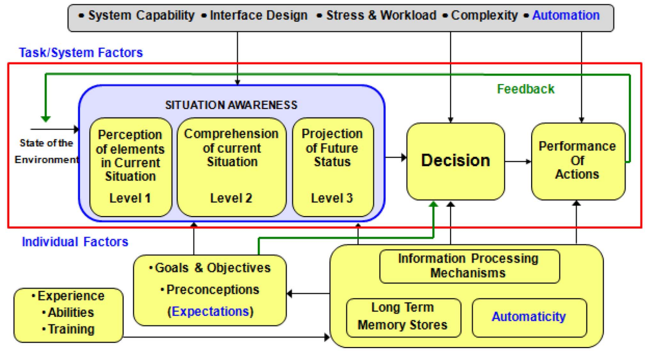

Fig. 2. Situation Awareness (SAW) Model

Level 0 – Data Assessment
Level 1 – Object Assessment
Level 2 – Situation Assessment
Level 3 – Impact Assessment
Level 4 – Process Refinement
Level 5 – User Refinement
Level 6 – Mission Management

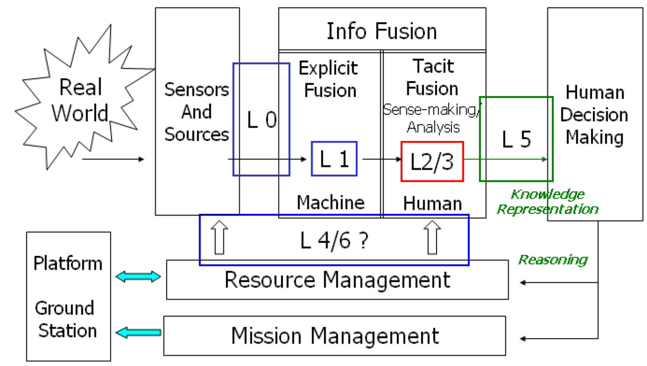

Fig. 3. Data Fusion Information Group (DFIG) model

The Decision stage is carried out at the SAW projection level. The Action stage closes the OODA loop by carrying out actions according to the adaption made in the previous stage.

SAW involves the events, states, condition, and activities of the environment dynamics as to time and space from which some situations arise (in particular those changes that occurred in the environment over some time interval). A *situation* is defined by a specific state after a sequence of events (with intermediate states, and activities with pre and post conditions). The situation is concerned with the comprehension of the environment features, and with the evolvement of these features over time.

SAW decision making mechanisms are critical for problem-solving processes that are preformed every time step for a situation from which data is collected at level 0 information fusion according to the Data Fusion Information Group Model [19], [20].

B. Situation Assessment

Situation assessment takes place at level 2 (SAW comprehension) in data fusion models. The Data Fusion Information Group Model levels include (Fig. 3):

In the DFIG model, the goal was to separate the information fusion (IF) (L0–L3) and resource management (RM) functions (L4–L6) [21], [22].

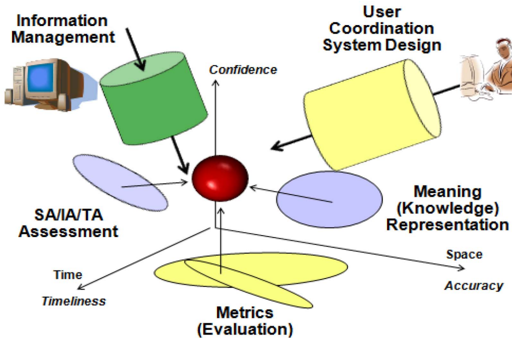

Fig. 4. Situation Uncertainty

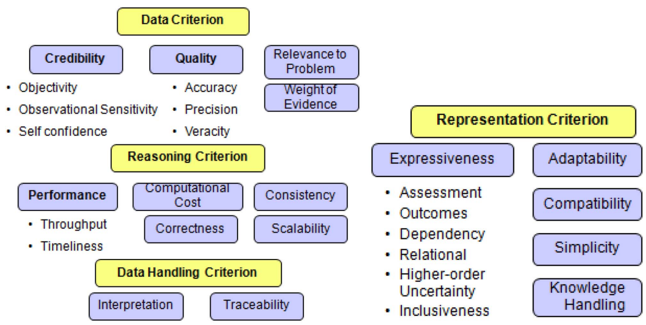

Fig. 5. URREF Categories

For UTM systems, there is both the resource management across sensors, users, and the mission (SUM) to coordinate with the objects, situations, and threats. The elements of the airspace need to be provided to air traffic controllers for enhanced SAW. Two integral concepts for Level 5 "User Refinement" information fusion are displays to support usability [23] and information management systems that are trustworthy [24].

Uncertainty of a situation is based on information, assessment, and knowledge (shown in Fig. 4).

A binding element between the levels of fusion to reduce uncertainty is an ontology [25], [26]. The URREF model provides an ontology that supports the interaction between low-level information fusion (LLIF) and high-level information fusion [27].

4. UNCERTAINTY REPRESENTATION AND REASOING EVALUATION FRAMEWORK

The URREF was developed and used for analysis over imagery [28], detection [29], and text data [30]. The URREF supports uncertainty analysis [31] such as for trust [32] applications. The URREF can advance methods for image quality [33], object recognition [34], and object tracking [35]. Inherently, it is the ontology of metrics of uncertainty that can support DSS.

Recent efforts include applications for rhino poaching assessment [36], maritime anomaly detection [37], and cyber analytics [38]. The URREF developments are meant to support decision making [39] and context [39]. The ontology can resolve the decades old problem of

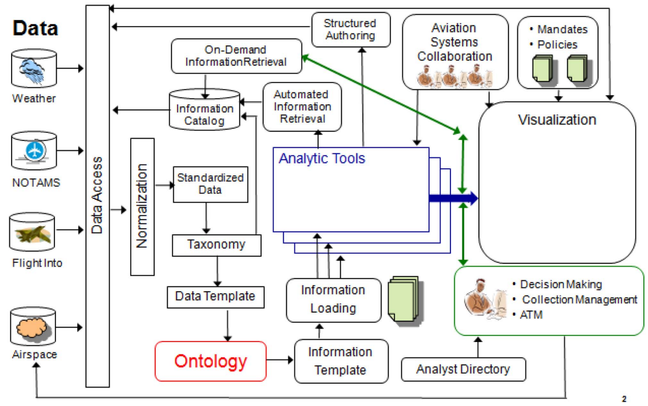

Fig. 6. Use of Ontologies for avionics analytics

relevance metrics in Simultaneous Tracking and Identification (STID) methods [40, 42].

A. URREF Ontology

The key elements from the URREF include data quality issues of accuracy, precision, and veracity (as shown in the current categories of the URREF in Fig. 5) within an OODA architecture. While accuracy and prediction have been explored, *veracity* requires further inspection. More details on the URREF are available at the Evaluation of Technologies for Uncertainty Representation (ETUR) working group (http://eturwg.c4i.gmu.edu/).

B. Ontologies for Air Traffic Management

There is an emergence of interest of the use of ontologies for ATM and aerospace technologies [43–48]. Examples include the Federal Aviation Administration (FAA) Next Generation Air Transportation System (NextGen) [49] and the Single European Sky ATM Research (SESAR) [50] systems. In order to frame the discussion, Fig. 6 highlights an example of how ontologies are included in an avionics system analysis. Using the incoming data from weather, flight profiles, and airports; that data needs to be accessed and normalized. Structuring the data is enabled with templates and ontologies. The structured ontology organizes the information (including syntactic and semantic metadata) for analytic tools. The resulting analytics supports visualization for aviators and Air Traffic Controllers (ATCs). Examples include mandates, current reports, and airspace information. Hence, ontologies afford a common method to organize, process, and share data.

For air traffic management, System Wide Information Management (SWIM) including the ATM Information Reference Model (AIRM) [51], the Information Service Reference Model (ISRM), and the SWIM Technical Infrastructure (SWIM-TI) are being developed [52]. The concept of SWIM is an emerging concept to manage information for aviation systems for various ATM networks [53]. The SWIM approach defines concepts for ATM as well as specifies what kind

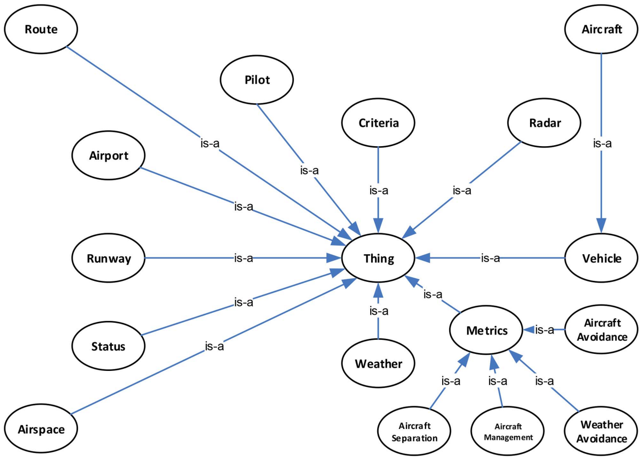

Fig. 7. Main OWL components of the AAO

of information has to be shared, and what stakeholders have to share such information [54]. An AIRM example requiring ontologies is semantic filtering of notices to airmen [55].

