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Airport airside safety index

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Fuzzy multicriteria analysis
Risk analysis

ABSTRACT

Rapidly growing air traffic and increasingly unstable climatic conditions have brought great pressure to bear on airport and airline Safety Management Systems (SMSs). Each item of airport infrastructure is designed to certain environmental specifications, which defines the pilot's perception of the risk of air accidents or incidents. This paper presents a fuzzy-logic methodology for measuring aviation accident risks at airports, based on the perceptions of a sample of pilots operating at the airport in question. The methodology is applied to two airports in the city of Rio de Janeiro. The results show the pilots' perceptions related to the most likely types of accident and the risks that should be prioritised in airport and airline SMSs.

1. Introduction

Safety in air transport depends on complex back-office operations, involving airlines, air traffic control and the airport, along with other essentials. However, the final in-flight decision lies with the pilots, who have their own risk perceptions. This paper presents a fuzzy-logic methodology for measuring pilots' perceptions of aviation accident risks at airports in view of meteorological conditions. It is based on a sample of pilots operating at two particular airports.

When air transport accidents do occur, they cause major material and psychological damage, undermining confidence among passengers and the general public (Squalli, 2010). Accordingly, although safety conditions are exceptionally good in air transport, as compared with rail, road and water transport, safety management is a fundamental factor for the sustainability of this service. Accidents are rare, largely precluding statistical approaches (Button and Drexler, 2006; Hale, 2001; Wong et al., 2009a), but most can be identified to occur in procedures close to airports, mainly in landings, final approaches and take-offs. Boeing (2010) shows that, from 2000 to 2009, 21% of accidents with fatal victims occurred during landing, 13% during final approach, 12% during take-off and 9% during initial climbing. A historical analysis shows that 29% of air accidents are associated with meteorological conditions (Benedetto, 2002).

Although the meteorological causes associated with risks in approach, landing, take-off and initial climb operations are well known, methodologies for analysing the cause-and-effect relations of meteorological conditions in the proximity of airports do not take account of pilots' perceptions, which have direct effects on their behaviour, notwithstanding all their training for handling adverse meteorological situations. Pilots' risk perception represents a synthesis of all the conditions surrounding the procedures of the activity of piloting an aircraft. A knowledge of pilots' risk perceptions in relation to possible accidents due to meteorological conditions at a given airport can guide safety managers in air traffic control at airports and in airlines.

The variables involved and the various types of risk point to a multicriteria problem where there are characteristic relations of cause and effect. As aviation accidents are rare, it is extremely complex to use a statistical approach or other mathematical modelling of the associated cause-and-effect relations. This paper thus suggests a fuzzy multicriteria approach for estimating indices at various levels to reflect the meteorological airport safety conditions. These indices can be used to establish airport procedures and to define specific training for pilots who operate at airports where indices for certain risks are high; they can also contribute to air traffic control.

Safety management takes place in an increasingly dynamic, complex environment and constantly confronts a variety of risks and uncertainties. You et al. (2013) pointed to pilots' risk perception as an important skill to examine in relation to hazardous flight situations. They also stated that risk perception is frequently

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considered a contributing factor in aviation accidents. Accordingly, it is imperative that safety managers in airport air traffic control and in airlines consider pilots' perceptions among the risk factors that may possibly affect air operations. More than that, however, they should examine how these factors interact and form a risk perception and how to balance subjective assessments and objective information in evaluating risks and uncertainties, as well as how to take decisions on corrective action to control and mitigate the risks identified.

Safety management studies endeavour to establish mathematical relationships of cause and effect by analysing environmental aspects, human failures and equipment failures (Ale et al., 2010; Wong et al., 2009a, 2009b). This study seeks to widen that analytical horizon to contemplate pilots' perceptions through a fuzzy multicriteria methodology. When pilots respond to questionnaires on risks, they are actually weighing much more than meteorological conditions. They are considering runway conditions, navigational aids, the quality of air traffic control, obstacles in the Airport Safety Area (ASA), conditions of the aircraft operating at the airport and, above all, their personal ability to deal with adverse situations at the airport in question. Including this set of variables in a mathematical model poses two major difficulties: the first is how to establish reliable data; and the second, how to estimate significant coefficients for the influence of each variable, given the small number of accidents at each airport. Pooling analysis of cross-section and time-series data helps boost the number of observations; on the other hand, it aggregates airports with very different characteristics in the same analysis. The fuzzy approach, in addition to not requiring historical data (because these are embedded in the pilots' perceptions), makes it possible to consider all the intervening factors in synthesis through the pilots' experience.

