Dutch Journal of Finance and Management
2023, 6(2), 25209
e-ISSN: 2542-4750
https://www.djfm-journal.com/
Research Article
OPEN ACCESS

Fuzzy electre model for the characterisation of aeronautical operational risks in the approach and landing phase

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Citation: Leal, E. P., Peña, A., Sepúlveda-Cano, L., and Carvalho, J. V. (2023). Fuzzy electre model for the characterisation of aeronautical operational risks in the approach and landing phase. Dutch Journal of Finance and Management, 6(2), 25209. https://doi.org/10.55267/djfm/14129

ARTICLE INFO

Received: 11 Nov 2023
Accepted: 28 Dec 2023

ABSTRACT

One of the significant challenges facing the aviation sector is the management of risks arising from its flight operations, especially in the approach and landing phases, where pilot experience and training are of great importance and where the most significant incidents for air safety occur. Therefore, this paper proposes a model inspired by the structure of a Fuzzy ELECTRE model for managing the operational risks that arise in the approach and landing phases that can lead to safety events. Thanks to the analysis of the literature collected, the management criteria and risk parameters to be taken into account for these two flight phases were shown following air safety manuals such as the International Civil Aviation Organization (ICAO) manual, and where the data obtained was obtained qualitatively thanks to the implementation of surveys with expert pilots, whose information served as the primary input for the characterisation of risks. Following the structure of the proposed model, five (5) reference risk scenarios management were constructed using the previous information, and an analysis of the dominance and discrepancy of a risk scenario vs. the previously established reference scenarios was carried out. Finally, it can be concluded that the proposed model allowed the quantitative-qualitative characterisation for managing the most relevant risks in the approach and landing phases, integrating the expertise of experts in this area.

Keywords: Data analysis, Management Risks, Operational risks, Aviation safety, Approach and landing phases, Fuzzy Electre model

INTRODUCTION

Today, with technological advances and globalisation, identifying a situation that generates negative consequences is a competitive advantage for achieving companies' strategic objectives, and operational risks are the most common (Loyaga & Malqui, 2019). According to the Basel II agreements (2006), operational risks generate losses based on inadequacy and/or failures in the processes, whether due to human, technical, or external factors and are primarily applied in the financial sector. In addition, Faberio (2022) defines operational risks as "a group of components such as procedures, policies, organisational structure, through which companies identify, control, measure, and monitor them".

In the aeronautical sector, operational risk management is based on operational safety, which aims to "proactively mitigate operational safety risks before they result in aviation accidents or incidents" (ICAO, 2018). According to Zhang & Mahadevan (2021), its management has been based on fatal accidents in the industry over time. Although its frequency is not the highest, its impact has become catastrophic, causing loss of human lives, economic losses, environmental damage, and severe media and political repercussions (Bills et al., 2023, p. 1). The latest safety report of the International Civil Aviation Organization (ICAO) indicates that the accident rate has shown unstable behaviour over the last ten (10) years, maintaining three (3) accidents per million departures. However, this rate has increased in the last three (3) years, thanks to air traffic recovery after the COVID-19 pandemic (ICAO, 2023). While the desirable goal of aviation operations would be the elimination of severe accidents and incidents, which are unattainable, operational safety systems have been the cornerstone for safety management and risk analysis to strike a balance between "production" and "protection" in the aeronautical sector (Ríos et al., 2018, p. 74). The latter shows that managing the risks associated with aviation operations is still a management and technological challenge.

Thanks to the implementation of risk management systems in aeronautical operations, it has been possible to determine the risks that have arisen over the years based on historical accidents. According to the International Air Transport Association (2022), the majority of accidents recorded between 2017 and 2021 occurred during the approach phase (10%) and landing (60%), both fatal and non-fatal. On the other hand, in the latest Statistical Summary of Commercial Jet Airplane Accidents by Boeing (Boeing, 2023), in recent decades, most safety-related accidents have focused on the approach (15%) and landing (31%) phases.

In light of the above, risk assessment during the approach and landing phases is essential to comply with safety parameters required by national and international civil aviation organisations. In recent years, proactive risk identification methodologies with quantitative and qualitative approaches have been implemented to detect anomalous behaviours and quantify the associated risk in flight operations, ground operations, or their combination (Odisho et Truong, 2021; Zang & Mahadevan, 2019). Among proactive performance indicators, various tools and models within data analytics record detailed and comprehensive information throughout a flight, relying on anomaly detection techniques for this collected information (Zhao et al., 2021). To detect possible links between recorded data and the risk of operational safety events or accidents during flight, many researchers have implemented different mathematical models (Rey et al., 2021), many of which, through statistical analysis, enable an operator to use this information to assess the overall state of operational performance (Puranik, 2018).

