Historical Data Analysis and Modelling for Drone Intrusions in Airports

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***Abstract*—Airport operations are particularly susceptible to unauthorized drone intrusions and an increasing of the awareness is required in regard to this phenomenon. This work describes a quantitative assessment of the historical features of drone intrusions in airports, by using different public databases with reports about real sightings. The available features are modelled in terms of probability distributions. Also, a risk classification model is proposed by means of supervised machine learning. Lastly, a preliminary analysis is provided for the definition of an Airport Vulnerability Index with respect to drone intrusions.**

***Keywords*—drone intrusions, airport operations, vulnerability index, threat analysis, risk analysis**

I. INTRODUCTION

Recent advances in drones' technology allowed the emergence of a new wide range of applications, but have also posed new serious threats, regarding both safety and security. Airport operations are particularly susceptible to drone intrusions since airports might not be physically isolated from unauthorized drones. This is evidenced by the high number of drone incidents occurred across Europe and by the different degrees of disruptions on aerodrome operations [1], with the prime example of the 33-hours paralysis of London Gatwick airport on 19-21 December 2018, due to the overflying of an unknown number of drones [2]. In addition to the safety impacts, these episodes may seriously affect the economic costs of airport and airline operations [1], [3].

Thus, the only way to protect the airport is to build a robust Drone Intrusion Management System (DIMS) that leverages on different building blocks, from the detection up to the mitigation systems. Indeed, as proposed by the European Union Aviation Safety Agency (EASA) in the counter-drone action plan [4], aerodromes shall be prepared to mitigate risks from unauthorised drone use, shall support the assessment of the risks related to unauthorized drones, and shall implement counter-drone measures from a global safety perspective. As a consequence, an effective DIMS has to increase the awareness about drone intrusions and has to establish procedures and protocols to manage them, with minimum impact on the operations. Also, this requires the setting of some risk assessment methodologies for airport operations, which explicitly consider the features of drone intrusion, possibly from a quantitative point of view. This methodology should be consistent with the observation that, even if each drone incident is specific, several common factors may arise and their evaluation may be applied for risk analysis [1].

This work reports an assessment of **historical features** related to the feared phenomenon of unauthorized drone intrusions in airports, starting from the available public databases containing real sighting data. The abovementioned features may be qualitative or quantitative indicators about the historical evolution of the phenomenon, such as averages, standard deviations, trends, etc. Moreover, this works checks the feasibility of the **modelling** of such features, in terms of **probability distributions** and **risk classification models** for airport drone intrusions, also based on machine learning techniques. These models may be used to estimate the risk of drone intrusions and to forecast future evolutions and trends for local airports, paving the way to the definition of a data-driven and performance-based management process within the DIMS. They may also be used in future simulation environments about drone intrusions, currently unavailable.

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Lastly, a preliminary analysis is discussed in regard to the novel definition of an **Airport Vulnerability Index** (**AVI**) with respect to drone intrusions. Such index may potentially quantify the exposure or the susceptibility of an airport in regard to unauthorized drone intrusions, by explicitly considering the influence of different dimensions of the airport's context (e.g., social, economic, etc.). Thus, the AVI may be used to provide estimations and predictions about drone intrusions in an airport, based on the exposure of the airport itself.

To the best of our knowledge, this is the first study that investigates the quantitative assessment of the historical features of airport drone intrusions, by using jointly databases of different countries. Moreover, from a methodological perspective, this is the first work that proposes: the definition of a risk classification model of drone intrusions in airports, based on machine learning techniques; the estimation of an AVI related to drone intrusions, including the influence of social and economic dimensions. In regard to the risk assessment of airport drone intrusions, the improvements are: the identification of common risk factors in different countries; the preliminary study of risk classification models and vulnerability indexes.

The remainder of this article is organized as follows. Section II presents the background, by describing both the related work and a review of available public databases for sighting reports about drone intrusions in airports. Section III reports the assessment results of the historical features for the selected reports. Section IV describes the analysis performed for feature modelling. Section V reports the preliminary analysis for the AVI definition. Section VI highlights conclusion and future work. In the following, the terms UAV (Unmanned Aerial Vehicle), UAS (Unmanned Aerial System) and sUAS (small UAS) are used in reference to drones.

II. Background

A. Related Work

Some works have been published to analyse drone-related threats and to investigate real incidents, by considering the available reports about sightings and unauthorized intrusions. However, most of the work regard the technological analysis of possible anti-drone solutions ([5], [6], [7]), instead of providing risk assessment approaches.

Reference [8] provides a survey about the threats of drones (mainly for cyber-attacks) and their vulnerabilities (especially regarding communication links). Some incidents are mentioned about civil drones and a list of safety and security concerns is provided. Instead, reference [9] provides a survey of UAV attacks in the military context. Even if the generic features of UAV malpractices are highlighted, the paper analyses significant episodes of UAV military attacks. Reference [10] represents a first significant report about the effects of UAS attacks and intrusions in the civil airspace. In detail, this reference is a research report with an analysis of 921 UAV incidents in the US airspace, from December 2013 to September 2015. The envisaged incidents are only sightings (i.e., an incident with a UAV not representing an immediate threat of collision) and close encounters (i.e., near mid-air collisions between a manned aircraft and a UAV). An analysis of the aggregated data is reported in terms of: close encounters proximity; UAV type; manned aircraft type and operation. Databases of the Federal Aviation Administration (FAA) and of the National Aeronautics and Space Administration (NASA) are used as sources for incident records.