This study conducts a brief review of the literature on air transport safety analysis and fuzzy multicriteria analysis (FMA). It proposes an analytical methodology involving FMA concepts for identifying pilots' risk perceptions at certain airports as regards possible accidents influenced by meteorological conditions at the airports.

2. Literature review

2.1. Airport safety and risk assessment

It is not intended here to review all the literature on risk management, but rather to select articles addressing airport risk. Traditionally, the causal and probabilistic approach has been used to evaluate risk in civil aviation (Janic, 2000; Netjasov and Janic, 2008). Hale (2002) examined airport risk evaluation using models based on historical, causal data. In historical models, risks are calculated separately for each type of aircraft using the airport, and accident probabilities are classified into six scenarios, i.e., during landing: veer-off, overrun and undershoot; and during take-off: veer-off, overrun and overshoot. Meanwhile, the causal analysis starts with the accident and works backwards to whatever triggered the event.

Kirkland et al. (2004) discussed the need for models for evaluating risk at any airport, using available data on past accidents for that purpose. They developed models showing the annual probability of aircraft overruns occurring as a result of aborted landings and take-offs, as well as the distance from the runway end to where the wreckage is located. They mentioned that adverse meteorological conditions and their effects on the runway probably constitute driving factors in overruns. Wong et al. (2006) compared exposure of flights to a series of meteorological factors, such as visibility, ceiling, temperature, crosswinds, tailwinds, and visual or instrument meteorological conditions. They used statistical techniques to calculate the nature and critical levels of meteorology-related parameters as risk factors in aviation accidents.

Wong et al. (2009a, 2009b) presented a methodology for evaluating risk at, and in the vicinity of, airports. The first part of their article addressed methodological advances in accident frequency models and the second part examined accident locations, making it possible to stipulate the necessary dimensions of the Airport Safety Area (ASA). Valdés et al. (2011) proposed a risk model for runway overrun and landing undershoot using probability analysis as their technical support. They determined whether or not risk levels at a given airport were acceptable. For that purpose, they used historical data on accidents in the vicinity of the runway.

From the literature review above, it can be seen that there are still relatively few studies of airport risk analysis. Kangari and Riggs (1989) warned that risk factors cannot always be quantified numerically and, accordingly, they suggested a linguistic approach.

2.2. Fuzzy logic in multicriteria transport risk assessment

Fuzzy set theory was introduced by Zadeh (1965) as a generic approach to expressing the various different types of uncertainty inherent to human systems. He argued that our ability to make precise, significant claims about systems behaviour diminishes to the extent that they become more complex and proposed using fuzzy sets and approximation methods to model such systems. Fodor and Roubens (1994) presented the mathematical details of the inferential process of FMA. The literature contains a large number of FMA applications to problem hierarchisation, spanning numerous fields of knowledge. These papers have focussed on developing the Multicriteria Analysis technique, based on the contribution of fuzzy logic to representing uncertain data (Kahraman et al., 2006). The applications are diverse: for instance, facility location selection (Kahraman et al., 2003), tender selection problem (Deng, 1999), identification of fault behaviour risk in work system (Dağdeviren et al., 2008) and others. Fuzzy set theory has also undergone a number of methodological developments, among them comparisons among fuzzy methodologies and between these and other methodologies, as in the papers by Deng (1999) and Chang (1996).

Masalonis and Parasuraman (2003) applied fuzzy signal detection theory (SDT) techniques, combining fuzzy logic and conventional SDT, to empirical data. Two studies involving detection of aircraft conflicts in air traffic control were analysed using both conventional and fuzzy SDT. Lee (2006) developed quantitative modelling to evaluate risk factors relating to safety in aviation, using the fuzzy linguistic scale method and others as technical support. The scale used by Lee was: very high, high, middle, low and very low. He developed an application to risk factors connected with aircraft components, such as the aircraft structure, hydraulic system and so on. Hadjimichael (2009) developed a fuzzy expert system for aviation risk assessment for airlines to monitor risk indices for their individual flights based on an extensive set of airline data.