According to Taghipour et al. (2020), many studies have focused on the implementation of machine learning models as tools to address multiple problems through data-driven methodologies, aiming to assist aviation safety experts in facilitating the process of extracting data from aviation incidents (Dong et al., 2021, p. 1). Zang & Mahadevan (2019) developed a model using the risk level to measure the severity of operational events during flight. Avrekh et al. (2020) implemented an unsupervised generative model for anomaly detection in high-dimensional time series data to detect operational anomalies in flight. In another group of articles, Benoit et al. (2023) demonstrate a data-driven methodology for estimating the collision risk probability of aircraft in the flight phase, combining Monte Carlo simulation and Extreme Value Theory (EVT), effectively assessing modelled collision risk probabilities. Caetano (2022) identified outliers that could influence the safety of aviation operations through operational and meteorological data using a random forest classification model with an accuracy exceeding 96%, while Midtford et al. (2022) created a runway assessment system with a decision tree classification model to identify slippery conditions of aircraft on icy runways and a regression model to predict the slipperiness level, using meteorological data and runway reports to reduce the percentage of crashes and/or runway excursion or incursion.

In the context of the literature review, this article proposes a model based on data inspired by the structure of the Fuzzy ELECTRE method. For managing aeronautical operational risks, the proposed model uses the selection of risk alternatives or scenarios aims to improve decision-making in the face of risk management in aeronautical approach and landing operations to determine preference and priority within complex problems by integrating both qualitative and quantitative data (Memarzadeh et al, 2020). The results obtained by the proposed model demonstrate its stability in characterising the risk vs. the operational management in the approach and landing phases using different risk scenarios, integrating both qualitative information from experts and quantitative information from the International Civil Aviation Organization (ICAO) and International Air Transport Association (IATA) manuals.

Accordingly, the article will present a first section introducing the literature and contextualising the problem according to scientific literature in this knowledge area. In a second part, theoretical concepts that underpin the characterisation of risk associated with aeronautical operations will be presented according to the structure of the proposed model. In a third part, an analysis and discussion of results will be conducted to evaluate the model's stability in characterising risk, and finally, a series of conclusions to guide future work in this knowledge area.

METHODOLOGY

Risk management plays a fundamental role in the aviation sector due to the importance of ensuring flight safety, preventing catastrophic events that could endanger the lives of people on board and on the ground, and preserving the integrity of aircraft (Chan, 2023). In order to contribute to solving the problem, the following methodology is proposed.

Experimental Study Design

For creating a model that allows risk management in operational safety in the approach and landing phases, five (5) factors were taken: human factors, procedures in the approach and landing phases, technical factors, and external factors. According to the review of regulations and literature, the total number of factors was assessed based on 18 risk criteria, as indicated in **Table 1**.

Table 1. Risk factors and criteria

Factor	Criteria
HUMAN FACTOR	Pilot training and competence
	Pilot decision making
	Situational awareness
	Fatigue
	CRM
	Application of procedures, checklists and operating manuals
APPROACH PHASE PROCEDURES	Descent profile of the aircraft
	Approach type
LANDING PHASE PROCEDURES	Flaps and landing gear management
	Minimum Decision Altitude (MDA) and Decision Altitude (DA)
	Landing speed
	Threshold of the runway
TECHNICAL FACTOR	Software and systems status
	Aircraft structure condition
EXTERNAL FACTORS	Runway conditions for landing
	Radio aids available on the airfield
	Meteorological conditions
	Obstacles and BASH (Bird Aircraft Strike Hazard) on the approach and landing trajectory

In order to evaluate these factors, each criterion was analysed by six experts from the aviation industry (pilots who fly different types of aircraft and have different years of flight experience, located in different cities in Colombia and the United States, such as Bogotá, Medellín, and Miami). Based on this analysis, a structured survey was created with 38 questions for each criterion and factor, as shown in **Table 1**, in line with the bibliographic sources stipulating global aviation operational safety regulations (ICAO, 2018). These questions were generated based on possible risk scenarios to which pilots may be exposed, where the response options are directly related to the Saaty scale (**Table 3**). These are the multiple options that the pilots had to give their opinion according to their perception and experience in each of the cases exposed in the questions posed. These surveys were conducted virtually in October 2023, with an approximate duration of one hour per pilot surveyed, where the survey intends to identify the critical factors of risk management in approach and landing operations.