Reference [11] is focused in more detail on the analysis of UAV threats from the point of view of airport security by considering real incidents. Two categories of incidents have been considered: sightings where a pilot or air traffic controller spotted a drone not posing an immediate threat of collision and near mid-air collisions. The observation period has been from May 2014 to May 2018 and has retrieved a population of 139 incidents, using FAA and NASA databases. Furthermore, reference [12] reports a research to understand: the characteristics of UAS sightings; the impact of a UAS sighting on airport operations; the current perspective of airport personnel regarding the risk of UAS at airports. The work has analysed 6551 UAS sighting reports, recorded from September 2016 to August 2019. The sighting reports have been retrieved from FAA's database. Statistics have been assessed about: temporal aspects (time of year and time of day of the sighting); reporting source; response (notification to law enforcement, evasive action of the manned aircraft's pilot, etc.); altitude and position of the UAS. Reference [13] regards the protection of airports from UAS, too, but it is more focused on cyber-attacks and counter-drone sensing technologies. Anyway, a section is dedicated to a brief qualitative analysis of some UAV incidents.

B. Public Record Databases

Some public databases are available to report data about drone sightings, especially (but not only) near airports. In detail, the public online databases that have been considered in this work are: FAA UAS Sighting Reports [14] and UKAB (UK Airprox Board) sUAS Reports [15].

FAA has been collecting UAS sighting reports since November 2014. These reports are available to the public and contain information about UAS sightings by different actors, e.g., commercial pilots, general aviation, citizens, law enforcement officers, etc. Each sighting report includes the following information: the day; the US State and the city; a narrative summary. In detail, the narrative summary may include data about: the source of the sighting report; the altitude of the UAS; the name of the nearby airport; the distance from the UAS sighting location to the nearby airport; the issue (if any) of a Mandatory Occurrence Report (MOR); the notification (if any) to a law enforcement department; the model (if any) of the sighted UAS; the distance (if any) of the sighted UAS from a manned aircraft. Fig. 1 illustrates some examples of FAA UAS sighting reports [16].

UKAB has been recording sUAS sightings in the UK since 2010 by registering four categories of vehicles: drones; balloons (including toy and research balloons); model aircraft; unknown objects. Reports are initially provided by pilots in a narrative form. Then, UKAB reviews the report and specifies the related record, which has a structured form with the following fields: Airprox number; sighting date; aircraft of the reporting pilot; sighting object (drone, balloon, model aircraft, or unknown object); sighting position; reported location; risk level. The latter attribute is related to the risk of collision with a manned aircraft and it is expressed according to the following ratings [17]:

- A – risk of collision (aircraft proximity in which serious risk of collision has existed);

- B – safety not assured (aircraft proximity in which the safety of the aircraft may have been compromised);
- C – no risk of collision (aircraft proximity in which no risk of collision has existed or risk was averted);
- D – risk not determined (aircraft proximity in which insufficient information was available to determine the risk involved, or inconclusive or conflicting evidence precluded such determination);
- E – met the criteria for reporting but, by analysis, it was determined that normal procedures, safety standards and parameters pertained.

Fig. 2 illustrates some examples of UKAB reports, whose file [18] includes also an evaluation of the aggregated sighting data by providing a processing according to different data groupings (e.g., by risk, by month, by altitude, etc.).

Day of Sighting	State	City	Summary
01/04/2020	GEORGIA	ATLANTA	PRELIM INFO FROM FAA OPS: ATLANTA, GA/UAS INCIDENT/2005E/ATLANTA TRACON ADVISED CESSNA C150, REPORTED BLUE AND GREEN UAS 300 FEET BELOW ACFT AT THE 12 O'CLOCK POSITION WHILE W BOUND AT 4,300 FEET 23 N ATL. NO EVASIVE ACTION TAKEN. FULTON COUNTY PD NOTIFIED.
02/04/2020	TEXAS	DALLAS	PRELIM INFO FROM FAA OPS: DALLAS, TX/UAS INCIDENT/2258C/ADDISON ATCT ADVISED CESSNA C172, REPORTED A UAS AT 2,000 FEET 10 E OF ADDISON ARPT. NO EVASIVE ACTION REPORTED. LOCAL LAW ENFORCEMENT NOTIFIED.
03/04/2020	MONTANA	HELENA	PRELIM INFO FROM FAA OPS: HELENA, MT/UAS INCIDENT/1644M/HELENA ATCT ADVISED H60, REPORTED A UAS AT 450 FEET. NO EVASIVE ACTION REPORTED. LEO NOTIFICATION NOT REPORTED.

Fig. 1. Examples of FAA UAS sighting reports [16].

Airprox No	Date	Year	Aircraft	Object	Latitude	Longitude	Alt	Reported Location	Risk
2020135	24/08/2020	2020	A321	Drone	N5127	W0004	04500	London TMA	C
2020140	25/09/2020	2020	Tutor	Drone	N5100	W00221	02000	London FIR	C
2020142	16/09/2020	2020	Hawk	Model Aircraft	N5028	W00413	00300	London FIR	C
2020144	11/10/2020	2020	Cirrus 22T	Drone	N5118	E00001	01600	London FIR	C
2020148	10/10/2020	2020	C150	Unknown	N5129	E00035	4000	London TMA	C
2020150	16/10/2020	2020	A321	Unknown	N5128	W00024	01700	London CTR	A
2020155	16/10/2020	2020	PA31	Drone	N5127	W00023	02000	London CTR	B

Fig. 2. Examples of UKAB sUAS sighting reports [18].

