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Prediction of aircraft safety incidents using Bayesian inference and hierarchical structures

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ABSTRACT

Today, aviation is immersed in a shift from old-fashioned reactive and compliance-based safety approaches towards proactive and performance-based methods and tools. Stakeholders have to monitor, gather and analyse safety-related data and information in order to anticipate and predict actual and emerging safety risks. In this context safety analytics and statistics need to evolve to forecast future safety performances and risks.

This research adopts an innovative statistical approach involving the use of Bayesian inference and Hierarchical structures to develop statistical estimation and prediction models with different complexities and objectives. The study develops and analyses five Bayesian models of increasing difficulty, two basic and three Hierarchical models, which allows us to explore safety incident data, efficiently identify anomalies, assess the level of risk, define an objective framework for comparing air carriers, and finally predict and anticipate incidents.

1. Introduction

Aviation product and service providers and safety oversight authorities around the world are moving from traditional reactive and compliance-based safety and operational approaches towards new proactive and performance-based tools and methods (ICAO, Third Edition, 2013).

As such, nowadays, aviation stakeholders not only have to monitor, gather and analyse safety-related data and information, but also must identify, anticipate and predict safety-related trends and proactively address actual and emerging safety risks. Such a shift introduces a parallel need for new safety indicators and new statistical methods suitable for modelling accidents and incidents, and their evolution.

The reporting and evaluation of less serious safety events is of prime importance in safety analysis. Statistics on less serious incidents can potentially provide a great deal of information as they are more frequent and reporting is simpler. ICAO, EASA, EUROCONTROL and the FAA (EUROCONTROL and FAA, 2012), and other safety authorities, have put a lot of effort into identifying common information and performance indicators for use in safety monitoring. Specifically, ICAO Annex 13 (ICAO, 2010) requires States to establish accident and incident reporting systems to gather information on real or potential safety shortcomings. European Regulation (EU) No 376/2014 (European Union, 2014) mandates the reporting, analysis and follow-up of incidents in civil aviation. Furthermore, the European Union developed the ECCAIRS database (European Co-ordination Centre for Accident and Incident Reporting Systems), which offers standard and flexible accident and incident data collection, representation, exchange and analysis tools.

A combination of reactive, proactive and predictive analytics is required to exploit the potential of safety data to give feedback about operational hazards and risks. In this context safety analytics and statistics need to evolve from the analysis of reactive indicators towards a more predictive perspective, to forecast future safety performance and risk.

Over recent decades, there has been substantial research on the use of modern statistical techniques to predict safety incident and accident precursors in other modes of transport, specifically road transport (Lord, et al., 2005). The statistical models commonly used include Binomial, Poisson and Poisson-gamma (or negative binomial). The tools used to develop predictive models include random-effect models (Miaou & Lord, 2003), generalised estimating equations (GEE) (Lord & Persaud, 2000), and Markov Chain Monte Carlo (MCMC) methods (Qin, et al., 2004).

Within the context of aviation, there is limited available research that compares different predictive modelling approaches, identifies the most appropriate statistical models for forecasting safety events, or helps to predict safety performance (Drees, 2014; Di Gravio, et al.,

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2015; Janic, 2000; Kunimitsu Iwadare, 2015; Knecht, 2015; Panagiotakopoulos, et al., 2014).

Two modern statistical tools that are increasingly being used for predictive applications in areas such as microbiology, sociology, psychology, econometrics, structural engineering, nuclear physics, and so on, are Hierarchical structure and Bayesian models.

Relevant academic literature gives interesting examples of the types of aviation issues to which Bayesian techniques can be applied. Examples include: Spatial Analysis of Pilot Fatality Rates in General Aviation Crashes (Curriero et al., 2002); Probability of Midair Collision During Ultra Closely Spaced Parallel Approaches (Houck & Powell, 2003); Analysis of Failure Risk in Engine Rotor Disks (Enrigth and Huyse, 2003); Probabilistic Forecasts for Aviation Traffic (Bhadra & Shaufele, 2007); and A Probabilistic Influence Diagram for Landing Runway Overrun Excursion Risk Analysis (Sanchez Ayra, 2015). Object-oriented Bayesian network (OOBN) has also been used to integrate the safety risks contributing to an in-flight loss-of-control aviation accident, allowing to quantitatively drawing inferences about changes to the states of the accident shaping or causal factors (Ancel et al. (2015)).

In this research, we have adopted an innovative statistical approach as opposed to the reactive methodologies used up to now. This distinctive approach involves the use of Bayesian inference to develop statistical estimation and prediction models with different complexities and objectives. One of the most noteworthy features of Bayesian inference is that it allows us to easily develop Hierarchical Models, with differing orders of complexity, that have different objectives. It also enables us to evaluate the predictive efficacy of the models and to compare them with one another. In a discipline such as air safety, a hierarchical structure is extremely useful since it is conceptually consistent with techniques already in use in the sector, such as Bayesian networks or fault trees.

