

Bayesian Networks for Decision-Making and Causal Analysis under Uncertainty in Aviation

Rosa Maria Arnaldo Valdés,
V. Fernando Gómez Comendador,
Alvaro Rodriguez Sanz, Eduardo Sanchez Ayra,
Javier Alberto Pérez Castán and Luis Perez Sanz

Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/intechopen.79916>

Abstract

Most decisions in aviation regarding systems and operation are currently taken under uncertainty, relying in limited measurable information, and with little assistance of formal methods and tools to help decision makers to cope with all those uncertainties. This chapter illustrates how Bayesian analysis can constitute a systematic approach for dealing with uncertainties in aviation and air transport. The chapter addresses the three main ways in which Bayesian networks are currently employed for scientific or regulatory decision-making purposes in the aviation industry, depending on the extent to which decision makers rely totally or partially on formal methods. These three alternatives are illustrated with three aviation case studies that reflect research work carried out by the authors.

Keywords: Bayesian networks, prediction, classification, risk, anomaly detection, causal modelling, uncertainty

1. Introduction

Technical and managerial decision-making is a critical process in any industry and any business. Information is a fundamental cornerstone in the decision process, although sometimes its availability and quality are limited or affected by uncertainty.

Uncertainty refers to the stochastic behaviour of a system and to the uncertain values of the parameters that describe it. Most decisions in aviation systems and operation are currently

taken under the assumption that the values of the parameters describing the system performance are equal to their estimates. However, this postulation is only valid as long as there are sufficient data or precise expertise for an accurate estimation of the system parameters. This is not the case in many occasions, particularly when the system, product or process is new and limited measurable information about its performance is accessible. Additionally, in many occasions, decision makers in aviation do not count with the assistance of formal methods and tools to help them cope with all those uncertainties in the decision-making process, particularly when it is necessary to evaluate risks or perform causal analysis.

A systematic approach for dealing with uncertainties in aviation and air transport is possible through Bayesian analysis. Bayesian Networks (BNs) have been broadly applied to decision-making problems in a wide variety of fields because they combine the benefits of formal probabilistic methods, understandable easily visual form, and efficient computational tools when exploring consequences and risks.

In this chapter, we revise the advantages of applying BNs to aviation and air transport decision-making problems in environments affected by uncertainty. We characterise typical problems existing in aviation and air transport, which could benefit from this systematisation; and describe recent research work carried out in this field. More particularly, the chapter illustrates works performed by the authors regarding:

- i. How Bayesian reasoning can support an integrated methodology to assess and evaluate compliance with system safety goals and requirements when there is uncertainty in the assessment of systems performances.
- ii. How Bayesian networks can be used to evaluate the risk of runway excursion at an airport and decide whether an airline will be authorised to operate at that airport vis-a-vis of the operational risk.
- iii. How causal analysis through a BN can be used to understand the interdependencies between factors influencing performance and delay (drivers and predictors) at busy airports.

2. Bayesian networks for decision-making in aviation

In general, we may consider three main ways that Bayesian networks are currently employed in causal and risk analysis for scientific or regulatory decision-making purposes in the aviation industry. While in general decision makers prefer to rely on formal infrastructures to back up its decisions, the extent up to what they totally or only partially trust on the formal methods is in the origin of this triple approach.

- i. In the first way, the Bayesian reasoning assumes the entire process of evaluation and decision. In this case, the Bayesian approach applies to all the phases and steps in the process and estimations, and decisions respond to an overall Bayesian framework. Typical decision problems normally tackled with this approach addresses questions such as:

- Should a company be allowed to operate at a new airport?
- Does an on-board system satisfy the prescribed safety objectives?
- Should a new aircraft model be certified and allowed to fly?

Those in favour of this approach sustain that Bayesian reasoning is able to provide such an all-inclusive and formal scheme to arrive at decisions, and that applying a scientifically homogenous approach to all the phases of the decision-making process guarantee coherent, objective and solid decisions. Those against this approach claim that with this approach, the Bayesian analyst is put in charge and takes over the entire process and endeavour. Although widely applied in other industries, its use is still rare in aviation.

- ii. In the second option, Bayesian methods can be used just to estimate probability distributions. In this case, Bayesian analysis is still a central piece of the decision-making process, although it is not anymore in charge of the whole process. Typical questions addressed by this application of Bayesian methods are:

- What are the odds of an aircraft suffering a runway overshoot?
- What is the probability that a flight will experience a delay?
- What is the probability that passengers will lose their flight?

In this case, Bayesian analyst furnishes the quantities and probability distributions that will help managers to take informed decisions but will not condition their decision, which might be influenced by other factors. Therefore, the decision process is formally isolated from the Bayesian analysis.

- iii. At the opposite end, Bayesian methods can be used to select or parameterise input distributions for a probabilistic model. In this case, neither the model nor the decision process rely on the Bayesian methods. Bayesian analysis is reduced at a basic role and is used to estimate the input parameters to many complex models, instead of answering questions directly. This is the simplest application of Bayesian methods in a decision-making process, and it normally constitutes the first application when Bayesian methods are introduced in a new industry.