Key developments for SESAR and NextGen include the potential for ontological capabilities.

5. ONTOLOGY AND UNCERTAINTY

This section presents foundations of the AAO and the integration of URREF in the AAO to include uncertainty.

A. Avionics Analytics Ontology

The syntax (symbols and rules) of the Avionics Analytics Ontology (AAO) is based on the Description Logic (DL) syntax structure. However, the implementation language for the ontology ultimately defines the syntax to semantically specify and describe ontology elements. The OWL and the Protégé tool [56] are selected to realize the ontology for the approach proposed.

The main OWL components to be created are the concepts (classes), properties for individuals, and instances of classes (individuals) are shown in Fig. 7. These components are set for AAO as follows:

- *Classes (concepts)*. They are conceptually defined as classes (special datatype) in object-oriented programming languages. Thus, they can be atomic classes (stand-alone ones) or associate classes (subclasses) along with "is-a" links. The main AAO classes are: vehicle (aircraft), radar, criteria, pilot, route, airport, runway, status, airspace, weather, and metrics. Fig. 5 shows the above is-a relations between classes.
- *Properties (roles)*. They are basically relationships between classes (or eventually individuals). The OWL allows for properties on objects (based on classes) or data (specific values). The first version of AAO only includes properties for objects as follows: hasRadar, hasPilot, hasRoute, hasTakeoff, hasLanding, hasAirspace, hasRunnay, hasStatus, hasVeracity, and hasWeather.
- *Individuals (instances)*. They are instances of classes (objects), e.g. a Boeing 747-800 is an individual (instance of the class "aircraft").

The main AAO classes are:

- *Aircraft* (as a subclass of *Vehicle*): any type of aircraft falls into this category, including manned and unmanned fixed-wing or rotatory-wing air vehicles.
- *Route*: all the air corridors (as a collection of waypoints) for different airspace regions for aircraft falls into this category. They are defined by departure point to arrival point. However, no specification of waypoints is required for this first version of AAO.
- *Airport* (as a subclass of Aerodrome): all the aerodromes mostly for commercial air transport fall into this category. They are distinct from aviation airfields and military airbases.
- *Runway*: any runway from aerodromes falls into this category, runways have an identification code.
- *Status*: the class "Status" in the AAO is only defined to define the condition of runways.
- *Airspace*: any aerial region above a territory (portion of the atmosphere) controlled by a country.
- *Weather*: all weather conditions falls into this category.
- *Criteria*: the criteria defined in section 4.B is notated in this category. This class is from the URREF and it is actually the link between the AAO and the URREF. A subclass of *Criteria* is *Veracity*.
- *Radar*: all types of radar used in aeronautics falls into this category.
- *Metrics*: the metric assessment as defined in section 4.B falls into this category.

Table I presents AAO classes, examples of their instances, and some properties associated to them. Appendix A shows details of the hierarchical structure of the AAO.

DL operators are considered as different types of property restrictions in ontologies: quantifier restrictions such as existential and universal restrictions, hasValue restrictions (counting operators such as "less than or equal to" and "more than or equal to"), as well as cardinality restrictions such minimum and maximum cardinality restrictions. Also, complex classes can be created by means of simpler classes described based on logical operators like "*or*" and "*and*".

Property restrictions along with classes and individuals are the building block to define axioms. Terminological axioms (usually based on operators such as inclusion, equivalence, etc.) are in the TBox, e.g., "Aircraft_A *subclass of* AircraftcannotLand *and* AircraftcanTakeoff", and "ClearSky *subclass of* GoodWeather *and* VeryGoodWeather". A set of assertional axioms (facts or assertions) are in ABox, e.g., "AircraftcanLand *equivalent to* Aircraft *and* (hasRoute *only* Landing)", and "VeryBadWeather *equivalent to* Weather *and* (Tornado *or* microburst)".

TABLE I.
Examples of the AAO Classes, Instances, and Properties

Class	Subclass	Instance	Property: Class	Property: Instance
Vehicle	Aircraft (Aircraft_x is a subclass of Aircraft)	e.g. B787 is an instance of Aircraft_x	hasRoute hasPilot hasPeople hasRadar hasSystem	hasWingspanValue
Route	Route_A	e.g. LAX-DWF is an instance of Route_A	hasAirspace hasTakeoff hasLanding hasNearbyAirport hasAirport	
Airport	Airport_II	e.g. LAX is an instance of Airport_II	hasRunway	
Runway	Runway_IA	e.g. 18L/36R is an instance of Runway_IA	hasStatus hasLanding hasTakeoff hasAirspace	
Status	Available Unavailble			
Airspace	Airspace_IV	e.g. USAAirspace airspace is an instance of Airpace_IV	hasWeather	hasSeparation
Weather	BadWeather	e.g. NewarkWeather		
Criteria	Veracity	e.g. Very low veracity	hasVeracity	
Radar	LWRS SWRS AWRS T-KFJK F-KNEL F-KEWR	e.g. JFKRadar	hasStatus	hasSensitivity
Metrics	WeatherAvoidance AircraftAvoidance AircraftManagment AircraftSeparation		hasWingspanValue	

The ABox and the TBox form the AAO knowledge base and are shown in Fig. 8. Details of the TBox and ABox axioms are shown in Appendix B.

Reasoners are the engine for the knowledge-based queries. They not only apply inference rules but also check semantic consistency on ontologies. These reasoning engines are able to deduce logical questions from axioms defined in ontologies. Fig. 9 shows the asserted classes of the AAO, including the added concepts (Criteria and Radar) and their relations.

Aircraft have radars (that detect them) which in turn have veracity for the information provided by them. Aircraft also have aairports and routes.

Fig. 10 shows the inferred classes of the AAO as result of executing the reasoner. This figure shows some example of AAO inferences as follows (from top to bottom). Airport I, II, and III are take-off and landing airports (aircraft can take off and land). Airspace I, II, and IV are flying airspace. Route C and D have landing. However, Route D has no take-off. Aircraft C and D can land in their corresponding airports. Bad weather includes storms and thunderstorms.

B. Semantic Uncertainty

Semantic uncertainty in the context of this paper is achieved by means of endowing the AAO with the URREF. Thus, the AAO is combined with the URREF ontology. The focus is on the input information coming from the ATM sensing systems (in particular, the land radars) which is taken into account through the URREF *InputCriteria* concept. The approach particularly targets *Veracity* (in sensed data) as one of the key concept from the URREF to establish the *Credibility* concept (URREF class).

The DSS provides ATC operators with ontological decision-making support based on the sensed data and

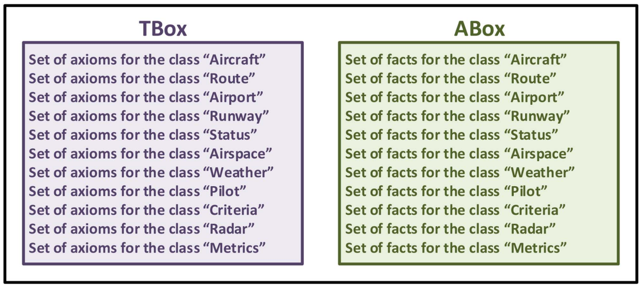

Fig. 8. AAO knowledge base: TBox and Abox (only new axioms and facts)

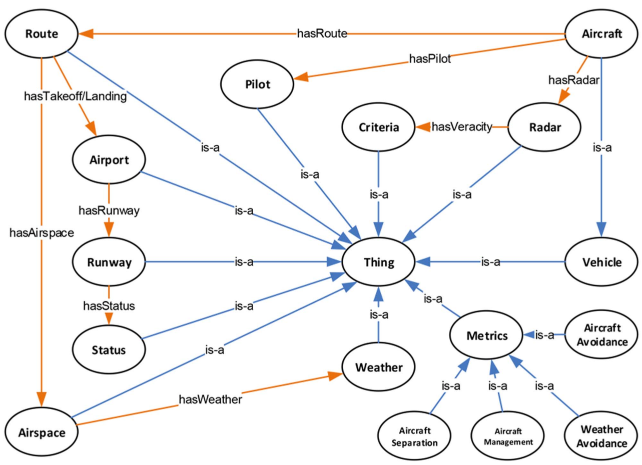

Fig. 9. Asserted AAO classes

processed information. The veracity of the input has an impact on decision outcomes, and it is the main driver for right decisions to be taken. Hence, veracity is important to be researched for valid analysis in the AAO. Thus, the URREF-endowed AAO is expected to improve DSS accuracy, and ultimately DSS effectiveness when decisions are taken by the AAO to support ATC operators.

