Analysis of Airspace Infringements in European Airspace

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Abstract— **Airspace infringements (AIs) can be defined as the unauthorised entry of an aircraft in controlled airspace. AIs are one of the primary concerns of the general aviation (GA) in Europe because such incidents can reduce the distance between different types of air traffic, increasing the risk of a catastrophic mid-air collision. Although previous studies of EUROCONTROL identified the key topic of AIs in GA, there are concerns about the effectiveness of the analysis of safety incident reports of AIs. This paper proposes a robust safety analysis methodology for AIs involving GA in Europe. Firstly, the studies conducted by EUROCONTROL in relation to the AIs are reviewed and a methodology is proposed to find contributory factors of AIs from incident reports. Subsequently, relationships between these are factors are investigated using contingency tables and log linear models and these factors are ranked regarding their frequency of occurrence. Finally, two severity models are developed using the contributory factors. Incident data from the Norwegian Air Navigation Service Provider Avinor between 2008-2012 were used for this analysis after an assessment for their quality. The results indicate that the ANSP should focus on GA pilots, flying in the springtime in southern Norwegian airspace, in particular ensuring appropriate navigation and communication skills.**

Keywords-component; airspace infringement; incident analysis; safety; general aviation

I. INTRODUCTION

The distinction between uncontrolled and controlled airspace ensures that only those aircraft known to air traffic control (ATC) can fly in the latter and thereby ensure the safety of the airspace. Therefore, any aircraft that enters controlled airspace without prior permission causes considerable problems for ATC, any other aircraft in its vicinity as well as for the infringing aircraft itself. Such a situation may reduce the separation between aircraft to a critical level and has the potential to lead to a catastrophic mid-air collision. This unauthorised entry of an aircraft into a controlled airspace can be defined as an airspace infringement (AI).

AIs represent one of the most frequently reported types of incidents in Europe and involve mainly general aviation (GA) aircraft [1]. The European incident reporting scheme changed in 2010 leading to a 25% increase in the total annual number of AIs reported. Of the approximately 250 incidents reported in that year, 25% were not analysed either because of lack of adequate information to assess their severity or lack of time to do so. As for their impact on safety, approximately 70% of the incidents analysed led to a loss of separation with another aircraft in 2010. Given this high proportion of incidents that could not be analysed, there are serious concerns regarding the efficacy of the methods used to report and to analyse such incidents.

Such concerns about the analysis of AIs, given their potential catastrophic impact, suggests the need to develop a robust safety analysis methodology for AIs involving GA in Europe and this paper aims to do this by using AIs from the Norwegian Air Navigation Service Provider (ANSP) *Avinor* involving GA. In particular, this paper shows that mathematical relationships can be used in the incident analysis of AIs only if high-quality safety data are used such as those of Avinor. Using the proposed methodology, relationships between contributory factors can be found and the impact that these factors have on the safety effect can be estimated.

The paper is organized as follows. Section II reviews existing studies conducted by EUROCONTROL in relation to the AIs and Section III outlines the methodology used in this paper and the data that will be used. In Section IV, the *Avinor* database is described and assessed in terms of its quality. Section V focuses on the contributors of AIs and compares the content of the taxonomies obtained from the literature review with that obtained in the safety data; it also estimates associations between contributors, and designs mathematical models for the severity. This is then followed by a discussion of the results including the relevance for the ANSP in preventing future AIs before concluding.

II. LITERATURE REVIEW OF THE ANALYSIS OF AIRSPACE IINFRINGEMENTS IN EUROPE

In a series of studies conducted by EUROCONTROL between 2007 and 2008, retrospective analysis of AIs attempted to identify both the parties responsible for and the events that can lead to an incident as well as the likely contributory factors. The first study used a relatively small sample of 423 incident reports from nine European countries that occurred between 2004 and 2005 [2]. The analysis indicated that AIs are more frequent in GA than in commercial aviation; however, the absence of sufficient information about the taxonomy of contributory factors and the event sequence of the AIs meant that the severity of the incidents could not be determined. This limitation was partially overcome by outlining the safety barriers that could prevent an AI [3].

