Forecasting and assessing consequences of aviation safety occurrences

Abstract

Aviation safety is essential for the healthy growth and sustainability of the global economy. The implementation of Safety Management Systems to support safe service delivery has become one of the most important goals within the airline industry over the last years. However, in most cases the involved organisations use unsophisticated methods based on risk matrices for the development of such systems. In this paper, we present models to forecast and assess the consequences of aviation safety occurrences as part of a framework for aviation safety risk management at state level.

Keywords: Aviation safety, Risk management, Bayesian forecasting, Multiattribute utility, Decision analysis

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1. Introduction

Air transport is fundamental for the development of modern societies and safety is one of its key features: various organisations like the International Civil Aviation Organization (ICAO), the Federal Aviation Administration (FAA), the European Aviation Safety Agency (EASA) or EUROCONTROL have aimed at making aviation the safest transportation mode since their creation. As a result, the ICAO binds the 191 signatory states of the Chicago Convention to develop their national Safety Management Systems (SMS) aimed at properly managing aviation safety (AS) in their respective countries. Indeed, the viability of an aviation organisation depends largely on its ability to preserve the public perception of its safety. This requires a constant balance between service costs and safety goals, making risk management essential for sustainability.

Despite a high safety level in aviation worldwide, occurrences continue to take place. As an example, in our context, we need to consider 88 different types of occurrences, ranging from *bird strikes* to *runway excursions* going through *engine failures* and *loss of control*. As proposed by ICAO (2013), each of such occurrences is classified into one of five severity classes: *Accident* (1); *Serious Incident* (2); *Major Incident* (3); *Significant Incident* (4); and, finally, *Occurrence without safety effect* (5). Thus, we may talk, for example, about a severity 3 engine failure occurrence.

In earlier work, Rios Insua et al. (2016a), we have presented a framework to support AS risk management at state level. It employs decision analysis (French & Ríos Insua, 2000) and includes as stages: (a) providing forecasting models for the numbers of various types of occurrences; (b) forecasting models for the occurrence severity classes; (c) forecasting models for the consequences of occurrences; (d) the construction of a multiattribute utility model to assess such consequences; and, finally, (e) using such models to screen riskier occurrences and assign resources optimally to mitigate aviation hazards. In particular, the framework is used by an AS state agency to decide how to allocate their resources, specifically their inspection capabilities, to improve AS in a country taking into account technical and financial constraints. This facilitates the preparation of the national SMS and overcomes standard AS risk management practice based on risk matrices (e.g. ICAO (2013), Ayres Jr et al. (2009), FAA (2007) and McIntyre (2002)), with well known defects, Cox (2008). Netjasov & Janic (2008) provide a review of other AS approaches, including Bayesian belief networks (Ale et al., 2009). However, such approaches tend to be not integrated within appropriate decision making structures.

In this paper, we present in full detail stages (c) and (d). Besides being key ingredients for our risk management methodology, the models presented allow us to forecast and assess consequences of AS occurrences, thus being of interest not only for aviation authorities, but also for insurance companies, aviation operators and aircraft companies. Given the above mentioned emphasis on risk matrices in AS, which focus on qualitative global impacts in an ordinal scale (typically, 1-5), it is no surprise that relatively little work on assessing AS consequences is available. Sobieralski (2013) provides a review of the scarce literature on the topic which we complement in Section 3.1 below. Our contributions include the identification and structure of objectives typically relevant in AS from a state perspective; the provision of models to forecast and asses such AS consequences; and, finally, a model to globally assess such consequences. We view all of the above models as templates, in the sense that an organisation could use them as starting points to be refined and adapted to their own data and circumstances.

In what follows, we shall make a distinction about various aircraft types: T1, general aviation, aerial works, or business aviation, with less than 19 passengers; T2, regional flights (< 100 seats); T3, continental flights (< 200 seats); T4, intercontinental flights (> 200 seats). T2, T3 and T4 refer to aircrafts engaged in commercial aviation.

2. Aviation safety objectives and multiattribute evaluation

2.1. Objectives

AS occurrences may entail very negative consequences in terms of lives and costs. Through risk management, we aim at minimising them. Each organisation must determine their relevant consequences for risk management purposes. They will typically vary from private organisations, say an airline, to state organisations, like a national AS agency. They may also vary for different countries. We present here the consequences considered relevant in our case, which may serve as initial information for other organisations, specially if they are governmental. Recall that the context of our problem refers to an AS public agency that aims at introducing a risk management plan outlining a resource allocation procedure to improve AS in the corresponding country, as part of developing their national SMS.

After a brainstorming process and a literature review, in particular based on EUROCONTROL (2013), the incumbent organisation (the Spanish Aviation Safety and Security Agency, AESA) decided to focus on the objectives hierarchy in Figure 1, which portrays the chosen objectives and subobjectives as well as the corresponding attributes. Clemen & Reilly (2013) and Keeney (2009) provide details on designing hierarchies of objectives.