This application is of particular interest when there are too little data available to sustain statistical analysis, and the only source of available information should be obtained from expert knowledge. Most decisions in aviation are taken under the assumption that the values of the parameters describing the system performance are equal to their estimates, which is only valid as long as there are sufficient data or precise expertise for an accurate estimation of the system parameters. It is not the case in many situations, particularly when the system, product or process is new and tiny measurable information about its performances is accessible. In these cases, BNs represent a framework of causal factors linked by conditional probabilities, which are elicited from aviation experts. Best-expert estimates will use the best available and accessible data.

Typical questions answered by this approach are:

- What is the distribution of partial and total failures of an aircraft component?
- What is the in-service time of an aircraft component?
- What is the uncertainty about the probability of a critical event? and
- How can we characterise uncertainty about the aircraft trajectories or delays?

When talking about the different areas of aviation, the application of Bayesian networks is not homogeneous. Several respected research groups and authors have initiated the application of BNs in aviation. In fact, literature nowadays is wide enough to support reviews as the ones recently performed by Broker in [1] or Roelen in [2], about BN applications for aviation risk estimation.

Aviation safety and risk analysis are by far the domain where more BN applications can be found. A thoughtful revision shows that this technique is particularly useful to provide additional insights into problems of “low probability-high consequence,” such as the aviation safety domain where events occur very infrequently.

- In [3], Bayesian Belief Networks are applied to model a number of safety defensive barriers in Air Traffic Control environment from airspace design, through tactical control, and from the operation of aircraft safety net features to a potential accident.
- In [4], Luxhoj and Coit used Bayesian networks to model a certain aircraft accident type known as Controlled Flight Into Terrain (CFIT).
- In [5], the authors develop causal models for air traffic using “event sequence diagrams, fault-trees and Bayesian belief nets linked to form a homogeneous mathematical model suitable as a tool to analyse causal chains and quantify risks...”.
- Some authors [6] have developed an inclusive aviation safety model to evaluate management decisions potential impact.
- Ref. [7] introduces a BN for the evaluation of flight crew performance, and Delphi technique to complement data from accident reports
- Problems at very low level of detail regarding safety in operational issues have also benefited from the application of Bayesian methods [8].
- Reducing aviation safety risk is a matter of concern also for NASA, who focuses on the reasoning of selecting Object-Oriented Bayesian Networks (OOBN) as the technique and commercial software for the accident modelling [9].
- In [10], a BN analysis model is established by using 10 years of flight crew members’ error data in China civil aviation incidents to analyse the probability distribution of flight crew members’ errors in civil aviation incidents analysis.
- Several models have attempted to explain various factors influencing aeronautical accidents: human, organisational, environmental and airport infrastructure factors. The model by [11] permits to evaluate the influence of these factors and identify the dependence and relationship among them.

- A very initial attempt to assess aviation security can be found at [12], which addresses the evaluation and mitigation of security risks in the aviation domain and realises a multi-dimensional approach of complex systems.
- Bayesian networks are capable of providing real-time safety monitoring functionalities, like those in [13] that integrates automatic video analysis algorithms and Bayesian models to detect anomalous behaviours of ATCs and spatiotemporal details about how errors due to fatigue and distractions eventually lead to near-ground incidents/accidents.
- In [14], Arnaldo et al. used Bayesian inference and hierarchical structures to predict aircraft safety incidents.

The second domain where more BNs can be found is operational analysis, particularly delays optimisation. BNs represent a paradigm shift in the study of aviation delays because they have a structure that is machine-learned from data and do not require assumptions about “causal” patterns; they can produce estimates even in situations with sparse or limited data, and they can be used well in advance of the actual flight, as they can predict based on only partial evidence.

- In [15], the random characteristics of civil aviation safety risk are analysed based on flight delays, using a BN to build an aviation operation safety-assessment model based on flight delay.
- The propagation of micro-level causes to create system-level patterns of delay, a problem difficult to assess by traditional methods, has been assessed with BNs to investigate and visualise propagation of delays among airports, demonstrating greater predictive accuracy than using linear regression [16].
- In [17], a new Bayesian Network algorithm, Negotiating Method with Competition and Redundancy (NMCR), demonstrate excellent performances in estimating of arrival flight delay, especially in flight chains mainly operated in China.
- The NextGen Advanced Concepts and Technology Development Group of the FAA (Federal Aviation Administration) have tackled this problem by developing Bayesian Networks for Departure Delay Prediction [18].
- The aviation supply chain has also been modelled through Bayesian networks to minimise delays causing factors [19].
- Another relevant case on airport delay analysis can be found in [20]. This chapter develops a functional analysis of the operations that represent the aircraft flow through the airport airspace system. By considering the accumulated delay across the different processes and its evolution, different metrics are proposed to evaluate the system’s state and its ability to ensure an appropriate aircraft flow in terms of time saturation.

Another area that has received attention from Bayesian experts is the modelling of airline risk considering reliability data, maintainability data and management data.