In order to improve the weak taxonomy of contributory factors of AIs, a survey of GA pilots, who are the main contributors of AIs, was designed in the second study [3]. GA pilots were chosen randomly from 28 European countries to answer a questionnaire regarding their view on the contributory factors of AIs and likely mitigation measures. The contributory factors proposed by the pilots differed from those of the first study and were mainly related to: pilot behaviour, pilot skills e.g. the misuse of aeronautical data, and knowledge of the rules and procedures of flying. These pilot-related factors also contribute to other incidents and accidents in GA [4, 5].

The third study used a sample of reports of approximately 100 AI incidents that occurred in the areas surrounding Geneva and Zurich airports in Switzerland, and in conjunction with a discussion with GA pilots at the aviation clubs [6]. This study confirmed that while the safety data used could identify scenarios in which AIs may occur, they are inappropriate for developing taxonomy of contributory factors and for assessing the severity of AIs incidents. Such information can be found from discussions or surveys with the GA pilots but their outcome depends to a large extent on the design of the interview/survey and the available resources. An inappropriate interview strategy, such as that in the third study conducted by EUROCONTROL, is unlikely to determine the detailed factors. A well-designed survey such as that conducted by the Safety Regulation Group of the CAA UK, can result in an exhaustive taxonomy [7]. This taxonomy was developed using approximately 2500 responses of GA pilots, who were based in the UK, in the period July 2001 and January 2003 [7].

Although these studies identified the major areas of contributory factors, concerns were raised regarding the effectiveness of the analysis of safety incident reports. Therefore, this paper examines how useful the current incident reporting scheme is for the analysis of AIs by using incidents from *Avinor* and describes the basic characteristics of AIs.

III. METHODOLOGY

The analysis in this paper is separated into two distinct parts. The first part focuses on the descriptive statistics of AIs. Before that, the given data are coded and new data fields are created if it is necessary. The data fields are grouped together under logical arrangements. For example, flight phase, call sign and type of aircraft are grouped together. Some of missing data might be replaced with data from other data fields. If, for instance, the infringing airspace class of an incident is missing, such information can be found in its description. The new dataset is then assessed to find to what extent the data are accessible, consistent, complete and relevant using four criteria [8]. Each of these criteria should be over 50% to ensure reliable results.

The criterion of accessibility aims to find how many variables the dataset can provide without any further modifications. It is computed by identifying which post data processing variable already exists in the database (explicit), is modified for the purpose of the analysis (inferred) or is newly created (implicit). The counts (N) of these three types of variables are used to estimate the accessibility of the data as (1) shows. The criterion of consistency estimates the percentage of data that are reported with the same way within each variable (consistent). If a variable is either recoded or newly coded for the purpose of this analysis, it is also considered. The total number of variables for the three types of variables is used as (2) shows.

Completeness of the dataset is equal to the difference of the percentage of the complete data and missing data as (3) indicates. The percentage of missing data is estimated for each variable and the arithmetic average of all the missing data is calculated. Last but not least, the criterion of relevance, which is shown in (4), aims to find how many data fields are relevant to the required variables. For this analysis there are eight groups.

$$\text{accessibility} = \frac{0.04 \times \mathrm{N_{inferred}} + 0.16 \times \mathrm{N_{implicit}} + 0.80 \times \mathrm{N_{explicit}}}{\text{Number of variables}} \tag{1}$$

$$\text{consistency} = \frac{0.04 \times \mathrm{N_{newly\ coded}} + 0.16 \times \mathrm{N_{recoded}} + 0.80 \times \mathrm{N_{consistent}}}{\text{Number of variables}} \tag{2}$$

$$\text{completeness} = 100 - \text{arithmetic average of missing values percentage} \tag{3}$$

$$\text{relevance} = \frac{1}{8}\sum_{i=1}^{8} \frac{\mathrm{N_{relevant\ ,i}}}{\mathrm{N_{request\ ,i}}} \times 100 \tag{4}$$