III. Historical Feature Assessment

A. Assessment of FAA Reports

Several references already provide an analysis of FAA UAS sighting reports ([10], [11], [12]), as discussed in section II.A. Such references are mostly focused on the past years and do not provide a review of 2020. To the contrary, this work proposes an assessment focused on FAA UAS sighting reports in 2020. A detailed processing has been performed by assessing trends, especially for altitude and airport distances of the sightings. The assessment has also considered the fact that the year 2020 is not fully representative for the air transport sector compared to previous years, due to the pandemic of coronavirus disease 2019 (COVID-19). The FAA sighting data cover all the 2020 months, with the exception of August. The total 2020 sightings were 1474, while the mean and standard deviation of the number of sightings per month are 134 and 43.3, respectively. Fig. 3 shows that less sightings have been reported during: March and April, probably due to COVID-19; January, November and December, probably due to the lower temperatures, to the shorter daylight hours, and to the lower levels of air traffic. Instead, more sightings have been reported in summer, as a possible consequence of the higher temperatures and of the higher levels of air traffic. Moreover, Fig. 4 reports a histogram, in percentage, of the sighting times. The higher-density time slot for the sightings is within 13:00 and 14:00. Almost zero sightings were reported from 22:30 to 6:00.

Fig. 5 provides a scatter plot of: the sighting location altitude as Above Ground Level (AGL) altitude (in feet, in logarithmic scale); the horizontal distance (in nautical miles) of the sighting location with respect to the nearby airport. The sighting location refers to the position of the manned aircraft, whose pilot has emitted the sighting report. In Fig. 5, the most critical sightings (in red) are related to altitudes less than 2500 ft and horizontal distances less than 5 NM (Nautical Miles). In general, as shown, most of sightings occur when the aircraft are within 10 NM from airports, whereas the sighting altitude is quite invariant with respect to the horizontal distance. This may be attributed to both the following features: the drones often fly nearby the airports; the visibility of the drones is greater in proximity of the airports with respect to the pilots of manned aircraft because of their lower altitude. However, a general conclusion for this assessment cannot be derived and the previous consideration is strictly referred to FAA data. Indeed, the sightings are expected to be mainly recorded in the proximity of airports because these areas have more control. Anyway, the database includes reports about sightings which occurred far from airports. Moreover, it includes even some reports generated by actors not belonging to the ATM community (e.g., police ground units signalling drones over public sites or public demonstrations).

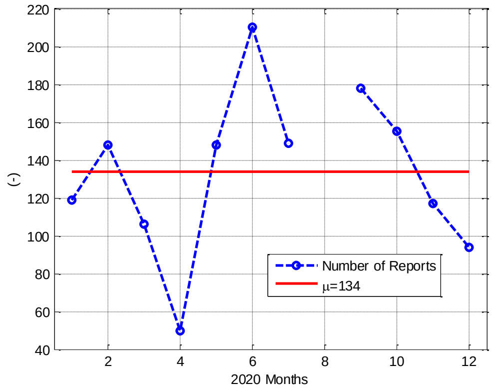

Fig. 3. Monthly occurrences of FAA reports in 2020.

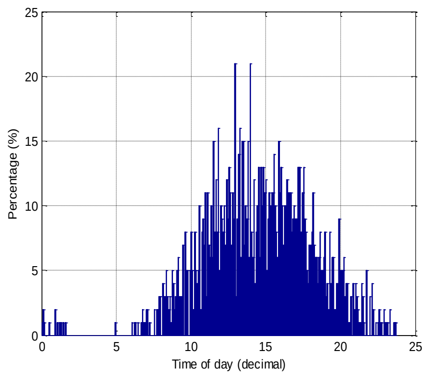

Fig. 4. By-time distribution of FAA reports in 2020.

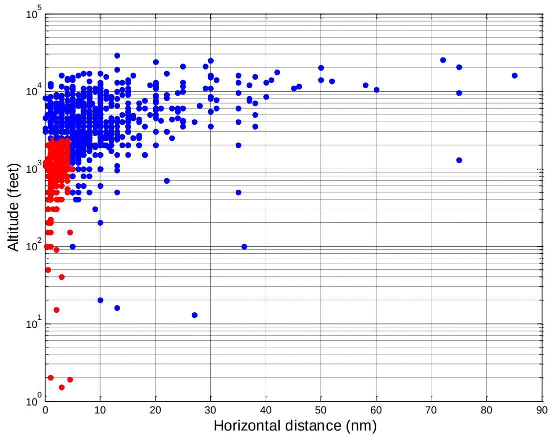

Fig. 5. Scatter plot of the airport distance and the sighting location altitudes of FAA reports in 2020.

B. Assessment of UKAB Reports

UKAB already provides a processing of their reported data about sUAS sightings [18]. However, in this work, an additional processing and assessment have been performed to focus on the sightings in the vicinity of airports or affecting airport operations, whereas the available UKAB's processing refer to all the sightings. The coordinates of the impacted (i.e., nearby) airports have been retrieved from the OpenFlights Airports Database [19].