- Some attempts have been made to approach software health management based on a rigorous Bayesian formulation to monitor the behaviour of software and operating

system, to perform probabilistic diagnosis, and to provide information about the most likely root causes of a failure or software problem. Three realistic scenarios from an aircraft control system were considered: (1) aircraft system-based faults, (2) signal handling faults, and (3) navigation faults due to inertial measurement unit (IMU) failure or compromised Global Positioning System (GPS) integrity [21].

- Ref. [22] covers the construction of a probabilistic risk analysis model for the jet engines manufacturing process, based on BN coupled to a bow-tie diagram. It considers the effects of human, software and calibration reliability to identify critical risk factors in this process. The application of this methodology to a particular jet engine manufacturing process is presented to demonstrate the viability of the proposed approach
- BN has also been designed for fault detection and isolation schemes to detect the onset of adverse events during operations of complex systems, such as aircraft and industrial processes [23].
- Another relevant work on fault diagnosis is the one by [24] to study automatic fault diagnosis of IFSD (in-flight shutdown).
- In the area of maintenance, BNs are also applied for improving Human reliability analysis (HRA) in visual inspection [25].

Finally, one of the most attractive probabilistic modelling framework extensions of Bayesian Networks for working under uncertainties from a temporal perspective, Dynamic Bayesian Networks (DBNs), has also had some applications in aviation.

- DBNs have been used to model abnormal changes in environment's data at a given time, which may cause a trailing chain effect on data of all related environment variables in current and consecutive time slices.
- In [26], an algorithm is proposed for pilot error detection, using DBNs as the modelling framework for learning and detecting anomalous data, based on the actions of an aircraft pilot, and a flight simulator is created for running the experiments. The proposed anomaly detection algorithm has achieved good results in detecting pilot errors and effects on the whole system.
- Another application to dynamic operational problems can be found in [27], where the variables which affect the Helicopter's real-time aviation decision process are represented on Structure Variable Discrete Dynamic Bayesian Network, building up a model that could be used in real-time aviation decision process in perpetual variational air combat.
- From a point of view, less operational and more economical, BNs also help the aviation industry and dynamically recommend airline managers relevant contents based on predicting passengers' choice to optimise the loyalty.

The remaining sections of the document illustrate the application of each one of the three options, enumerated at the beginning of this section, through three aviation case studies that reflect research works carried out by the authors.

3. Case study 1: Bayesian framework for safety compliance assessment and acceptance under uncertainty

In [28], we present a good example where Bayesian reasoning assumes the entire process of evaluation and decision. This work presents an integrated methodology, based on Bayesian inference, to assess and evaluate compliance with system safety goals and requirements when there is uncertainty in the assessment of systems performances.

Compliance assessment process is addressed in this work as a Bayesian decision problem:

$$B = \langle A, N, P, W, U \rangle, \quad (1)$$

where

- A states for the decision maker actions space, $a_i, A = \{a_1, a_2, \dots, a_n\}$
- N represents the space of possible “states of nature”, i.e. magnitudes about which there is uncertainty, $N = \{Ns_1, Ns_2\} = \{Cs, \overline{Cs}\}$
- P represents the space of uncertainties about the state of nature of the system, $P = \{P(Ns_1), P(Ns_2)\} = \{P(Cs | D, I), P(\overline{Cs} | D, I)\}$
- W represents the set of decision outcomes, $W = \{W_{11}, W_{12}, \dots, W_{ij}, \dots, W_{nm}\}$
- U represents the set of utility functions, $U = \{u_{11}, u_{12}, \dots, u_{ij}, \dots, u_{nm}\}$

Each combination $(a_i, Ns_j) \in C = A \times N$ determines a consequence of a course of action for the decision maker. The utility function $u_{ij}(c)$ defines the predilections of the decision maker on a course of action a_i for a system with a state of safety compliance Ns_j .

The overall process of safety compliance assessment is addressed through a Bayesian approach as illustrated in **Figure 1**. The rectangle at the left-hand part of the figure represents a decision node, which displays the three potential actions, a_i , which the decision maker can take as a result of the safety compliance process:

- a_1 - Judge the system compliant;
- a_2 - Judge the system as non-compliant; or
- a_3 - Judge the information insufficient.

The circles denote random nodes, which represent the “states of nature”, that is, the actual state of system compliance, Ns_j , where

- $Ns_1 = Cs; Ns_2 = \overline{Cs}$

Being the notation of C_s the event that the system is actually compliant, whereas \overline{Cs} denotes the event that the system is not actually compliant. The uncertainties in the states of nature P_j