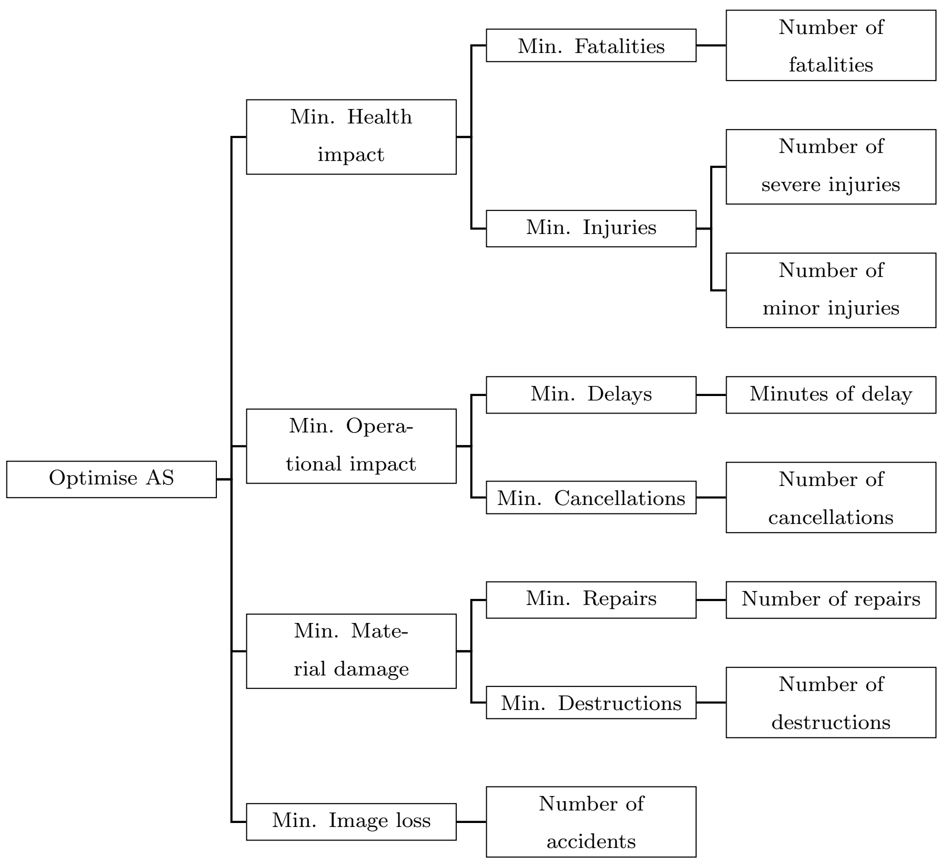


Figure 1: Objectives of aviation safety management at state level

We started with a generic objective, *optimise AS*, which we specified through four sub-objectives:

- *Minimise health impacts*, associated with aviation induced deaths and injuries;

- *Minimise the operational impact* produced by unsafe aviation operations;
- *Minimise material damages* caused by safety occurrences; and, finally,
- *Minimise country image loss* associated with the lack of AS.

The first sub-objective was further decomposed into two referring to *minimising fatalities* and *injuries*. The attributes chosen to evaluate them were natural and correspond, respectively, with the number of fatalities and injuries in two categories, severe and minor, as defined by EUROCONTROL (2013). In AS, ICAO (2013) describes a fatality as *any person who suffers a fatal injury, resulting in death within thirty days of the date of an accident.* It is the most feared consequence in AS occurrences. An important example refers to the 583 dead in 1977 at the Tenerife North Airport (Spain) after the collision of two aircrafts. Similarly, ICAO (2013) defines an injured as *any person who suffers a non fatal injury as a result of: being in the aircraft; or in direct contact with any part of it, including parts which have become detached from the aircraft; or direct exposure to jet blast.* A relevant example refers to 64 injuries, including 7 severe ones, in 1988 due to a detachment of the ceiling of the cabin of an airplane during takeoff, forcing the pilot to make an emergency landing at Kahului.

The second sub-objective was also broken down into two, referring to *minimising delays* and *cancellations* induced by occurrences. Indeed, one of the associated negative consequences are the delays in takeoff or landing after the expected scheduled time (above 15 minutes, according to the FAA), which may induce significant costs to individuals and airlines and, in general, the aviation system in a state. As an example, Cook & Tanner (2011) report that around 750.000 flights in 2009 suffered some kind of delay in the European Union (EU), with an approximate associated cost of 1.25 M€. We shall estimate the delay induced by AS occurrences in minutes. On the other hand, when a flight is cancelled we must assume costs such as accommodation, transport or catering. The chosen attribute for this consequence was the number of cancellations due to such occurrences.

The third sub-objective referred to *minimising material damages* induced by occurrences. To reflect this, two subobjectives and their attributes were proposed: the number of destroyed aircrafts and the number of aircrafts requiring repair during the corresponding management period. For certain occurrences, and depending on their severity, it will be necessary to inspect the damaged parts and repair the aircraft cell. Moreover, after several accidents, repair might not be possible and it would be necessary to replace the aircraft. In terms of AS risk management, both destructions and repairs entail considerable costs that a state should take into account and promote their minimisation.

Finally, we did not need to further decompose the fourth sub-objective, *minimisation of image loss*. Image costs would be based on the media coverage that occurrences receive. In general, we assume that the more severe the occurrence is, the higher the image loss will be. This should be taken into account, as we are focusing on risk management at state level, and image may affect key economic sectors such as tourism. However, a natural attribute that allows us to evaluate this consequence was not readily available. One alternative would be to construct an artificial ordinal scale, say from 1 to 10. Level 1 would be associated with a situation of minimal image impact (for example, a severity 5 occurrence with no consequences that would not appear in the media); similarly, level 10 would be associated with a maximum impact accident with total destruction of the aircraft and numerous fatalities (for example, the Germanwings 2015 case that led the world press for several weeks), with a very negative image for a country. Henceforth, we would associate each of the levels with a qualitative description of severity with respect to image. However, as described in Brownlow & Watson (1987), we prefer to adopt a proxy variable that mitigates the ambiguities in such constructed scale. Thus, we shall use the number of accidents (occurrences of severity 1) suffered by commercial aircraft transport as a proxy for country image loss. These are the occurrences which will make it to the media and, presumably, are highly correlated with negative image impact.

In summary, through an AS risk management plan, the initial aim of the organisation would be to minimise over the relevant planning period the number n_F of fatalities; n_{H_1} and n_{H_2} of minor and severe injuries, respectively; the minutes t_D of delays and the number n_C of cancellations induced by occurrences; the numbers n_R of damaged and n_{HL} of destroyed aircrafts; and, finally, the number s^1 of commercial aviation accidents.

2.2. Multiattribute evaluation

We describe now the preference model agreed with the organisation to assess the consequences of AS plans. Among other things, this will allow us to forecast the costs associated with AS over the planning period as outlined in Section 4.8. If these are deemed high, we should look for appropriate risk management interventions, whose impact would again be evaluated with the aid of the proposed preference model. Thus, we need the regulator utility function, modelling its preferences and risk attitudes. For this, we use the concepts of measurable multi-attribute value function (Dyer & Sarin, 1979) and relative risk aversion (Dyer & Sarin, 1982).

2.2.1. A multi-attribute value function

First, under appropiate and sufficiently general preference independence conditions, González-Ortega et al. (2018), we aggregate the consequences through a measurable value function

$$v(n_F, n_{H_1}, n_{H_2}, t_D, n_C, n_{HL}, n_R, s^1) = \\ - c_F n_F - \sum_{i=1}^{2} c_{H_i} n_{H_i} - c_D t_D - c_C n_C - c_{HL} n_{HL} - c_R n_R - c_I s^1 \quad (1)$$

where c_F is the cost of each fatality; c_{H_i} are the costs of minor ($i = 1$) and severe ($i = 2$) injuries; c_D is the cost per minute of delay; c_C is the cost of a cancellation; c_{HL} is the cost of a destroyed aircraft; c_R is the cost of a repair; and, finally, c_I is the image cost. The negative signs are due to the fact that we deal with costs to be minimised, whereas in the decision analytic jargon value functions should be maximised. We describe now how did we assess such costs. As several of them have a somewhat cotentious nature, we performed a robustness analysis of their impact over the results of the entailed resource allocations.