Fig. 6 shows the evolution of the yearly occurrences of UKAB reports affecting airports. The decrease starting from 2018 may be attributed to the drone-related legislation events in the UK, which start in 2018. The decrease during 2020 may be attributed to COVID-19. Instead, Fig. 7 reports the scatter plot of the distributions of the airport distances and the altitudes. Such plot shows that most of the sightings occur in proximity of the airports, i.e., with a distance less than 20 NM. To the contrary, the altitudes exhibit a more uniform distribution, especially for altitudes lower than 5000 feet. However, as highlighted for FAA data in section III.A, a general conclusion for this assessment cannot be derived and the previous consideration is strictly referred to UKAB data. Also in this case, most of the sightings are expected to be recorded in the proximity of airports.

Table 1 reports the yearly average of the risk levels, jointly with the standard deviation and the confidence level of the results. For the purposes of the proposed processing, risk level has been converted in a numerical expression by the following mapping: A $\rightarrow$ 5; B $\rightarrow$ 4; $\cdots$; E $\rightarrow$ 1. Data confirm that the risk features do not present a significant yearly variation, except for 2020, which is characterized by COVID-19.

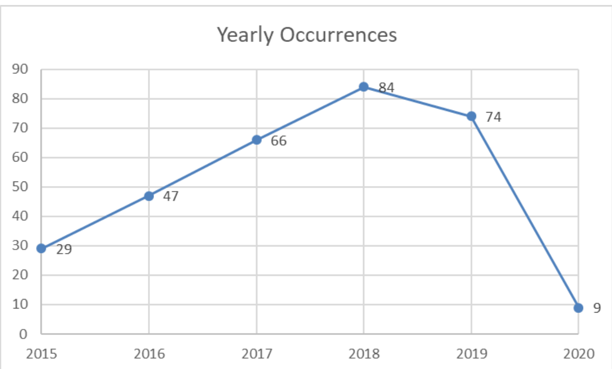

Fig. 6. Yearly occurrences of UKAB reports affecting airports.

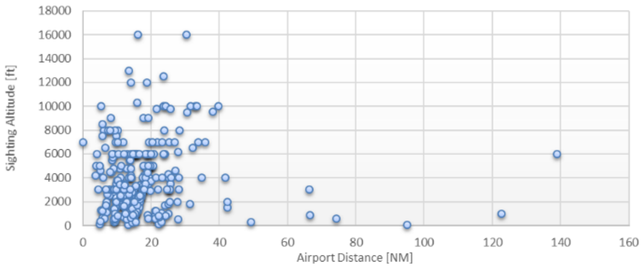

Fig. 7. Scatter plot of the airport distance and the sighting location altitudes in UKAB reports.

TABLE I. YEARLY STATISTICS OF THE RISK IN UKAB SUAS SIGHTING REPORTS AFFECTING AIRPORTS.

Year	Risk (Sample Mean Estimation)		
	Sample Mean	***Standard Deviation***	***Confidence Interval of Sample Mean (95%)***
2015	3.96	1.18	0.43
2016	4.23	0.81	0.23
2017	3.87	0.98	0.24
2018	4.07	0.88	0.19
2019	3.97	0.95	0.22
2020	3.22	1.09	0.71

C. Assessment Results

Even if with some specific differences, there are some similarities between the assessment of FAA and UKAB reports. These especially concern the evolutions of airport distances and sighting altitudes, which exhibit traits in common, such as the followings:

- the airport distances are mainly concentrated over small distances since most of sightings occur when the aircraft are near to airports;
- altitudes have a distribution extended on a wide range;
- the scatter plots have similar clustering patterns.

The deviations regarding the sighting occurrences may be attributed to the characteristic contexts (e.g., to the socio-economic contexts), as further explained in the vulnerability index study in section V.

IV. Feature Modelling

Starting from the assessment results of FAA and UKAB reports, some models have been built with the following objectives: to fit theoretical **probability distributions** to the historical features of the phenomenon of unauthorized drone intrusions in airports; to draw inferences from data and to check the feasibility of building **risk classification models**, accepting some features of the phenomenon of unauthorized drone intrusions in airports. Clearly, such results are specific for the adopted records of FAA and UKAB, even if some similarities may arise, also in regard to other distributions for different contexts (i.e., different airports in different countries). For the sake of brevity, this section reports only the results for the feature modelling of UKAB reports.

The reference data (i.e., sampled historical features) for the modelling are UKAB reports in the vicinity of airports or affecting airport operations. Given the structure of the available data, this work has analysed the fitting of some theoretical probability distributions to the features of the phenomenon of unauthorized drone intrusions in airports, related to the sighting altitude and the airport distance.

Firstly, a model has been built for the distributions of the altitude locations (in feet). In detail, a **Rayleigh** model and a **Weibull** model [20] have been designed to compare their accuracies. The following are the features of the achieved models: Weibull – mean 3709.27, variance 7.69092e+06; Rayleigh – mean 4119.1, variance 4.63605e+06. Fig. 8 reports the fitting with the real data (sample data), in terms of density function and probability distribution, for both the Reayleigh model and the Weibull model. Such figure shows how the Weibull distribution turns out to be more accurate to fit the distribution of the occurrences of the altitude locations.