Bagirgan and Karasahin (2009) used fuzzy multi-criteria analysis to determine accident risk-prone sections on highways presently in use or at the construction or project stage, and to propose the necessary precautions. Balmat et al. (2009) presented a fuzzy approach to maritime risk assessment applied to safety at sea. The aim of their study was to define automatically an individual ship risk factor that could be used in a decision-making system.

Markowski et al. (2009) reasoned that fuzzy logic deals with uncertainty and imprecision and is an efficient tool for solving problems in these circumstances. Li et al. (2010) argued that system reliability and safety assessment focus not only on the risks caused by hardware or software, but also on the risks caused by human

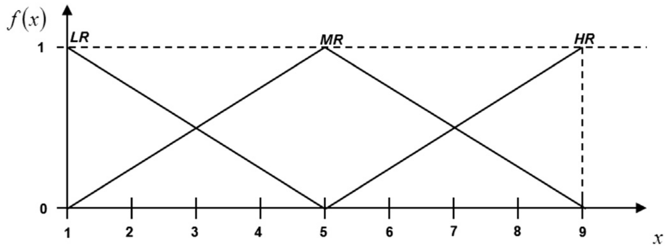

Fig. 1. Linguistic term (input).

error. They added that there are uncertainties in traditional human error risk assessment due to its measures of probability and consequence severity. They thus considered fuzzy logic an appropriate tool to deal with risk assessment involving human judgement.

Scholars have pointed out that the characteristics of FMA make it an efficient tool for solving problems where knowledge uncertainty may occur. The use of fuzzy logic to define indicators offers the possibility of obtaining indices closer to reality, particularly in situations where events are rare, as is the case with air transport accidents.

3. Analytical methodology

When designing a fuzzy system, the first thing to do is to choose the input and output fuzzifications, which entails determining linguistic terms. The next step consists of building the table of fuzzy rules describing the behaviour of the system. Finally, in order to convert the fuzzy output into usable form, a defuzzification method must be applied to transform the results into crisp outputs (Rondeau et al., 1997). The key element that guides decision making in fuzzy modelling is the rule in the general form:

If (A – observed event – input), Then (B – resulting event – output).

For example, the observed events and resulting events are expressed by linguistic terms (Figs. 1 and 2, respectively). These linguistic terms endeavour to represent the complexity of the measurement.

The fuzzy input set A (Fig. 1) and fuzzy output set B (Fig. 2) can be represented, respectively, by Equations (1) and (2), below.

$$A = \{x, f(x),\ x \in R \text{ and } f(x) \in R | 1 \leq x \leq 9 \text{ and } 0 \leq f(x) \leq 1\} \tag{1}$$

$$B = \{y, f(y),\ y \in R \text{ and } f(y) \in R | 1 \leq y \leq 5 \text{ and } 0 \leq f(y) \leq 1\} \tag{2}$$

For example, a given input can be measured into three categories (Fig. 1): low risk (LR), medium risk (MR) and high risk (HR). This is how people tend to reason about the scale when asked to

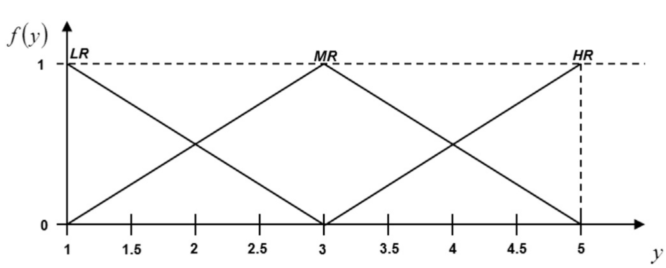

Fig. 2. Linguistic term for result (output) indicators.

classify something. An expert, however, if asked to rate a given input on a scale of 1–9, where 1 is the best situation and 9 the worst, might point to the number 6, for instance. Considering the linguistic term in Fig. 1, the expert could be said to have indicated a situation falling between medium and high risk, i.e., where there is a medium risk (MR) component and another high risk (HR) component, as reflected on the $f(x)$ axis, where 0 (zero) represents no fit with the classification and 1, total fit with the classification. According to the linguistic term in Fig. 1, $f(x_{LR})$, $f(x_{MR})$ and $f(x_{HR})$ could be represented by Equations (3)–(5), where x is a real number ranging from 1 to 9.