First of all, to estimate the expected cost c_F associated with a fatality, we use the concept of value of statistical life (VSL) presented, for example, in Viscusi & Aldy (2003). This entailed thorough discussions with the agency management given the involved ethical issues, see Ale et al. (2015, 2018) for perspectives on the topic. In the end, we adopted the reference value for Spain in EUROCONTROL (2013), which is 1.65 M€. Other estimations could be used, e.g. Thaler & Rosen (1976) or Miller (2000). Similarly, to evaluate the costs associated with both types of injuries, $c_H = (c_{H_1}, c_{H_2})$, we use the concept of value of a statistical injury (VSI) through a fraction of the VSL, depending on the severity of the injury, as reflected in Table 1, adapted from EUROCONTROL (2013).

Table 1: Proportion of injury cost by severity. From EUROCONTROL (2013).

Severity	**VSL proportion**
Minor	0.2625
Severe	0.7625

The costs associated with delays refer only to operational ones. Among other things, those may be due with the fact that passengers should be provided with extra catering at the plane or airport. EUROCONTROL (2013) provides a cost decomposition of components associated with delays. We consider two types of costs: (1) *Delay with network effect*, including the effect of consequential delay caused either to the aircraft incurring the initial delay or to other aircraft; (2) *Delay without network effect*, otherwise. To approximate the costs per minute delayed, we adopt the EUROCONTROL perspective that distinguishes three scenarios (low, base, high). Accordingly, we decided to use the triangular distributions described in Table 2.

Table 2: Parameters of the triangular distribution to forecast costs by type of delay.

Kind of delay	**Cost (€/min)**
With network effect	$c_{D_1} \sim \mathcal{T}(26.2, 90.1, 127.8)$
Without network effect	$c_{D_2} \sim \mathcal{T}(14.9, 52.9, 78.6)$

Based also on EUROCONTROL (2013), the costs associated with a cancellation include: service recovery; crew and catering; loss of future value; and, finally, operational savings. c_C designates the cost of cancellation by type of aircraft with estimated values summarised in Table 3.

Table 3: Average cancelling cost for commercial scheduled flight. EUROCONTROL (2013).

Aircraft type	**Flight cancelled (€)**
T2	3700
T3	17300
T4	81000

To define costs of repair/maintenance, we used a triangular distribution considering three different scenarios (low, base, high), Galway (2007). If c_{R_1} designates the minimum, c_{R_2} the modal and c_{R_3} the maximum costs, the model will be $c_R \sim \mathcal{T}(c_{R_1}, c_{R_2}, c_{R_3})$. Table 4 provides the cost (in Euros), suggested in EUROCONTROL (2013), to perform maintenance depending on the type of aircraft, as well as the estimated cost in case of destruction.

Table 4: Estimated aircraft maintenance and destruction costs.

Aircraft type	**Maint. Cost (Euro)**			**Hull loss Cost (M€)**
	Low	**Base**	**High**	
T1	139	162	310	2
T2	306	671	1149	20
T3	977	1656	2518	80
T4	3119	3553	5533	250

Finally, to estimate the image costs c_I, we used a procedure based on expert judgement with r AS experts, Dias et al. (2018). We assume that the experts face a base scenario in which there are A accidents with F fatalities. Then, we could ask the following question to the experts: *If the number of accidents increase in A_1 units, how many fatalities x would you consider so that the perceived impact is the same as in the previous scenario?* Thus, experts must assign the value x such that they find equally preferred the AS scenarios

$$(F, A) \sim (x, A + A_1). \tag{2}$$

To facilitate the task, we used an iterative scheme designed to assess x bounding it from above and below. Suppose now that the i-th expert provides the answer

$$(F, A) \sim (x^i, A + A_1), i = 1, \ldots, r. \tag{3}$$

Under appropriate preference independence conditions, French & Ríos Insua (2000), and assuming constant results in the other criteria, the values associated with both consequences should coincide so that $c_F \cdot F + c_I^i \cdot A = c_F \cdot x^i + c_I^i \cdot (A + A_1)$ and

$$c_I^i = -\frac{c_F(x^i - F)}{A_1}, i = 1, \ldots, r. \tag{4}$$

To aggregate the opinion of experts, we could use averages. To verify the consistency of the assessment, we may repeat the procedure with other attributes. In our case, after proceeding with two experts, we obtained $c_I^1 = 0.41$, $c_I^2 = 0.97$, which we aggregated through their average, obtaining $c_I = 0.69$.

2.2.2. Risk attitude

The involved organisation declares constant risk aversion with respect to v. Then, the utility function will be strategically equivalent to

$$u(v) = -\exp(\omega v), \tag{5}$$

with $\omega > 0$ designating the risk aversion coefficient, Keeney & Raiffa (1993). To determine ω, we may use the probability equivalent (PE) method as in Farquhar (1984). Let v_* and v^* be the worst and best values attained, respectively; v_1, an intermediate value between such consequences; and, finally, ϕ a value such that the lottery leading to v^* with probability ϕ and v_* with probability $(1-\phi)$ leaves the AS manager indifferent with respect to obtaining v_1 for sure. Then, $u(v_1) = \phi$ and we may solve the system

$$\begin{aligned} \phi &= \rho - \varrho \exp(\omega v_1), \\ 1 &= \rho - \varrho \exp(\omega v^*), \\ 0 &= \rho - \varrho \exp(\omega v_*), \end{aligned} \tag{6}$$

ρ, ϱ and ω which allows as to estimate the utility function parameters.

3. Forecasting aviation safety occurrence consequences

3.1. Review

We start by providing a brief review of earlier literature on forecasting models available for the AS consequences presented in Figure 1. Such models do not fully cover our predictive needs, given our segmentation according to occurrence type and severity and aircraft type, motivating our proposals in Section 3.2.

There are comparatively few studies that cover issues concerning forecasting aviation fatalities, e.g. Belcastro & Foster (2010), Clancy (1960) or Grabowski et al. (2005). Pikaar et al. (2000) and Janssen & Ale (2000) provide methods to calculate third-party risk around airports based on three main elements: accident rate model, accident location model and accident consequence model. Thorpe (2003) provides a compilation of accidents due to bird strikes leading to fatalities. The annual reports of Boeing (2013) and EASA (2013), and the Aviation Safety Network (ASN) data base provide accurate data on fatal accidents.