In regard to the distribution of the airport distances (in NM), a **Burr** model [21] has been used, which has been designed with the following features: mean 17.3066; variance 119.523. Fig. 9 reports the fitting with the real data (sample data), in terms of density function and probability distribution.

An additional modelling objective has been the building of a model for the classification (i.e., estimation) of the risk level of the intrusion according to the other sighting data. This objective may be useful to verify the possibility of: estimating (according to a model-based approach) the risk of drone intrusions when such information is not explicitly provided or assessed by the sighting sources; monitoring the temporal evolutions and trends of the risks of drone intrusions, even for databases lacking of risk information. A model has been built for the classification of the risk level of a drone unauthorized intrusion (according to the criteria provided in II.B) as a function of the following features (i.e., inputs): the sighting altitude; the distance of the nearby airport with respect of the intrusion location; the affected airport. Thus, the proposed target function represents a **risk classification function**, working on the previous features as inputs. This function may be useful for estimating the risks of drone intrusions, even starting from databases lacking of an explicit risk information.

The available UKAB reports about airports, in number of 310, have been used for the training of the classification model. In detail, a **Fine Gaussian Support Vector Machine** (SVM) [22] has been designed according to a **supervised learning** approach for machine learning. The adopted algorithm for the supervised learning analyses the training data and infers the risk classification function, which can be used for mapping new examples without labels (i.e., without the explicit risk levels, as in sighting records that do not report this information). The designed model has a kernel scale of 0.43 and has achieved an accuracy of 64.2%. Given that the model has been developed in order to provide a feasibility check, a detailed validation (e.g., considering overfitting problems) has not been performed. Fig. 10 (left) reports a scatter plot of the model predictions, by highlighting both the correct and the wrong classifications, as a function of the airports and the airport distances. The article does not illustrate the dependency of the classification with respect to sighting altitudes just for the sake of brevity. Instead, Fig. 10 (right) reports the confusion matrix of the developed model, which shows the good accuracy for higher risk levels.

Clearly, the proposed model is just an example of classification model for the phenomenon of drone intrusions in airport. Greater accuracies are expected by using: larger training data (i.e., more labelled sighting reports with the risk levels); additional inputs for the classification (e.g., the time of the day, meteorological and visibility conditions, the intruder size, etc.).

V. AIRPORT VULNERABILITY INDEX

A **vulnerability index** is usually defined as a measure of the susceptibility of people, communities or regions to natural or technological hazards [23]. Thus, it represents a measure of the exposure of the system or the community under study with respect to the reference hazards. A vulnerability index shall consider the versatile nature of vulnerability by a acknowledging its different dimensions [23]. Indeed, generally speaking, vulnerability is influenced by a set of conditions and processes resulting from physical, social, economic and environmental factors, which increase the susceptibility of a system or community to the impact of hazards. For all these reasons, a vulnerability index is an "umbrella", i.e., it may be defined as a **composite index**, which is a "multidimensional" ensemble of multiple indexes. In this sense, this index combines the different dimensions of vulnerability.

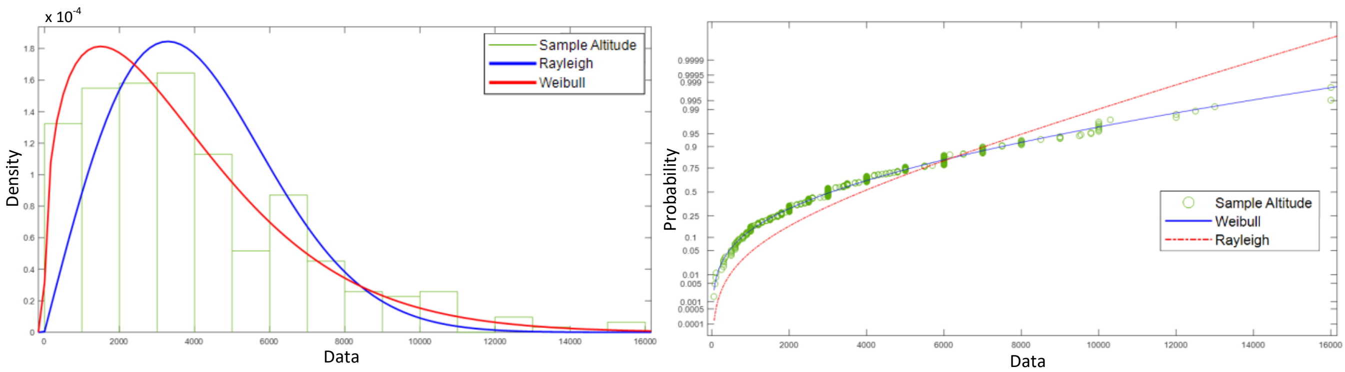

Fig. 8. Fitting with sample data, in terms of density function (left) and probability distribution (right), of the models for altitude locations in UKAB reports.