The second part of the analysis is related to the contributory factors of AIs in a country. Factors that might have contributed to the incident are identified for each incident separately mainly from the narratives of the controller and the investigator of the incident. This is a loop procedure that initiates with an initial taxonomy of contributory factors that are obtained from the studies of EUROCONTROL and the Safety Regulation Group of the CAA UK [2, 3, 6, 7]. This taxonomy is modified when a new factor is found to contribute to the incident or an existed factor has a wide meaning or overlaps with other factors. For each factor that is true for an incident, its variable is coded with 1 otherwise with 0.

Relationships between contributory factors can be determined using statistical models such as two-way contingency tables and log-linear models [9]. Contingency tables can be described as frequency tables that present two categorical variables, which represent the contributory factors,

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at the same time. If two binary categorical variables are used, the table will be consisted of two rows and two columns that will represent the level of each variable. Cells represent the joint frequency of each of these two levels and this is known as cell frequency. The significance of the contingency tables is tested by comparing the observed frequencies and the critical value of the chi-square test. This test, however, is inefficient for more than two variables and log linear models are used. Log linear models can find relationships between levels of categorical variables, which are known as partial associations, because variables are not distinguished between independent and dependent variables as contingency tables do.

Apart from finding relationships between factors, mathematical models can be used to identify factors that are more likely to occur and factors that are more likely to influence the safety effect of an AI. Such models are widely used in the long-standing road safety sector [10-13]. What they assume is that frequency and severity of an incident are mutually independent which means that a factor that frequently contributes to an incident might have smaller effect on safety [10]. These models can represent frequency and severity either separately or combined for count data. The latter can find misidentified or unidentified relationships between frequency and severity when the model splits the predictions into two levels: the frequency and severity [10]. At the first level, contributory factors are ranked individually and in pairs regarding their frequency of occurrence.

At the second level, severity is assessed in two forms: the safety effect on the aircraft involved and on the Air Traffic Management (ATM) service. These two variables of severity are categorical and have the value of 0 and 1, which are named as no impact and significant respectively. The former represents incidents that have no impact on severity or cannot be analysed reflecting ESARR class D and E. The latter represents incidents that have been classified by the ANSP as serious, major and significant and these correspond to ESARR class A, B and C respectively [14]. For a two-level dependent variable, binary discrete choice models are used to estimate the likelihood of each of the levels of the severity [15]. The analysis of each incident is the key advantage of discrete choice models over those that aggregate incidents.

The model that is used in the paper follows a binomial distribution and has a logit link function as (5) indicates. The simplest form of the utility function, which is the linear function, is used in this paper as it is show in the right hand side of (5). The independent variables x are binary variables with values 0 and 1 and represent factors, such as contributory factors. As (6) shows, the probability that the safety effect of an incident i will be classified as significant equals to the exponential of the utility function over the sum of the exponential of the utility plus one. The probability that the safety effect of an incident i will be classified as no impact is equal to one minus this probability. Such binary logistic regression models are calibrated using the maximum likelihood estimation, which means that the model with the highest value of likelihood is chosen. For goodness-of-fit measures, the Akaike Information Criterion and Bayesian Information Criterion were used. For further details of the mathematical formulation of the model see [15].

$$\text{Logit}\left(P_i(\text{a})\right) = \text{LN}\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \tag{5}$$

$$P_i(a) = \frac{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k)}{1 + \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k)} \tag{6}$$

IV. AIs in Norwegian Airspace

A. *Structure of database and its quality assessesment*

Avinor database consists of 19 fields that can be classified into seven relevant groups based on their definition. Each group consists of categorical, coded or narrative data fields. For the five-year period between 2008 and 2012, 530 AIs were recorded. In Table I, the letters (N), (R) and (M) correspond to a new variable that is created for this analysis, a variable that already exists in the database and missing data respectively. What was used to modify the already existing variables and to complete any missing data when it was appropriate were the narratives of incidents from the air traffic controller and the incident investigator.