$$f(x_{LR}) = \begin{cases} 0, & \text{if } x \geq 5; \\ \frac{5-x}{4}, & \text{if } 1 \leq x < 5. \end{cases} \tag{3}$$

$$f(x_{MR}) = \begin{cases} 1 - \frac{x-5}{4}, & \text{if } 1 \leq x \leq 5; \\ \frac{9-x}{4}, & \text{if } 5 \leq x \leq 9. \end{cases} \tag{4}$$

$$f(x_{HR}) = \begin{cases} 0, & \text{if } x \leq 5; \\ \frac{x-5}{4}, & \text{if } 5 < x \leq 9. \end{cases} \tag{5}$$

Accordingly, each classification will have a mathematical expression to define $f(x)$ for any given evaluation. Thus, for $x = 6$, $f(x_{LR})$ will equal 0 (zero), $f(x_{MR})$ will equal 0.75 and $f(x_{HR})$ will equal 0.25. Analogous reasoning can be applied to outputs. In this study, linguistic terms on a scale of 1–5 were used for airport risk analysis inputs. The rules of the decision-making process (If x, Then y) are subject to weights (W). This weighting reflects the relative influence of the rule on the output, because the output comprises joint operation of the rules according to pre-established criteria. Ishibuchi and Nakashima (2001) examined the effect of rule weights in fuzzy rule-based classification systems, illustrating the effect of rule weights by drawing classification boundaries using fuzzy If–Then rules. Given those elements, set theory tools are used for the fuzzification process and then for defuzzification. Defuzzification means converting fuzzy grade output to crisp output. Lee (1990) suggested that, unfortunately, there is no systematic procedure for choosing a defuzzification strategy. The centroid method is the most appealing and popularly used in many applications (Perumal and Nagi, 2012). It computes the centre of the area under the curve of the fuzzy output set. It was considered an appropriate method for the purposes of this study. The output from this process furnishes an index resulting from applying the inputs at the observation unit being monitored, according to a fuzzy model defined for the analysis (The MathWorks, 2002). Using this index built up through various inputs in keeping with expert opinions, a risk level is ascertained for each category of risk indicators in relation to the others.

A three-level structure was used (Low risk – 1, Medium risk – 3 and High risk – 5) for the experts' measurements of the primary inputs and intermediary outputs. Intermediary outputs (which are inputs to subsequent levels of aggregation) and final outputs (for calculating the risk indicators for the airport) are also measured using a basic linguistic term with a three-level structure.

The literature on aviation accidents offers some indications for rating the primary meteorological conditions (Wong et al., 2006). Although when pilots analyse risk conditions at a given airport they clearly consider all the variables that form the background to their knowledge, our analysis will focus on meteorological conditions, which can be classified (Benedetto, 2002; Wong et al., 2006), as in Fig. 3, into:

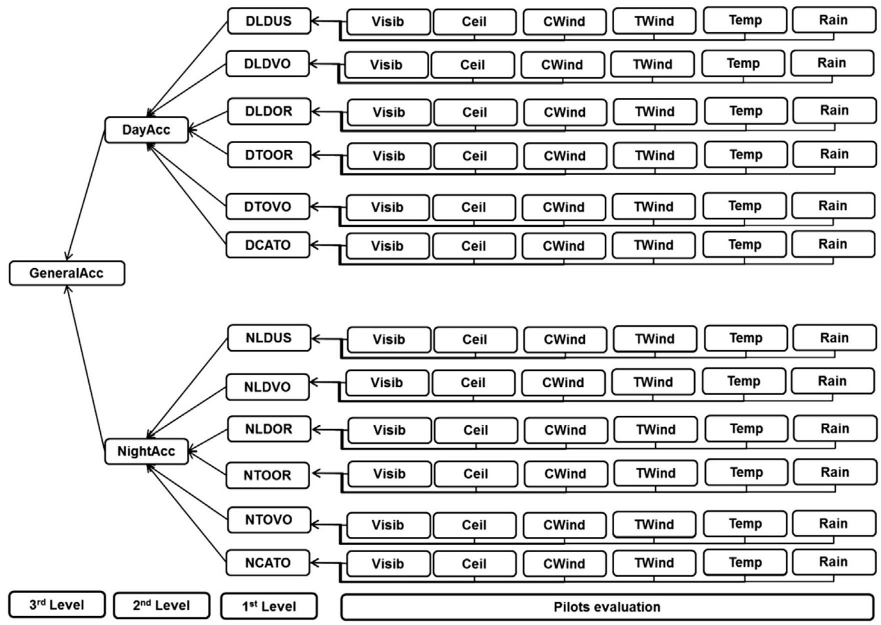

Fig. 3. Structure of the airport risk management case study.