Veracity metrics are based on the confusion matrix. This matrix is a "true" table that allows for definition and specification of true positives, false positives, true negatives, and false negatives when classifying possible outcomes from a process. Confusion matrices are useful for assessment of sensing systems, in particular for detection of objects/targets, e.g. radars detecting aircraft.

The above statistical classification approach is well known and used in other domains such as machine learning to analyse system accuracy by deferring and identifying elements. Hence, the confusion matrix approach of veracity assessment is attractive for predictive analytics and its statistical measures utilizing well-known attributes of: Sensitivity, Accuracy, Precision, Credibility, and Timeliness.

Typically, these statistical metrics include correlation and normalization for a probabilistic measure. Using probability theory affords Bayesian estimation, and filtering techniques.

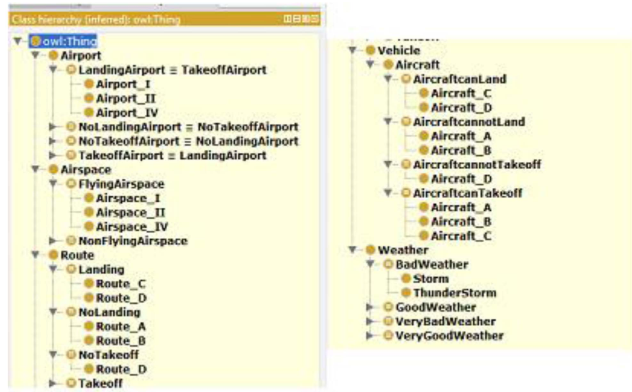

Fig. 10. Inferred AAO classes

The metric approach considered in this paper only focus on the source sensitivity (i.e., the sensor's which comes along with proximity range to the target) to estimate veracity. Thus, the veracity of the sensed data is estimated based on the sensor's sensitivity (*ObservationalSensitivity* subclass of the URREF *Credibility* class), and the range (distance between the sensor and the weather condition). A radar is the sensor in question in this paper. The spectrum defined for ObservationalSensitivity is as follows:

- 0–5%, Very low sensitivity.
- 5–25%, Low sensitivity.
- 25–70%, Regular sensitivity.
- 70–95%, High sensitivity.
- 95–100%, Very high sensitivity.

The radar's range is as follows:

- <50 Km, Very close range.
- 50–150 Km, Close range.
- 150–250 Km, Medium range.
- 250–400 Km, Far range.
- >400 Km, Very far range.

The above radar's sensitivities are combined with the radar's ranges as radars are located at different distances from what is sensed. This combination allows for the estimation of the veracity of the gathered information. This actually has an impact on the veracity metrics. The veracity metric is calculated as follows:

$$V_R = S_R \times R_R \tag{1}$$

Where V_R is the veracity, S_R is the sensitivity, and R_R is the range of the radar. This veracity is notated in the AAO in the URREF class *Veracity* by means of the following subclasses: *VeryLowVeracity*, *LowVeracity*, *RegularVeracity*, *HighVeracity*, and *VeryHighVeracity*. Likewise, the individual veracity for each radar is assigned to the property (object property) *hasVeracity*.

6. APPLICATION EXAMPLES

This section presents application examples of the approach proposed in this paper. They are based on realistic scenarios.

Fig. 11. Area of interest in the US airspace

A. Operation Context

The case study is meant to be as realistic as possible. It involves a dataset from a flight tracking service (Flightradar24 [4]). The dataset records all flights of aircraft with ADS-B transponders. It has 390,607 records generated between 17:00 and 18:00 UTC on 1st April 2017 (approx. 109 records streamed per second). Nevertheless, there is about a revisit rate of 30 second on every aircraft.

The airspace area of interest (Fig. 11) is that from the US airspace, entailing arrivals/departures from the north of Newark Liberty International Airport (code EWR). Three radar systems are considered for the case study: the F-KNEL1 radar from Lakehurst Maxfield Field Airport (code NEL), the T-KJFK16 radar from John F. Kennedy International airport (code JFK), and the F-KEWR1 radar from EWR.

Each of the above radars can cover the above area. However, they usually track aircraft depending on how far aircraft are from the radars and what is the destination of the flights. F-KNEL1 belongs to a military airfield in New Jersey and usually tracks aircraft approaching from or departing to the US east coast. T-KJFK16 tracks landed or arriving/departing flights in JFK. F-KEWR1 tracks landed or arriving/departing flights in EWR. Additionally, EWR has weather updates (from weather forecast and radars) to assist aircraft when lading or departing.

The case study considers Flight BA185, a British Airways flight from London Heathrow (code LHR) to EWR, that is planned to land in EWR. The FAA defines airplane design groups according to aircraft wingspans. The BA185 airplane is a Boeing 777-200, which belongs to group V (52–65 m of wingspan). Table II presents the details for Flight BA185 obtained from the Automatic Dependent Surveillance-Broadcast (ADS-B) dataset.

Two airspace situations are considered when Flight BA185 is approaching EWR: Scenario 1 entails weather conditions ahead of Flight BA185, and Scenario 2 entails potential collision of Flight BA185 with UAVs.

TABLE II.
FLIGHT BA185 DETAILS

Dataset Record						
Time (UTC)	Latitude	Longitude	Altitude	Heading	Speed	Radar
17:01:59	40.7683	−74.5569	5675	177	299	F-KNEL1
17:03:56	40.6111	−74.543	5100	168	269	F-KNEL1
17:07:57	40.4859	−74.348	3075	62	183	F-KNEL1
17:10:09	40.5561	−74.251	2900	25	173	F-KNEL1
17:10:24	40.5667	−74.2442	2650	25	170	F-KNEL1
17:11:00	40.5925	−74.228	2075	26	161	F-KNEL1
17:11:27	40.6088	−74.2176	1700	25	135	F-KNEL1
17:11:54	40.6248	−74.2076	1375	25	138	F-KNEL1
17:12:40	40.651	−74.191	800	26	133	T-KJFK16
17:16:01	40.6991	−74.1669	0	275	30	F-KEWR1

B. Scenario 1: Aircraft in Weather

The first scenario considers Flight BA185 approaching EWR for landing (17:01:59–17:10:09 UTC in Table I). The airplane has descended (altitude 5675 feet) down to 2900 feet in such a period. Flight BA185 took off from LHR and is scheduled to land in EWR. Weather conditions are assumed to be deteriorated in the north of the US east coast. However, the weather is good for landing in EWR.

The information provided by the weather forecast from Satellite Weather Radar Systems (SWRSs) and Land Weather Radar Systems (LWRSs) are considered accurate and true. They have a high sensitivity although the later are considered to have slightly lower sensitivity than the former. Additionally, commercial airplanes are equipped with an Airborne Weather Radar systems (AWRSs) (located in the aircraft nose) which allows for detection of the intensity of convective weather conditions such as massive hails, powerful lighting, and excessive precipitation (strong downdraft), e.g. microbursts. This alternative weather radar source is considered to have the highest sensitivity (of the three weather radars) when the weather in question comes from the area ahead the airplane. Thus, it is used as a very credible reference for the calculation of veracity metrics and the sensitivities for weather forecast are assumed as follows:

- AWRS sensitivity ($S_{AWRS} = 0.99$)
- SWRS sensitivity ($S_{SWRS} = 0.75$)
- LWRS sensitivity ($S_{LWRS} = 0.55$)

The above weather radar sensitivities are combined with the radar ranges as radars are located at different distances from the weather condition. Thus, veracity metric is calculated as follows:

$$V_{xWRS} = S_{xWRS} \times R_{Xwrs} \tag{2}$$

Where V_{xWRS} is the veracity, S_{Xwrs} is the sensitivity, and R_{xWRS} is the range of the type of radar x (A: airborne, S: satellite, and L: land).

