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Analysis of accident precursor data for Mid Air Collision occurrences using expert-build Bayesian Network model and Information Theory

Schon Z.Y. Liang Cheng[1, 2], Rosa María Arnaldo Valdés[1], Victor Fernando Gómez Comendador[1], Ricardo Román Cordón[3]

[1]Department of Sistemas Aeroespaciales, Transporte Aéreo y Aeropuertos, School of Aerospace Engineering, Universidad Politécnica de Madrid (UPM)

Plaza Cardenal Cisnero, 3, 28040 Madrid, Spain; rosamaria.arnaldo@upm.es, fernando.gcomendador@upm.es

[2]Division of Aeronautic, Space & Defence, ALTRAN Innovacion

Calle Campezo,1, 28022 Madrid, Spain; schon-zy.liang@altran.com

[3]Industrial Development Area, Department of Technological and Industrial Management, ISDEFE

Calle Beatriz de Bobadilla, 3, 28040, Madrid, Spain; rroman@isdefe.es

Abstract

Causes leading to loss of Separation (LOS) in serious and major incidents are considered as potential precursors for Mid-Air Collision (MAC) accident. This paper attempts to model the likelihood of these precursors combining Bayesian Networks (BN), which are based on expert-built, and Information Theory (IT). BN provides the analysis of LOS contributing factors and the multi-dependent relationship of causal factors identified from real Air Traffic Management (ATM) incident reports, while IT contributes to the identification of LOS precursors providing the most information. The combination of these two techniques allows us using data on causes and precursors of LOS to define warning scenarios. These precursors could forecast a serious LOS with severity A and B, and consequently the likelihood of a MAC. The methodology is illustrated with a case study that encompasses the analysis of LOS severity A and B that have been notified within the Spanish airspace during a period of four years.

Keywords:

aviation safety; ATM; loss of separation; mid-air collision; Bayesian network approach; information theory; entropy

1. Introduction

During the last decade, the rate of Mid-Air Collision (MAC) between large commercial aircraft presents a meaning reduction. However, the safe separation between aircraft being one of the key safety challenges in aviation, especially for development of the new generation of Air Traffic Management (ATM) System (SESAR and NextGen). Traditionally, this topic was included on the safety risk list – ‘Significant 7, which was derived from worldwide fatal accidents and high-risk occurrences analysis. From 2017 EASA declared airborne collision as the top safety priority [1].

In spite of the importance, MAC rarely occurs and its relevant data are scarce. Due to the high-consequence nature, but low-frequency occurrence, MAC is not well captured and represented by conventional statistical models. Under the situation that the accident data lack the sufficient sources for modelling, risk analysis methods based on precursors are considered an efficient, therefore, a promising tool for this purpose [2].

An accident precursor is an event without catastrophic or severe consequences but that could have developed into an accident if additional safety barriers had failed [3] [4] [5] [6] [7]. This precursor concept has been explored in several safety-critical industrial sector for analysis of accidents, such sector as gas and oil accidents [8], nuclear power accidents [9] [10], space shuttle explosions [6], transport accidents [11] [12], etc.

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Frequently, accidents are preceded by a series of precursors. Gaining insight into MAC's main precursors offers an opportunity to decrease the risk of MAC. These precursors are known as events of LOS or 'loss of separation', which occur more often in airspace without necessarily having adverse or catastrophic consequences.
According to ICAO (International Civil Aviation Organisation) standards, when the safety separation minima prescribed in a controlled airspace by ATS (Air Traffic Services) authorities is not observed, then a LOS between in-flight aircraft would surely happen. Different categories of severity are established based on the seriousness of the consequences impacted by the LOS. And the severity of a LOS is defined by the risk of collision (risk of becoming in a MAC), according to the achieved separation minima between the involved aircraft and their rate of proximity. In Europe, Eurocontrol has defined five categories of severity [13], depending on the severity range they are divided into:

A. 'Serious incident', a high risk of collision;
B. 'Major incident';
C. 'Significant incident';
D. 'Not determined';
E. 'No safety effect'.

Recently, the increasing number of reports related to losses of the in-flight separation minima between commercial aircraft worries of all interested parties to share the outcomes of investigations so that they can improve mitigations. According to the Airborne Conflict Safety Forum, approximately 150 LOS per million flights have occurred in European-controlled airspace [14]. Historical data shows that each flight receive 15 instructions on average from air traffic controller while flying en-route, meaning one LOS per 100,000 instructions of air traffic controller.
Even the number of LOS is small compared to the volume of traffic. Due to the potential consequences of LOS, it is considered the main proxy and a precursor to a potential MAC. Consequently, the analysis of influential factors and the multi-dependent relationship between causal factors of LOS incidents provides an effective support to mitigate LOS and to prevent MAC from happening.
EASA has published a document related to industry best practices identifying relevant LOS precursors to be monitored through FDM (Flight Data Monitoring) programs [15]. This program presents a limitation, which it only focuses on precursors that can be monitored from the data recorded on board. From an ATC (Air Traffic Control) perspective, LOS occurrence investigation and their precursors are not ingrained due to, from one side, the inherent complexity of such incidents and, from other side, lack of available information for their detailed analysis. For this partial approach compensation, the official reports of LOS investigations are taken as this research source. Such reports have already been published by the official States Incident Investigation Authorities.
This paper attempts to model the probability of severe LOS near accidents combining the Bayesian Networks (BN) and Information Theory (IT). As the starting step, The BN model is used to detect LOS contributing factors and establish the multi-dependent relationship between them. This technique is widely used for risk analysis [16] [17] and decision-making [18] [19] in complex systems, i.e. the ATM system. The uncertainty contained in LOS scenarios makes the BN model as preferred candidate for this case study. As the next step of this study, the IT is applied to identify the information provided by LOS precursors. The combination of both techniques allows the use of LOS precursors to portray perceptive warning scenarios, which might forecast a near accident and anticipate a MAC accident.
This research work aims to exploring BN and IT for precursor-based risk analysis of major accidents known as MAC in aviation sector. This proposed method combines principles from Quantitative Risk Analysis, Bayesian Network modelling and Information Theory, to infer the likelihood of catastrophic accidents using a set of LOS data collected during a period of four consecutive years in Spanish airspace.

2. Methodology

Figure 1 presents the proposed methodology following the indicated main phases and steps. The methodology is applied with causal-effect analysis for serious and major LOS incidents as the starting point. In this first phase, from the analysis related to the notification of occurrences and investigation reports, it aims to detect all precursors leading to serious and major LOS incidents. During this phase, following a determined analysis procedure, data collected from serious and major incident reports are identified into events and factors, which are interpreted as precursors to accidents that might occur in the future. For accomplishment of this objective, standardised analysis methodologies and taxonomies are applied in this process.
During the second phase, a BN model is developed and validated using the correlation between events and factors as the basis. This model provides a quantitative cause–effect map that recreate serious and major LOS scenarios. The model also contains the estimated likelihood based on the number of reports investigated, the new relationships that are established as the target of this model and the known relationships that were detected by previous researchers.
In the third phase, the concept of entropy and the principle of Information Theory are used to assess the precursor which are most correlated to when a serious or major LOS incident occurs. In the last phase, this information is

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applied to define predictive scenarios. Additionally, ROC (Receiver Operating Characteristic) curve is used to evaluate the most effective predictive scenario.
In the following sections, the preceding steps are described in more detail.

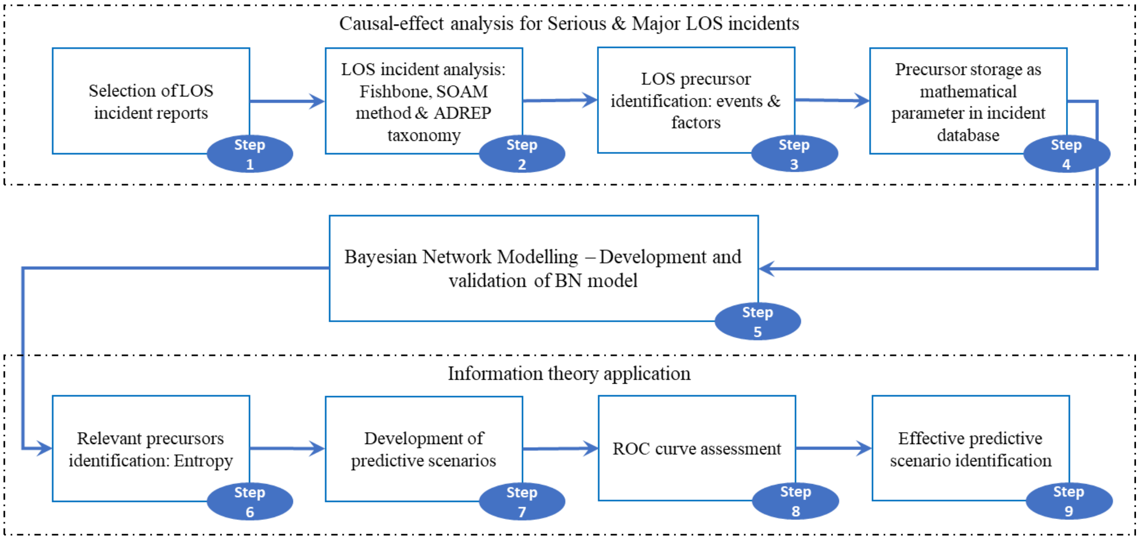

Figure 1: Methodology steps.