TABLE I Avinor Database Processing

Variable topic	Original variable	Postdata processing variable	
Incident general information			
Incident reference	Reference number	-	
Location	Location	Southern/Northern	(R)
Date	Date	Month	(N)
Time	Time	Light Conditions	(R,M)
Year	Year	Year	(R)
Description			
By controller	By controller	Narrative	(R)
By investigator	By investigator	Narrative	(R)
Aircraft			
Call sign	Call sign	-	
Flight phase	Flight phase	Flight phase	(R,M)
Model	Model	Civil or Military	(N)
Two-way radio contact	-	Time of contact	(N)
Air Traffic Controller			
Workload	Workload	Workload	(R,M)
Controller's contribution	Controller's contribution	Controller's contribution	(R,M)
Severity assessment			
Aircraft involved	Aircraft	Aircraft involved	(R,M)
ATM	ATM	ATM	(R,M)
Environment			
Weather relevant	Weather relevant	Weather relevant	(R)
Weather report	Weather report	Weather report	(R)
Light conditions	Light conditions	Light conditions	(R,M)
Airspace			
Type	Type	Type	(R,M)
ICAO class	ICAO class	ICAO class	(R)
Traffic density	Traffic density	Traffic density	(R,M)
Contributory factors			
Contributory factor	-	Contributory factor	(N)
Attributor	-	Attributor	(N)
Category	-	Category	(N)

Prior any analysis, the quality of the database was assessed based on the criteria outlined in Section III. The values for the criteria were in excess of 50% except that of the relevance. Low relevance means that there were less relevant variables than the required for analysis though the value is close to the 50% threshold, and given the values of the other criteria, this data can be used for further analysis. The values of the criteria are shown in Table II.

TABLE II QUALITY ASSESSMENT OF AVINOR DATABASE

Qualitative criterion	**Relevance**	**Completeness**	**Accessibility**	**Consistency**
Percentage %	48.5	88.24	60.20	62.20

B. *Descriptive statistics*

AIs in Norwegian airspace usually involved GA aircraft flying in visual flight rules (VFR) at daylight, involving just a single aircraft as shown in Table III. Approximately 75% of the incidents occurred at the en-route flight phase. In terms of airspace, 54% of the aircraft involved infringed Airspace Class D and 31% infringed Airspace Class C. The pilot of the GA aircraft was attributed as the causal agent of the incident in 71% of the AIs, with his/her inadequate navigation and communication skills as the biggest contributors to this.

TABLE III DESCRIPTIVE STATISTICS OF AIS IN NORWAY BETWEEN 2008 AND 2012

Classes	**Frequency**	**Percentage**
Involved aircraft		
1	466	87.92%
2	59	11.13%
3	5	0.94%
Aircraft type		
Civil	424	80.15%
Military	84	15.88%
Unknown	21	3.97%
Flight phase		
Standing/Take off	19	3.58%
En-route	402	75.85%
Approaching/Landing	67	12.65%
Unknown/Null	42	7.92%
Airspace Class		
A and B	3	0.57%
C	164	30.94%
D	286	53.96%
E	1	0.19%
G	20	3.77%
Other	3	0.57%
Unknown/Null	53	10.00%
Causal Agent		
Pilot	380	71.70%
Controller	150	28.30%
Pilot and Controller	49	9.25%
*Causal category**		
Pilot navigation skills	-	45.56%
Pilot communication skills	-	21.32%
Controller skills	-	19.39%
Equipment	-	10.99%
Environmental	-	2.75%

*More than one category is involved

1) *Seasonality of AIs*

A rapid increase in the number of incidents is noticed in March and April, when the weather conditions allow GA pilots to start flying again following a long period of inactivity during the winter, as shown in Figure 1. Therefore, the period between March and April can be assumed to be the transition period from the inactive season. AIs in winter were almost exclusively due to military activity.