For the analysis and validation of the proposed model, a qualitative description of each risk scenario was undertaken according to the impact criteria defined by the International Civil Aviation Organization (ICAO) (**Table 2**). This table delineates the structure of each risk scenario based on the categories that align with Basel agreements regarding operational risk management (AA, A, BB, B, C). Furthermore, it incorporates qualitative information from expert pilots through the previously defined structured survey.

Table 2. Qualitative description of operational risk scenarios

Gravity	Significance
Catastrophic (C)	This risk scenario occurs when, during ground or flight operations, the aircraft or equipment and human lives are lost.
Hazardous (B)	This risk scenario may arise from a significant reduction in operational safety margins, physical stress, or a workload to the extent that reliance on operational personnel to perform their tasks accurately or completely can no longer be assured. Severe injuries to individuals and/or substantial damage to the aircraft can occur during operations, whether on the ground or in flight.
Major (BB)	This risk scenario may arise from a significant reduction in operational safety margins, and it's related to the operational personnel's capacity to tolerate adverse operating conditions, such as an increase in workload or conditions affecting their efficiency. A severe incident and individual injuries may occur during ground or flight operations.
Minor (A)	This risk scenario occurs when discomfort or operational limitations arise during either ground or flight operations, prompting the pilot or crew to implement emergency procedures or a minor incident occurring.
Negligible (AA)	In this risk scenario, a few consequences may arise that may impact individuals or the aircraft.

Note. Adapted scale from the Manual of Operational Safety Management (ICAO, 2018).

The responses from the consulted experts regarding each risk scenario's criteria were qualitatively characterised using the Saaty scale (**Table 3**) (Comas et al., 2020).

Table 3. LT decision-maker's view and decision-making (Rouyendegh & Erol, 2012)

LT	Scale
Extremely good (EG)	9
Very good (VG)	7
Good (G)	5
Medium bad (MB)	3
Bad (B)	2
Very bad (VB)	1

Note. Adapted scale from the Intuitionistic Fuzzy ELECTRE model. International Journal of Management Science and Engineering Management (Rouyendegh & Erol, 201, p. 5).

Fuzzy ELECTRE model

For the characterisation of a risk scenario P_o, this section proposes a model inspired by the structure of a Fuzzy ELECTRE model, which incorporates a series of concordance and discrepancy matrices to select a risk scenario that enables risk management with scenario P_o (Peña et al., 2018). It is important to highlight that the Fuzzy ELECTRE model is commonly used to address the uncertainty generated by the large amount of qualitative information from experts in decision-making across different knowledge areas. Selecting a desirable option is based on a set of concordance and discrepancy matrices (Rouyendegh & Erol, 2012). Due to its design, the proposed model integrates a series of criteria for characterising a risk scenario through linguistic variables in accordance with the Saaty scale, as outlined in **Table 3**.

Modelling Criteria as Linguistic Variables.

According to each of the qualities that define the Saaty scale, the structure of the fuzzy sets associated with each number defining this scale can be observed in **Table 4**. The transition between the qualities in **Table 3** and the fuzzy sets associated with **Table 4** leads to representing a risk criterion as a fuzzy set. **Figure 1** shows the structure of the fuzzy sets associated with each criterion per risk scenario. In this way, these sets can be defined through three parameters: low (l), indicating the lower limit of each fuzzy set; (m) medium, indicating the central value or representative value of each criterion, while (u) upper ($l \leq m \leq u$) indicates the maximum value associated with each fuzzy set (**Table 4**). This set structure will allow the modelling of the uncertainty associated with characterising a risk scenario for the approach and landing phases.

Table 4. Fuzzy conversion scale 1-9

Intensity of significance	Triangular fuzzy scale
1	(1, 1, 1)
2	(1.6, 2.0, 2.4)
3	(2.4, 3.0, 3.6)
5	(4.0, 5.0, 6.0)
7	(5.6, 7.0, 8.4)
9	(7.2, 9.0, 10.8)

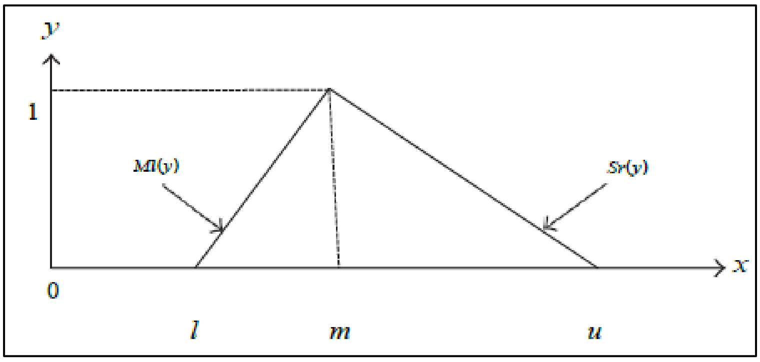

Figure 1. Triangular scale

Note. Adapted scale from The Intuitionistic Fuzzy ELECTRE model. International Journal of Management Science and Engineering Management (Rouyendegh & Erol, 2012, p. 3).