2.1. Causal-effect analysis for serious & major LOS incidents

This first phase consists of four steps: 1) selection of LOS incident reports, 2) LOS incident analysis, 3) LOS precursor identification and, 4) precursor storage as mathematical parameter in incident database.
In step 1, the evaluating of occurrences and their reporting present prime importance in safety analysis, as well as investigations after the fact. They provide relevant information for detecting safety-related trends and foreseeing safety risks [20].
According to European Regulation (EU) No 376/2014 [21], air traffic controllers, pilots, aviation maintenance technicians, aircraft ground handlers and airport managers are required to report occurrences to the competent authorities. Considering ICAO Annex 11 [22] as basis, every state that in its airspace an air traffic LOS is occurred should provide the appropriate investigation. In Spain, air traffic incidents are reported to a State Investigation Office, which analyses and compiles the incident data for publication in reports [23]. In this research, the data collected from LOS investigation reports are the main source containing information related to the LOS occurrence severity, contextual and factual data, and the results of investigation as required by aviation regulations. The incident reports can be divided in three basic blocks: i) incident scenario data, ii) the testimonies of involved agents and, iii) recommendations provided by the investigating office. In this study, a period of four years of occurrences and reports has been considered.
Step 2 consists of the analysis of LOS incident reports and the identification of their precursors. In this process, standardised methodologies and taxonomies are applied to incident report analysis, and therefore, precursor identification.
In the analysis process, the combined method of fishbone sequential diagram [24] with SOAM approach [25] is employed for incident report analysis. The factual data are processed with criteria defined in EAM 2/GUI 8 [26] to identify influential factors and adverse events, which are extracted and encoded by applying ADREP taxonomy [27].
The adverse events present a direct correspondence as events in ADREP taxonomy [28] as events, while the influential factors extracted from reports depending on their ontology can be identified as DFs (Descriptive Factors) or EFs (Explanatory Factors). Events are interpreted as stages or effects that set in motion the incident, meanwhile, both DFs and EFs are causes of failures in this cause–effect relationship. Furthermore, these three components: 'events, DFs and EFs' are identified as 'precursors' in step 3.
As a result of this process, incident reports are transformed from texts to simple sets of data formed by events and factors (precursors), which could be stored as mathematical parameters in an incident database (Step 4).
One incident database that contains events and their associated factors presents advantages such as the generation of groups based on different criteria. Then, a map of the correlation between these groups can be depicted to simplify the causal model construction, which could provide predictive features to determine precursors in future ATM incidents.

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With this procedure, incident scenarios can be presented by a chronological vision and separated by events and factors. Hence, the traceability between report and analysis is preserved.

2.2. Development and validation of BN model

The aim of this second phase is developing a model that would have a predictive feature to determine the adverse events and associated causes in future ATM incidents (step 5). In a similar situation, researchers Wilson & Huzurbazar [29] and Khakzad [30] suggested that conventional safety models such as the FT (Fault Tree) model, compared to BN model, lack capacity to capture the specific features in a complex system.

A BN is a probabilistic graphic approach used to provide a mathematical method of reasoning for the detection of uncertain variables. The BN model consists of a DAG (Directed Acyclic Graph), which reflects the relationship between a set of stochastic variables using nodes and arcs. The nodes are variables and the arcs represent probabilistic or functional influence linking two nodes [31]. The strength of the connections between both nodes is measured and presented through the CPT (Conditional Probabilistic Table) [32].

In mathematical concept, the BN represents a joint probabilistic distribution P(U) of variables U = {A1, A2, A3, …, An}. Such distribution could be discrete or continued, based on the conditional independency and chain rule [33] included in the network as:

$$\mathrm{P(U)} = \prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{P}\left(\left(\mathrm{A_i} \middle| \mathrm{Pa(A_i)}\right)\right) \qquad \textbf{(1)}$$

where $\mathrm{Pa(A_i)}$ is the parent set of $\mathrm{A_i}$ and P(U) is the joint probabilistic distribution in BN.

In BN model for LOS incident analysis, depending on the levels in consideration [30], the Bayes Theorem is applied to update the prior occurrence probability of events or factors. Thus, providing new inputs called evidence E to yield the posterior consequence probability by applying the following equation:

$$\mathrm{P(U|E)} = \frac{\mathrm{P(U,E)}}{\mathrm{P(E)}} = \frac{\mathrm{P(U,E)}}{\sum_{\mathrm{U}} \mathrm{P(U,E)}} \qquad \textbf{(2)}$$

Equation (2) shows either probability updating or probability prediction. In updating the analysis, the P(factor | event) is evaluated, showing the occurrence of a particular factor when the occurrence of a specific event is known [34]. In predictive analysis, conditional probabilities of P(event | factor) are calculated, specifying the probability of a particular event when the occurrence of a specific factor is known. Indeed, the values of P(event | factor) can be estimated with GeNIe software [35]; on the contrary, the values of P(factor | event) are calculated directly and collected in a CPT.

In a CPT, each event can be associate with one or more factors. This evidence assumes that there are one or more supporting causes behind a LOS incident. Moreover, in this BN model, all events and factors are defined in two states: present and absent.

2.3. Information theory application

Common causes or influential factors are presented in MAC accidents and LOS incidents in the form of initiating events and factors. The occurrence of a serious or major LOS and its causes would contain information related to the final accident. This relation between causes can be quantified using the concept of mutual information. Among the LOS causes, which with the highest mutual information are more informative, i.e. if one cause presents itself, it reduces the uncertainty related to the potential occurrences leading to an accident (step 6).

If a LOS is considered as a random variable with mass function P(z), the amount of uncertainty associated with this value 'z' can be measured by the entropy H(Z) applying the next equation:

$$H(Z) = -\sum_{z\in Z} P(z) log P(z) \qquad \textbf{(3)}$$

The conditional entropy of Z known the probability of the cause Y is another random variable defined as:

$$H(Z|Y) = -\sum_{z,y} P(z) log \frac{P(z,y)}{P(y)} \qquad \textbf{(4)}$$

The mutual information of Z and Y, I(Z, Y), can be defined in the uncertainty of Z given the observation of Y:

$$I(Z,Y) = H(Z) - H(Z|Y) = \sum_{z,y} P(z,y) log \frac{P(z,y)}{P(z)P(y)} = \sum_{z,y} P(y)P(z|y) log \frac{P(z|y)}{P(z)} \qquad \textbf{(5)}$$

The calculation of conditional probabilities is accessible from the corresponding BN, which allows a quick and easy update of the mutual information when a new set of data become available.

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2.4. Development and evaluation of predictive scenarios

The identification of influential factors (events and factors) that contain the most relevant information can be used to establish the probability of an accident. The most informative influential factors could be interpreted as a binary classifier.

Different predictive scenarios could be developed using these influential factors (step 7) and their performances are assessed by a ROC curve (step 8), which is a graphical tool to evaluate the performance of a model—specially a binary classifier, based on the threshold of discrimination. However, the most effective predictive scenario is required to identify for performing this analysis (step 9).

In Figure 2, a ROC curve presents the True Positive Rate (TPR) versus the False Positive Rate (FPR), with FPR on the horizontal axis and TPR on the vertical axis. The diagonal line, also called line of no-discrimination, divides the space into three areas: the space above the no-discrimination line that represents good predictions; the space below the no-discrimination line that represents poor predictions; and the points along the line of no-discrimination that represent a random result.

For a determined threshold, TPR is the ratio of actual positives that are correctly identified as indicated in Equation (6). FPR is the ratio of actual false positives that are correctly identified as indicted in Equation (7).

$$TRP = \frac{TP}{TP+FN} \qquad \textbf{(6)}$$

$$FPR = \frac{FP}{FP+TN} \qquad \textbf{(7)}$$

TP is true positives, FP is false positives, FN is false negatives and TN is true negatives.

Finally, the accuracy of the classifier can be defined as follows:

$$ACC = \frac{TP+TN}{FT+FP+TN+FN} \qquad \textbf{(8)}$$

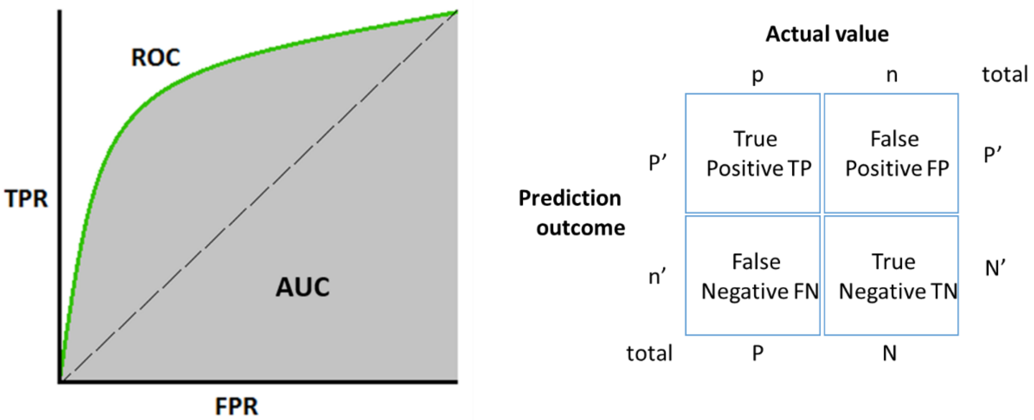

Figure 2: ROC curve for a binary classifier.

3. Case study: assessment of 4 years of LOS in Spanish Airspace

As sample of the proposed methodology application, a set data of LOS occurrences during four consecutive years is considered in this case study. According to the procedure illustrated in Figure 1, the application implies three basic phases and nine detailed steps in total.

For the purpose of clarity, this chapter is divided in three main sections, which detail all steps followed in each phase:

- Phase 1: Causal-effect analysis for serious & major LOS incidents
- Phase 2: Development and validation of BN model
- Phase 3: Information theory application

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3.1. Case study phase 1: Causal-effect analysis for serious & major LOS incidents (steps 1 thru 4)

Firstly, historical data and LOS reports are selected for this analysis (step 1). In Spain, air traffic occurrences are notified and reported to the authorities for analysis. If an occurrence is critical, then one investigation is opened and the results are published [23]. These reports involve all ATM incidents scenarios, collecting the testimonies of implicated individuals, and the conclusions and recommendations provided by the investigation agency. In summary, all incidents reported in period of four years $\{U\}$ for analysis are classified by five categories and counted as illustrated in Figure 3.

Previous to precede the incident analysis, incident reports are selected following next criteria:

- Selection by incident severity: serious (severity A) or major (severity B) incident;
- Selection by incident category: LOS or SMI;
- Selection by type of flight: limited only to commercial aircraft involved in the incident scenario;
- Selection by operating phase: when the incident occurred, none of involved aircraft was operating at the final approach phase or before achieving the second segment of the take-off.