(1) visibility – Visib;
(2) ceiling – Ceil;
(3) temperature – Temp;
(4) tailwinds – TWind;
(5) crosswinds – CWind; and
(6) rain – Rain.

Risk studies generally classify accidents into: Landing Overrun (LDOR), Landing Undershoot (LDUS), Landing Veer-off (LDVO), Take-off Overrun (TOOR), Crash after Take-off (CATO) and Take-off Veer-off (TOVO) (Hale, 2002; Wong et al., 2009a). The letter D or N is added as a prefix to indicate Day or Night.

The analytical methodology developed here uses three fuzzy levels for risk indicators, as shown in Fig. 3. More details on the field surveys are provided later in the paper. The primary indicators are those obtained by field survey with the pilots. The primary indicators provide the crisp value for the meteorological condition perceived by the pilot, giving risk indicators for each accident type by period (day – D and night – N) at each airport. Each meteorological variable is assigned a weight by pilots, indicating its influence on a given risk. These are used to weight the fuzzy rules table. The aggregation of the various meteorological factors to form the risk index for each accident reflects the pilot's perception of the combination of the various factors they observe at a given airport. The pilots assign this aggregation a weight for each type of accident. The fuzzy accident indicators are then aggregated at the period level (DayAcc and NightAcc). Different weights are then assigned to day and night indicators. These two indicators at the period level are then aggregated into one fuzzy indicator at the overall airport level (GeneralAcc). This thus yields a consistent cause-and-effect system, making it possible to monitor risk parameters at the accident, period and overall levels. This methodology, in addition to affording a clear, transparent view of how pilots perceive the problem of airport risk, offers a simulator that enables managers to evaluate the impact of improvements to given indicators on the overall risk analysis context, at the three levels of management: by accident (day or night), all accidents by period, and overall risk at the airport.

4. Case study

Brazil's major airports are administered by the *Empresa Brasileira de Infraestrutura Aeroportuária* (Infraero), a public enterprise founded on 31 May 1973 for the purpose of setting up the main airports in Brazil and administering, operating and exploiting them commercially and industrially. Infraero administers 67 airports, ranging from large international facilities through to small general aviation airports. In 2010, it recorded movement of 155 million passengers embarked plus disembarked, corresponding to about 97% of total movement observed at Brazilian airports.

This case study concentrates on Rio de Janeiro "Galeão/Antonio Carlos Jobim" International Airport and Santos Dumont Airport, two airports located in the city of Rio de Janeiro and administered by Infraero, both handling regular traffic and located at approximately sea level. Galeão Airport stands on an island in Guanabara Bay about 20 km from Rio de Janeiro city centre and operates with international and domestic traffic. It is the fourth largest airport in Brazil in terms of passenger movements: in 2010 it processed 12.3 million passengers and recorded 123,000 landings and take-offs. Its airside infrastructure, the best in the country, comprises two landing and takeoff runways in an open V, the main runway having a Category II Instrument Landing System. The landing and takeoff runways are 4 km and 3.18 km long, respectively. Santos Dumont Airport, meanwhile, operates domestic traffic only and is the fifth largest airport in Brazil in terms of passenger movement. It stands on the edge of Guanabara Bay, close to Rio de Janeiro city centre, making it very convenient as a passenger airport. In 2010, it processed around 7.8 million passengers and recorded 126,500 aircraft landings and takeoffs. Its airside infrastructure is relatively limited, with a 1.32 km main runway and a 1.26 km auxiliary runway, used only when it is impossible to use the main runway. There is no possibility of expanding its runways, because that would involve extending landfill into Guanabara Bay, an option severely restricted by environmental protection agencies. As navigational aids, the main runway has a Precision Approach Path Indicator.