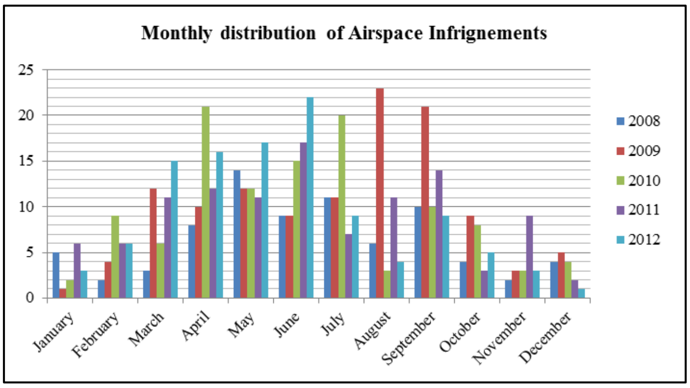

Figure 1. AIs per month

2) *Environmental conditions*

Almost all AIs occurred during daylight. It was impossible to obtain both the actual time at which the incident occurred, as well as information about the visibility conditions; as such information is not included in incident reports.

3) *Location of AIs*

Approximately 80% of AIs occurred in Southern Norwegian airspace due to the attractive weather conditions for recreational pilots. Particular airspace areas attracted more pilots, such as that adjacent to Bardufoss airport (ENDU) located near to flying schools. Further investigation of areas with higher demand is required.

4) *Two-way radio contact*

The time that the two-way radio contact between the pilot and the controller was established was examined following the recommendation of the study of EUROCONTROL [6]. For 60% of the incidents, the pilot entered controlled airspace without any contact with the controller. Under these circumstances, controllers and pilots are unaware of the intentions of the infringing aircraft and traffic must keep a safe distance from the infirming aircraft, if the aircraft is visible. For approximately 25% of the incidents, either the pilot or the controller established contact after the aircraft entered controlled airspace and for approximately 11% of the incidents, the pilot neglected the rejection or the instructions of clearance.

5) *Controller workload and traffic density*

In Figure 2, about 70% and 65% of the incidents occurred at low traffic density of the infringed sector and at low controller workload respectively. However, these subjective terms could not be determined by the controllers for almost 50% of data in 2012. This is an area of incident reporting that requires considerable improvement.

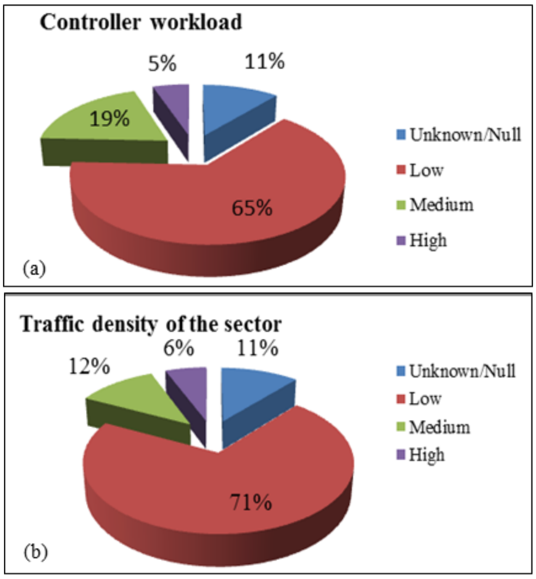

Figure 2. (a) Controller workload and (b) traffic density

6) Severity classification

The severity assessment of the incidents changed during the study period. Until 2012, it was based on the potential of the incident, which was found inappropriate for assessing the safety effect of the aircraft involved because essential information was missing. For the purposes of this study, the severity of the flight is analysed only for the period between 2008 and 2011. As shown in Figure 3, incidents were more likely to be classified as ESARR class C for the impact on the safety of the flight whereas 95% of the incidents had no impact on safety of the ATM in 2012 [14].