There are also some works in relation to forecasting injuries in aviation including Dambier & Hinkelbein (2006), who made a detailed analysis of occurrences in Germany in 2004 presenting the results by aircraft type, time period, or severity; and O'Hare et al. (2003), who performed a comparative analysis of occurrences in New Zealand during 1988-1994, from which they identified environmental factors causing injuries due to AS occurrences.

In relation with flight delays, Sternberg et al. (2017) present an analysis of the available literature on flight delay prediction summarizing the most researched trends in this problem and comparing methods used to build forecasting models. Khanmohammadi et al. (2016) propose a multilevel input layer artificial neural network model to predict delays of incoming flights at JFK. Our focus will be on delays induced solely by AS incidents. Ayra et al. (2016) provide an example in relation with unintended slide deployment.

Long & Hasan (2009) present a simulation model to estimate flight delays and cancellations under all operating conditions including inclement weather; Mukherjee et al. (2006) propose models to estimate average flight delay and cancellation probabilities based on percentiles of the distribution of the congestion level faced at an airport; and Lemke et al. (2009) investigate time series forecasting and forecast combination methods applied to airline cancellation data. Rupp & Holmes (2006) present a detailed study of causes and factors of cancellations, whereas Xiong & Hansen (2013) determine the importance of such main factors.

Maintenance is extremely important to prevent accidents, delays or cancellations. Also costs can be reduced if a failure occurrence is forecasted and maintenance planned accordingly. There are some works about maintenance and repairs in the field of aviation. For example, Ghobbar & Friend (2003) compare different methods to forecasting spare parts demand in aircrafts or Kontrec et al. (2015) who propose an approach that supports the decision making process in planning and controlling spare parts in aircraft maintenance systems to minimise downtimes and/or delays. Our emphasis will be on the complementary problem of how various aviation occurrences may induce maintenance and repair costs.

Fatal accidents, apart from material losses, generate additional costs for organisations, such as negative effects on airline reputation. Chalk (1987) analyses the effects of various fatal accident concluding that manufacturers of aircraft involved in major accidents suffered a decrease in their market value of around 4% after one such. Squalli & Saad (2006) assess the impact of consumer perceptions about the safety level of airlines on enplanement. Lu et al. (2006) present the ten critical events which led to airline accidents after a review of 189 final accident reports from the National Transportation Safety Board and provide models to predict the likelihood of such critical events.

3.2. *Models to forecast aviation safety occurrence consequences*

We present now our models to predict the eight consequences of Figure 1 associated with AS occurrences. By later aggregating over all of them, we could predict the consequences associated with an AS plan, say over a year, which is the planning period adopted to ellaborate and update the SMS. Finally assessing them with the value and utility functions presented in Section 2.2 would allow us to assess risk comprehensively.

In some cases, we shall need to make a distinction about the type of aircraft involved using the T1-T4 classification above. Furthermore, our models will typically depend on occurrence severity and type. For each model, we start by providing several motivating facts and hypothesis.

3.2.1. *Fatalities*

According to the ICAO definition, there are only fatalities in class 1 occurrences (accidents). Note though that there does not necessarily have to be fatalities in an accident, neither do all passengers and cabin crew have to die.

Model. We predict the number n_F of fatalities in an accident with the model

$$n_F = p_F \cdot q \cdot M, \tag{7}$$

where p_F designates the proportion of fatalities, estimated through model (8) below; q is the aircraft occupancy degree estimated with model (11); and, finally, M is its maximum occupancy. p_F will depend on the type of aircraft and occurrence, whereas q and M will depend just on the aircraft type.

For p_F, we propose a mixture model

$$p_F \sim \tau_1 I_0 + \tau_2 \mathcal{B}e(a_F, b_F) + \tau_3 I_1, \tag{8}$$

where τ_1 designates the proportion of accidents with no fatalities; τ_2, that of accidents with fatalities and survivors; and, finally, τ_3, that of accidents with no survivors, with $\tau_1 + \tau_2 + \tau_3 = 1$, $\tau_i \geq 0, i = 1, 2, 3$. I_0 is the degenerate distribution at 0 (no occupant dies); $\mathcal{B}e(a_F, b_F)$ is a beta distribution, with parameters a_F and b_F, modelling the proportion of fatalities in accidents when there are fatalities and survivors; and, finally, I_1 is the degenerate distribution at 1 (all occupants die).

We make inference about the weights τ_i with a Dirichlet-multinomial model [1]. We assume a prior $(\tau_1, \tau_2, \tau_3) \sim \mathcal{D}ir(a_1, a_2, a_3)$. If in ϑ^1 accidents (for the occurrence type of interest, with the relevant aircraft type) there were ϑ^1_1 without fatalities; ϑ^1_2, in which not all occupants died; and, finally, in ϑ^1_3 all died, the posterior would be

$$(\tau_1, \tau_2, \tau_3)|data \sim \mathcal{D}ir(a_1 + \vartheta^1_1, a_2 + \vartheta^1_2, a_3 + \vartheta^1_3). \tag{9}$$

To perform inference about p_F, when $0 < p_F < 1$, we use a Beta-binomial model. Initially, $p_F \sim \mathcal{B}e(a_F, b_F)$. If the available data is $((o_1, f_1), \ldots, (o_g, f_g))$, with o_i occupants and f_i fatalities in the g accidents that led to some fatalities, the posterior distribution will be

$$p_F|data \sim \mathcal{B}e\left(a_F + \sum_{i=1}^{g} f_i, b_F + \sum_{i=1}^{g} (o_i - f_i)\right). \tag{10}$$

For the occupancy q, the prior distribution is $q \sim \mathcal{B}e(c_F, d_F)$. If we have the occupancy proportions $(p_{O1}, \ldots, p_{Ol})$ in l flights, the posterior distribution would be

$$q|data \sim \mathcal{B}e\left(c_F + \sum_{i=1}^{l} p_{Oi}, d_F + \sum_{i=1}^{l} (1 - p_{Oi})\right). \tag{11}$$

[1]For the Dirichlet-multinomial and beta-binomial models appearing, when referring to non informative priors we shall use uniform ones with parameters equal to 1. Berger et al. (2015) describe other possibilities.