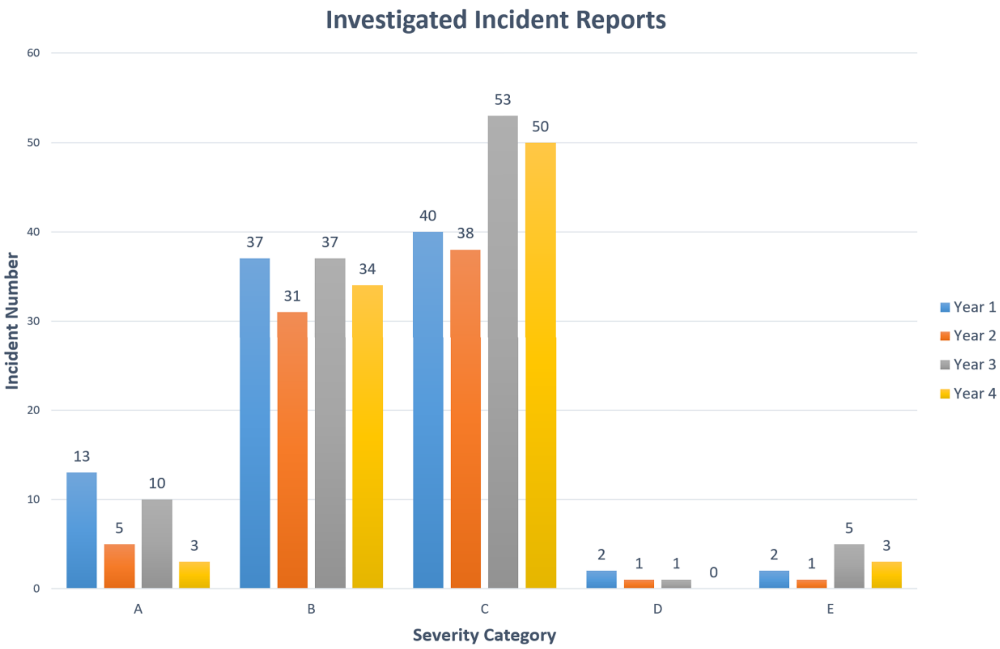

Figure 3: Spanish investigated incidents during four consecutive years

These datasets contain events and factors extracted from reports (step 2) as results of the analysis, which depict a causal-effect map of selected LOS. Precursors related to loss of separation incidents are identified, filtered (step 3), and registered as mathematical parameters in an incident database (Step 4).

3.2. Case study phase 2: Development and validation of BN model (step 5)

With expert knowledge and frequency data, the BN model proposed was constructed using GeNIe software. For the assessment of MAC precursors, several stages were followed during the BN modelling.

Stage 1: extraction of LOS key factors and determination of BN nodes. This last one is considered as the basic step for BN model structure. The nodes have two important properties, one presents the type of LOS at each incident, and the other determines the kind of precursors of a LOS. In general, three categories of nodes can be considered in ATM incidents.

- Adverse events. They are interpreted as effects or stages that establish the LOS incident.
- Influential causes. Influential factors are extracted from incident reports and can be considered as DFs and EFs, which are causes of failures. Then, the precursors are identified with these three components: events, DFs and EFs.
- The type of LOS at each incident. LOS are classified with the associated severity.

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One detail should be noted, during the BN model construction, not all extracted influential factors from reports were used for data processing. The EFs have rarely been collected due to incidents not being as strictly investigated as accidents, consequently, the reliability of this case study would be damaged. Therefore, only DFs are considered for this BN modelling.
In this BN model, events and DFs have been divided into five groups:

- Group 1 of events, parent nodes, related to A/C systems or flight crew's operations.
- Group 2 of events, parent nodes, related to ATM systems or operations.
- Group 3 of DFs, children nodes, related to A/C systems or flight crew's operations.
- Group 4 of DFs, children nodes, related to ATM systems or operations.
- Group 5 of DFs, children nodes, related to the interaction of operations between flight crew and ATM.

The dependency condition between parent and child nodes, as well as the conditioned independence of each node are assumed. The explicit hypothesis is P (xi | x1 ⋯ xi-1) = P (xi | parents (Xi)). It means that, a DF is conditionally independent of the other DFs when an event (parent node) is detected. Additionally, each event or factor is defined as a taxon and due to the characteristic of taxonomy, these events or factors are independent of each other. Finally, regarding the default options provided by GeNIe, all nodes in the network are defined as chance-general.
Stage 2: determination of the BN structure. The structure of BN is a causality chain that derived from expert knowledge and logic analysis.
The results reached in the first phase of this case study (steps 1 to 4) are used for the BN structure construction. In this phase all results (events and factors) are registered as mathematical parameters in an incident database (step 4). The correlation between events and factors is used as the basis for the posterior development and validation of the proposed BN model.
Stage 3: the BN presentation based on probability theory. During one investigation, sometimes the information provided by experts are limited in determinate area, then it is difficult to gather enough data related to causal factors presented in incidents from all operational perspectives. Therefore, the assignment of conditional probabilities is simplified with the BN analysis.
Prior probabilities are assumed to follow a multinomial distribution, with the parameter vector $\theta_1, \theta_2,\ldots, \theta_n$ where n is the number of states of variable x and $\theta_k = P(x = x_k|p)$, for $1 \leq k \leq n$; the parameter θ posses the Dirichlet distribution $\theta \sim D[\propto_1, \propto_2, \ldots, \propto_n]$, with $\propto_i > 0$ $(i = 1, \ldots, n)$, and $\sum_{i=1}^{n} \theta_i = 1$. The parameters $\propto_i$ represent counts of past cases that are stored as a summary of experience in the database produced in step 4.
As a default option, the 'clustering algorithm' of GeNIe was used for belief updating in the Bayesian network. A clustering algorithm is trained for small and simple network, it is considered as the fastest exact algorithm for belief updating in BN. This algorithm works in two phases in the junction tree: (1) compilation of a directed graph, and (2) probability updating.
Stage 4: BN structure learning. Two kinds of learning are presented in BN structure. One consists of verifying the structure of BN and remove weak connections between nodes by massive data sets. The other involves deciding the BN structure by data reasoning. In this proposed BN model, the structure has been decided based on the study of phase 1 and expert knowledge.
Table 1 and Table 2 present the CPT of the correlation between events and DFs into serious and major LOS scenario. Their derived DAG is represented in Figure 4 as a correlation map. The proposed BN model is illustrated in Figure 5.
Stage 5: BN parameters learning. The Bayes method uses prior density and posterior density to learn and assess parameters. BN also uses the above process to learn parameters after collecting and accumulating relevant data. In the practical application, conjugate prior is used to simplify the parameter learning of BN. In Bayesian theory, the conjugate means that the posterior distributions as well as the prior distributions are in the same probability distribution family. Then the prior and posterior can be identified as conjugate distributions; moreover, the likelihood function of the prior is identified as conjugate prior. A conjugate prior is an algebraic convenience, providing a closed-form expression for the posterior. In this proposed BN model, prior probabilities and posterior probabilities have the same distribution family – Dirichlet distribution.
Stage 6: validation. The procedure of validation is the same described in [36]. The BN model is validated using the validation functionality provided by the GeNIe software [37]. Three alternatives are available: a) Test only, b) K-fold cross validation and c) Leave One Out. For this proposed model, K-fold cross validation is applied, one data file of 1000 records is generated by GeNIe and used to compile the validation. The validation accuracy of all nodes is 0.945 and for individual node it is calculated with GeNIe.
Stage 7: sensitivity analysis. A simple sensitivity analysis with DFs as target is done to identify highly sensitive parameters, which affect the reasoning results significantly. Basically, GeNIe applies algorithms proposed by Kjaerulff and van der Gaag for this kind of analysis. As results, Figure 6 shows the most sensitive parameters of the network when DFs related to Flight Crew-ATM are identified as target and, Figure 7 presents the most sensitive parameters with DFs related to both Flight Crew and ATM set as target. In both figures, it can be observed that the

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DFs with low likelihood are less sensitive and cause less impact on their corresponding events and, on the contrary, the DFs with high likelihood present more influence over events in the BN model.

Table 1: CPT of events and descriptive factors under scenario of LOS in commercial aviation – Severity A

Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
1230000	Communication systems	1.15E-02	7.14E-02	12232800	Pilot's operation of communication equipment	1.15E-02	5.00E-01
2020201	ANS erroneous clearance	3.45E-02	2.14E-01	22060100	ATM's monitoring of A/C	1.15E-02	1.00E-01
				24010703	ATC provision of flight information	1.15E-02	1.00E-01
				25050000	ATM service personnel operating procedures/instructions	2.30E-02	2.00E-01
2020202	ANS clearance to wrong altitude	1.15E-02	7.14E-02	24010704	ATC provision of a minimum safe flight level/altitude/height/sector altitude	1.15E-02	6.67E-02
2020300	Communication between pilot and ANS	6.90E-02	4.29E-01	12251800	Pilot's radiotelephony phraseology	1.15E-02	5.56E-02
				12252600	Pilot's air/ground/air communication	4.60E-02	2.22E-01
				22080101	ATM's internal coordination of civil sectors in the same unit	2.30E-02	1.11E-01
				24010101	ATC use of phraseology	1.15E-02	5.56E-02
				24010102	ATC use of readback/hearback error detection	4.60E-02	2.22E-01
				24010103	Blocked communication	2.30E-02	1.11E-01
				24010107	ATC requirement for the acknowledgement of information by the Pilot	1.15E-02	5.56E-02
				24010301	ATC requirement for the acknowledgement of information by the ATCO	1.15E-02	5.56E-02
2020508	Clearance deviation - approach	1.15E-02	7.14E-02	23020400	ATC use of clearance procedure	1.15E-02	3.33E-01
4010100	ANS operational communications	2.30E-02	1.43E-01	12252600	Pilot's air/ground/air communication	1.15E-02	6.67E-02
				22080101	ATM's internal coordination of civil sectors in the same unit	1.15E-02	6.67E-02
				24010102	ATC use of readback/hearback error detection	1.15E-02	6.67E-02
4010400	ANS conflict detection and resolution	1.38E-01	8.57E-01	22060100	ATM's monitoring of A/C	3.45E-02	5.26E-02
				22080303	Revision of ATM's coordination procedures	1.15E-02	1.75E-02
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.75E-02
				22100700	Familiarization with traffic during the hand-over/take-over	1.15E-02	1.75E-02
				22120100	ATM's strategic planning for conflict detection	5.75E-02	8.77E-02
				22120200	ATM's tactical execution of the conflict detection strategy	6.90E-02	1.05E-01
				22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring	1.15E-02	1.75E-02
				23010300	Clearance procedure	3.45E-02	5.26E-02
				24010604	ATC provision of a short term conflict alert (STCA) warning	2.30E-02	3.51E-02