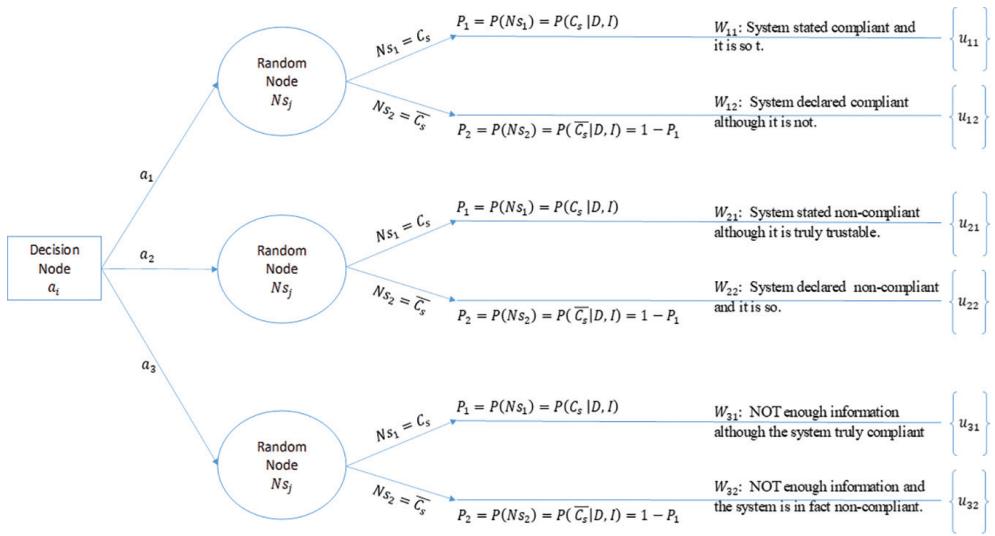


Figure 1. Bayesian decision tree for safety acceptance of a system.

are provided by the Bayesian estimation process. The belief or uncertainty about the compliance state of the system C_s is dependent on the data D and information I available.

- $P_1 = P(Ns_1) = P(C_s | D, I)$;
- $P_2 = P(Ns_2) = P(\bar{C}_s | D, I) = 1 - P_1$

Each of the branches of the tree represents the set of possible (unpredictable) outcomes W_{ij} that can occur under each action taken by the decision maker. The six possible outcomes, in this case, correspond to:

- W_{11} : The system is stated compliant and it is so;
- W_{12} : The system is declared compliant although it is not;
- W_{21} : The system is stated non-compliant although it is truly trustable;
- W_{22} : The system is declared non-compliant and it is so;
- W_{31} : The decision maker has no enough information although the system truly compliant;
- W_{32} : The decision maker has no enough information and the system is in fact non-compliant.

Safety compliance is assigned a probability of being true, which represents the decision maker uncertainty (or state of knowledge), about its truth or falsity. Namely, the uncertainty on the state of nature of the system compliance considering previous knowledge and information is expressed as: $P(Ns_n) = P(C_s | D, I)$, where a proposition D stands for data and I stands for background information. This framework subscribes to the concept that probability is not a

frequency, rather a measure of uncertainty, belief or a state of knowledge. That is, probability allows doing plausible reasoning in cases where we cannot reason with certainty.

The result is the predictive probability that the system meets the safety objectives for what it has been designed, considering the envelope of data, knowledge and information gathered from the system during its design, production and operation.

To that aim, compliance assessment is redefined as the determination of the degree of belief in the fulfilment of the applicable failure probability objectives by the candidate system, for all failure conditions N. The whole system is considered compliant if all the λ_n satisfy their pertinent failure safety objective O_n . In this step, the principles of Bayesian inference are applied to improve the estimation of the system/ component rate of failure λ_n .

The conditional probability distribution $P(\lambda_n | D, I)$ describes then the uncertainty in the parameter under study (λ_n) considering new events D and the prior understanding of the system I. It represents the sampling distribution of the rate of failure conditional upon the observed data and information and is precisely the form required for decision-making without the need for approximation. It is determined using the Bayes' theorem:

$$P(\lambda_n | D, I) = \frac{P(D|\lambda_n, I) \times P(\lambda_n | I)}{P(D|I)} \quad (2)$$

where

- $P(\lambda_n | D, I)$ corresponds to the posterior distribution. The posterior distribution will be the foundation for all inference about the parameter λ_n ;
- $P(D|\lambda_n, I)$ corresponds to the likelihood distribution, sometimes referred as sampling;
- $P(\lambda_n | I)$ is the prior distribution; and
- $P(D|I)$ is the failure of unconditional or marginal probability D.

Epistemic uncertainty is incorporated through the Prior distribution $P(\lambda_n | I)$. It epitomises the degree of belief in model parameters λ_n and defines an initial state of knowledge. Prior distribution can be non-informative or informative. Non-informative priors include very little fundamental info regarding the unknown and facilitates data dominate the posterior distribution. Other terms for non-informative priors are diffuse priors, vague priors, flat priors, formal priors, and reference priors. Informative priors provide essential information about the unknown parameter. Historical data and expert judgement can be incorporated into the prior probability distribution. Although the prior can take the form of any distribution, conjugate priors simplify the evaluation of the previous equation and allow analytical solutions avoiding the use of numerical integration. In practice, the Bayesian approach often leads to intractable integrals and numerical simulation procedures need to be adopted. Normally, due to the complexity of the distributions, the solution of Equation has to be accomplished by numerically Markov Chain Monte-Carlo (MCMC) simulation.

The resulting posterior distribution, $P(\lambda_n | D, I)$, stands for updated knowledge about λ_n and is the basis for all inferential statements about λ_n .