Aggregate Fuzzy Importance Weight Matrix (AFIW)

One of the matrices that integrate information from experts based on each criterion grouping each risk scenario is the AFIW (Aggregated Fuzzy Importance Weight) decision matrix, considering the limits defined by the fuzzy sets presented in **Figure 1**.

$$AFIW_{lv,i} \qquad (1)$$

Where: lv: represents each of the boundaries of the fuzzy sets l, m, u. i indicates each of the criteria that characterise each of the risk scenarios. The above matrix was consolidated from the decision matrices associated with each risk scenario's characterisation and each criterion that defines a risk scenario. According to the above, the decision matrices for each of the boundaries defining the risk scenarios are as follows:

$$w_{lv,i} = \sum_{j=1}^{ns} md_{lv,j,i} \qquad (2)$$

Where:$w_{lv,i}$: Represents the sum of each entry for the matrix lv, for each j-scenario and each i-criteria. $md_{lv,j,i}$: Represents the entry of the i-criteria associated with the j-risk scenario for the fuzzy level lv (l,m,u). ns: Indicates the number of risk scenarios considered by the model. For the normalisation of each risk criterion, the estimation proceeds with the geometric mean according to Equation (3):

$$l_{lv,j} = (l_1 \times l_2 \times \dots \times l_{nc})^{1/nc} \qquad (3)$$

Where: $l_{lv,j}$: indicates the fuzzy limit-based geometric mean (lv: $\{l, m, u\}$), for each of the j-risk scenarios, where nc i represents the number of criteria associated with each risk scenario. Subsequently, the Fuzzy ELECTRE model normalises the weights associated with each criterion for each of the fuzzy limits (lv: $\{l, m, u\}$) defining the fuzzy sets (Equation (4) (5)):

$$\widehat{w}_{lv} = \frac{\tilde{G}_j}{\tilde{G}_T} = \frac{(l_j, m_j, u_j)}{(\sum_{j=1}^{k} l_j, \sum_{j=1}^{k} m_j, \sum_{j=1}^{k} u_j)} = \left(\frac{l_j}{\sum_{j=1}^{k} u_j}, \frac{m_j}{\sum_{j=1}^{k} m_j}, \frac{u_j}{\sum_{j=1}^{k} l_j}\right). \qquad (4)$$

$$\widetilde{w_{lv}} = [\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n]. \quad (5)$$

Building upon the decision matrices described in Equation (3), the model incorporates a fuzzy decision matrix, which is denoted and defined in Equation (6):

$$X_{j,i} = \frac{x_{lv,j,i}}{n_{lv}} \quad (6)$$

Where:$X_{j,i}$: represents the decision matrix for the j-scenario and i-criteria. From this matrix, the normalised decision matrix is obtained in Equation (7):

$$r_{j,i} = \frac{X_{j,i}}{\sum_i^{nc} X_{j,i}} \quad (7)$$

In order to determine the concordance and discrepancy matrices that allow the characterisation of a risk management scenario compared to a set of reference scenarios, the process involves obtaining the decision matrices. These decision matrices are denoted and defined in Equation (8):

$$\hat{v}_{j,i} = r_{j,i} \times \widehat{w_{lv}}. \quad (8)$$

Dominance and Discrepancy Analysis

According to the normalised decision matrices mentioned earlier, we proceed to determine the dominance and discrepancy of an evaluation of P_o scenario about j-risk scenario used as a reference. In this manner, dominance is indicated and defined as follows:

$$C^1_{a_1a_2} = \sum_{j*} w_l, \qquad C^2_{a_1a_2} = \sum_{j*} w_m, \qquad C^3_{a_1a_2} = \sum_{j*} w_u, \quad (9)$$