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Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
				27030000	ATC monitoring of sector traffic load	1.15E-02	1.75E-02
4010600	ANS handing over/taking over procedure	3.45E-02	2.14E-01	22080101	ATM's internal coordination of civil sectors in the same unit	3.45E-02	4.29E-01
				23010300	Clearance procedure	1.15E-02	1.43E-01
4050300	Failure of surveillance	1.15E-02	7.14E-02	22060100	ATM's monitoring of A/C	1.15E-02	5.00E-01
				24010705	ATC provision of delay related information	1.15E-02	5.00E-01
4070400	Air space capacity reduction	4.60E-02	2.86E-01	22080103	ATM's internal coordination of military sectors in the same unit	1.15E-02	1.25E-01
				22100300	Airspace during the hand-over/take-over	1.15E-02	1.25E-01
				27030000	ATC monitoring of sector traffic load	2.30E-02	2.50E-01
				27050200	Factors relating coordination with ATFM	1.15E-02	1.25E-01
				41100300	Runway obstruction	1.15E-02	1.25E-01
				52020400	Tailwind	1.15E-02	1.25E-01
				52031400	Cloud amount restricting visibility	1.15E-02	1.25E-01

Table 2: CPT of events and descriptive factors under scenario of LOS in commercial aviation – Severity B

Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
1230000	Communication systems	1.15E-02	1.37E-02	21010900	Headsets	1.15E-02	5.00E-01
				24010103	Blocked communication	1.15E-02	5.00E-01
2020201	ANS erroneous clearance	8.05E-02	9.59E-02	25050000	ATM service personnel operating procedures/instructions	5.75E-02	5.00E-01
				27030000	ATC monitoring of sector traffic load	2.30E-02	2.00E-01
				24010105	ATC call-sign confusion	1.15E-02	1.00E-01
				23020400	ATC use of clearance procedure	1.15E-02	1.00E-01
				12230900	Pilot's operation of emergency brakes	1.15E-02	1.00E-01
				23020700	ATC use of descent procedure	1.15E-02	1.00E-01
				22060100	ATM's monitoring of A/C	1.15E-02	1.00E-01
2020202	ANS clearance to wrong altitude	1.61E-01	1.92E-01	25050000	ATM service personnel operating procedures/instructions	1.15E-01	6.67E-01
				22120100	ATM's strategic planning for conflict detection	1.15E-02	6.67E-02
				27030000	ATC monitoring of sector traffic load	2.30E-02	1.33E-01
				23020400	ATC use of clearance procedure	1.15E-02	6.67E-02
				12240600	The rate of descent of the aircraft	1.15E-02	6.67E-02
				22060100	ATM's monitoring of A/C	5.75E-02	3.33E-01
				23020500	ATC use of climb procedure	1.15E-02	6.67E-02
				24010105	ATC call-sign confusion	1.15E-02	6.67E-02
2020300	Communication between pilot and ANS	1.38E-01	1.64E-01	12252600	Pilot's air/ground/air communication	4.60E-02	2.22E-01
				24010102	ATC use of readback/hearback error detection	8.05E-02	3.89E-01
				12251800	Pilot's radiotelephony phraseology	2.30E-02	1.11E-01
				24010101	ATC use of phraseology	4.60E-02	2.22E-01
				52031600	Thunderstorm	1.15E-02	5.56E-02

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Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
				12251400	Pilot's action in respect to instruction	1.15E-02	5.56E-02
				24010105	ATC call-sign confusion	1.15E-02	5.56E-02
				22060200	ATM's monitoring of frequencies	1.15E-02	5.56E-02
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	5.56E-02
2020505	Clearance deviation - take-off	3.45E-02	4.11E-02	23020600	ATC use of departure procedure	1.15E-02	3.33E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	3.33E-01
				23020500	ATC use of climb procedure	1.15E-02	3.33E-01
				22050100	A/C performance differences	2.30E-02	6.67E-01
				23020400	ATC use of clearance procedure	1.15E-02	3.33E-01
2020506	Clearance deviation - en-route	6.90E-02	8.22E-02	23020700	ATC use of descent procedure	2.30E-02	3.33E-01
				24010703	ATC provision of flight information	1.15E-02	1.67E-01
				23020500	ATC use of climb procedure	3.45E-02	5.00E-01
				22090000	ATM's traffic transfer	1.15E-02	1.67E-01
				12251800	Pilot's radiotelephony phraseology	1.15E-02	1.67E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.67E-01
				52020400	Tailwind	1.15E-02	1.67E-01
				23010300	Clearance procedure	1.15E-02	1.67E-01
				23010200	AWY/Route approach procedure	1.15E-02	1.67E-01
2020508	Clearance deviation - approach	2.30E-02	2.74E-02	24010101	ATC use of phraseology	1.15E-02	3.33E-01
				12210900	Pilot's obstacle clearance judgement	1.15E-02	3.33E-01
				12251400	Pilot's action in respect to instruction	1.15E-02	3.33E-01
				52031400	Cloud amount restricting visibility	1.15E-02	3.33E-01
				22050100	A/C performance differences	1.15E-02	3.33E-01
2020509	Clearance deviation - holding	1.15E-02	1.37E-02	23020400	ATC use of clearance procedure	1.15E-02	1.00E+00
2020513	Clearance deviation - special procedure	2.30E-02	2.74E-02	12251400	Pilot's action in respect to instruction	2.30E-02	1.00E+00
				24010102	ATC use of readback/hearback error detection	2.30E-02	1.00E+00
2020517	Deviation from clearance - assigned flight level	1.03E-01	1.23E-01	12251500	Pilot's action in respect to ATC clearance	8.05E-02	7.78E-01
				52020500	Crosswind	2.30E-02	2.22E-01
				22060100	ATM's monitoring of A/C	1.15E-02	1.11E-01
				12232800	Pilot's operation of communication equipment	1.15E-02	1.11E-01
				24010102	ATC use of readback/hearback error detection	1.15E-02	1.11E-01
				12251400	Pilot's action in respect to instruction	1.15E-02	1.11E-01
				52031600	Thunderstorm	1.15E-02	1.11E-01
				11222000	Speed-attitude correction system	1.15E-02	1.11E-01
				12230900	Pilot's operation of emergency brakes	1.15E-02	1.11E-01
				12252200	Pilot's action in respect to standard operating procedure	1.15E-02	1.11E-01

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Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	1.11E-01
2020519	Deviation from clearance - assigned or specified speed	2.30E-02	2.74E-02	12251500	Pilot's action in respect to ATC clearance	1.15E-02	5.00E-01
				12240700	The flying speed of the aircraft	1.15E-02	5.00E-01
				12252600	Pilot's air/ground/air communication	1.15E-02	5.00E-01
2020522	Deviation from clearance - climb/descent conditional clearance	1.15E-02	1.37E-02	24010101	ATC use of phraseology	1.15E-02	1.00E+00
				12210500	Pilot's perception of visual/oral warning	1.15E-02	1.00E+00
2020805	Deviation from approach procedure	3.45E-02	4.11E-02	24010703	ATC provision of flight information	2.30E-02	6.67E-01
				23020300	ATC use of approach procedure	3.45E-02	1.00E+00
				24010101	ATC use of phraseology	1.15E-02	3.33E-01
2100100	Diversion due to weather conditions	3.45E-02	4.11E-02	52031400	Cloud amount restricting visibility	1.15E-02	3.33E-01
				52010200	Instrument meteorological conditions	1.15E-02	3.33E-01
				52021200	Turbulence in cloud	1.15E-02	3.33E-01
2170200	Wrong runway selected	1.15E-02	1.37E-02	21040200	ATM's information data system	1.15E-02	1.00E+00
				24010304	Information input error in the ATC operations	1.15E-02	1.00E+00
4010100	ANS operational communications	1.49E-01	1.78E-01	22080203	ATM's coordination with an adjacent civil sector	6.90E-02	4.00E-01
				22090000	ATM's traffic transfer	6.90E-02	4.00E-01
				22080101	ATM's internal coordination of civil sectors in the same unit	2.30E-02	1.33E-01
				24010703	ATC provision of flight information	1.15E-02	6.67E-02
				23020700	ATC use of descent procedure	1.15E-02	6.67E-02
				22080103	ATM's internal coordination of military sectors in the same unit	1.15E-02	6.67E-02
				22100600	Briefing for the hand-over/take-over	2.30E-02	1.33E-01
				22080201	ATM's coordination with an adjacent civil unit	1.15E-02	6.67E-02
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	6.67E-02
				24010106	ATC transfer of communication	1.15E-02	6.67E-02
4010200	ANS operational information provisions	2.30E-02	2.74E-02	24010703	ATC provision of flight information	2.30E-02	1.00E+00
				27030000	ATC monitoring of sector traffic load	1.15E-02	5.00E-01
4010300	ANS separation provision	2.30E-02	2.74E-02	24010703	ATC provision of flight information	2.30E-02	1.00E+00
				21020103	ATM's use of the instrument landing system	1.15E-02	5.00E-01
				23020300	ATC use of approach procedure	1.15E-02	5.00E-01
				22060100	ATM's monitoring of A/C	1.15E-02	5.00E-01
				23020700	ATC use of descent procedure	1.15E-02	5.00E-01