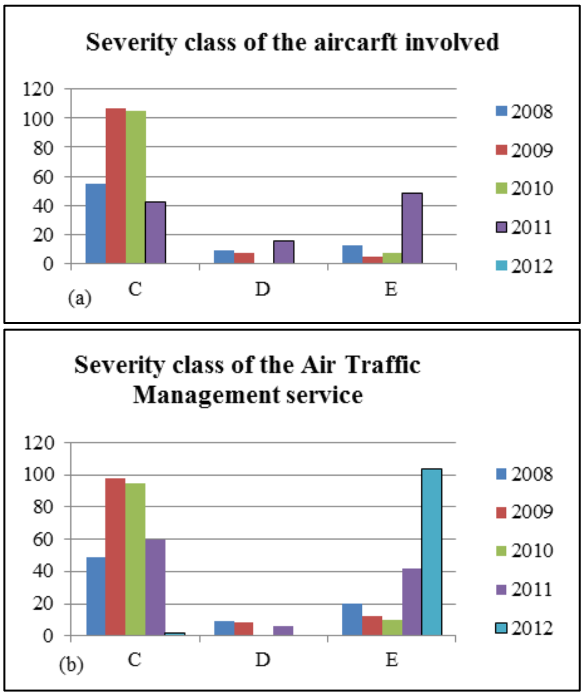

Figure 3. Severity classification of (a) aircraft involved and (b) ATM service

V. Contributory Factors of AIs

A. Taxonomy of contributory factors

The contributory factors that are obtained from the literature review and the safety data of Norway are classified into the following thirteen categories.

i. Aeronautical information,
ii. Airspace design,
iii. Air traffic management infrastructure,
iv. Communication skills of the pilot,
v. Environment,
vi. Equipment,
vii. Human factors,
viii. Navigation skills of the pilot,
ix. Organizational factors,
x. Procedures,
xi. Regulation,
xii. Skills of the controller and,
xiii. Training of the pilot.

The factors found in the Norwegian data differed from those of the other taxonomies highlighting the diversity of reporting of such AI incidents between nations as well as the differences between incident analysis and pilot interviews. It was possible to identify the quality of the flight plan, which is considered important in the other studies mentioned and to distinguish the inadequate knowledge of navigation into three factors: inadequate knowledge of the airspace structure, of airspace procedures and, of airspace boundaries. On the other hand, some factors related to the skills and behaviour of the pilot were unobserved, reflecting the limitations of the data that ANSP collects.

B. Ranking of contributory factors

The contributory factors were ranked individually and in pairs, independently of the total number of factors of each incident. As Table IV indicates, the most frequent factor was the poor/no of radio contact between the pilot and the controller, followed by the use of wrong frequency by pilots, which was four times less than the first contributory factor. Almost all the frequent factors had a pilot cause. In situations in which GA was involved, the aircraft flew in the southern Norwegian airspace or the aircraft flew between October and March, as Table V shows. In considering pairs of contributors, the pair ‘no/poor radio contact’ and ‘the use of wrong radio frequency’ was ranked first. When an aircraft flew in the northern airspace of Norway, the most frequent pair of contributors was ‘the no/poor radio contact’ and ‘the inadequate coordination between the controllers’.

TABLE IV. RANKING OF SINGLE CONTRIBUTORY FACTORS

Ranking	Contributor	Frequency
1	No/Poor radio contact	317
2	Use of wrong frequency	68
3	No/Poor Flight Plan	58
4	Inadequate knowledge of airspace boundaries	56
5	Inadequate knowledge of airspace procedures	49
6	Loss of awareness	47
7	Unfamiliar airspace and/or route	45
7	No/Poor air traffic controller coordination	45

TABLE V. RANKING OF PAIRS OF CONTRIBUTORY FACTORS

Contributor								Aircraft type		Location		Month	
No/Poor radio contact	Use of wrong frequency	Poor/Lack flight plan	Inadequate knowledge airspace boundaries	Inadequate knowledge airspace procedures	Loss of awareness	Unfamiliar airspace and/or route	Inadequate coordination between controllers	Military	General aviation	Northern airspace	Southern airspace	October to February	March to September
X	X							2	46	13	35	9	39
X		X						2	20	2	25	6	21
X			X					25	11	11	26	12	25
X				X				1	12	1	12	1	12
X					X			1	10	2	9	2	9
X						X		11	17	13	15	3	25
X							X	9	25	15	19	10	24