These two airports were selected because they display quite different operating conditions, but are subject to similar meteorological conditions. In addition, the pilots who operate at Santos

Table 1
Data for Galeão Airport.

		Visib	Ceil	Temp	TWind	CWind	Rain
DayAcc	*W* Day	0.45	0.45	1.00	0.27	0.18	0.27
$W = 1.00$	DLDUS $W = 0.82$	1.06	1.06	1.06	1.06	1.13	1.25
	DLDVO $W = 0.93$	1.06	1.06	1.00	1.31	1.75	2.00
	DLDOR $W = 0.77$	1.00	1.00	1.00	1.25	1.00	1.31
	DTOOR $W = 0.77$	1.00	1.00	1.06	1.31	1.00	1.25
	DTOVO $W = 1.00$	1.06	1.00	1.00	1.06	1.31	1.69
	DCATO $W = 1.00$	1.06	1.25	1.19	1.38	1.13	1.81
NightAcc	*W* Night	0.87	0.71	1.00	0.43	0.28	0.45
$W = 1.00$	NLDUS $W = 0.82$	1.13	1.13	1.06	1.06	1.13	1.44
	NLDVO $W = 0.93$	1.31	1.25	1.00	1.50	1.94	2.13
	NLDOR $W = 0.77$	1.00	1.00	1.00	1.38	1.06	1.50
	NTOOR $W = 0.77$	1.00	1.00	1.06	1.38	1.00	1.31
	NTOVO $W = 1.00$	1.06	1.00	1.00	1.13	1.44	1.81
	NCATO $W = 1.00$	1.06	1.31	1.13	1.38	1.13	1.88

W – Weight.

Table 2
Data for Santos Dumont Airport.

		Visib	Ceil	Temp	TWind	CWind	Rain
DayAcc	*W* Day	0.46	0.39	1.00	0.17	0.26	0.29
$W = 0.96$	DLDUS $W = 0.59$	5.00	2.50	1.13	3.63	2.06	3.69
	DLDVO $W = 0.38$	2.25	2.25	1.06	2.81	4.00	4.56
	DLDOR $W = 1.00$	3.44	3.13	1.31	4.38	3.19	4.63
	DTOOR $W = 0.36$	1.81	1.41	2.25	4.31	2.25	4.13
	DTOVO $W = 0.97$	1.75	1.06	1.06	2.38	2.19	3.63
	DCATO $W = 0.85$	3.19	3.31	1.44	3.88	2.56	3.94
NightAcc	*W* Night	0.62	0.58	1.00	0.20	0.33	0.36
$W = 1.00$	NLDUS $W = 0.59$	3.75	2.81	1.06	3.88	2.19	3.88
	NLDVO $W = 0.38$	2.88	2.88	1.06	3.50	4.31	4.81
	NLDOR $W = 1.00$	3.81	3.81	1.25	4.63	3.67	4.88
	NTOOR $W = 0.36$	2.56	1.44	2.25	4.56	2.81	4.56
	NTOVO $W = 0.97$	2.38	1.13	1.06	3.00	3.00	4.00
	NCATO $W = 0.85$	3.81	3.94	1.69	4.25	3.00	4.25

W – Weight.

Dumont Airport also operate at Galeão, facilitating comparative risk perceptions.

5. Data

Data were collected through interviews with an experienced group of pilots, who frequently operate at the airports considered in the case study. The methodology entailed training both interviewer and interviewee in order to ensure the quality of the responses. The field study involved a data survey which takes a considerable time to explain to the interviewee, who is an expert in the subject matter, but nonetheless is not familiar with the analytical methods. A pilot was used as the interviewer in order to improve communication with the other pilots. This interviewer first applied a draft version structured questionnaire to three experienced pilots. This process informed preparation of the final version, which was then applied by the same interviewer to a sample of experienced pilots. The interviews were held during intervals in the pilots' duties at the airports studied. The pilots interviewed had to fit the study criteria (flying time, lengthy experience as a pilot and familiarity with the two airports). The interviews were conducted independently so as to prevent one pilot's opinion influencing another's view.

The preliminary interview of pilots revealed that perceptions differ by weight among meteorological variables, types of risk and between day and night. Accordingly, the data collection questionnaire involved polling the pilots' opinions of four aspects by airport:

(1) the degree of influence of each meteorological variable on each risk, both during the day and at night (1–5);
(2) the weight of each variable by risk type (0–1);
(3) the weight of each risk during the day and at night (0–1); and lastly
(4) the weight of the overall set of risks during the day and at night (0–1).