3.2.2. Injuries

Observe first that in an occurrence there does not necessarily have to be injuries, neither do all passengers and cabin crew have to be injured. Besides, we expect that the greater the severity of the occurrence, the higher the number of injuries will be. When forecasting this consequence, we shall segment according to aircraft type.

Model. We consider three proportions p_{h_i}, $i = 1, 2, 3$ for the three types of survivors ($i = 1$, minor injured; $i = 2$, severely injured; $i = 3$, uninjured), following a model

$$p_H = (p_{h_1}, p_{h_2}, p_{h_3}) \sim \alpha_H \cdot I(0, 0, 1) + (1 - \alpha_H) \cdot \mathcal{D}ir(h_1, h_2, h_3), \tag{12}$$

where α_H designates the proportion of occurrences in which no survivor is injured and $I(0, 0, 1)$ is the degenerate distribution in which there are no wounded occupants. p_H will depend on the type of aircraft and occurrence.

We make inference about the weight α_H with a Beta-binomial model. We assume a prior $\alpha_H \sim \mathcal{B}e\,(a_H, b_H)$. If in χ occurrences (of the occurrence type of interest, with the relevant type of aircraft) there were χ_1 with no injured occupants, the posterior distribution is

$$\alpha_H | data \sim \mathcal{B}e\,(a_H + \chi_1, b_H + (\chi - \chi_1))\,. \tag{13}$$

With regard to the proportions of injured occupants, if the available data are $\{(n_1^1,\ n_2^1,\ n_3^1),\ldots,(n_1^k,\ n_2^k,\ n_3^k)\}$, where n_i^j represents the number of injured occupants with severity $i \in \{1, 2, 3\}$ in the j-th occurrence, $j \in \{1, \ldots, k\}$, the posterior distribution would be

$$p_H | data \sim \mathcal{D}ir\left(h_1 + \sum_{i=1}^{k} n_1^i, h_2 + \sum_{i=1}^{k} n_2^i, h_3 + \sum_{i=1}^{k} n_3^i\right). \tag{14}$$

Finally, the number $n_H = (n_{h_1}, n_{h_2}, n_{h_3})$ of injuries for a given occurrence type is predicted through

$$n_H = p_H \cdot q \cdot (1 - p_F) \cdot M, \tag{15}$$

where p_F, q and M are as in Section 3.2.1.

3.2.3. Delays

Note first that severity 1 occurrences produce a cancellation, not entailing delay. For severity 5 occurrences, delays are not considered relevant. We assume, therefore, that significant delays may hold only for severity 2, 3 and 4 occurrences. However, there does not necessarily have to be delays for these types of occurrences. In addition, delays will be relevant only for T2, T3 and T4 aircrafts. Finally, we consider two types of delay (EUROCONTROL, 2013): *with* and *without network effect*. We assume that severity 2 and 3 occurrences may entail delays with network effect, whereas severity 4 produce delays without such effect.

Model. The delay t_D associated with an AS occurrence is predicted with the model

$$\begin{aligned} t_D = p_{d_0} I_0 + p_{d_1} F_{d_1} + p_{d_2} F_{d_2}, \\ p_{d_0} + p_{d_1} + p_{d_2} = 1, \\ p_{d_0}, p_{d_1}, p_{d_2} \geq 0, \end{aligned} \tag{16}$$

where p_{d_0} represents the proportion of occurrences with no delay; p_{d_1}, the proportion of occurrences with delay without network effect; p_{d_2}, the proportion of occurrences with delay with network effect; I_0 is the distribution degenerate at 0 (no delay); and, finally, F_d describes the non-zero delays (distinguishing cases with or without network effect, respectively designated by d_2 and d_1).

Starting from a non-informative Dirichlet distribution, the posterior would be

$$(p_{d_0}, p_{d_1}, p_{d_2})|data \sim \mathcal{D}ir(1 + x_0, 1 + x_1, 1 + x_2), \tag{17}$$

where x_0 is the number of occurrences without delay; x_1, the number of occurrences without network delay and, finally, x_2, the number of occurrences with network delay.

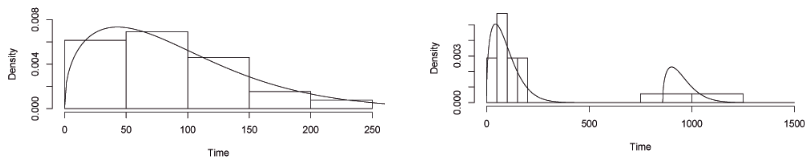
Based on the model in Ayra et al. (2016), we assume that $F_{d_1} \sim Wei(\gamma = 0, \beta_1, \eta_1)$, where $Wei(\gamma, \beta, \eta)$ designates the Weibull distribution with three parameters

$$f(t|\gamma, \beta, \eta) = \beta \frac{(t-\gamma)^{\beta-1}}{\eta^\beta} \exp\left(-\left(\frac{t-\gamma}{\eta}\right)^\beta\right), \tag{18}$$

whereas for delay type F_{d_2} we consider a mixture

$$F_{d_2} \sim p_r \cdot Wei(\gamma = 0, \beta_2, \eta_2) + (1 - p_r) \cdot Wei(\gamma, \beta_3, \eta_3), \tag{19}$$

where $\gamma \sim \mathcal{U}(a_D, b_D)$ and p_r follows a Beta-binomial model. To make the model operational, we use the delay distributions associated with the occurrence in Ayra et al. (2016), reflected in Figure 2.



(a) Without network effect (F_{d_1})

(b) With network effect (F_{d_2})

Figure 2: Representation of time delay (in minutes)

The parameters of models (18) and (19) are summarised in Table 5

Table 5: Model parameters to forecast delays

p_r	γ	β_1	η_1	β_2	η_2	β_3	η_3
$\mathcal{B}e(2.15, 0.72)$	$\mathcal{U}(11, 16)$	1.7	47.15	1.3	110.58	1.4	98.23

3.2.4. Cancellations

Severity 1 occurrences always lead to cancellations. For severity 2-4 occurrences, 2.02% of the cases lead to a flight cancellation, corresponding to the average proportion of cancellations, according to the US DoT (`http://www.transtats.bts.gov/HomeDrillChart.asp`). For T1 type aircrafts, we will not consider the case where a cancellation occurs, since it is not relevant. The other categories are treated jointly.