The distribution $P(D|\lambda_n, I)$ represents the chance of the data D and model aleatory uncertainties. It represents inefficiencies in the data collection as well as the failure mechanism or the failure model. Likelihood functions commonly used in safety assessment are binomial, Poisson, or exponential ones.

Finally, $P(D|I)$ is just a normalisation constant.

$P(C_{sn} | D, I)$ can be inferred from the posterior distributions $P(\lambda_n | D, I)$ through marginalisation of the parameter λ_n , as indicated in the following equation.

$$\begin{aligned} P(C_{sn} | D, I) &= \int_{\lambda} P(O_n, \lambda_n | D, I).d\lambda = \\ \int_O^{O_n} P(O_n | \lambda_n)P(\lambda_n | D, I).d\lambda &= \int_O^{O_n} P(O_n | \lambda_n) \frac{P(D | \lambda_n, I) \times P(\lambda_n | I)}{P(D | I)}.d\lambda \end{aligned} \quad (3)$$

Eq. (3) computes an average of the model uncertainty integrating the sampling distribution $P(O_n | \lambda_n)$ over the posterior distribution $P(\lambda_n | I)$. The output is a predictive probability of a failure condition meeting its safety objective.

This Bayesian framework espoused is exemplified over a practical case. This practical case corresponds to a real situation with current hypothesis, requirements and data: a new ANSP initiates the provision of Tower Control and CNS (Communications, Navigation and Surveillance) services at the new international airport of Castellón (Spain).

The service provider is subject to supervision by the National Aeronautical Authority and must demonstrate compliance with applicable safety requirements. At Castellón airport, air navigation service comprises ground-based radio navigation aids, very high-frequency omnidirectional range (VOR), distance measuring equipment (DME), and precision approach and landing aids, instrument landing system (ILS). The functionalities of each of these systems and the applicable requirements are regulated at international level. Providers of air navigation services must prove that their operating procedures and working methods are compliant with the prescriptions and standards of ICAO Annex 10. They must guarantee the accuracy, continuity, availability and integrity, as well as the quality level, of their services.

4. Case study 2: runway excursion

In [29], the authors work on a representative example of the option where Bayesian methods are used to estimate probability distributions. Statistics about commercial aircraft fleet accident produced by Boeing (2012) states that around 37% of the accidents took place during landing and final approach flight phases, and among them, runway excursions accounted for 25% of all accidents. In particular, within the runway excursions, those that are produced by a too long landing (overrun excursion) represent 96%, and the 10-year moving average during 1992–2011 indicates a deteriorating tendency.

This section summarises the work done by the authors to develop a Bayesian model to evaluate the runway overrun risk at a given airport and operational conditions. The model allows comparing the probability of excursion at landing at several runways or airports. The model relates overrun probabilities with possible generating factors, then suggesting the outline of mitigation actions.

The probabilistic influence diagram for runway overrun Bayesian network (see **Figure 2**) is based on the information from safety authorities, operators and manufacturers [30–32]. The network combines expert judgement and data analysed with the aid of the GeNIE SW.

The critical variable chosen as network outcome is “the remaining runway at 80 kt (I), measured in ft”, since, as indicated by the FSF SLGs [33], the risk of a runway overrun increases significantly if when there are just 2000 ft. (610 m) of landing distance available (LDA) the aircraft is not decelerated below 80 kt. The nodes in the network account for:

- Relevant Runway. It is a categorical variable: (A).
- Crosswind component at threshold. Unit of measurements is knots: (B).
- Speed of the aircraft which it is discretised to the nearest integer in the avionic: (kt).
- Tailwind component at threshold. Unit of measurements is knots: (C).
- Stabilised/unstabilised state at the approach: (D).
- Maximum reverse thrust, which describes the maximum reverse thrust is applied during ground roll. It is measured in seconds: (E).
- Autobrake state at landing, which has three values: low, medium, and no autobrake: (F).
- Difference between the Indicated AirSpeed (IAS) and the Final Approach Speed (Vapp): (G)

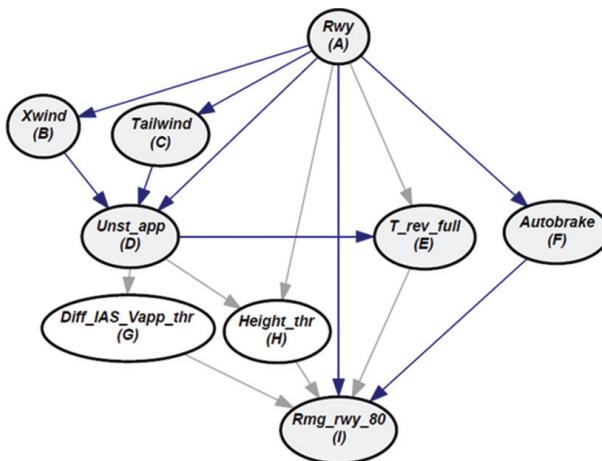


Figure 2. BN for overrun events.

- Aircraft height at threshold, measured in feet (ft): (H).

The safety issue analysed in this work is among the group of most frequently reported accident/incident types all over the world, and it is considered as a big threat to aviation safety. Runway excursions take place with very low frequency, but their consequences may be quite severe. Very low probabilities of occurrence are an added challenge for a risk analyst. Reducing landing overruns is a priority for international aviation organisations that are actively investigating and proposing safety strategies to contain this risk.