The experts' determination of the weights involves their evaluating the intensity of the factor in the corresponding risk factor (level 1, 2 or 3; Fig. 3). Accordingly, 21 highly experienced pilots (each with more than 10,000 flight hours and more than 15 years' experience piloting large commercial aviation jet airliners), who operate at both airports, were selected to describe their risk perceptions in terms of the classification presented in the methodology for primary risks on a scale of 1–5 for each risk variable (i.e. Visib, Ceil, Temp, TWind, CWind and Rain), for each risk type (i.e. LDOR, LDUS, LDVO, TOOR, CATO and TOVO). They offered their opinions on individual risks during both daytime and night-time periods; the weights for each variable and each risk were assigned from 0 to 1. In applying the methodology, the average of the pilots' perceptions was used for each indicator of risk perception. The fuzzy indicators were calculated on a risk perception scale of 1–5, where 1 represents low, 3 medium and 5 high.

Tables 1 and 2 show the pilots' average assessment for Galeão and Santos Dumont airports, respectively. The pilots did not indicate major differences in weight between day and night, only a small difference at Santos Dumont Airport, where Day was considered as weight 0.96 and Night, 1.00. However, the weights for meteorological variables can be observed to differ significantly from day to night at both airports. Temperature proved the most important item (weight = 1.00) at both airports. During the day, the other meteorological variables have less influence on risk indicators than at night. For example, Visibility at Galeão Airport has weight 0.45 during the day and weight 0.87 at night. Rain at night is the meteorological variable that caused most risk perception among the pilots, at both Galeão Airport (NLDVO = 2.13) and at Santos Dumont Airport (NLDOR = 4.88). Among the types of accident studied, TOVO and CATO carried most weight at Galeão Airport, both during the day and at night. At Santos Dumont Airport, meanwhile, LDOR carried most weight in defining the fuzzy indicator for both Day and Night.

6. Results and discussion

Fig. 4 shows the results of the calculation of fuzzy indicators of risk perception for Santos Dumont and Galeão airports. There are marked differences between the two airports. At Galeão Airport, there are practically no risk perceptions relating to meteorological conditions, and no significant difference between day and night periods. At Santos Dumont Airport, meanwhile, perceptions are close to medium risk, which would be a score of 3. Note also that there is a substantial difference between the indicators for the day and night periods (2.16 for day and 2.72 for night). Although the indicators for accident risk are closely grouped, the main concern during the day is Landing Veer-off (with an indicator of 2.16) and, at night, Crash after Take-off (at 2.33). This concern is warranted in that one of the symbols of Rio de Janeiro City, Sugarloaf Mountain, a small hill about 400 m high, stands at 3700 m from one of the runway ends. At the other end, also at some distance, is the bridge connecting Rio de Janeiro City with the town of Niterói on the other side of Guanabara Bay.

These are two airports with quite distinct operating conditions, although subject to very similar meteorological conditions. From 1952 to 2011, according to data from the Aviation Safety Network – ASN (Flight Safety Foundation, 2011) there were "no occurrences in