Model. To predict cancellations we use a Beta-Bernoulli model

$$\begin{aligned} X|p_c &\sim \mathcal{B}er(p_c), \\ p_c &\sim \mathcal{B}e(a_c, b_c), \end{aligned} \tag{20}$$

where $X = 1(0)$ indicates whether (not) the flight is cancelled and p_c is the probability of cancellation for a certain type of occurrence and severity. Then, if there are n occurrences under the conditions in which x cancellations occur, we have

$$p_c|data \sim \mathcal{B}e(a_c + x, b_c + (n - x)). \tag{21}$$

Finally, for m occurrences, the number n_C of cancellations could be predicted pointwise with

$$\hat{n}_C = m \cdot \frac{a_c + x}{a_c + b_c + n}. \tag{22}$$

3.2.5. Repairs and destructions

Consistent with the ICAO (2013) definition of severity, destructions will happen only for severity 1 occurrences. For severity 5, no repair is required. Furthermore, repairs for severity 1 to 4 occurrences may not necessarily happen. The degree of repair will depend on the type of aircraft and occurrence.

Model. Firstly, for severity 1 occurrences, aircraft damage is described with a multinomial model

$$\mathcal{M}(1; p_{m_1}, p_{m_2}, p_{m_3}), \tag{23}$$

where $\sum_j p_{m_j} = 1$ and $p_{m_j} \geq 0$, where subscripts 1, 2 and 3, respectively, indicate that the aircraft has not been damaged, has been completely destroyed or requires maintenance. If $((n_1^1, n_2^1, n_3^1), \ldots, (n_1^k, n_2^k, n_3^k))$ are the available data, where n_i^j represents the number of aircraft with grade destruction i during the j-th year, $j = 1, \ldots, k$, the posterior would be

$$p_m|data \sim \mathcal{D}ir\left(1 + \sum_{j=1}^{k} n_1^j, 1 + \sum_{i=1}^{k} n_2^j, 1 + \sum_{i=1}^{k} n_3^j\right), \tag{24}$$

assuming we start from a uniform Dirichlet prior.

To perform inference over p_m for occurrence classes 2-4, we use a Beta-binomial model noting that no destructions then happens. A priori, we assume $p_m \sim \mathcal{B}e\left(a_m, b_m\right)$. If for severity 2-4 occurrences with the relevant aircraft type there were n_1 occurrences without damage to the aircraft and n_3 with damage, the posterior would be

$$p_m|data \sim \mathcal{B}e\left(a_m + n_3, b_m + n_1\right). \tag{25}$$

3.2.6. Image loss

As mentioned in Section 2.1, we use the number of accidents involving aircrafts of types T2, T3 or T4 as a proxy to assess image loss.

Model. Let X be the number of occurrences of certain type and $p = (p^1,\ p^2,\ p^3,\ p^4,\ p^5)$ a vector designating the proportion of occurrences for each severity class with $p^i \geq 0$, $\sum_{i=1}^{5} p^i = 1$. Let $s = (s^1, s^2, s^3, s^4, s^5)$ be a vector with the number of occurrences of each severity class with $s^i \geq 0$ and $\sum_{i=1}^{5} s^i = X$. We use a multinomial-Dirichlet model

$$\begin{aligned} s|p, X &\sim \mathcal{M}(X; p^1, p^2, p^3, p^4, p^5),\\ p &\sim \mathcal{D}ir(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5). \end{aligned} \tag{26}$$

Assuming that the data available until the beginning of the k-th period are $((s_1^1,\ s_1^2,\ ...,\ s_1^5),\ldots,(s_{t-1}^1,\ s_{k-1}^2,...,s_{k-1}^5))$, where s_j^i represents the number of occurrences of severity $i \in \{1,2,3,4,5\}$, in period $j \in \{1,\ldots,k-1\}$, then, the posterior distribution is

$$p|data \sim \mathcal{D}ir\left(\alpha_1 + \sum_{i=1}^{k-1} s_i^1, \ldots, \alpha_5 + \sum_{i=1}^{k-1} s_i^5\right). \tag{27}$$

For the proportion of accidents, we use the distribution

$$\hat{p}^1 \sim \mathcal{B}e\left(\alpha_1 + \sum_{i=1}^{k-1} s_i^1, \sum_{j=2}^{5}\left(\alpha_j + \sum_{i=1}^{k-1} s_i^j\right)\right). \tag{28}$$

Finally, the number s^1 of accidents is predicted through

$$s^1 = p^1 \cdot X, \tag{29}$$

where, to estimate X, we would use the class of models outlined in Rios Insua et al. (2016a).

3.2.7. *Forecast aggregation*

The previous models allow us to predict the consequences of an AS occurrence depending on the aircraft type and/or severity. By aggregating over different types of occurrences and their number over, say, a year, we can predict the annual consequences associated with AS. This would be performed by simulation leading to the corresponding predictive distributions. We should emphasise here that this aggregation must take into account the correlations between different types of occurrences, either due to common causes or because one type of occurrence is a precursor of another, Rios Insua et al. (2016b). Finally, we would assess the predictive distributions with the value and utility functions of Section 2.2 to complete risk assessment.

4. Case

We illustrate the models proposed in Section 3.2 with examples coming from a case study. For each attribute, we end up counting the number of models implemented in that case study.

4.1. *Fatalities*

We forecast the number of fatalities caused by a *Loss of Control* occurrences. To estimate p_F, we used data available from ASN, which records accidents worldwide since 1919. We web scrapped this information considering only data since 1968, when substantial improvements in AS occurred (EASA, 2011). We include only civil aircraft accidents. In addition, we segmented the information based on the type of aircraft involved, according to our T1-T4 classification. ASN contains only information about accidents in which there was at least one fatality or the aircraft sustained substantial damage including its destruction. According to ICAO (2015), these represent about 10% of the accidents. This is taken into account to predict the number of fatalities. Table 6 summarises posterior parameters for the *loss of control* occurrence depending on aircraft type, stemming from non-informative priors.

Table 6: Posterior point estimates to forecast fatalities due to loss of control.

	$\hat{\tau}_1$	$\hat{\tau}_2$	$\hat{\tau}_3$	$\hat{p}_F$	$\hat{q}$
T1	0.11	0.17	0.72	0.78	0.41
T2	0.07	0.24	0.69	0.83	0.42
T3	0.02	0.18	0.8	0.94	0.47
T4	0.06	0.19	0.75	0.93	0.29

We proceed analogously for the other 87 types of occurrences, thus totaling 352 fatality forecasting models (one for each type of occurrence and aircraft).