The discrepancy for normalised decision matrices is denoted and defined as follows:

$$D^1_{a_1a_2} = \frac{\sum_j + \left|v^1_{a_1j^+} - v^1_{a_2j^+}\right|}{\sum_j \left|v^1_{a_1j} - v^1_{a_2j}\right|}, D^2_{a_1a_2} = \frac{\sum_j + \left|v^2_{a_1j^+} - v^2_{a_2j^+}\right|}{\sum_j \left|v^2_{a_1j} - v^2_{a_2j}\right|}, D^3_{a_1a_2} = \frac{\sum_j + \left|v^3_{a_1j^+} - v^3_{a_2j^+}\right|}{\sum_j \left|v^3_{a_1j} - v^3_{a_2j}\right|} \quad (10)$$

Finally, the most dominant scenario is assessed, with the most significant differentiation from the other scenarios.

$$C^*_{a_1a_2} = \sqrt[z]{\prod_{z=1}^{Z} C^z_{a_1a_2}}, \qquad D^*_{a_1a_2} = \sqrt[z]{\prod_{z=1}^{Z} D^z_{a_1a_2}}, \quad (11)$$

$$C(a_{1,}a_2) \geq \bar{C}, \quad D(a_{1,}a_2) \geq \bar{D}. \quad (12)$$

Experimental Validation

For the risk assessment during the approach and landing phases, the first step involved conducting an extensive literature review on aviation risk management, using as a reference the International Civil Aviation Organization Operational Safety Manual (ICAO, 2018) and the Federal Aviation Administration (FAA) Safety Management System Manual (FAA, 2022). This review aimed to identify a set of risk management criteria common to these operational ICAO safety manuals in the context of risk scenarios during an in-flight aircraft's approach and landing stages. Following the identification of these criteria, the next step was to define a series of risk scenarios, considering each criterion's qualitative characterisation as per the manuals. In this phase of the process, it is expected that the risk criteria can be grouped into five (5) risk categories or scenarios, in alignment with the Basel Committee on Banking Supervision's operational risk categories (AA, A, BB, B, C) and according to the papers proposed by Peña et al (2019). Thus, the AA risk scenario represents a scenario with an insignificant impact on operations, while C represents the scenario with the highest or significant risk (j-scenario).

For the qualitative characterisation of the risk criteria (i-criteria) defining each of the previously defined risk management scenarios, the participation of a group of six (6) expert pilots in the field of aeronautical risk was enlisted. These pilots had validated experience in flying medium and heavy aircraft. Both captain and copilot pilots characterised the proven experience with varying years of experience. Thus, each risk criterion was evaluated for each scenario using qualitative features defined by the Saaty scale (**Table 3**). This characterisation was accomplished by implementing a structured survey where pilots responded to 38 questions. At this stage of the process, the expectation is to obtain the decision matrices. $\widetilde{v_{j,i}}$ (Equation 9), Which will allow assessing the dominance and discrepancy of a risk scenario P_o according to a series of reference scenarios.

In the third stage, the structural stability of the model was evaluated against each of the previously defined reference risk scenarios (AA, A, BB, B, C). Here, the model is expected to exhibit behaviour similar to that of a neural autoencoder model (refer to any autoencoder reference), wherein the risk characterisation for any given scenario (Output: O) should resemble the risk structure defining an input scenario (Input: I). The model is anticipated to respond accurately to the input of the five reference risk scenarios.

In a final stage, and to assess the dimensional stability of the proposed model, three additional risk scenarios were created by expert pilots, demonstrating varying levels of risk for the approach and landing phase of an aircraft (low (L), moderate (M), high (H)). Here, the model is expected to yield results such that for the L scenario, risk qualities align with categories AA, A; for the M scenario, the model should output risk characterisations corresponding to scenarios B and BB; While for risk scenario A, it is anticipated that the model will yield scenario C as the outcome.

Case Study

For the development of the case study, a total of three (3) risk scenarios (AA, A, B) were considered, and a total of three (3) evaluation criteria will be employed, where C1 represents human factors, C2 represents the risk associated with the approach phase, while C3 represents the risk associated with the landing phase. The Saaty scale (**Table 3**) was used to characterise these risk scenarios, and the participation of two (2) expert pilots (DM1, DM2) was involved. In **Table 5**, the qualitative characterisation of any given risk scenario (P_o), can be observed, while **Table 6** presents the qualitative characterisation of the reference scenarios (AA, A, B) according to the expert pilots' considerations based on the established risk criteria for the case study.