The work carried out by the authors in this study uses public information provided by safety agencies, operators and manufacturers; as well as expert judgement and data to create an influence diagram and a probabilistic model.

The model is illustrated with a case study in which three runways are benchmarked in terms of runway excursion risk. The critical event considered to evaluate the risk of runway excursion was the probability that the aircraft not being below 80 kts when just 2000 ft. (610 m) of LDA remains $\Pr(I < 2000)$. The case study is a representative of the decision problems, and airline has to cope with when opening new routes and evaluating operation at new airports or with new fleet. To illustrate the usability of the model and its benefits, the case study uncovered the following issues:

- For this specific case study, the Bayesian network and the supporting data allow discarding correlation between cross and tailwind components.
- Although in general, landing with windy, both crosswind and tailwind components, increases the probability of unstabilised approach, however, tailwind influence is not so determinant at runways 2.
- The variables with the toughest effect on the lasting runway at 80 kt were:
 - i. the LDA, available landing distance,
 - ii. the used of the autobrake system, and
 - iii. the difference between the Vapp and the IAS at the threshold.
- Height at the threshold and maximum reverse thrust variables does have a minor effect on the risk of excursions at the three compared runways.
- The network faithfully reflects operational aspects the propensity to pitch down prior to the threshold to increase the distance available for landing, commonly known as “ducking under” effect.
- The probability of slowing the aircraft at 80 kt in the last 2000 ft. of the runway rises as wind, both components crosswind and tail, increase, except for runway 2.
- Crosswind results are coherent with normal operations. With a severe crosswind, the use of the autobrake system is recommended, since it is more difficult to control and decelerate the aircraft.
- Unstabilised approaches are prone to the most hazardous conditions.

- Longer periods of maximum reverse thrust operation, favour reduction of remaining runway at 80 kt, and consequently have a negative effect on risk of runway excursion. Prolonged operation of the maximum reverse thrust may indicate difficulties to decelerate the aircraft during the ground roll. This variable could then be used as a proxy for runway excursion risk by the airlines Flight Data Monitoring (FDM) teams.
- Runway excursion risk increases with longer operation of reverse thrust, which might be an indicator of difficulties to slow down during the ground run. Accordingly, it is recommended to consider this variable as a precursor of runway excursion risk, and closely monitored it in the Airline's Flight Data Monitoring (FDM) programs.

5. Case study 3: airport operation uncertainty characterisation

In [34], the authors analysed the aircraft flow through the Airport focusing on the airspace/airside integrated operations and characterising the different temporal aircraft operation milestones through the airport based on an aircraft flow's Business Process Model and Airport Collaborative Decision-Making methodology. Probability distributions of the factors influencing aircraft processes are estimated, as well as conditional probability relationship among them. The work turned up in a Bayesian network, which manages uncertainties in the aircraft operating times at the airport. This case study constitutes a representative example of the third manner Bayesian networks are currently employed decision-making purposes in the aviation industry.

The work is based on the collection and analysis of nearly 34,000 turnaround operations at the Adolfo Suárez Madrid-Barajas Airport and concluded with several lessons learned regarding the characterisation of delay propagation, time saturation, uncertainty precursors and system recovery.

The BN structure is represented in **Figure 3** and the network variables. It was organised in different layers attending to the nature of the data to facilitate the understanding of the causal relationships among influence parameters. Colours in **Figure 3** represent the different BN layers.

- Nodes 1–5 refer to meteorological conditions.
- Nodes 6–13 count for variables regarding the arrival airspace: timestamps and congestion metrics (throughput, queues and holdings).
- Nodes 14–15, 26 and 38–39 refers to the airport infrastructure.
- Nodes 16, 22–25 and 40 account for the operator, aircraft, route and flight data.
- Nodes 17–21, 27–37 and 41–42 include data about airside operational times and flight regulations
- Nodes 43–49 stand for delay causes.

The probabilistic Bayesian Network is able to predict outbound delays probability distribution given the probability of having different values of the causal control variables, and by setting a