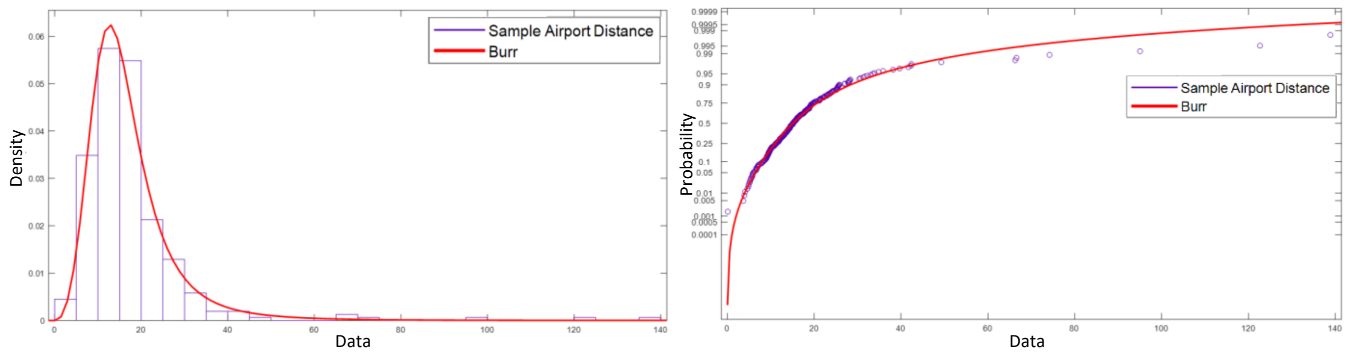

Fig. 9. Fitting with sample data, in terms of density function (left) and probability distribution (right), of the models for airport distances in UKAB reports.

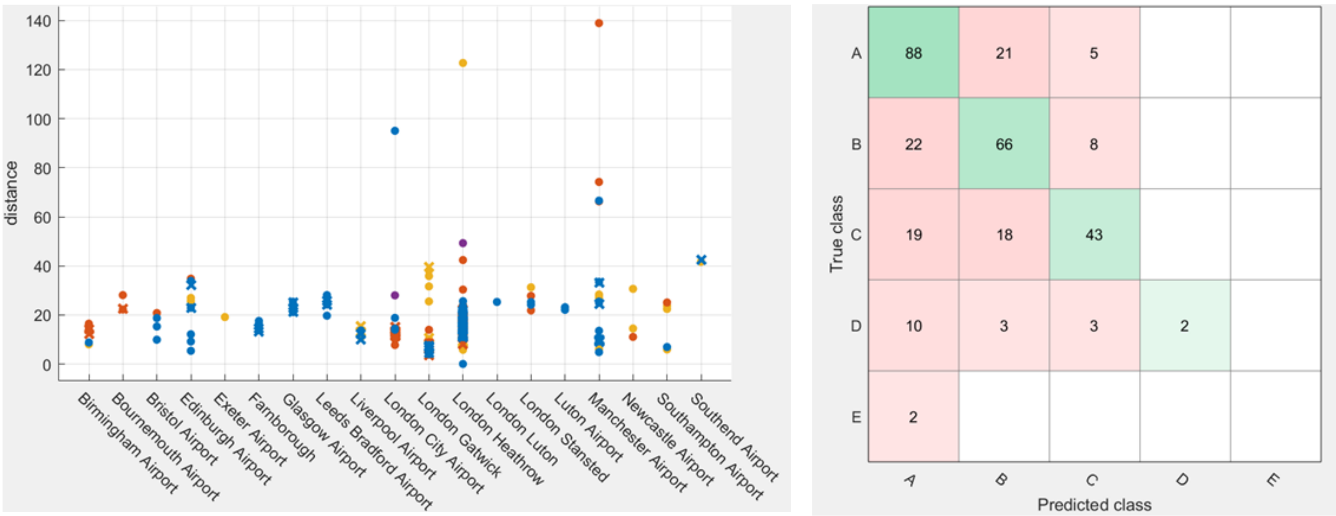

Fig. 10. Scatter plot of the predictions of the risk classification model for UKAB reports - "○" for correct and "x" for wrong (left); confusion matrix of the designed risk classification model (right).

This work has performed a preliminary analysis to verify the possibility of defining an **Airport Vulnerability Index** (**AVI**) to quantify the exposure or susceptibility of an airport with respect to unauthorized drone intrusions. An exhaustive definition of the AVI shall address the quantification of a **threat exposure** (wherein the threat is represented by the unauthorized drone intrusions in airports), by breaking it down into a threat likelihood and a threat mitigation. Thus, the following relationship holds

$$\mathrm{AVI} = f\big(P(\mathrm{drone}), M(\mathrm{drone})\big) \qquad (1)$$

In (1), $P(\mathrm{drone})$ is the likelihood function of a drone intrusion in the reference airport for the AVI, $M(\mathrm{drone})$ is the mitigation function of a drone intrusion in the reference airport, and $f(\cdot)$ is the combination function of the threat likelihood and the threat mitigation for the definition of the threat exposure (i.e., the AVI). Moreover, given that the definition of a vulnerability index has to address the different vulnerability dimensions, both $P(\mathrm{drone})$ and $M(\mathrm{drone})$ may generically be expressed as a multidimensional combination of different functions, each one related to a single dimension. For example:

$$P(\mathrm{drone}) = g(d_{\mathrm{soc}}(\cdot), d_{\mathrm{econ}}(\cdot), d_{\mathrm{ecol}}(\cdot), \cdots) \qquad (2)$$

The functions $d_{\mathrm{soc}}(\cdot)$, $d_{\mathrm{econ}}(\cdot)$, $d_{\mathrm{ecol}}(\cdot)$, etc., represent **dimensional influence variables** for the AVI. They quantify the influence of a given dimension (respectively, the social dimension, the economic dimension, the ecological dimension, etc.) of the airport's context. For example, $d_{\mathrm{soc}}(\cdot)$ may address the influence of relevant social factors of the community around the airport, such as the presence of drone regulations and the average level of compliance to the regulations themselves. Instead, $d_{\mathrm{econ}}(\cdot)$ may address the economic aspects related to the trends of drone market in the area.