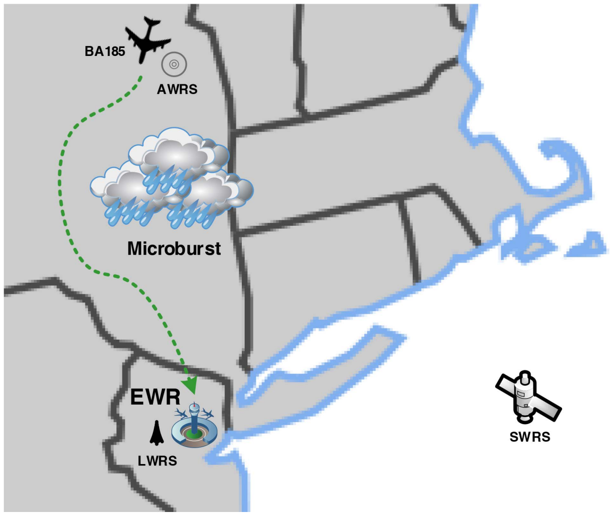

Fig. 12. Scenario 1 in the airspace area of interest

Absolute weights (100) for radar ranges are considered in scenario 1 depending on their distance to the weather condition. The following weights are assumed for AWRS range (the closest to the weather condition).

R_{AWRS} = {Very close = 100, Close = 0, Medium = 0, Far = 0, Very Far = 0}

Then,

$$V_{AWRS} = S_{AWRS} \times R_{AWRS} = 0.99 \times 100 = 99\%$$

Therefore, for AWRS 99% (True) and 1% (false).

The following weights are assumed for SWRS range (the closest to the weather condition).

R_{SWRS} = {Very close = 0, Close = 100, Medium = 0, Far = 0, Very Far = 0}

Then,

$$V_{SWRS} = S_{SWRS} \times R_{SWRS} = 0.75 \times 100 = 75\%$$

Therefore, for SWRS 75% (True) and 25% (false).

The following weights are assumed for LWRS range (the closest to the weather condition).

R_{LWRS} = {Very close = 0, Close = 0, Medium = 100, Far = 0, Very Far = 0}

Then,

$$V_{LWRS} = S_{LWRS} \times R_{LWRS} = 0.55 \times 100 = 55\%$$

Therefore, for LWRS 55% (True) and 45% (false).

Scenario 1 also supposes Flight BA185 and the ATC in EWR are concerned about the weather condition (microburst) when approaching the EWR airport from the northeast. Fig. 12 shows the above scenario 1.

The information provided by the AAO can be visualized by ATCs to support their decisions on the above situation (also, aviators and pilots of remotely-piloted aircraft could make use of this information). They can run AAO queries as to the weather condition in proximity (ahead) of Flight BA185 airway. This also provides suggestions about what to do with Flight BA185 to avoid any potential risk that jeopardize the flight safety. The query is regarding possibilities for an airplane (Flight BA185 in this case) to encounter adverse weather conditions that make aircraft change their route. The rerouting possibilities are:

- Very low chances of re-routing (0–19%),
- Low chances of re-routing (20–39%),
- Medium chances of re-routing (40–59%),
- High chances of re-routing (60–79%), and
- Very high chances of re-routing (80–100%).

The above rerouting possibilities are directly related with the radar veracities as calculated for V_{xWRS}. Thus, V_{AWRS} means a very high chance of re-routing, V_{SWRS} means a high chance of re-routing, and V_{LWRS} means a medium chance of re-routing if a microburst is detected by the above radars.

Fig. 13 shows AAO query results including veracity metrics (top of the figure) for scenario 1 along with AAO queries for each of the radars that detects the weather condition (bottom of the figure). The weather information is provided by three weather radars: AWRS (onboard the Boeing 777-200, i.e. Flight BA185), SWRS (weather forecast), and LWRS (from EWR). AWRS is the most veracious radar (S_{AWRS} = 0.99 and R_{AWRS} = 100; very close)) for this weather condition (NewarkWather_1) since such a radar is closely placed near the weather situation. SWRS is less sensitive and is further (from the weather condition) than AWRS (S_{SWRS} = 0.75 and R_{SWRS} = 100; close), and LWRS is the least sensitive and the furthest one (from the weather condition) of the three weather radars (S_{LWRS} = 0.55 and R_{LWRS} = 100; Medium). Therefore, the veracity of the query is 100% when the weather information is from AWRS, the veracity of the query is 75% when the weather information is from SWRS, and the veracity of the query is 55% when the weather information is from LWRS.

The query inference results (from Fig. 14) suggest that (from left to right):

1. Flight BA185 must slightly change route (to avoid weather condition; NewarkWather_1) on its way to EWR for landing (very high chance of rerouting). The veracity of this query is based on a veracity of 99%, i.e., when AWRS detects the microburst weather condition ahead of Flight BA185. This suggestion is the most veracious out of the three suggestions.
2. Flight BA185 should slightly change route on its way to EWR for landing (high chance of rerouting). The veracity of this query is based on a veracity of 75% when SWRS detects the microburst weather condition ahead of Flight BA185. This suggestion is less veracious than suggestion 1.
3. Flight BA185 could slightly change route on its way to EWR for landing (high chance of rerouting). The veracity of this query is based on a veracity of 55% when LWRS detects the microburst weather

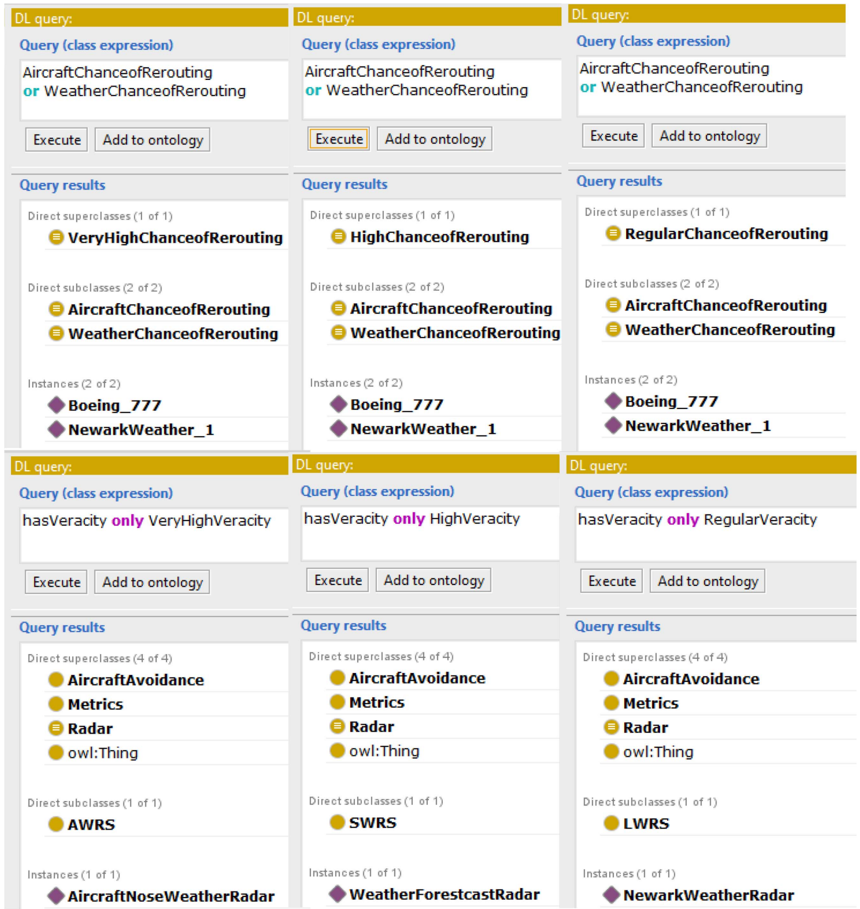

Fig. 13. Querying results to assess situation in scenario 1

condition ahead of Flight BA185. This suggestion is most less veracious of the three suggestions.

Fig. 14 shows the reasoning path (in green colour) followed by the reasoner to determine the AAO query results ("aircraft chance of Rerouting" and ("weather chance of Rerouting").

C. Scenario 2: UAVs in AirSpace

The second scenario considers the approach of Flight BA185 to EWR for landing as in scenario 1, although a different time segment is considered (17:11:27–17:16:01 UTC in Table I). The airplane has descended (altitude 1700 feet) down to 0 feet in such a period. The weather condition (microburst) from scenario 1 has been left behind. However, Flight BA185 is supposed to face a new challenge (before landing in EWR) which is airspace invasion due to three Unmanned Air Vehicles (UAVs) flying nearby EWR.