C. Associations between contributory factors

The associations between the categorical variables of the safety data were investigated using the cross tabulation method and the log linear analysis for two and more than two categorical variables respectively. For this study, the tests were run by the Statistical package IBM SPSS Statistics 19.0 and in certain cases variables had to be combined under logical arrangements because of the low expected frequencies. For example, the two categorical variables, which described the attributors of an incident, were replaced by the binary variable that indicates if the pilot is involved or not in the incident.

Table VI shows the results of selected important associations of the factors are statistically significant at the 95% and 90% level of confidence, indicating the Pearson's value of the test and those associations where the expected cell frequency is below five. The results of the statistical models indicate that more factors are statistically associated with the type of the aircraft than the involvement of the pilot in the incident, highlighting the differences between GA and military. The location of the incident is statistically associated with the light conditions at the time of the incident. Apart from this, the location is related to the navigation and communication skills of the pilots, such as the quality of the flight plan, the wrong choice of radio frequency and the loss of situational awareness.

TABLE VI. ASSOCIATIONS OF VARIABLES AT 95% (ORANGE), 90% (BLUE) AND 90% (GREEN FOR PARTIAL ASSOCIATIONS) LEVEL OF CONFIDENCE

	Aircraft type	Pilot involved	Location	Pilot involved / Factor / Aircraft type
Summer period	0.00 (L)	0.63 (L)	0.04	0.76 (L)
No/Poor flight plan	0.09 (L)	0.17 (L)	0.06	0.15 (L)
Inadequate knowledge of airspace structure	0.24 (L)	0.38 (L)	0.64 (L)	0.36 (L)
Inadequate knowledge of airspace procedures	0.01 (L)	0.25 (L)	0.02	0.18 (L)
Inadequate knowledge of airspace boundaries	0.00 (L)	0.20 (L)	0.79	0.15 (L)
Loss of awareness	0.02 (L)	0.27 (L)	0.02	0.19 (L)
Wrong frequency	0.01 (L)	0.17 (L)	0.93	0.01 (L)
Unfamiliar airspace and/or route	0.03 (L)	0.18 (L)	0.00	0.20 (L)
No/Poor radio contact	0.00	0.00	0.02	0
Light Condition	0.00 (L)	0.22 (L)	0.02 (L)	0.33 (L)

D. Severity models

Two models were calibrated to estimate the safety effect on the safe operation of the aircraft involved (Severity of aircraft) and the safety effect on the ability to provide safe ATM service (Severity ATM) using binary logistic regression models as discussed in Section III. The models were calibrated using 420 incidents that occurred between 2008 and 2011 in which they were reported in a consistent way as explained in Section IV.

Using the binary variable of severity of aircraft, the best model, this is the one that has the highest value of the log-likelihood, has three degrees of freedom as Table VII indicates. These parameters are the involvement of the pilot, the month and the location that the incident occurs and inadequate knowledge of airspace procedures of the pilot, which has not been found a frequent contributory factor at the first stage of the combined model. That impact that these parameters has on the probability that the incident will be classified as significant is measured with the odds of the parameters. If, for example, the pilot is involved in the incident which occurred in September in northern Norway and the pilot has inadequate knowledge of the airspace procedures, the probability that the incident will be classified as major is 0.981 and the probability that the incident will be classified as no impact is (1-0.981=0.019).