Table 5. Approximate Distance Matrix ADM

ADM			
	Criteria	**DM1**	**DM2**
P0	C1	G	G
	C2	G	G
	C3	VG	G

Table 6. Reference Risk Scenarios

ADM			
Risk Scenario	**Criteria**	**DM1**	**DM2**
AA	C1	G	G
	C2	B	VG
	C3	B	VG
A	C1	MB	MB
	C2	VG	G
	C3	G	G
BB	C1	G	MB
	C2	G	MB
	C3	G	MB

According to the fuzzy sets defined by Saaty's scale (**Table 4**), the ADM matrix can be quantitatively expressed using three decision matrices, as shown in **Tables 7**, **8** and **9**, where $w_{lv,i}$ is obtained from Equation (3), while the decision matrices are for the levels lv: $\{l\ (lower), m\ (medium), u\ (upper)\}$ an be estimated by using Equations (4), (5), and (6) for each j-risk scenario.

Table 7. Lower Fuzzy Decision Matrix

Risk Scenario	C1	C2	C3	
P0	4	5	6	
AA	4	3.8	3.8	
A	2.4	5	4	
BB	3.2	3.2	3.2	
$w_{l,i}$	13.6	17	17	
ll,i	4.97157201	6.72395081	6.63307547	
		Average of the above values		18.3285983
$w_{l,i,n}$	0.27124671	0.3668557	0.36189759	

Table 8. Medium Fuzzy Decision Matrix

Risk Scenario	C1	C2	C3	
P0	5	6	7	
AA	5	4.5	4.5	
A	3	6	5	
BB	4	4	4	
$w_{m,i}$	17	20.5	20.5	
mm,i	6.6943295	8.65349742	8.57261888	
		Average of the above values		23.9204458
$w_{m,i,n}$	0.27985806	0.36176154	0.3583804	

Table 9. Upper Fuzzy Decision Matrix

Risk Scenario	C1	C2	C3	
P0	6	7	8	
AA	6	5.2	5.2	
A	3.6	7	6	
BB	4.8	4.8	4.8	
$w_{u,i}$	20.4	24	24	
uu,i	8.53654393	10.6941652	10.6209152	
		Average of the above values		29.8516242
$w_{u,i,n}$	0.35687228	0.44707215	0.44400992	

Based on the above decision matrices, the construction of the AFIW matrix can be seen in **Table 10** (Equation 1).

Table 10. Aggregate Fuzzy Importance Weighted

Criteria	l	m	u
C1	0.271246711	0.279858058	0.35687228
C2	0.366855703	0.361761545	0.44707215
C3	0.361897586	0.358380398	0.44400992

According to **Tables 7**, **8** and **9**, we proceed with the derivation of the matrix $X_{j,i}$ (Equation (6) from the averages of the inputs associated with each i-criteria and each j-scenario, resulting in the decision matrix as shown in **Table 11**.

Table 11. Fuzzy Decision Matrix $X_{j,i}$.

Risk Scenario	C1	C2	C3
P0	**5**	**6**	**7**
AA	**5**	**4.5**	**4.5**
A	**3**	**6**	**5**
BB	4	4	4
Amount	8.66025404	10.404326	10.5

In order to carry out the dominance and discrepancy analysis of scenario P_o about the reference scenarios (AA, A, BB, B, C), the normalisation of the normalised decision was carried out $r_{j,i}$ of Equation (7).

Table 12. Normalised Decision Matrix ($r_{j,i}$)

Risk Scenario	C1	C2	C3
P0	0.57735027	0.5766832	0.66666667
AA	0.57735027	0.4325124	0.42857143
A	0.34641016	0.5766832	0.47619048
BB	0.46188022	0.38445547	0.38095238

In **Table 13** (lower), **Table 14** (medium), and **Table 15** (upper), the matrices can be observed $\hat{v}_{j,i}$, which will allow analysing the dominance and discrepancy of a scenario (P_o) concerning each of the reference scenarios. These matrices are derived from the Equation (8).

Tabla 13. $\hat{v}_l$ matrix (lower) - Weighted normalised decision matrix

Risk Scenario	C1	C2	C3
P0	0.15660436	0.21155952	0.24126506
AA	0.15660436	0.15866964	0.15509897
A	0.09396262	0.21155952	0.17233218
BB	0.12528349	0.14103968	0.13786575

Table 14. $\hat{v}_m$ matrix (medium) - Weighted normalised decision matrix

Risk Scenario	C1	C2	C3
P0	0.16157612	0.2086218	0.23892027
AA	0.16157612	0.15646635	0.1535916
A	0.09694567	0.2086218	0.17065733
BB	0.1292609	0.1390812	0.13652587

Table 15. $\hat{v}_u$ matrix (upper) - Weighted normalised decision matrix

Risk Scenario	C1	C2	C3
P0	0.2060403	0.257819	0.29600661
AA	0.2060403	0.19336425	0.19028996
A	0.12362418	0.257819	0.21143329
BB	0.16483224	0.17187933	0.16914664