The three drones are: a small UAV (sUAV) that is a small-unmanned quadcopter which wheelbase is 0.5 m, a medium UAV (mUAV) that is a medium-unmanned airplane with 1.5 m of wingspan, and a huge UAV (hUAV) that is a large-unmanned airplane which wingspan is 20 m. The UAVs are flying at different altitudes and locations around the EWR airport during the landing of Flight BA185. These UAVs fly high enough to dangerously come close to Flight BA185 while descending from 1700 down to 0 feet in about four and a half minutes. The sUAV has a non-contactable remote pilot, and it is less than 300 m away from Flight BA185. The mUAV is more than 1100 m away from Flight BA185. The hUAV is less than 900 m away from Flight BA185. The mUAV and the hUAV have contactable remote pilots.

The information provided by the dataset for F-KNEL1, T-KJFK16, and F-KEWR1 radars (as specified in the ADS-B) dataset) is considered fully accurate and true since they come from real measurements. These radars are used as a very credible reference for the calculation of veracity metrics. Hence, the sensitive of the above radars is 0.99 when they manage to track the aircraft of interest. The remaining radars (that do not track the aircraft in the dataset) are considered to have smaller sensitivities. This makes sense since they do not track the above aircraft. Such a sensitivity difference along with the range of the radar has an impact on the veracity metrics.

The sensitivities for aircraft detection are assumed as follows (from 17:01:59 to 17:11:54 where F-KNEL1 tracks Flight BA185):

- F-KNEL1 sensitivity ($S_{\text{F-KNEL1}} = 0.99$)
- T-KJFK16 sensitivity ($S_{\text{T-KJFK16}} = 0.80$)

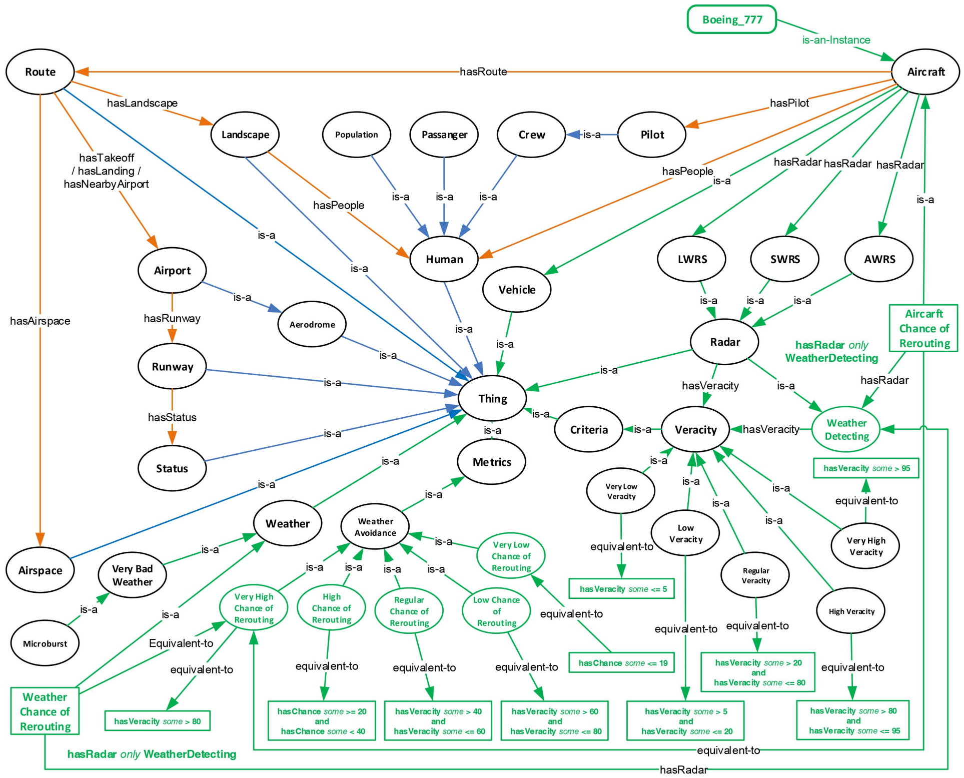

Fig. 14. Reasoning behind the queries for airspace situation in scenario 1

- F-KEWR1 sensitivity ($S_{F\text{-}KEWR1} = 0.60$)

The following weights are assumed for radar ranges:
$R_{F\text{-}KNEL1}$ = {Very close = 100, Close = 0, Medium = 0, Far = 0, Very Far = 0}
$R_{T\text{-}KJFK16}$ = {Very close = 0, Close = 100, Medium = 0, Far = 0, Very Far = 0}
$R_{F\text{-}KNWR1}$ = {Very close = 0, Close = 0, Medium = 100, Far = 0, Very Far = 0}

The calculation of the veracity metric is based on equation (1), similar to the calculation in scenario 1.

The above three radars track Flight BA185 in the period considered by the case study (Table I). They have $S_{BA185} = 0.99$ (when they track Flight BA185) so they are a fully-truthful source for both radars. However, the tracking of the UAVs (i.e., sUAV, mUAV, and hUAV) is assumed to be done by any of the above radars that have difference veracities (V_{sUAV}, V_{mUAV}, and V_{hUAV}). The combination of two or more veracities given by the multiplication of the veracities. Table III shows examples of the impact of having different veracities when detecting aircraft based on the radar used for detection.

Fig. 15 shows the above scenario 2.

The information provided by the AAO can be visualized by ATCs to support their decisions on the above situation (also, aviators and pilots of remotely-piloted aircraft could make use of this information). They can run AAO queries as to the impact of the proximity of the UAVs on Flight BA185. This also provides suggestions about what to do with Flight BA185 or the

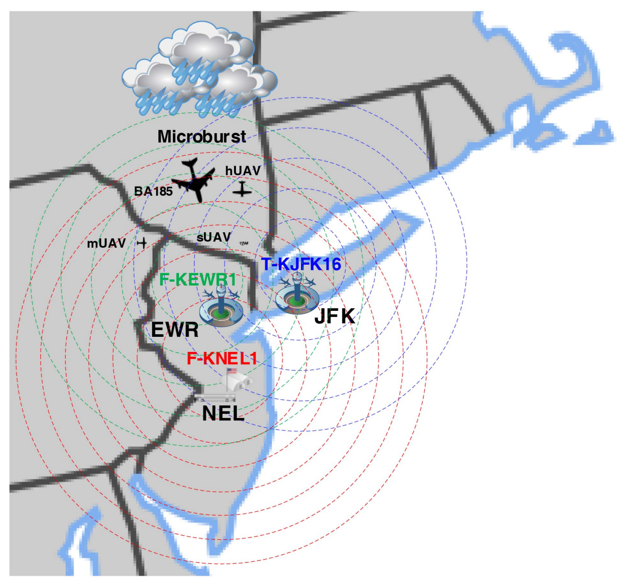

Fig. 15. Scenario 1 in the airspace area of interest

UAVs to avoid any potential air collision. The query is regarding chances for air collision: very low risk of collision (0–19%), low risk of collision (20–39%), medium risk of collision (40–59%), high risk of collision (60–79%), and very high risk of collision (80–100%). These collision possibilities are directly related with the radar veracities as calculated for V_{BA185} and V_{xUAV}.

Scenario 2 considers six different airspace situations (veracities are taken from Table III):

1. F-KNEL1 detects the three UAVs, and Flight BA185.

TABLE III.
VERACITY METRICS (TRUES IN %)

S_{BA185}	S_{xUAV} (solo)			S_{sUAV}, S_{mUAV} & S_{hUAV} (all)					
	KNEL1	KJFK16	KEWR1	KNEL1 & KNEL1 & KNEL1	KJFK16 & KJFK16 & KJFK16	KEWR1 & KEWR1 & KEWR1	KNEL1 & KJFK16 & KJFK16	KNEL1 & KEWR1 & KJFK16	KNEL1 & KEWR1 & KEWR1
F-KNEL1	98	79.2	59.4	96.06	51.2	21.38	62.73	47.05	35.28
T-KJFK16	79.2	64	48	80	40.96	17.28	50.69	38.02	28.52
F-KEWR1	59.4	48	36	60	30.72	12.96	38.02	28.52	21.38

The veracity of this query is 98% ($V_{xUAV} = 99 * V_{BA185} = 99$). The most veracious radar from the ADSB dataset.