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Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
4010400	ANS conflict detection and resolution	5.17E-01	6.16E-01	23010201	Surveillance radar element of a precision approach radar system approach	1.15E-02	1.75E-02
				22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring	1.26E-01	1.93E-01
				24010703	ATC provision of flight information	4.60E-02	7.02E-02
				23010300	Clearance procedure	1.15E-02	1.75E-02
				22060100	ATM's monitoring of A/C	5.75E-02	8.77E-02
				23020700	ATC use of descent procedure	8.05E-02	1.23E-01
				22110200	ATM's updating of a flight plan	1.15E-02	1.75E-02
				23020600	ATC use of departure procedure	1.15E-02	1.75E-02
				23020400	ATC use of clearance procedure	4.60E-02	7.02E-02
				27060100	ATC assistance to the ATC in recovering control of traffic	2.30E-02	3.51E-02
				22120100	ATM's strategic planning for conflict detection	3.45E-02	5.26E-02
				23020300	ATC use of approach procedure	2.30E-02	3.51E-02
				24010102	ATC use of readback/hearback error detection	2.30E-02	3.51E-02
				22120200	ATM's tactical execution of the conflict detection strategy	2.30E-02	3.51E-02
				22130200	ATM's vertical conflict resolution	8.05E-02	1.23E-01
				12252600	Pilot's air/ground/air communication	1.15E-02	1.75E-02
				24010604	ATC provision of a short term conflict alert (STCA) warning	5.75E-02	8.77E-02
				52031600	Thunderstorm	1.15E-02	1.75E-02
				22090000	ATM's traffic transfer	1.15E-02	1.75E-02
				22130300	ATM's conflict resolution by planned controller action	1.15E-02	1.75E-02
				24010101	ATC use of phraseology	1.15E-02	1.75E-02
				27030000	ATC monitoring of sector traffic load	2.30E-02	3.51E-02
				24010605	ATC provision of airborne proximity warning	1.15E-02	1.75E-02
				12251500	Pilot's action in respect to ATC clearance	1.15E-02	1.75E-02
				25050000	ATM service personnel operating procedures/instructions	3.45E-02	5.26E-02
				24010105	ATC call-sign confusion	1.15E-02	1.75E-02
4010500	ANS handling of accidents/incidents/emergency	1.15E-02	1.37E-02	23020800	ATC use of emergency procedure	1.15E-02	1.00E+00
				22060100	ATM's monitoring of A/C	1.15E-02	1.00E+00
				26070000	ATM handling of A/C unusual/emergency situation	1.15E-02	1.00E+00
				23010700	Emergency procedure	1.15E-02	1.00E+00
4010600	ANS handing over/taking over procedure	4.60E-02	5.48E-02	22080203	ATM's coordination with an adjacent civil sector	2.30E-02	2.86E-01

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Adverse Events (E)	Event Definition	P(E)	P(E|Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF|E)
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	1.43E-01
				27030000	ATC monitoring of sector traffic load	2.30E-02	2.86E-01
				22090000	ATM's traffic transfer	1.15E-02	1.43E-01
				22080101	ATM's internal coordination of civil sectors in the same unit	1.15E-02	1.43E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.43E-01
				27010300	ATC rostering/sector opening in relation to expected traffic	1.15E-02	1.43E-01
4050300	Failure of surveillance	1.15E-02	1.37E-02	21030401	ATM's use of secondary area radar	1.15E-02	5.00E-01
4070400	Air space capacity reduction	4.60E-02	5.48E-02	52010200	Instrument meteorological conditions	1.15E-02	1.25E-01
				27030000	ATC monitoring of sector traffic load	3.45E-02	3.75E-01
				24010301	ATC requirement for the acknowledgement of information by the ATCO	1.15E-02	1.25E-01
				23021100	ATC use of holding procedure	1.15E-02	1.25E-01
				22100300	Airspace during the hand-over/take-over	1.15E-02	1.25E-01

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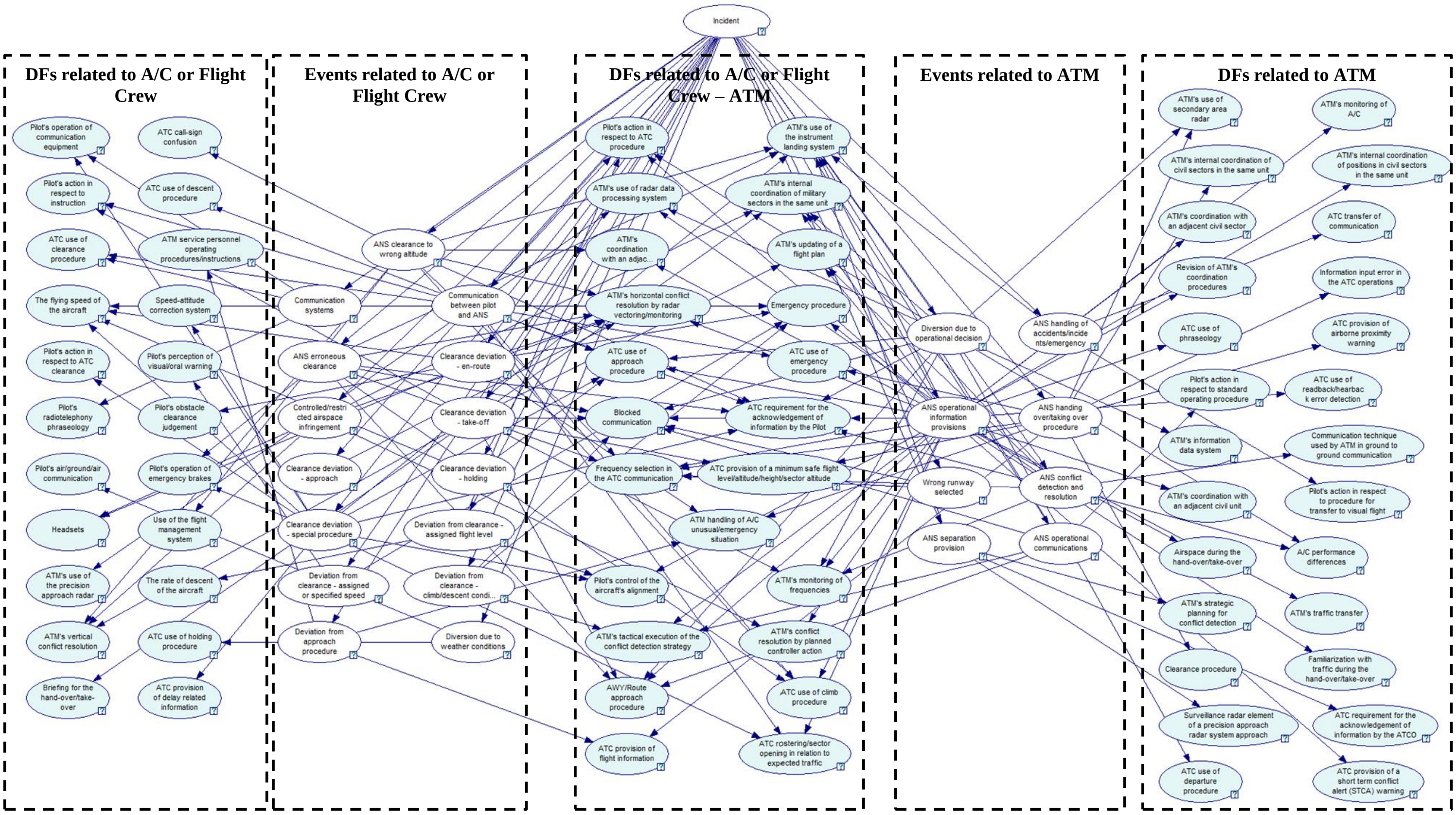

Figure 4: BN model for LOS serious & major incidents in commercial aviation

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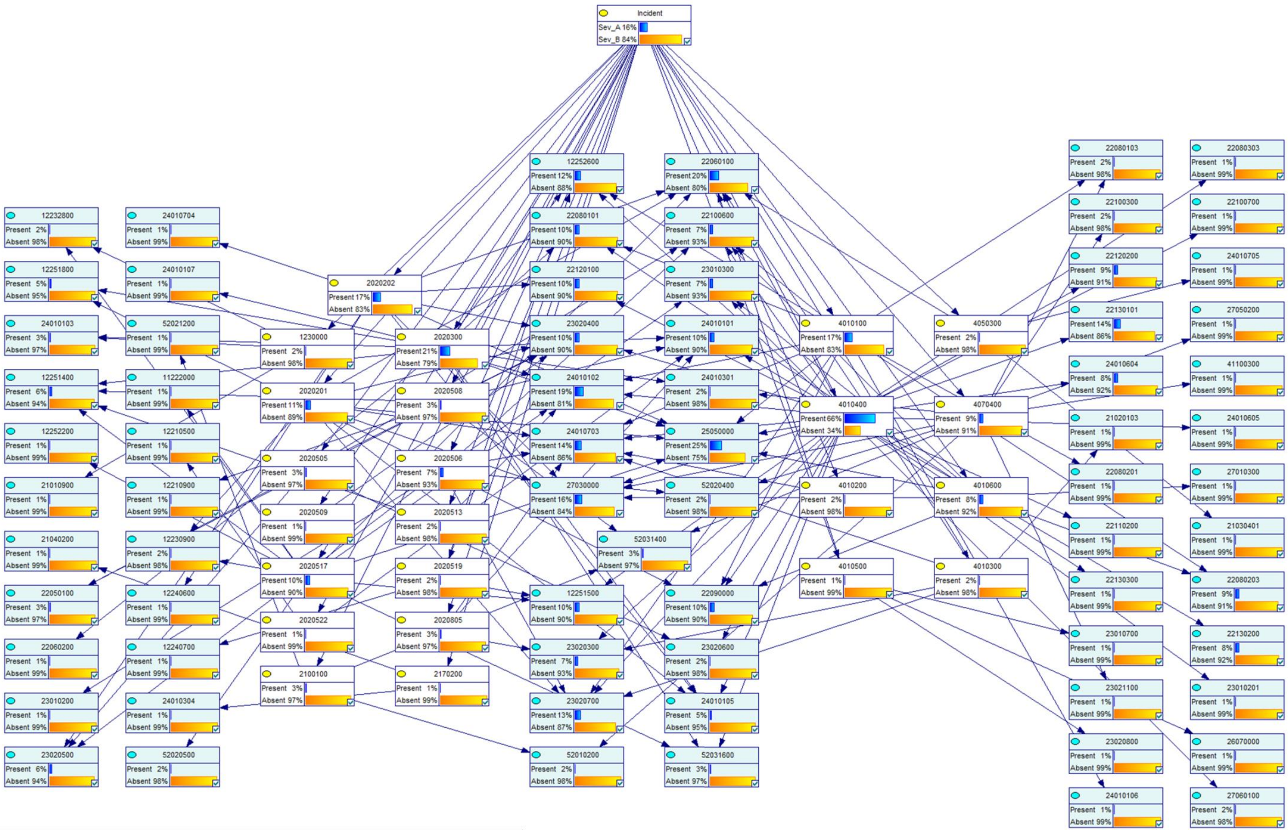