4.2. Injuries

We illustrate the model with the *Engine Failure* occurrence type. We use the European Coordination Centre for Aviation Incident Reporting Systems (ECCAIRS) database, including data from occurrences over the period 2010-2014. We segment the information according to the type of aircraft involved (T1-T4). Table 7 summarises the model parameters for this occurrence depending on aircraft type, stemming from non-informative priors.

Table 7: Model parameters to forecast injuries due to engine failure.

	n_{h_1}	n_{h_2}	n_{h_3}	$\hat{p_{h_1}}$	$\hat{p_{h_2}}$	$\hat{p_{h_3}}$	a_H	b_H	α_H	$\hat{q}$
T1	41	10	3294	0.013	0.003	0.984	298	32	0.903	0.85
T2	11	2	12599	0.0010	0.0002	0.9988	285	3	0.989	0.70
T3	1	0	98602	0.00002	0.00001	0.99997	938	2	0.998	0.73
T4	0	0	41340	0.00002	0.00002	0.99996	177	1	0.994	0.83

As ECCAIRS does not include data on the number of uninjured occupants, we estimate it through $n_{h_3} = q \cdot M - (n_{h_1} + n_{h_2} + n_F)$.

Proceeding similarly for the other 87 types of occurrences, we require 352 models for injury forecasting.

4.3. Delays

We illustrate the model with the *Abrupt Maneuver* occurrence. According to data in ECCAIRS, there were 39 occurrences during 2010-2014 of which: 4 were severity 1; 3, severity 2; 6, severity 3; 21, severity 4; and, finally, 5 of severity 5. According to model (17), we estimate p_{d_1} and p_{d_2} pointwise through

$$\hat{p}_{d_1} = \frac{21}{30} \cdot \frac{23}{37} = 0.44; \hat{p}_{d_2} = \frac{9}{30} \cdot \frac{23}{37} = 0.19, \tag{30}$$

where $\frac{23}{37}$ represents the proportion of occurrences involving delay, taken as the average of the $\mathcal{B}e(14, 23)$ distribution described in Ayra et al. (2016). The remaining parameters are in Table 5.

We proceed analogously for the other types of occurrences, totaling 88 delay models (one of each type of occurrence).

4.4. Cancellations

We apply the model to the *Engine Failure* occurrence. Table 8 shows the predictive expected occurrences (grouped by severities) over a year, using the predictive models outlined in Rios Insua et al. (2016a).

Table 8: Expected occurrences for *engine failure*.

	Severity				
Occurrences	1	2	3	4	5
550.17	14.30	13.20	66.02	192.55	264.1

The expected number of cancellations using equation (22), will be $n_C = 14.30 + 0.02\,(13.20 + 66.02 + 192.55) = 19.74$.

Analogously for the other types of occurrences, we thus build 88 cancellation models.

4.5. Repairs and destructions

We forecast the number of repairs due to *Runway Excursions*. For estimation purposes, we use data available from ASN and CIAIAC (2014) for severity

1 occurrences; for severity 2-4 occurrences, we use data extracted from ECCA-IRS. Table 9 summarises posterior parameters for the incumbent occurrence depending on the severity class and aircraft type, stemming from non-informative priors.

Table 9: Posterior model parameters to forecast repairs due to runway excursions.

Severity	Aircraft type	n_1	n_2	n_3	$\hat{p}_{m_1}$	$\hat{p}_{m_2}$	$\hat{p}_{m_3}$
1	T1	37	173	55	0.142	0.649	0.209
	T2	48	229	64	0.142	0.669	0.189
	T3	30	154	31	0.142	0.711	0.147
	T4	14	66	22	0.143	0.638	0.219
2-4	T2-T4	82	-	11	0.88	-	0.12

We proceed analogously for the other occurrences, thus totaling 792 maintenance and repair models (one for each type of occurrence and aircraft for destructions; one for each type of occurrence and aircraft for repairs of severity 1; and, finally, one for each type of occurrence for repairs of severities 2-4).

4.6. Image loss

Consider forecasting the number of accidents caused by *engine failures.* Table 10 shows the predicted occurrences and proportions of severity classes, where only T2, T3, T4 aircrafts are considered.

Table 10: Expected occurrences and model parameters to forecast occurrence severity classes for engine failure.

	Severity				
X	p^1	p^2	p^3	p^4	p^5
550.17	0.026	0.024	0.12	0.35	0.48

Then, the expected number of predicted accidents due to engine failure is $s^1 = E(X) \cdot E(p^1) = 550.17 \cdot 0.026 = 14.30$.

We proceed analogously for the other types of occurrences, thus totaling 88 image loss models.

4.7. Utility function

We specify now the utility function used in our case, based on the multiattribute evaluation model presented in Section 2.2. A perceived worst situation v_* corresponds to one in which, for each consequence, we take the worst observed value during the period of interest, in our case 2010-2014. As an intermediate situation v_1, we consider the average values in such years. Finally, as best situation, we adopt the best values over that period. Table 11 summarises the values for each consequence in the three scenarios, leading to $v_* = -950.96$, $v^* = -341.06$ and $v_1 = -587.58$.

Table 11: Worst, intermediate and best consequences caused by AS occurrences. Expected cost per unit of consequence

	Worst	Intermediate	Best	Unit cost
Fatalities	122	34	6	1.65
Severe Injuries	44	17	3	1.26
Minor Injuries	68	45	25	0.43
Delays	178617	155964	138596	0.00013
Cancellations	156	140	131	0.013
Repairs	1576	1436	1305	0.012
Destroyed aircrafts	11	8	5	54.18
Accidents	36	26	15	0.69
Value	-950.96	-587.58	-341.06	

A value of 0.2 for ϕ, in (6), was elicited from AS experts in the incumbent agency for v_1, using the PE method. Solving the system we get $\hat{\rho} = -0.03$, $\hat{\varrho} = -4.66$ and $\hat{\omega} = 0.005$. Figure 3 represents the corresponding utility function.