2. F-KJFK16 detects sUAV, mUAV and hUAV, and KNEL1 detects Flight BA185. The veracity of this query is 51.2% ($V_{xUAV} = 51.72 * V_{BA185} = 99$).
3. F-KEWR1 detects sUAV, mUAV and hUAV, and KNEL1 detects Flight BA185. The veracity of this query is 21.38% ($V_{xUAV} = 21.6 * V_{BA185} = 99$).
4. F-KNEL1 detects the sUAV and Flight BA185, F-KJFK16 detects the mUAV and the hUAV. The veracity of this query is 62.73% (S_{sUAV} and $S_{BA185} = 98 * S_{mUAV}$ and $S_{hUAV} = 64$).
5. F-KNEL1 detects the sUAV and Flight BA185, F-KEWR1 detects the mUAV, and F-KJFK16 detects the hUAV. The veracity of this query is 47.05% (S_{sUAV} and $S_{BA185} = 98 * S_{mUAV} = 60 * S_{hUAV} = 80$).
6. F-KNEL1 detects the sUAV and Flight BA185, F-KEWR1 detects the mUAV and the hUAV. The veracity of this query is 35.28% ($S_{sUAV} = S_{BA185} = 98 * S_{mUAV}$ and $S_{hUAV} = 36$).

Fig. 16 shows the inferred *AircraftChanceofCollision* class (top) and AAO query results (bottom) for each of the radars that detects the UAVs for airspace situation 1, 2, and 3, including veracity metrics for scenario 2. Fig. 17 shows AAO query results for airspace situation 4, 5, and 6.

The query inference results suggest that (from left to right):

1. sUAV and hUAV have clear chances of collision (very high risk of collision) and the veracity of this query is based on a sensitivity of 99% (and proximity of the radar to the aircraft) when F-KNEL1 detects the UAVs and Flight BA185 (top-left query in Fig. 16). Detection makes by means of NELRadar (F-KNEL1), bottom-left query in Fig. 16. These inference and query suggestion are the most veracious out of the six suggestions. Actually, the real one.
2. sUAV and hUAV have some chances of collision (medium risk of collision) and the veracity of this query is based on a sensitivity of 51.2% (and proximity of the radar to the aircraft). This veracity is not high enough to make a trusted decision when F-KJFK16 detects the UAVs and F-KNEL1 detects Flight BA185 (top-center query in Fig. 13). Detection makes by means of JFKRadar (T-KFJK16), bottom-center query in Fig. 16.
3. Bottom-right query in Fig. 16: sUAV and hUAV have low chances of collision (low risk of collision) and the veracity of this query is based on a sensitivity of 21.6% (and proximity of the radar to the aircraft). This veracity is very low to make a trusted decision when F-KEWR1 detects the UAVs and F-KNEL1 detects Flight BA185 (top-right query in Fig. 16). Detection makes by means of EWRRadar (F-KEWR1), bottom-right query in Fig. 16.
4. sUAV and hUAV have some chances of collision (medium risk of collision) and the veracity of this query is based on a sensitivity of 64% (and proximity of the radar to the aircraft). This veracity is not high enough to make a trusted decision when F-KNEL1 detects the sUAV and Flight BA185, F-KEWR1 detects the mUAV, and F-KJFK16 detects the hUAV. Query on the left of Fig. 17.
5. sUAV and hUAV have some chances of collision (medium risk of collision) and the veracity of this query is based on a sensitivity of 48% (and proximity of the radar to the aircraft). This veracity is not high enough to make a trusted decision when F-KNEL1 detects the sUAV and Flight BA185, F-KEWR1 detects the mUAV, and F-KJFK16 detects the hUAV. Query on the left of Fig. 17.
6. sUAV and hUAV have some chances of collision (medium risk of collision) and the veracity of this query is based on a sensitivity of 51.2% (and proximity of the radar to the aircraft). This veracity is not high enough to make a trusted decision when F-NEL1 detects the sUAV and Flight BA185, F-KEWR1 detects the mUAV and the hUAV. Query on the left of Fig. 17.

Query on the right of Fig. 17 suggests the mUAV has no risk of collision. The inference and query results make sense since the chance of collision is diminished as the veracity of the radars is decreased. However, the real chance of collision is very high (the one suggested in 1.), and it is actually the most veracious.

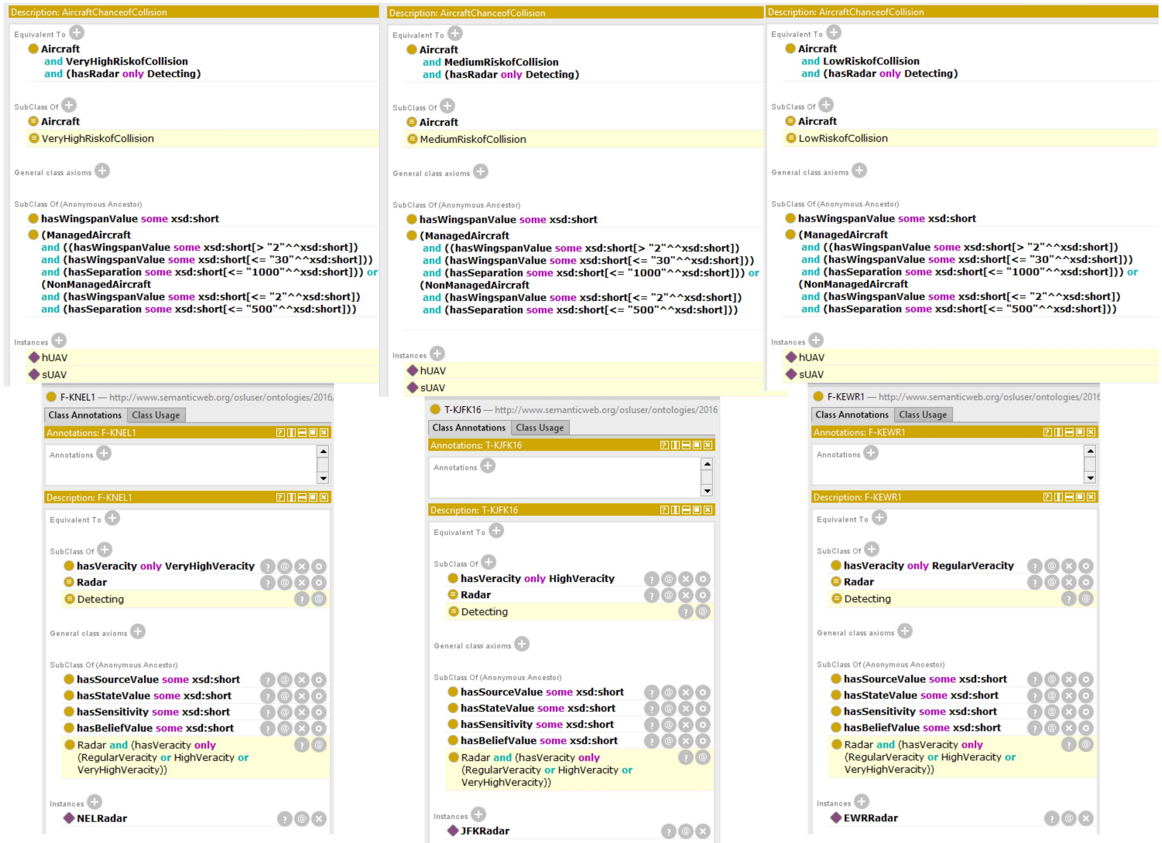

Fig. 16. Querying results and inferred classes to assess situation 1, 2, and 3.

D. Bayes' Risk Assessment

The assessment as to determine whether to alert the pilot is based on the information fusion analysis of Bayes' risk. The Bayesian estimate a posterior is the measurement given a possible collision.

$$P(\theta_j \mid x) = \frac{P(x \mid \theta_j)P(\theta_j)}{P(x)} \tag{1}$$

where $P(\theta_j)$ is the prior sensitivity of the radar configurations for each case $j = 1, \ldots 6$ (as those shown from left to right in Table III for multiple detection of all the UAVs, i.e., S_{sUAV}, S_{mUAV} & S_{hUAV}), and the conditional likelihood $P(x \mid \theta_j)$ is for a collision or no-collision given the radar measurements. To determine whether to send a semantic alert a pilot is based on the measurement, the potential range (distance), and type of the UAV. To determine the Bayes' risk, a loss function L was developed if no action (e.g., send an alert) was taken.

$$R(\alpha_j \mid x) = \sum_{j=1}^{6} L(\alpha_j \mid \theta_j)P(\theta_j \mid x) \tag{2}$$

where $L(\alpha_j \mid \theta_j)$ represents the three cases for loss if the range is j = {close, near, far}. The results were normalized. Given scenario 2, if there is a chance of collision, the best action is to alert the pilot. If there is lower chance of collision, the results still suggest sending a warning to the pilot of a potential collision.