Figure 5: GeNIe output of events and DFs during four consecutive years

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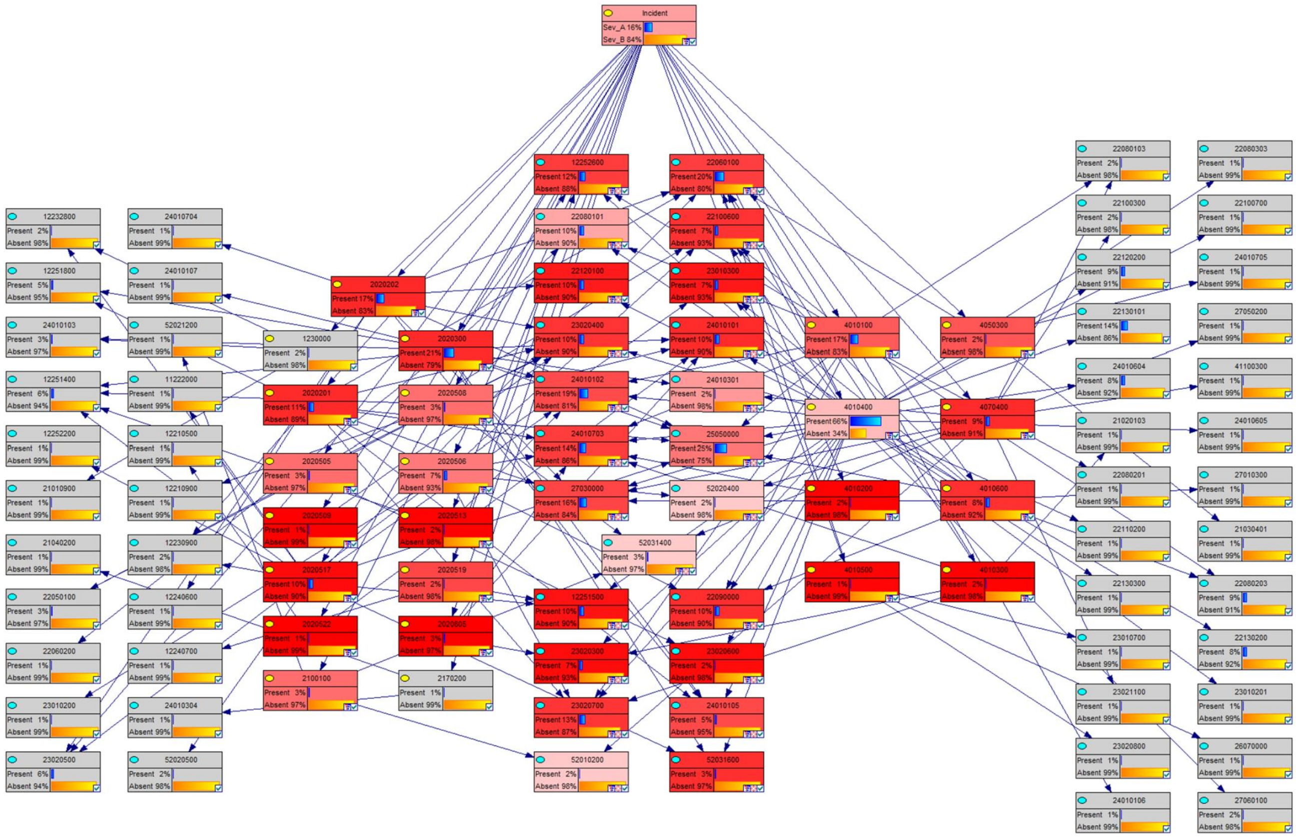

Figure 6: Results of the sensitivity analysis with common DFs between A/C and ATM as target

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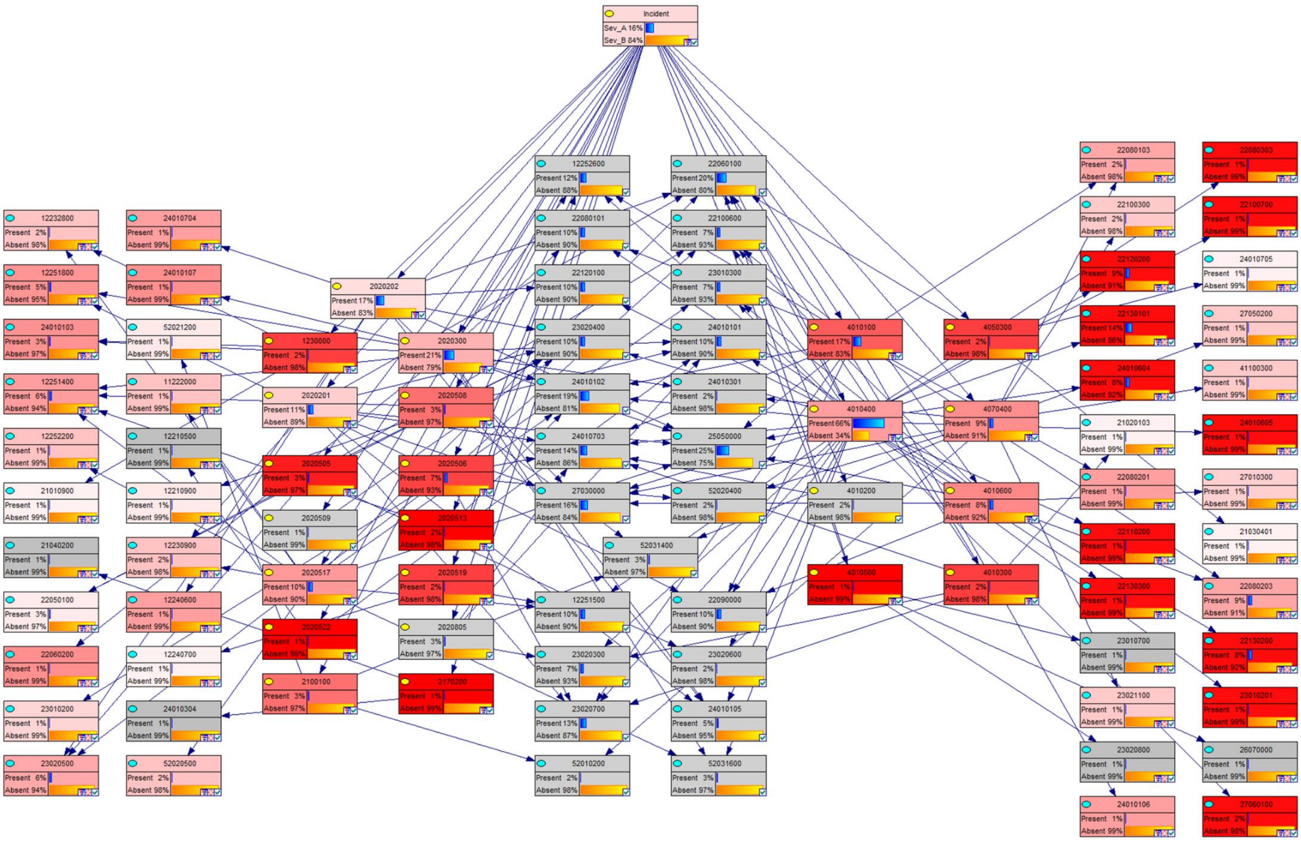

Figure 7: Results of the sensitivity analysis with DFs corresponding to A/C and ATM as target

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3.2. Case study phase 3: Information theory application (step 6 thru 9)

Once the BN has been validated, the entropy principle could be applied to identify the events and DFs with the most influential contribution to a LOS. Applying Equation (5), the mutual information of the serious/major LOS incidents with their events/DFs are calculated and presented in Figure 8 (Step 6). As can be seen, depending on the category of incident severity, the occurrence of the following DFs conveys the most information following the occurrence of a high-severity LOS:

1. Severity A.
    - DF 22120200: ATM’s tactical execution of the conflict detection strategy
    - DF 22080101: ATM's internal coordination of civil sectors in the same unit
    - DF 22120100: ATM's strategic planning for conflict detection
    - DF 12252600: Pilot's air/ground/air communication
    - DF 24010102: ATC use of readback/hearback error detection
    - DF 22060100: ATM's monitoring of A/C
2. Severity B.
    - DF 25050000: ATM service personnel operating procedures/instructions
    - DF 22130101: ATM's horizontal conflict resolution by radar vectoring/monitoring
    - DF 24010102: ATC use of readback/hearback error detection
    - DF 22060100: ATM's monitoring of A/C
    - DF 27030000: ATC monitoring of sector traffic load
    - DF 12251500: Pilot's action in respect to ATC clearance
    - DF 23020700: ATC use of descent procedure
    - DF 22080203: ATM's coordination with an adjacent civil sector
    - DF 22090000: ATM's traffic transfer
    - DF 24010101: ATC use of phraseology

The previous DFs are considered as the most informative precursors based on different severities. Different predictive scenarios can be developed using them as the predictive classifier (step 7). The performance of these scenarios should be examined by the ROC curve.
A total of 11 scenarios in severity A and 19 in severity B have been defined:

1. Severity A.

The first six correspond to each of the precursors independently. The seventh scenario corresponds to the combination of two precursors; the eighth, ninth and tenth scenarios correspond to the combination of three precursors and, finally, the last scenario corresponds to the combination of the six precursors previously identified.
For interpretation of this analysis, scenario 1 is chosen as a sample. In scenario 1 the DFs ‘22120200: ATM’s tactical execution of the conflict detection strategy’ is used to predict the occurrence of a LOS. TPR and FPR values are calculated according to Equations (6) and (7), where:

- TP is the number of times that both the classifier ‘22120200: ATM’s tactical execution of the conflict detection strategy’ and a LOS incident with severity A took place.
- FN is the number of times that the classifier ‘22120200: ATM’s tactical execution of the conflict detection strategy’ did not take place although a LOS incident with severity A occurred.
- FP is the number of times that the classifier ‘22120200: ATM’s tactical execution of the conflict detection strategy’ took place but no LOS incident with severity A occurred.
- TN is the number of times that neither the classifier ‘22120200: ATM’s tactical execution of the conflict detection strategy’ took place nor the LOS incident with severity A occurred.