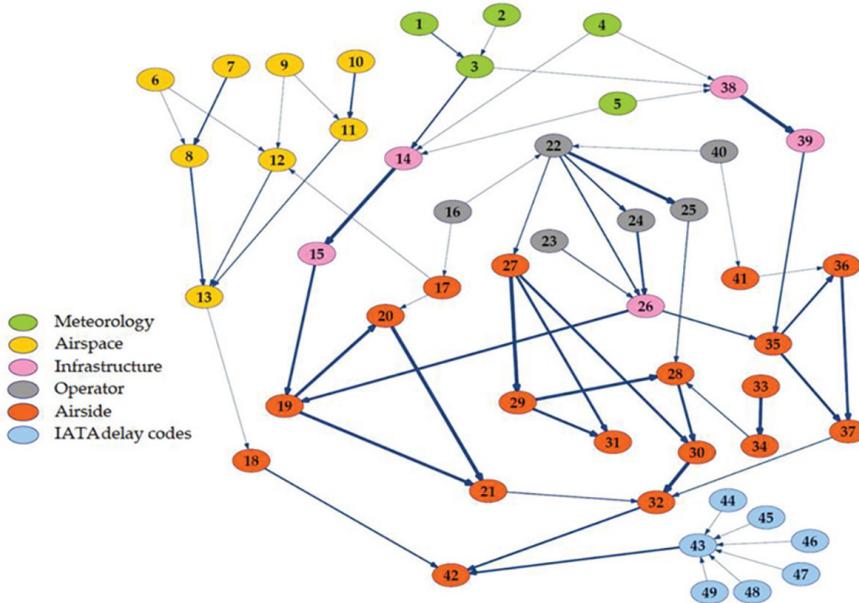


Figure 3. BN model to explain the interdependencies between factors that influence delay performance and system saturation.

target to the output delay, the model provided the optimal configuration for the input nodes. The main outcomes of this work were:

- the statistical characterisation of processes and uncertainty drivers and
- the causal model for uncertainty management (BN).

The case study showed that considering the 34,000 aircraft operations analysed Madrid Airport:

- Arrival delay increases and accumulates its impact over the day, due to network effects.
- However, departure delay does not follow arrival delay's pattern.
- The airport is capable of absorbing a fraction of the arrival delay.
- The main potential drivers for delay include:
 - i. time of the day,
 - ii. congestion at ASMA,
 - iii. weather conditions,
 - iv. amount of arrival delay,
 - v. scheduled duration of processes,
 - vi. runway configuration,

- vii. airline business model,
 - viii. handling agent,
 - ix. aircraft type,
 - x. route origin/destination, and
 - xi. existence of ATFCM regulations.
- Departure delay is highly influenced by the event of longer duration, which at the same time, are the event offering greater possibilities for recovery delays.

6. Conclusions

As stated at the introduction of this chapter, important decisions in aviation systems and operation are currently taken in less than optimal circumstances, under high levels of uncertainty, with only limited amount of data and reliable information, and without the assistance of formal methods and tools.

Based on a thoughtful revision of the available literature, to determine what domains in aviation and air transport Bayesian Networks applications, the chapter characterises the three main ways that Bayesian networks are currently employed for scientific or regulatory decision-making purposes in the aviation industry, depending on the extent to which decision makers rely totally or partially on formal methods:

- i. Bayesian reasoning assumes the entire process of evaluation and decision.
- ii. Bayesian methods are used just to estimate probability distributions.
- iii. Bayesian methods are used to select or parameterise input distributions for a probabilistic model.

These three alternatives have been illustrated with three case studies that reflect research work carried out by the authors and accounts for the following research questions:

- iv. Use of Bayesian decision theory under uncertainty to evaluate compliance with system safety goals and requirements.
- v. Runway excursion risks evaluation at an airport, using Bayesian networks to decide about airline initial operation considering the operational risk.
- vi. Understand the interdependencies between factors influencing performance and delay (drivers and predictors) at busy airports with using Bayesian networks.

In this work, the authors pretend to highlight the advantages of Bayesian networks as a useful systematic approach to help decision makers to cope with all those uncertainties and difficulties in the decision-making process, particularly when it is necessary to evaluate risks or perform causal analysis.

Author details

Rosa Maria Arnaldo Valdés*, V. Fernando Gómez Comendador, Alvaro Rodriguez Sanz, Eduardo Sanchez Ayra, Javier Alberto Pérez Castán and Luis Perez Sanz

*Address all correspondence to: rosamaria.arnaldo@upm.es

Air Space Systems, Air Transport and Airports Department, School of Aerospace Engineering, Universidad Politecnica de Madrid Plz. Cardenal Cisneros, Madrid, Spain

References

- [1] Brooker P. Experts, Bayesian belief networks, rare events and aviation risk estimates. *Safety Science*. 2011;**49**(8-9):1142-1155
- [2] Roelen A. Risk Models of Air Transport. Netherlands: Technische Universiteit Delft; 2008
- [3] Neil M, Malcom B, Shaw R. Modelling an air traffic control environment using Bayesian belief networks. In: 21st International System Safety Conference; Ottawa. 2003
- [4] Luxhoj J, Coit D. Modelling low probability/high consequence events: An aviation safety risk model. In: Annual Reliability and Maintainability Symposium 2006, RAMS '06; 2006
- [5] Ale BB, Bellamy L, Cooke R, Goossens L, Hale A. Towards a causal model for air transport safety an ongoing research project. *Safety Science*. 2006;**44**(8):657-673
- [6] Swets L, Zeitlinger. Aviation causal model using Bayesian Belief Nets to quantify management influence. In: Bedford, van Gelder, editors. Safety and Reliability. Tokyo: BALKEMA Publishers; 2003
- [7] Wei C, Shuping H. Evaluating Flight Crew Performance by a Bayesian Network Model. *Entropy*; March 2018
- [8] Castilho IX. Fault prediction in aircraft tires using Bayesian networks [MSc in Aerospace Engineering thesis]
- [9] Shih AT, Ancia E, Jones SM. Object-oriented Bayesian Networks (OOBN) for Aviation Accident Modeling and Technology Portfolio Impact Assessment, American Society for Engineering Management (ASEM) 33rd International Annual Conference. NASA; Oct 17-20, 2012
- [10] Wang Y, Liya J, Mei H. Human factors analysis model of flight crew members based on Bayesian network in China civil aviation incidents. In: The Twelfth COTA International Conference of Transportation Professionals; 2012
- [11] Bandeira MCGSP, Correia AR, Martins MR. Method for measuring factors that affect the performance of pilots. *Transporte*. 2017;**25**(2):156-169