In order to preliminarily verify the potential of the definition of the AVI index, an analysis has been performed starting from the available public record databases. As indicated by $P(\mathrm{drone})$ expression in the last equation, such analysis requires also some additional data to be used as dimensional influence variables, i.e., the economic-dimension influence, the social-dimension influence, etc. Given the preliminary nature of the analysis, only the following public socio-economic data have been found to be useful for the proposed activity in regard to FAA reports: the population of the States in the USA; the number of registered drones for each State in the USA. To the contrary, equivalent data have not been found for the UK in regard to UKAB reports. Thus, these reports have not been considered for this analysis. For the number of registered drones, note that FAA has released only one official report about drone registration location data up to 2016, which provides also the data about the population [24], [25]. The number of registered drones in 2020 has been estimated by considering a linear incremental factor according to the market trends. In detail, a parametric trend of +7% per year has been used.

Considering the available inputs, this work has aimed at providing a preliminary analysis for the estimator $\hat{P}(\text{drone})$ of the $P(\text{drone})$ function in the case of all the FAA airports in a given State and in a given year, as the following function of socio-economic data:

$$\hat{P}(\text{drone}) = h\big(d_{\text{soc}}(\cdot), d_{\text{econ}}(\cdot)\big) \tag{3}$$

In (3), $d_{\text{soc}}(\cdot)$ is related to the population and $d_{\text{econ}}(\cdot)$ is related to the number of registered drones. The stated definition of $P(\text{drone})$, jointly with the proposed evaluation method by means of the estimator $\hat{P}(\text{drone})$, sets a **modelling framework** for the threat likelihood as a part of the threat exposure. The mitigation function $M(\text{drone})$ has not been considered since the available FAA reports directly show only information about the occurrences of drone sightings, whereas they do not show information about the impacts and the mitigation actions in regard to the airports. The analysis has been performed at an aggregated State-level (and not at a local level for the single airports) since the available socio-economic indexes (population and number of registered drones) refer to a geographical State-scale. The analysis has been performed on a yearly time horizon, i.e., to develop a predictor of the number of drone intrusions in a given year.

For the purposes of this preliminary analysis, a check has been performed on the existence of *individual dependencies* between the terms in (3). For both the population and the number of registered drones, a quadratic trend has been observed in regard to the correlation with the number of drone sightings in the period 2016-2020 for FAA by-State airports. Thus, the (individual) estimator $\hat{P}(\text{drone})$ has been designed as a model $f(x)$ with a quadratic-polynomial structure, i.e.:

$$\hat{P}(\text{drone}) = f(x) = p_1x^2 + p_2x + p_3 \tag{4}$$

In (4), p_1, p_2 and p_3 are the fitting real coefficients, and x is the population or the number of registered drones in the reference State. Fig. 11 and Fig. 12 show the detailed results of the fitting models between the reference variables. For the first model (correlation fitting between the population and the cumulative number of drone sightings in 2016-2020), the following coefficients have been achieved:

- $p_1 = 3.635\text{e} - 07$;
- $p_2 = 0.01985$;
- $p_3 = 21.02$.

For the second model (correlation fitting between the number of registered drones and the cumulative number of drone sightings in 2016-2020), the following coefficients have been achieved:

- $p_1 = 1.202\text{e} - 07$;
- $p_2 = 0.01459$;
- $p_3 = -26.6$.

The accuracy of the proposed models has been evaluated by means of the coefficient of determination R^2. This is 0.8724 for the first model and 0.8821 for the second model. Thus, the achieved fitting models explain about the 87-88% of the variance in the correlation between the input variable (respectively, the population and the number of registered drones in a State) and the estimated variable (the yearly number of drone sightings in a State). Note that the low values of p_1 coefficients are related to the different scales of the inputs and of the outputs. Indeed, linear models (i.e., with $p_1 = 0$) exhibit less than 10% accuracy.

Such analysis suggests that: an estimator $\hat{P}(\text{drone})$ may be designed with respect to the population and to the local drone market; the population and the local drone market are influence variables in regard to the threat likelihood and the threat exposure for unauthorized drone intrusions in airports, determining respectively an **Airport Socio-Geographical Vulnerability Index** and an **Airport Socio-Economic Vulnerability Index**. Clearly, the proposed estimators are just examples for the definition of an effective AVI. More complete estimators are expected by using: additional databases of drone sightings, also for other countries (currently unavailable); additional data about other influence factor variables (e.g., drone regulations, airport's traffic, etc.).