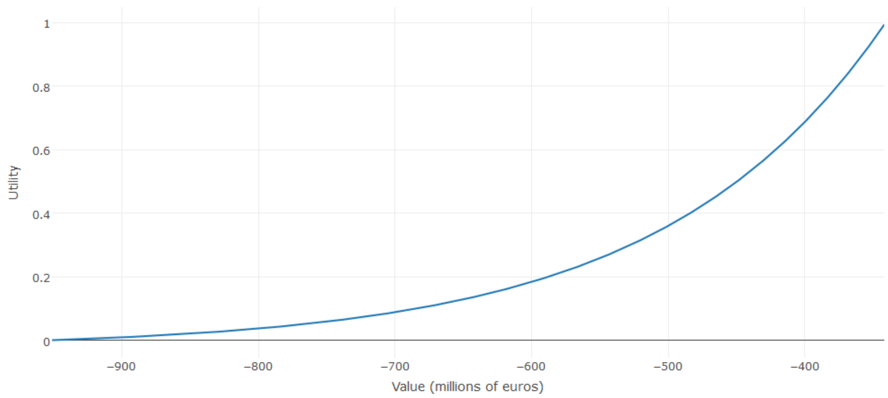


Figure 3: Utility function.

4.8. Forecast aggregation

Figure 4 provides the observed annual data over period 2010-2014 and the aggregated forecasts for the next year for four of the consequences in the incumbent case, based on the models proposed in Section 3.2 and the occurrence forecasting models in Rios Insua et al. (2016b). For each consequence we have added different symbols in the horizontal axis representing the observed data over the five years. Thus, for example, in the top left figure, the symbols ● or ◆ represent the number of observed accidents, 35 and 26 respectively, in years 2011 and 2014. The aggregated forecasts reasonably predict the consequences.

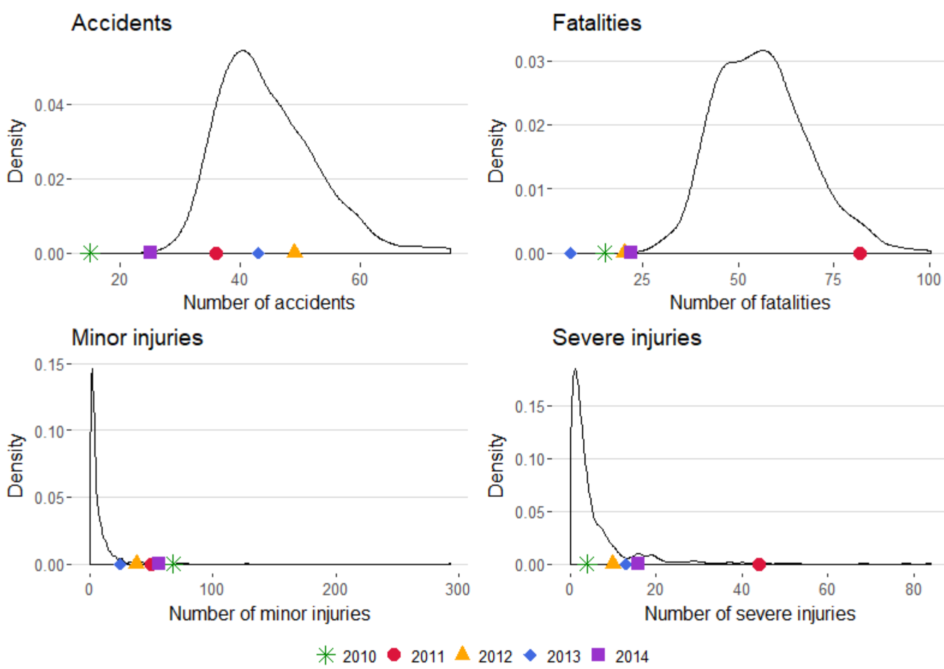


Figure 4: Annual AS consequence forecasts.

Observe that we could directly forecast the aggregated consequences. However, for risk management purposes we actually need the individual models for various types of occurrences and severities so as to guide interventions. Similar validation exercises were performed with the forecasts of consequences per occurrence, using the predictive distributions corresponding to all the models previously outlined.

We simulated 1000 times the values for each consequence in equation (1) providing the forecast distribution for the next year in the incumbent case, expressed as safety costs (equivalent in million of euros), completing the risk assessment for AS in the country. We represent it in Figure 5.

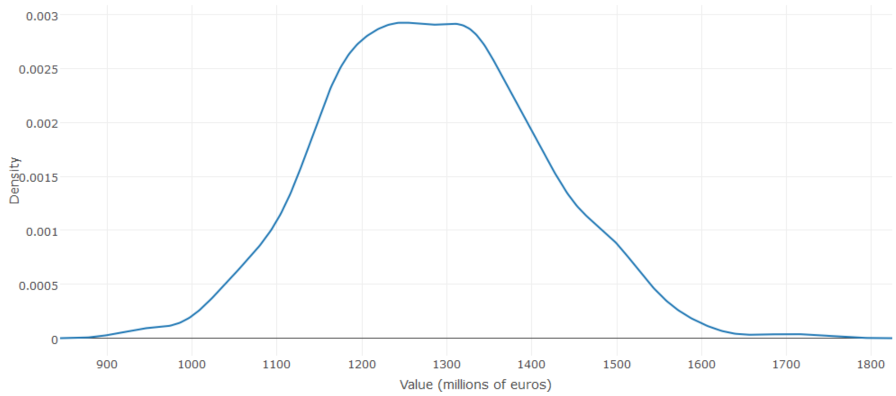


Figure 5: Annual AS cost forecast.

Clearly, given the high severity stakes at risk (the mean forecast is 1318.88, and the first and third quartiles are, respectively, 1226.82 and 1402.66) we should try to manage them, possibly with the methods described in Rios Insua et al. (2016a).

5. Conclusion

We have presented models to predict and assess the multiple consequences of occurrences associated with an AS plan. They are part of a framework for risk management in AS at state level which allows a government to decide how to allocate its resources to improve AS levels in a given country. The models described here are basic ingredients of the AS risk problem management and its use is key to monitor safety, screen hazards and allocate AS resources, as described in Rios Insua et al. (2016a). They are included in the RIMAS software supporting the implementation of the methodology.

From the perspective of a state associated with ICAO, eight consequences have been adopted: fatalities, severe and minor injuries, delays, cancellations, repairs, destructions and, finally, image loss. Other countries might select different consequences. Non-state actors in the aviation system would typically focus on consequences related with the profit and loss account of the organisation. The performance for such eight consequences can be assessed by choosing direct attributes, except for image loss. This depends on the awareness raised by such occurrence and we adopted as proxy the number of accidents involving commercial aviation transport.

We have adopted models for the prediction of such consequences for different types of occurrences, severities and aircrafts. For each of them, we have illustrated its use with a case, using data from relevant sources. We have proposed also a multi-attribute utility function to jointly assess the levels attained in the eight attributes. Such model allows a state to assess the safety consequences associated with an AS plan as a key activity to prepare the SMS.

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