- [12] Cioaca C, Boscoianu M. An introduction in the risk modeling of aviation security systems. Mathematics and Computers in Biology, Business and Acoustics. Lupulescu NB, Yordanova S, Mladenov V editors. Barsov, Romania; 2011
- [13] Kamala P et al. Automates human performacne monitoring for air traffic control safety through bayesian network modeling and video surveillance. International Journal of Computer Science and Information Technologies. 2015;6(5):4392-4396
- [14] RMA V, Fernando Gómez Comendador V, Sanz LP, Sanz AR. Prediction of aircraft safety incidents using Bayesian inference and hierarchical structures. Safety Science. 2018;104: 216-203
- [15] Wang H, Jun G. Bayesian network assessment method for civil aviation safety based on flight delays. Mathematical Problems in Engineering. 2013;2013(Article ID 594187):12
- [16] Xu N, Donohue G, Laskey KB, Chen CH. Estimation of delay propagation in the national aviation system using Bayesian networks. In: Proceedings of the Fifth USA/Europe Air Traffic management (ATM) R&D Seminar. Baltimore: 2005
- [17] Liu Y, Wu H. A remixed Bayesian Netwrok based algorithm for flight delay estimating. International Journal of Pure and Applied Mathematics. 2013;3:465-475
- [18] Cosmas A. Bayesian networks for departure delay prediction. In: NASA Ames Research Center Airline Operations Workshop; 2015
- [19] Yorukoglu M, Kayakutlu G. Bayesian network scenarios to improve the aviation supply chain. In: Proceedings of the World Congress on Engineering, WCE. London; 2011;Vol II
- [20] Rodríguez-Sanz Á et al. Analysis of saturarion at the airport and airspace integrated operations. A case study regarding delay indicators and their predictability. In: Twelfth USA/Europe Air Traffic Management Research and Development Seminar (ATM2017); 2017
- [21] Schumann J, Mbaya T, Mengshoel O. Software health management with Bayesian networks. Innovations in Systems and Software Engineering. December 2013;9(4):271-292
- [22] Pereiraa JC, Limaa GBA, Annibal. A bow-tie based risk framework integrated with a Bayesian belief network applied to the probabilistic risk analysis. Brazilian Journal of Operations & Production Management. 2015;12:350-359
- [23] Gautam B, Mack DL, Kouts XD. Learning Bayesian network structures to augment aircraft diagnostic reference models. IEEE Transactions on Automation Science and Engineering. Jan. 2017;14(1)
- [24] Huiling C et al. Research on in-flight shutdown fault diagnosis of civil aviation engine based on Bayesian networks. Advanced Materials Research. 2012;403-408:1416-1419
- [25] Wei Chen SH. Human reliability analysis for visual inspection in aviation maintenance by a Bayesian network approach. In: Transportation Research Record Journal of the Transportation Research Board. December 2014;2449(1):105-113

- [26] Saada M, Meng Q, Huang T. A novel approach for pilot error detection using dynamic Bayesian networks. *Cognitive Neurodynamics*. 2014;8(3):227-238
- [27] Gao PZX. Real-time aviation decision based on structure variable Bayesian network. In: 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE); 2010
- [28] Valdés RA, Fernando Gomez Comendador V, Sanz AR, Castán AP, Sanz LP, Ayra ES. Bayesian approach to safety compliance assessment and acceptance under uncertainty for air navigation service providers. *Safety Science*. Under revision
- [29] Sanchez Ayra E. Risk analysis and safety decision-making in commercial air transport operations [PhD thesis]; 2013
- [30] Nielsen T, Jensen F. *Bayesian Networks and Decision Graphs*. Berlin: Springer Publishing Company Inc; 2007
- [31] Cowell R, Dawid P, Lauritzen S, Spiegelhalter D. *Probabilistic Networks and Expert Systems: Exact Computational Methods for Bayesian Networks*. Springer; 2007
- [32] Cheng A, Dillard A, Hackler L, Van Der Geest P, Van Es G. Study of Normal Operational Landing Performance on Subsonic, Civil, Narrow-Body Jet Aircraft during Instrument Landing System Approaches. Federal Aviation Administration (FAA); 2007
- [33] FSF. Reducing the Risk of Runway Excursions. Flight Safety Foundation (FSF), Virginia U.S.; 2009
- [34] Rodríguez-Sanz Á, Comendador FG, Valdés RA, Pérez-Castán JA. Characterization and prediction of the airport operational saturation. *Journal of Air Transport Management*. 2018;69:147-172