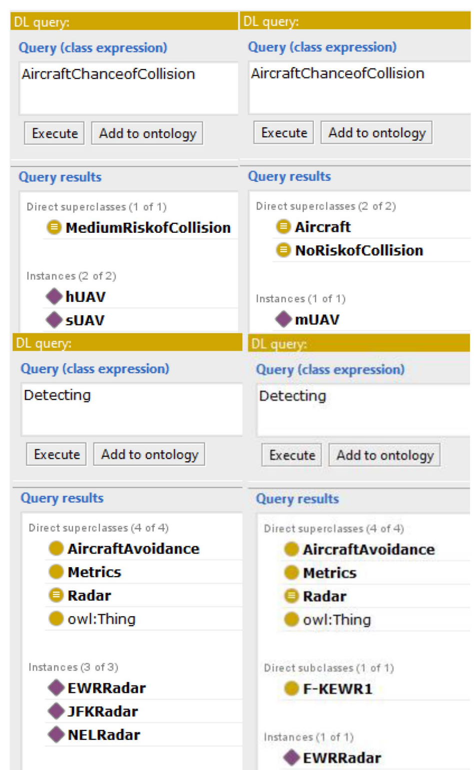

Fig. 17. Querying results to assess situation 4, 5, and 6 in scenario 2.

TABLE IV.
LOSS FUNCTION

	Case 1 High	Case 2 Medium	Case 3 Low	Case 4 Medium	Case 5 Medium	Case 6 Medium
Close	0	1	8	0	1	1
Near	0	2	1	3	3	3
Far	10	7	1	7	6	6

TABLE V.
BAYES' RISK

	Collision	No collision
Close	0.494548297	1.579050007
Near	1.416107104	2.413458212
Far	8.089344598	5.825970614
Sum	10	9.818479

From the first row of Table III {0.9606, 0.512, 0.2138, 0.273, 0.4705, 0.3528}, they total up 3.1364. Then, the prior probabilities (sensitivity/veracity) for the six cases are (by dividing each of them by the total): $P(\theta_j) = \{0.306083, 0.163244, 0.068167, 0.200006, 0.150013, 0.112486\}$.

The likelihood $P(x \mid \theta_j)$ for collision are {0.9606, 0.512, 0.2138, 0.273, 0.4705, 0.3528}, and for no collision is {0.0394, 0.488, 0.7862, 0.3727, 0.5295, 0.6472}.

The prior probabilities (Bayes denominator) $P(x) = P(\theta_j)$. $P(x \mid \theta_j)$ for collisions are {0.2938, 0.08358, 0.01457, 0.1255, 0.0706, 0.03968} which total up 0.627725, and for no collision is {0.0122, 0.07966, 0.0536, 0.0745, 0.0794, 0.0728} which total up 0.372275.

The posterior probabilities $P(\theta_j \mid x) = P(x)/0.627725$ for collisions are {0.4681, 0.1331, 0.0232, 0.1999, 0.1124, 0.0632}, and $P(\theta_j \mid x) = P(x)/0.372275$ for no collisions are {0.0329, 0.2140, 0.1440, 0.2002, 0.2134, 0.1955}.

The loss function $L(\alpha_j \mid \theta_j)$ is defined in Table IV.

The Bayes' risk $R(\alpha_j \mid x)$ (which formula is (2)) for the three cases for loss are shown in Table V.

Presenting the information in a semantically meaningful way by normalizing them based on the sum 10 and 9.818479 for collision and no collision, the Bayes' risk was inverted so as to represent the results as shown in Fig. 18.

For case collision assessments, the results are used as (1 is high, 2, 4, 5, 6 is medium, and 3 is low). The Bayes risk assessment is consistent with the ontology from which $> 0.95\%$ would be a collision confirmed; 0.95–0.85 for collision likely, and < 0.85 for collision possible. For values < 0.5, it is unlikely there would be a collision. From Fig. 18, when a collision is detected within a close range, the best action (reduce risk) is to confirm an alert. Likewise, when the UAV is near, a collision is likely, so a warning should be sent. If a collision range is detected far away, the normalized action is that there is enough time for future measurements to

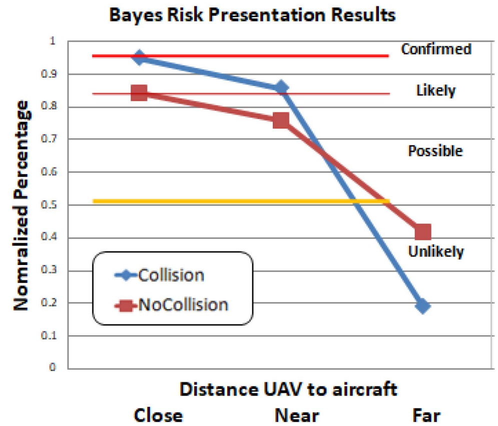

Fig. 18. Bayes' risk assessment results.

determine if a collision would result. On the other hand, the case of a no-collision also presents a semantically interesting result, as if the radars are sensitive and detect a UAV in close proximity to the pilot, a likely warning would result.

7. CONCLUSION AND FUTURE WORK

The paper proposed an Avionics Analytics Ontology (AAO) based on the Uncertainty Representation and Reasoning Evaluation Framework (URREF). The AAO is developed to provide situation awareness updates for aviators, air traffic controllers, and airport security personnel in support of ATM/UTM decision-making processes. The congestion of the airspace with UAVs was presented as use cases to demonstrate the workload reduction through an information fusion ontology methodology. Veracity was the measured degree of uncertainty to support credible reporting and airspace collisions. Examples involving two ATM/UTM operation scenarios where F-KNEL1, T-KJFK16, and F-KEWR1 radars (as specified in the ADS-B) determine the commercial aircraft (Flight BA185) collision analysis from a set of UAVs. The AAO results present a useful approach towards providing an integration method among uncertainties including semantic from operators, sensing from navigation, and situation from weather modeling updates.

Future research work will involve methods to improve veracity metrics. One of the relevant approach as an interesting veracity metric to be considered for further investigation is the big data veracity index [57]. It is based on three main dimensions to define veracity: objectivity (subjectivity), truthful (deception), and credibility (implausibility). The index approach deserves attention, but some research is required to deal with artificial autonomy (DSS) since the potential tools to support such a metric index are too human-oriented. The challenge is to develop supporting tools that allow for machine veracity metrics, e.g. radars. On the other hand, some future refinement on the integration of veracity (uncertainty) into the AAO will enhance usefulness. One of the inspiring methodologies (to deal with