According to above, in **Table 16**, **Table 17**, and **Table 18**, one can observe how the concordance matrices were obtained using Equation (9), comparing each entry of the P_o vs. the reference scenarios AA, A, BB. The unit (1) value represents the dominance of a criteria in the scenario. P_o, scenario against the reference scenarios AA, A, BB. The value of unity (1) represents the dominance of a criterion in the P_o scenario compared to criteria in each of the reference scenarios, while zero (0) signifies the absence of dominance. The final column in each of the concordance matrices represents the average of the entries that are unitary, multiplied by the entries in each of the fuzzy decision matrices (DM) for each fuzzy lv-limit (**Table 7**, **Table 8**, **Table 9**).

Table 16. Low Concordance Matrix

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	1	1	1	3	5.32
C1,0,2	1	1	1	3	5.28
C1,0,3	1	1	1	3	4.92

Table 17. Medium Concordance Matrix

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	1	1	1	3	6.4
C1,0,2	1	1	1	3	6.4
C1,0,3	1	1	1	3	6

Table 18. Upper concordance matrix

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	1	1	1	5	7.48
C1,0,2	1	1	1	5	7.52
C1,0,3	1	1	1	5	7.08

Tables 19, **20** and **21** display the discrepancy values associated with each entry of the normalised decision matrix (**Table 14** – Equation (10)). The final column in each of the aforementioned tables emerges due to the product between these matrices and each of the decision matrices (**Tables 7**, **8** and **9**).

Table 19. Low Discrepancy Matrix

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	0	0	0	2	0
C1,0,2	0	0	0	2	0
C1,0,3	0	0	0	2	0

Table 20. Medium Discrepancy Matrix

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	0	0	0	2	0
C1,0,2	0	0	0	2	0
C1,0,3	0	0	0	2	0

Tabla 21. Matriz de Discrepancia Upper

	C1	C2	C3	NF	C1,a1,a2
C1,0,1	0	0	0	2	0
C1,0,2	0	0	0	2	0
C1,0,3	0	0	0	2	0

Finally, for the risk characterisation of the scenario P_o, the averages of concordance and discrepancy are obtained for each reference scenario defined for this case study. According to Equations (11) and (12), the dominance of scenario P_o regarding each of the reference scenarios employed for this study, this leads us to conclude that the risk scenario P_o can be grouped under category AA, as depicted in **Figure 1**.

Table 22. Concordance and discrepancy matrix

Concordance		Discrepancy		Conc-Disc	Average
C0,1	6.4	**D0,1**	0	0	6.4
C0,2	6.4	**D0,2**	0	0	6.4
C0,3	6	**D0,3**	0	0	6
Average	6.26666667	**Average**	0		