The aim of this paper is to demonstrate that such techniques are applicable to the study of aviation safety data, and that they enable us to extract information about the magnitude of risk involved and to make predictions. As such, they may be used in preventive and predictive methodologies to improve the safety conditions under which airlines operate, thereby minimising the level of risk.

In this study, we developed and analysed five Bayesian models of increasing complexity. Specifically, there were two basic and three Hierarchical Models which allowed us to:

– Explore safety incident data and efficiently identify anomalies;
– Assess the level of risk;
– Define an objective framework for comparing air carriers, and finally;
– Predict and anticipate incidents.

The models are demonstrated and applied in a specific aviation industry “Commercial Air Transport and its safety” by the use and prediction of airline's safety occurrences; although the models could be applied to any safety industry. More specifically, the results of this study are illustrated using data of monthly incidents from four fleets of different models of aircraft belonging to Company A. The incidents correspond to: *Pilots Reports* in the technical log book about breakdowns or malfunctions of any aircraft system; subsystems or components *Faults or Failures Deferred*; *In-Flight Shutdowns*, *In-Flight Turn-Backs*, *Delays and Cancellations* for Technical Reasons; *Rejected Take-Offs* for technical reasons; Non-Stabilised Approaches; and *Flight Time Limitations* exceeded.

The models can be of great utility in aviation industry for safety oversight and safety improvement and they can be applied at three different levels:

(a) By the Safety Oversight Authority to identify sources of risk in Commercial Air Transport at national level, quantify the specific risks, compare different sources of risk and, most importantly, quantify the level of uncertainty and predict the future distributions of incidents.
(b) To benchmark the performance of different air carriers as it allows identifying the parameters that are characteristic of the safe operation of each operator and of the entire system. These parameters allow identifying and quantifying trends, to establish benchmarks to compare the current year’s performance with that of previous years, and to compare the performance of different companies.
(c) By the own airline to improve the safety conditions under which it operate. The airline may better evaluate the performance of the entire set of fleets of the Company regarding each category of events as well as analyse the spread of the incident rate of a fleet for a particular incident category compared to the overall rate for the entire Company. It could also identify those fleets that require most attention within a company and quantitatively compare the stress effect in one fleet compared to that in others.

The following sections explain the theory behind each of the models and the process used to design and evaluate them.

2. Model based Bayesian inference

Let us consider two possible outcomes, A and B, and assume that $A = A_1 \cup \cdots \cup_n^A$ where $A_i \cap_j^A = \varnothing$ for every $i \neq j$. Bayes’ theorem gives the following expression for the conditional probability of A_i given B:

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B)} = \frac{P(B|A_i)P(A_i)}{\int_{i=1}^{n} P(B|A_i)P(A_i)}$$

The above theorem can be used for inverse inference. B is the observed result, or outcome, and A_i represents the possible factors that cause B. Then, $P(B|A_i)$is the probability of B occurring when cause A_i is present, and $P(A_i|B)$ is the probability that A_i is responsible for the incident of previously observed outcome, B.

Bayes’ theorem is a very useful statistical tool for extracting information from data (Bernardo, 1994). Therefore, using observed data $(y_1, y_2, \ldots, y_n)$ and its posterior distribution $f(\theta|y_1, \ldots, y_n)$, which combines both prior and observed data, we can calculate certain information. This posterior distribution is central to the idea of Bayesian inference. This differs from frequentist statistics as, in prior distribution, all unknown parameters are considered to be random variables. As such, prior distribution must be defined at the outset. Prior distribution represents the state of knowledge before collecting any data. The objective is to determine the posterior distribution, $f(\theta|y)$, of the parameters θ given a set of observed outcomes.

Posterior distribution integrates both prior and observed data and information, and is a combination of prior distribution, $f(\theta)$, and probability, $f(y|\theta) = \prod_{i=1}^{n} f(y_i|\theta)$. Both distributions must then be completely specified to complete the Bayesian model.

The whole modelling procedure may be divided into four stages:

i. Construction of model;
ii. Calculation of posterior distribution;
iii. Analysis of posterior distribution, and
iv. Inference.

The final step is to use the model to predict probable outcomes. Bayesian inference offers an accurate and straightforward means of predicting future outcomes via calculated predictive distribution (Gelman, et al., 2013).

3. Safety incidents data and information

This study is based on the analysis of safety incidents that occurred to air operators and were registered in a national Mandatory Incident Reporting (MOR) system. The events or incidents that occur during aircraft operations are usually precursors to more serious accidents that