The values of TPR and FPR for this predictive classifier are 0.43, and the Accuracy (ACC) of the classifier is 0.57. For the rest of defined scenarios, the values of TPR, FPR and ACC are summarised in Table 3.

2. Severity B.

The first ten correspond to each of the precursors independently. The eleventh scenario is the combination of two most influential precursors; the twelfth scenario is the previous scenario with one influential precursor added, thus successively to the last scenario, which corresponds to the combination of the ten precursors already identified.

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As the same in the severity A, scenario 1 is taken as a sample for facilitating the interpretation. In scenario 1 the DFs '25050000: ATM service personnel operating procedures/instructions' is used to predict the occurrence of a LOS. TPR and FPR values are calculated according to Equations (6) and (7), where:

- TP is the number of times that both the classifier '25050000: ATM service personnel operating procedures/instructions' and a LOS incident with severity B took place.
- FN is the number of times that the classifier '25050000: ATM service personnel operating procedures/instructions' did not take place although a LOS incident with severity B occurred.
- FP is the number of times that the classifier '25050000: ATM service personnel operating procedures/instructions' took place but no LOS incident with severity B occurred.
- TN is the number of times that neither the classifier '25050000: ATM service personnel operating procedures/instructions' took place nor the LOS incident with severity B occurred.

The values of TPR and FPR for this predictive classifier are 0.30, and the Accuracy (ACC) of the classifier is 0.70. For the rest of defined scenarios, the values of TPR, FPR and ACC are summarised in Table 4.

Generally speaking, the value of TPR reflects the positive conditional probability of classifying/predicting the occurrence of the LOS. The prediction accuracies of aforementioned scenarios, both severity A and B, are depicted by the value of ACC. Additionally, Figure 9 and Figure 10 show the ROC curve analysis for all defined scenarios with both severities.

In practice, these results lead to great operational usefulness. Based on them, a program that monitors activities of the ATCs could be designed and implemented during standard operations. By monitoring the occurrence of identified DFs, it will be possible to anticipate or predict the occurrence of a high-severity LOS. This program will be extremely cost-effective; instead of complicated and wide supervisory programs. During the activity of an ATC, it will only require the monitoring of a few precursors that have the highest mutual information with the LOS.

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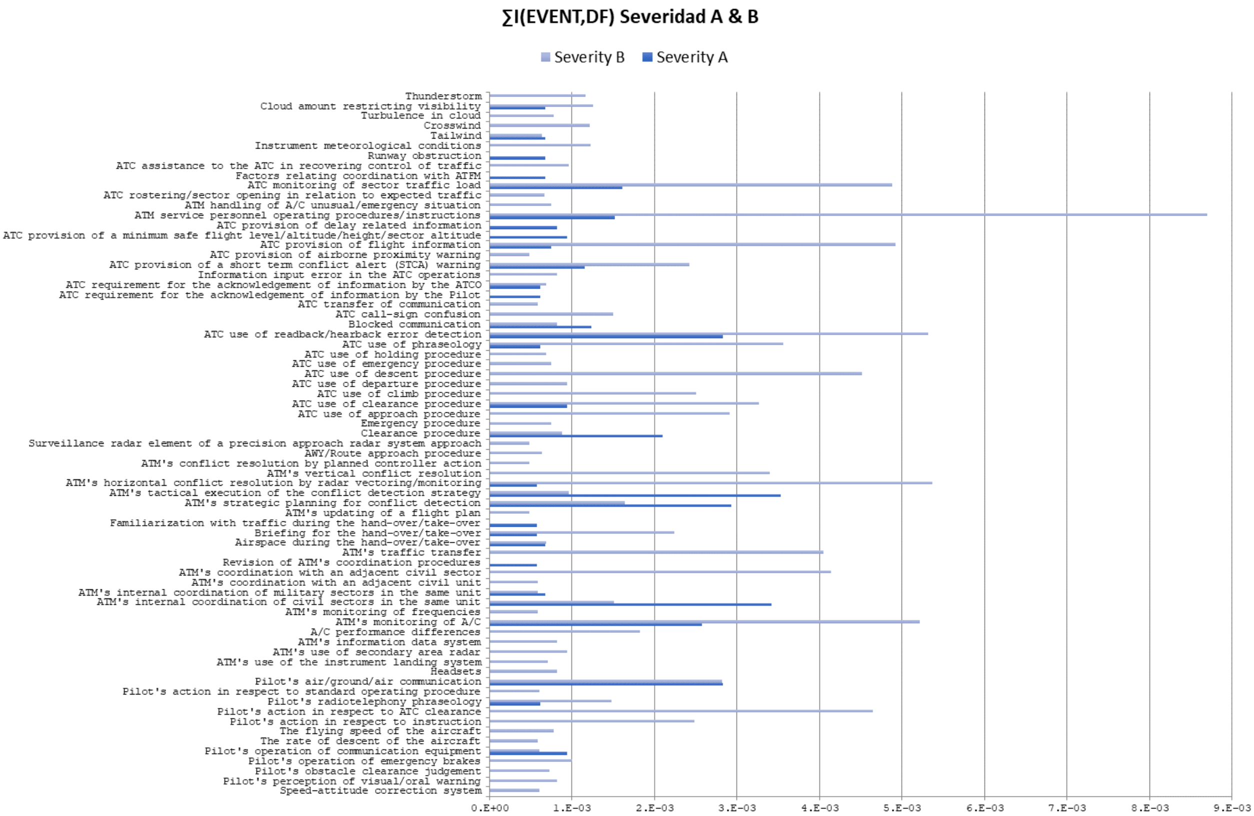

Figure 8: Mutual information for each DF in all events of serious & major LOS

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Table 3. Evaluation of predictive scenarios – Severity A.

Scenario	DFs in Each Scenario	TPR	FPR	ACC
1	22120200: ATM's tactical execution of the conflict detection strategy	0.43	0.43	0.57
2	22080101: ATM's internal coordination of civil sectors in the same unit	0.43	0.43	0.57
3	22120100: ATM's strategic planning for conflict detection	0.36	0.36	0.64
4	12252600: Pilot's air/ground/air communication	0.36	0.36	0.64
5	24010102: ATC use of readback/hearback error detection	0.36	0.36	0.64
6	22060100: ATM's monitoring of A/C	0.36	0.36	0.64
7	22120200+22060100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C	0.64	0.15	0.85
8	22120200+22060100+24010102: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATC use of readback/hearback error detection	0.79	0.06	0.94
9	22120200+22060100+12252600: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & Pilot's air/ground/air communication	0.79	0.06	0.94
10	22120200+22060100+22120100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATM's strategic planning for conflict detection	0.79	0.06	0.94
11	22120200+22080101+22120100+12252600+24010102+22060100: ATM's tactical execution of the conflict detection strategy & ATM's internal coordination of civil sectors in the same unit & ATM's strategic planning for conflict detection & Pilot's air/ground/air communication & ATC use of readback/hearback error detection & ATM's monitoring of A/C	0.93	0.00	1.00

Table 4. Evaluation of predictive scenarios – Severity B.

Scenario	DFs in Each Scenario	TPR	FPR	ACC
1	25050000: ATM service personnel operating procedures/instructions	0.30	0.30	0.70
2	22130101: ATM's horizontal conflict resolution by radar vectoring/monitoring	0.15	0.15	0.85
3	24010102: ATC use of readback/hearback error detection	0.16	0.16	0.84
4	22060100: ATM's monitoring of A/C	0.19	0.19	0.81
5	27030000: ATC monitoring of sector traffic load	0.16	0.16	0.84
6	12251500: Pilot's action in respect to ATC clearance	0.12	0.12	0.88
7	23020700: ATC use of descent procedure	0.16	0.16	0.84
8	22080203: ATM's coordination with an adjacent civil sector	0.11	0.11	0.89
9	22090000: ATM's traffic transfer	0.12	0.12	0.88
10	24010101: ATC use of phraseology	0.11	0.11	0.89
11	25050000+23020700: ATM service personnel operating procedures/instructions & ATC use of descent procedure	0.47	0.05	0.95
12	25050000+23020700+24010102: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection	0.59	0.01	0.99
13	25050000+23020700+24010102+22130101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring	0.67	0.00	1.00
14	25050000+23020700+24010102+22130101+22060100: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C	0.74	0.00	1.00
15	25050000+23020700+24010102+22130101+22060100+22090000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer	0.81	0.00	1.00