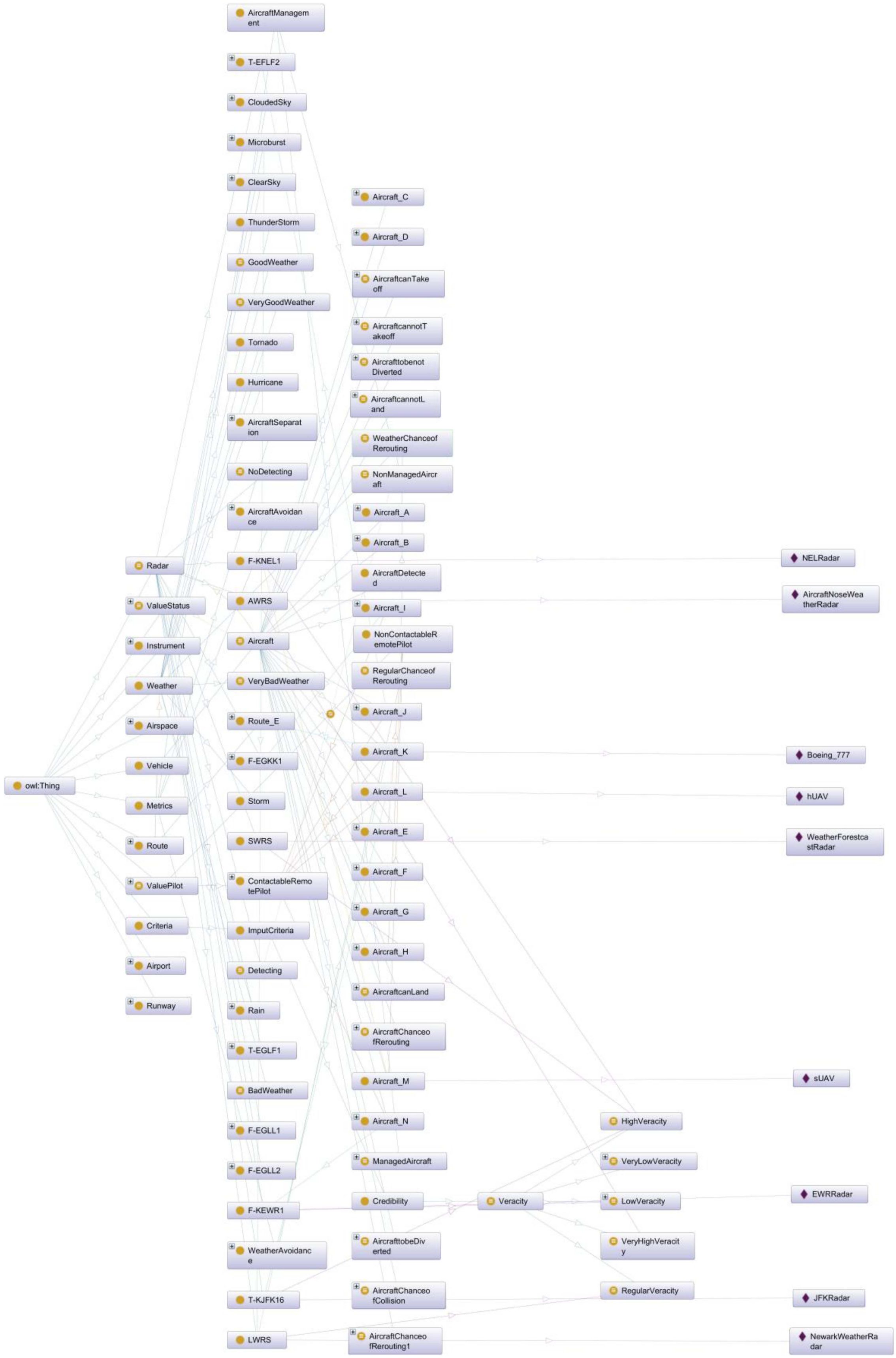

Fig. 19. Structure of hierarchy of the AAO

probabilistic uncertainty when making decision) is the Bayesian networks, e.g. BasesOWL [58] which is suitable for ontologies.

Future methods would also include physics-based and human-derived (PHIF) graphical information fusion methods where graph ontologies can be matched, associated, and extended for narratives [59, 60]. The application scenarios discussed in this paper are meant to easily demonstrate the benefits of the AAO-based DSS proposed. They are simple but realistic. However, further development of the AAO will consider demonstrations involving and targeting ATM operational performance indexes as those discussed by Civil Air Navigation Services Organisation (CANSO) [61] and SESAR Key Performance AREA [62]. For example, capacity and efficiency are listed are listed as operational metrics; while less defined metrics of societal metrics include safety, security, and environmental sustainability [63].

APPENDICES

APPENDIX A: AAO HIERARCHICAL STRUCTURE

Fig. 19 shows the structural hierarchy of the classes in the AAO.

APPENDIX B: TBOX AND ABOX

The axioms of the AAO TBox are shown below.

Aircraft (subclass of Vehicle)
Aircraft_K subclass of AircraftcannotLand and AircraftcanTakeoff
Aircraft_L subclass of AircraftcannotLand and AircraftcanTakeoff
Aircraft_M subclass of AircraftcanLand and AircraftcanTakeoff
Aircraft_N subclass of AircraftcannotLand and AircraftcannotTakeoff
AircraftcanLand subclass of Aircraft
AircraftChanceofCollision subclass of Aircraft
AircraftChanceofRerouting subclass of Aircraft

Route
Route_A subclass of Landing and Takeoff
Route_B subclass of NoLanding and Takeoff
Route_C subclass of Landing and Takeoff
Route_D subclass of Landing and NoTakeoff

Airport
Airport_I subclass of LandingAirport and TakeoffAirport
Airport_II subclass of LandingAirport and TakeoffAirport
Airport_III subclass of NoLandingAirport and NoTakeoffAirport
Airport_IV subclass of LandingAirport and TakeoffAirport

Airspace
Airspace_I subclass of FlyingAirspace
Airspace_II subclass of FlyingAirspace
Airspace_III subclass of NoFlyingAirspace
Airspace_IV subclass of FlyingAirspace

Weather
ClearSky subclass of GoodWeather and VeryGoodWeather
CloudedSky subclass of VeryBadWeather
Hurricane subclass of VeryBadWeather
Rain subclass of GoodWeather
Storm subclass of BadWeather
Thunderstorm subclass of BadWeather
Tornado subclass of VeryBadWeather
Microburst subclass of VeryBadWeather

Metrics
AircraftAvoidance subclass of Metrics
AircraftManagment of Metrics
AircraftSeparation subclass of Metrics
WeatherAvoidance subclass of Metrics

Criteria
ImputCriteria subclass of Criteria
Credibility subclass of ImputCriteria
Veracity subclass of Credibility
VeryLowVeracity subclass of Veracity
LowVeracity subclass of Veracity
RegularVeracity subclass of Veracity
HighVeracity subclass of Veracity
VeryHighVeracity subclass of Veracity

Radar
AWRS subclass of hasVeracity only VeryHighVeracity and Radar
SWRS subclass of hasVeracity only HighVeracity and Radar
LWRS subclass of hasVeracity only RegularVeracity and Radar
F-KNEL1 subclass of hasVeracity only VeryHighVeracity and Radar
F-KJFK16 subclass of hasVeracity only HighVeracity and Radar
F-KNEW1 subclass of hasVeracity only RegularVeracity and Radar

The facts of the AAO ABox are shown below.

Aircraft
AircraftChanceofCollision equivalent to Aircraft and (RiskofCollision and (hasRadar only Detecting)
AircraftChanceofRerouting equivalent to Aircraft and (ChanceofRerouting and (hasRadar only Detecting)
AircraftcanLand equivalent to Aircraft and (hasRoute only Landing)
AircraftcannotLand equivalent to Aircraft and (hasRoute only NoLanding)
AircraftcanTakeoff equivalent to Aircraft and (hasRoute only Takeoff)
AircraftcannotTakeoff equivalent to Aircraft and (hasRoute only NoTakeoff)

Route
Landing equivalent to Route and (hasLanding only LandingAirport)
NoLanding equivalent to Route and (hasLanding only NoLandingAirport)
Takeoff equivalent to Route and (hasTakeoff only TakeoffAirport)
NoTakeoff equivalent to Route and (hasTakeoff only NoTakeoffAirport)

Airport
LandingAirport equivalent to Airport and (has Airspace only FlyingAirspace)
NonLandingAirport equivalent to Airport and (has Airspace only NonFlyingAirspace)
TakingoffAirport equivalent to Airport and (has Airspace only FlyingAirspace)
NonTakingoffAirport equivalent to Airport and (has Airspace only NonFlyingAirspace)

Airspace
FlyingAirspace equivalent to Airspace and (not (NonFlyingAirspace))
NonFlyingAirspace equivalent to Weather and (hasWeather only VeryBadWeather)

Weather
VeryGoodWeather equivalent to Weather and (ClearSky or CloudedSky)
GoodWeather equivalent to Weather and (CloudedSky or Rain)
BadWeather equivalent to Weather and (Storm or ThuderStorm)
VeryBadWeather equivalent to Weather and (Hurrican or Tornado)

Metrics
RiskofCollision equivalent to (ManagedAircraft and ((hasWingspanValue some xsd:short[> ″2″^^xsd:short]) and (hasWingspanValue some xsd:short[<= ″30″^^xsd:short])) and (hasSeparation some xsd:short[<= ″1000″^^xsd:short])) or (NonManagedAircraft and (hasSeparation some xsd:short[<= ″500″^^xsd:short]) and (hasWingspanValue some xsd:short[<= ″2″^^xsd:short]))

Criteria
VeryLowVeracity equivalent to hasVeracity some xsd:short[>= ″5″^^xsd:short]
LowVeracity equivalent to (hasVeracity some xsd:short[> ″5″^^xsd:short]) and (hasVeracity some xsd:short[< ″25″^^xsd:short])
RegularVeracity equivalent to (hasVeracity some xsd:short[> ″25″^^xsd:short]) and (hasVeracity some xsd:short[< ″70″^^xsd:short]))
HighVeracity equivalent to (hasVeracity some xsd:short[> ″70″^^xsd:short]) and (hasVeracity some xsd:short[< ″95″^^xsd:short]))
VeryHighVeracity equivanlent to hasVeracity some xsd:short[> ″95″^^xsd: short]

Radar
Detecting equivalent to Radar and (hasVeracity only VeryHighVeracity)
NoDetecting equivalent to not(Detecting)

DECLARATION

The Avionics Analytics Ontology (AAO) used in this paper has been developed for specific airspace situations. It is based on intuitive knowledge gathered from an investigation done on trusted sources such FAA regulations. The AAO is at its early development stage (prototype) and it is a living approach as it is been continuously updated. It has not been validated yet. However, there is a plan to integrate the NASA ontology into the AAO, which will require validation for further development.

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