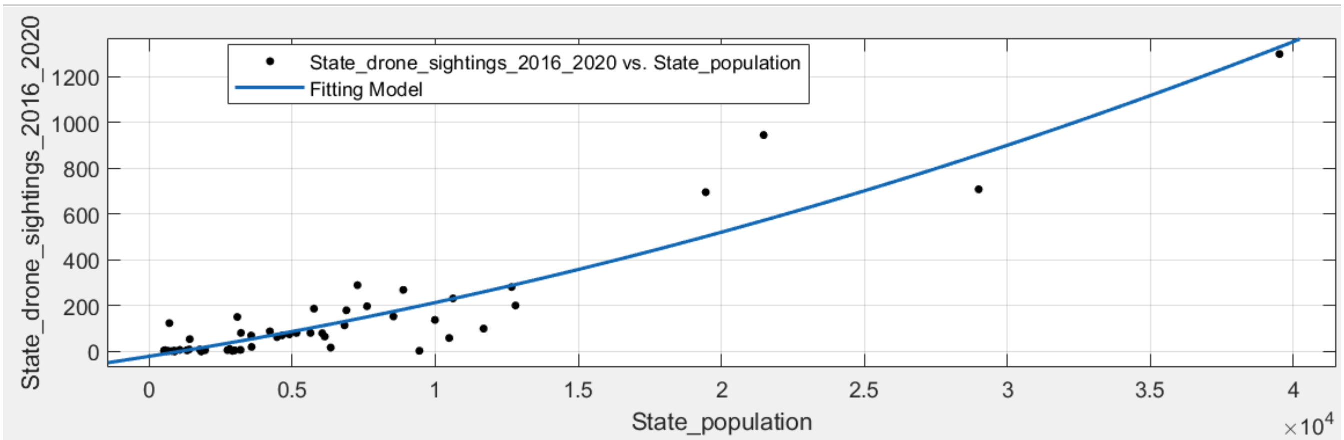

Fig. 11. Correlation fitting model between the State's population and the number of drone sightings (2016-2020) for by-State FAA airports.

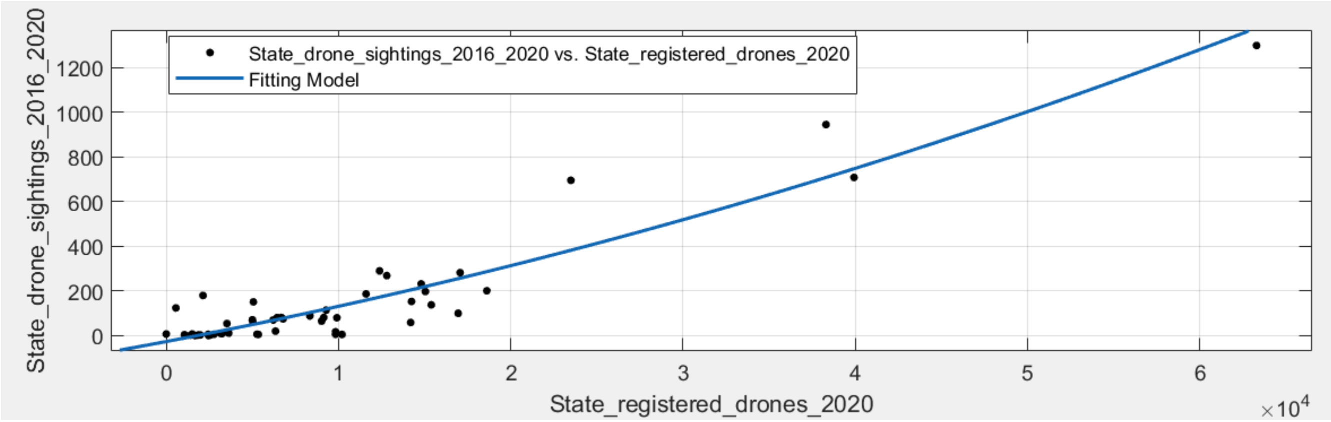

Fig. 12. Correlation fitting model between the State's number of registered drones and the number of drone sightings (2016-2020) for by-State FAA airports.

VI. Conclusion and Future Work

This work reports the processing of some public records (FAA and UKAB) of drone sightings in airports, by providing an assessment and a filtering in terms of several attributes, e.g., by time of the day, by State, by altitude, by airport distance, etc. Preliminary models have been designed for some reference features for the phenomenon of unauthorized drone intrusions in airports in order to check the feasibility of fitting probability distributions and building risk classification models by means of machine learning. A preliminary analysis has been performed for the definition of the AVI to quantify the threat exposure of an airport with respect to unauthorized drone intrusions, by including socio-economic and socio-geographical indexes.

The proposed concepts put the basis for a data-driven and performance-based management process within the DIMS of an airport. Besides, they aim to push the following objectives: the forecasting of the level of risk of drone intrusions in airport by leveraging historical data; the evaluation of quantitative indexes to support the decisions about the most appropriate actions for assuring the maximum level of security and for minimizing the impacts on airport operations.

Future work entails the refinement of the proposed models. Regarding predictive models, additional training data and inputs shall be collected and used for the design. Regarding the AVI, other correlations and dependencies shall be investigated, e.g., with: socio-cultural indexes considering the definition of a local regulatory framework and the aptitude to rule observance; indexes related the promptness of intervention in case of intrusion; etc. Also, other data are expected to influence an airport's exposure to drone intrusions, such as: the presence of drone regulations; the type of airport; the airport's traffic; the number of airport operations; the unmanned traffic (if any); the number of purchased drones in the region; etc. Fine-grain data would allow to tune an AVI for a specific airport. A systematic study shall be performed to include the proposed models: in a risk assessment framework of airport operations with respect to drone intrusions; in an accurate simulation environment about drone intrusions in airports.

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