The best model of the severity of ATM, as Table VIII outlines, consists of relatively frequent factors which can influence the performance of the controller. These factors are the existence and quality of pre-flight plan, which has larger effect on the probability that the incident will be classified as significant, the month that the incident occurs and the establishment or not of a two-way radio contact. For instance, if the incident occurs in April, there is a flight plan but the pilot is not in radio contact with the controller then the probability that the incident will be significant will be equal to 0.80 and the probability that the incident will be classified as no impact is (1-0.80=0.20). However, if the pilot is in contact with the controller, the probabilities will be equal to 0.48 and 0.52 respectively.

TABLE VII. BINARY LOGIT MODEL – SEVERITY OF AIRCRAFT

Parameter	Value	Odds	Significance
Intercept	-0.788	0.455	0.036
Pilot is involved	1.588	4.893	0.004
Summer period	0.321	1.379	0.321
Location of incident (South)	0.738	2.092	0.007
Indequate knowledge of airspace procedures	-0.662	0.516	0.095
Likelihood ratio chi square	19.45		
Log likelihood	-16.819		
Akaike's information criterion	43.637		
Bayesian Information Criterion	63.838		
Degrees of freedom	3		
Significance	0.001		
Level of confidence	95%		

TABLE VIII. BINARY LOGIT MODEL – SEVERITY OF ATM

Parameter	Value	Odds	Significance
Intercept	-1.984	0.137	0
Summer period	0.925	1.572	0.43
No/Poor flight plan	0.925	2.522	0.082
Radio contact	-0.428	1.535	0.233
Likelihood ratio chi square	7.529		
Log likelihood	-8.569		
Akaike's information criterion	23.139		
Bayesian Information Criterion	35.195		
Degrees of freedom	2		
Significance	0.023		
Level of confidence	95%		

VI. DISCUSSION

The analysis of Avinor data show that the traditional approach used to identify the contributory factors can be extended to analyse statistically the factors only when the safety data are accessible, consistent, complete and relevant. Such data enables to determine relationships between factors, to identify frequent factors as well as factors that are more likely to have an impact on severity. The way that data are collected has room for improvements in that, more relevant factors that can be provided from the controller, such as the altitude of the aircraft, to be collected.

The analysis of Avinor data has confirmed key characteristics of AIs by GA because of the relatively detailed narratives of the controllers. This has caused factors related to navigation and communication skills of the pilots, which were found only when pilots were interviewed in the second study of EUROCONTROL, to be identified. Factors that were not mentioned in the studies of EUROCONTROL have been found, such as the inadequate knowledge of airspace boundaries by pilots. This shows that detailed descriptions can identify factors that in other countries might not appear. Apart from these findings, the importance of the establishment of radio contact, which was identified in other studies, was found using the severity model of ATM.

This study has also succeed in confirming the importance of the quality of the flight plan, which has be recognised as an important factors by the GA pilots in the studies of EUROCONTROL, to prevent AIs and its negative consequences. Furthermore, the data confirms that a long inactive period for GA pilots especially in winter can reduce their performance and infringe controlled airspace. This inactivity as well as the location of the incident has a negative effect on safety of the aircraft involved and the ATM service as indicated by the severity models.

Such quantitative results including those of the quality assessment of the data can be of great use to the ANSP in that it enables the authority to focus on flying clubs located in particular geographical areas of southern Norway in the Spring months to inform GA pilots there about the procedures that they must follow. Last but not least, the airspace provider can use the results of the analysis to assess how pilots that fly near to the boundary of controlled airspace can be influenced by the use of new VFR flight planning and navigation software, such as the SkyDemon.

VII. CONCLUSION

Current incident reporting schemes across Europe restrict the analysis of AIs unless they posses a high data quality. Avinor possesses a high quality database of incidents for the analysis of AIs, which is consequently used in this paper. The statistical analysis methodology of such data can identify the most significant areas that should be further examined by the ANSP considering both the frequency that incidents occur and their severity. It should be noted that the analysis focused on the Norwegian airspace, and therefore, the results of this paper cannot be generalised in the European level. However, the methodology would be applicable to any nation that possesses such a high quality database. Further research should focus on a better understanding of the GA pilots' factors, and using a methodology of interviews and observations to obtain such factors.

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