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Scenario	DFs in Each Scenario	TPR	FPR	ACC
16	25050000+23020700+24010102+22130101+22060100+22090000+24010101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology	0.86	0.00	1.00
17	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance	0.90	0.00	1.00
18	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500+ 27030000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load	0.93	0.00	1.00
19	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500+ 27030000+22080203: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load & ATM's coordination with an adjacent civil sector	0.96	0.00	1.00

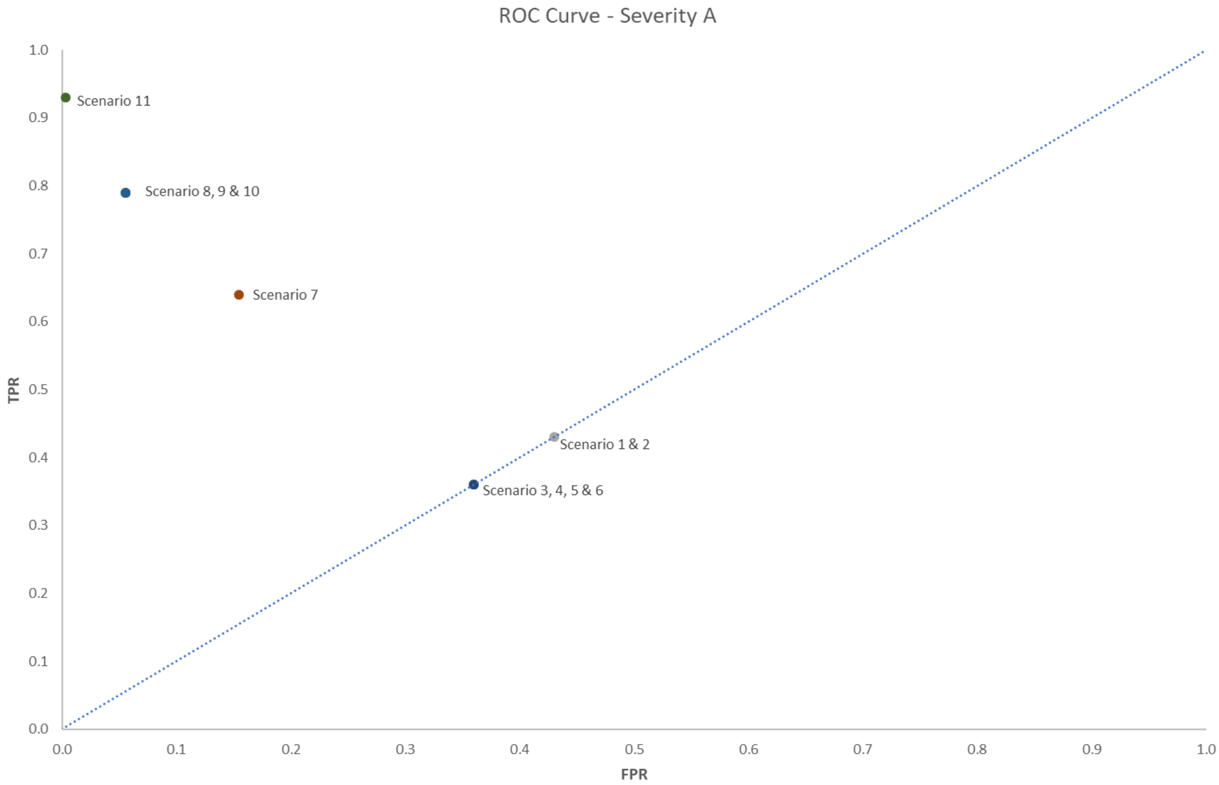

Figure 9: ROC curve using DFs of severity A as precursor data in the prediction of LOS

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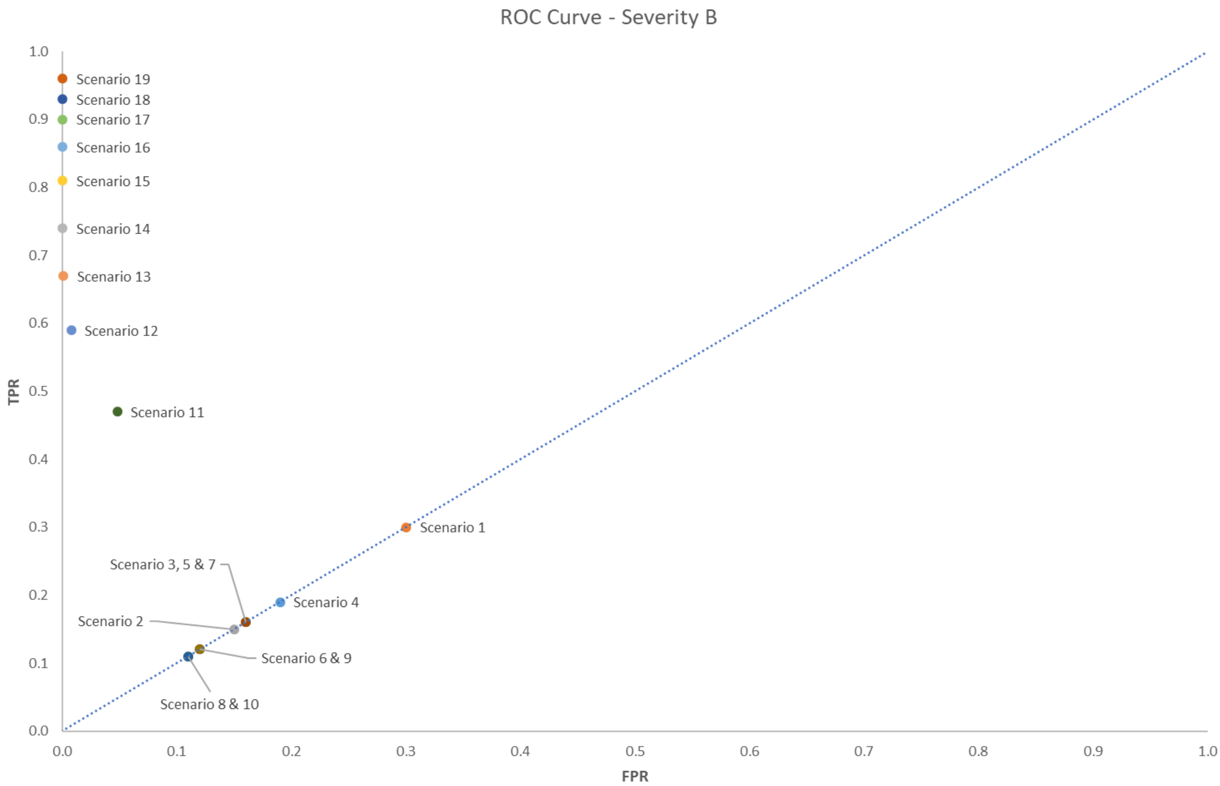

Figure 10: ROC curve using DFs of severity B as precursor data in the prediction of LOS

4. Conclusion

In this work, the authors have developed a method that combines principles from Quantitative Risk Analysis, Bayesian modelling, and Information Theory, to infer the likelihood of catastrophic accidents based upon precursor data.
The implementation baseline for this methodology details that major accidents and their links to near accidents arise from common initiating events and descriptive factors. Therefore, the occurrence of such events and DFs conveys essential information related to the probability of an extreme accident.
The methodology combines a complex BN Model created with the events and DFs extracted from serious/major LOS incidents and the application of Information Theory to quantify the mutual information. These events and DFs are later used to establish exhaustive predictive scenarios to anticipate the occurrence of severe LOS or MAC.

4.1. Benefits of the methodology application

This study illustrates how simple are inference methods to allow the exploration of information of simple operational errors to predict the likelihood of near accidents. Although there are other sophisticated approaches to the assessment of accident precursors, the added value of this information derives from the fact that near accidents frequently take place prior to major accidents. Therefore this method allows us to take advantage of an abundance of partially relevant data, which reflect operational issues and errors.
The processes, analyses, and modelling have demonstrated the detection of precursors for serious loss of separation incidents from simple reports and the construction of simple models for future incident prediction.
Within the present case study, a correlation between events and factors is set up and achieves predictive quality, which supports the identity of a set of events and factors that could occur with high probability in a new incident case.
In summary, the proposed methodology provides an in-depth diagnostic to serious loss of separation scenarios and predictive capacity for new incident analyses.

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4.2. Limitations

This methodology presents limitations as follows:

- Limitation on data source. The BN model is based on expert knowledge due to the quantitative limitation on incident data. Considering all events and factors extracted from reports could be occurring in other ATM occurrences not classified as incidents, this missing data might affect the accuracy of the information theory approach.
- Limitation on BN model. Uncertainty is inevitable presented in the BN model as other predictive models. To reduce its degree, the model needs to be updated continuously with new incident data.

4.3. Future work

- Based on the Heinrich pyramid theory, all factors that contribute on a high level of severity should be presented in the minor level. The correlation between the same DFs presented in severity A and B under selected scenarios need to be analysed.
- A new ATM safety monitoring program could be designed focusing on different perspective according to this methodology and the case study results. This program could be applied to real operations and implies improvement of the BN model using the real operational data as feedback.

Abbreviation

A/C	Aircraft
ADREP	Accident/Incident Data Reporting
ANS	Air Navigation Service
ATC	Air Traffic Control
ATCO	Air Traffic Control Officer
ATM	Air Traffic Management
ATS	Air Traffic Services
BN	Bayesian Network
CPT	Conditional Probabilistic Table
DAG	Directed Acyclic Graph
DF	Descriptive Factor
EASA	European Aviation Safety Agency
EF	Explanatory Factor
EU	European Union
FDM	Flight Data Monitoring
FN	False Negatives
FP	False Positives
FPR	False Positive Rate
FT	Fault Tree
ICAO	International Civil Aviation Organization
IT	Information Theory
LOS	Loss of Separation
MAC	Mid-Air Collision
NextGen	Next Generation Air Transportation System
ROC	Receiver Operating Characteristic
SESAR	Single European Sky ATM Research
SMI	Separation Minima Infringement
SOAM	Safety Occurrence Analysis Methodology
STCA	Short Term Conflict Alert
TN	True Negatives
TP	True Positives
TPR	True Positive Rate

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