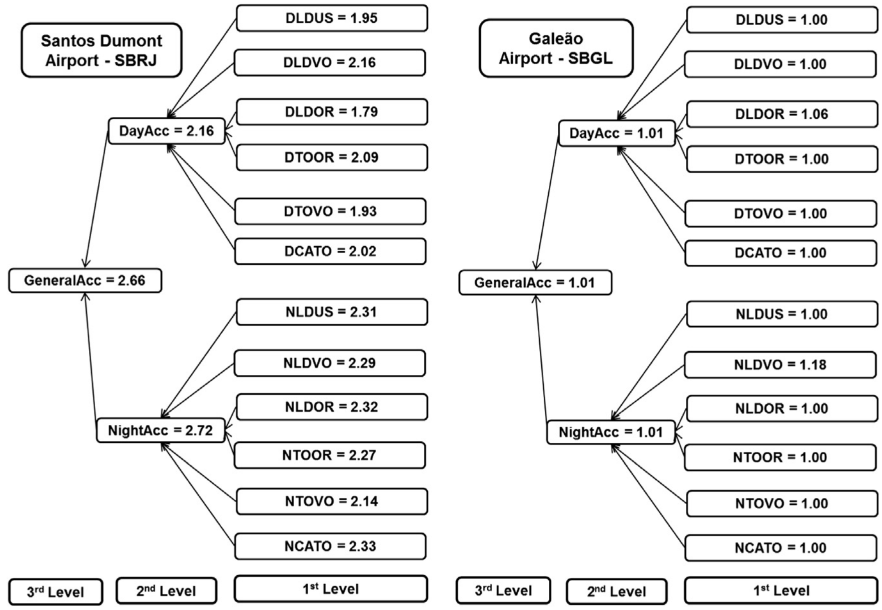

Fig. 4. Fuzzy indicators of pilots' perceptions of accidents.

the database of aircraft accidents at or near Rio de Janeiro – Galeão International Airport, RJ (SBGL)", while there were "21 occurrences in the ASN database of aircraft accidents at or near Rio de Janeiro – Santos Dumont Airport, RJ (SBRJ)". Some examples of accidents at Santos Dumont Airport are:

- 12 AUG 2010, Learjet 55C, *OceanAir Táxi Aéreo*, Phase: Landing, the airplane had reportedly returned to land, running off the end of runway 02R into the water of Guanabara Bay.
- 03 JUL 1997, Cessna 500 Citation I, *Riana Taxi Aéreo*, Phase: Takeoff, overran the runway by 50 m, ending up with its nose down in Guanabara Bay.
- 09 NOV 1994, Learjet 55, *Líder Táxi Aéreo*, Phase: Landing, crashed into Guanabara Bay after overrunning runway 20L.
- 06 SEP 1988, Cessna 550 Citation S/II, TAM – *Táxi Aéreo Marília*, Phase: Landing, Landed too far down the wet runway; overran across a road and came to rest on a breakwater.
- 31 AUG 1969, Learjet 23, *Instituto Brasileiro de Reforma Agraria*, Phase: Approach, Crashed in sea at the end of a Miami-Rio de Janeiro flight.

The variety among the 21 accidents observed at Santos Dumont Airport justifies the pilots' perceptions. This result shows that the pilots' opinion, processed using the fuzzy methodology, can be a significant indicator to guide the Safety Management System process. The proposed methodology can also be argued to assist managers in obtaining information for risk mitigation, focussing on very current perceptions and offering future indications. This is because models based on the past may be biased as a result of the dynamics of aviation industry technology, whose life cycles are increasingly short. Changing equipment, components, procedures etc. can significantly modify the scenario at an airport. A methodology not based on historical data can be very useful in circumventing this problem.

7. Conclusion

This study brings together two powerful analytical tools in a context of great complexity: identification of pilots' accident risk perceptions and FMA. The former, approaching accident risk through pilots' perceptions, offers a risk management system based on the opinion of experts directly involved in the operation, while the latter establishes itself as a multicriteria analysis tool that permits an approximation to the event classification model that is more closely analogous to human reasoning. This combination was expressed in the analytical system in Fig. 3 as an airport risk evaluation system. As emphasised in the literature, one of the greatest difficulties in analysing air transport accidents is the scarcity of data (Button and Drexler, 2006; Hale, 2001; Wong et al., 2009a). Accordingly, this study has sought to introduce a new perspective to airport risk analysis, designed to surmount the difficulty of obtaining data for analysis in this field. Another important characteristic of the methodology proposed in this paper is that it indicates the future outlook, in that it brings together the pilots' opinion on the likelihood of accidents at a given airport. As aviation is a highly dynamic sector, models based on past occurrences may not be valid for future aviation operating conditions. A further benefit of the methodology presented here is the ease with which it can be applied, both by airlines and by airport managers or regulatory bodies.

However, the methodology should be refined by considering construction of a risk evaluation system for a larger set of possibilities, involving a larger set of pilots and more factors (bird strike, for example). Despite the importance of increasing the number of interviewees, the training, interviewer coaching and interview time requirements make it difficult to expand the sample. Although FMA is a technique that considers the uncertainty in measuring factors, the application of the FMA alpha-cut technique is a proposal for future studies. This technique helps understand the indices' sensitivity to variations in the meteorological factors.

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