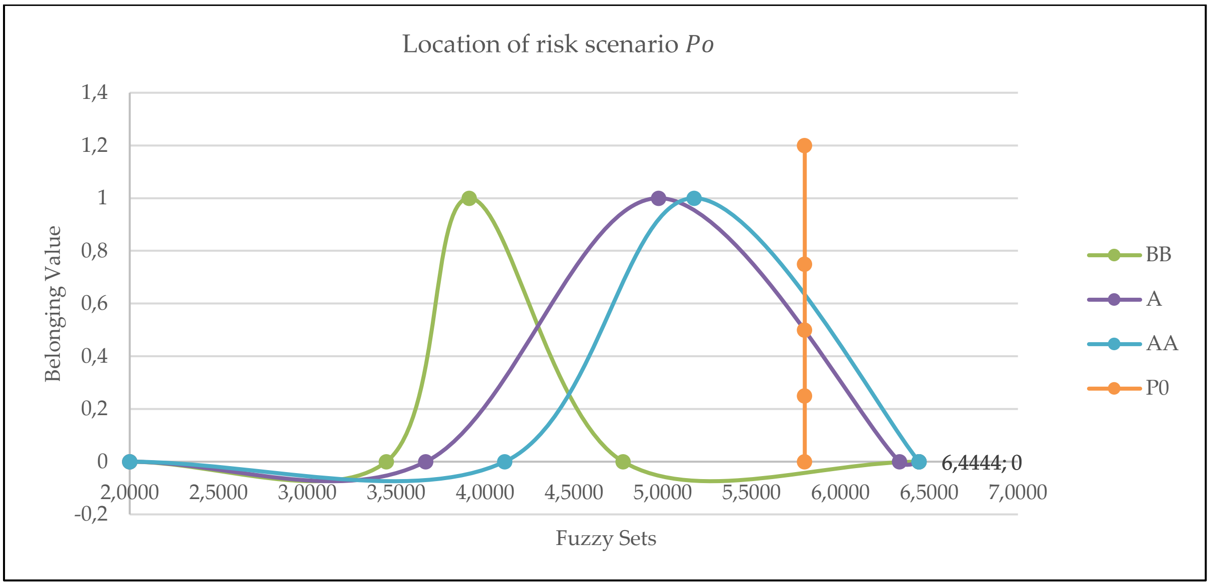

Figure 2. Location of risk scenario P_o (línea vertical) (vertical line) with respect to the fuzzy sets defined for each reference scenario

RESULTS

This bibliographic review allowed the identification of five (5) risk factors and eighteen (18) characterisation criteria, as shown in **Table 1**. Based on the identification of these risk factors and criteria, a total of five (5) risk management scenarios were configured, in which a total of five (5) aviation risk experts participated, as shown in **Table 2**. Here, the first factor identified in the literature was the human factor, in which the interaction between pilots is highlighted according to the training of each of the pilots and its influence on flight activities (ICAO, 2018). The second factor identified in the literature review was the risk associated with the approach phase, a critical flight stage in which the pilot receives authorisation from the control tower to initiate the approach and ends when the pilot reaches the final approach altitude (FAA, 2020). The third factor identified in the literature was the landing phase, the last critical stage of the flight phases, in which the aircraft touches down and ends when the aircraft comes to a complete stop, and the pilot must control the aircraft to touch down smoothly and stop safely (FAA, 2020). The fourth factor identified was the technical factor, in which aircraft design, construction, operation, and maintenance are highlighted. (ICAO, 2018). Finally, another of the factors identified was the factor associated with external factors, which are not directly related to the design, construction, operation, or maintenance of aircraft but which can affect aviation safety, such as meteorology, the conditions of the Bogotá and Rionegro airports, which were the scenarios taken into account in the case study as a reference for the survey conducted, as well as with air navigation facilities and services (ICAO, 2018).

Based on this analysis, the survey with the expert pilots (DM1 to DM6) showed that, although the expert pilots had the same concept of operational risk according to the ICAO manuals, their perceptions in each of the factors and management criteria varied according to their experience and according to the risk scale they were evaluating. For the expert pilots DM1 and DM2, the risk scales showed that they were proportional to the risk scenarios proposed, where if there is a catastrophic scenario, the possibility of a safety event occurring is exceptionally high and so on with the rest of the scenarios, particularly for the human factor and the approach and landing phases, as they are critical phases (Cadena and García, 2023). For the expert pilot DM3, the factors in which a safety operational event can occur for a catastrophic and dangerous scenario are the approach and landing phase and external factors about the human factor since it took into account the conditions of the terrain near the airport and how difficult it is to land in these, as well as conditions associated with the length and width of the runways and their manoeuvring capacity in case a safety event can occur in the approach and landing phases (Erazo, 2023). For the expert pilots DM4 and DM5, the questions and risk management scenarios were indifferent to the risk scales proposed; for these expert pilots, the simple fact of presenting a possible risk already generated a high probability, which could generate a catastrophic or dangerous safety event in these two flight phases (Garces and Gonzalez, 2023). For the expert pilot DM6, the risk scales were more critical when minor or insignificant safety events occurred, and their curve was upward since he considered that the human factor played a fundamental role in the case of alertness and situational awareness when there was no news in flight (Del rio, 2023). It is worth mentioning that although the risk factors were evaluated individually, if an operational safety event occurs, they are all related to each other, and safety events with multiple combined causes can arise.

After the surveys carried out with the expert pilots, the construction of five (5) risk scenarios (AA, A, BB, B, C) was carried out, it was evident that all the expert pilots agreed with the structure of each of the risk scenarios, when the reference scenario was configured according to the reference scenarios. In the particular case, the model identified the risk structure associated with the said scenario, as shown in **Figure 2**, and so on for the rest of the scenarios respectively, which clearly shows the stability of the model taking as a reference the traditional ELECTRE model and the proposed Fuzzy ELECTRE fuzzy model.

This research shows that the risk factors identified in the literature are relevant to the aviation sector, and expert pilots' perceptions vary depending on their experience and the scale of risk they are evaluating. The construction of risk management scenarios based on the perceptions of expert pilots is a useful tool for identifying and prioritising risk factors and developing risk management strategies.

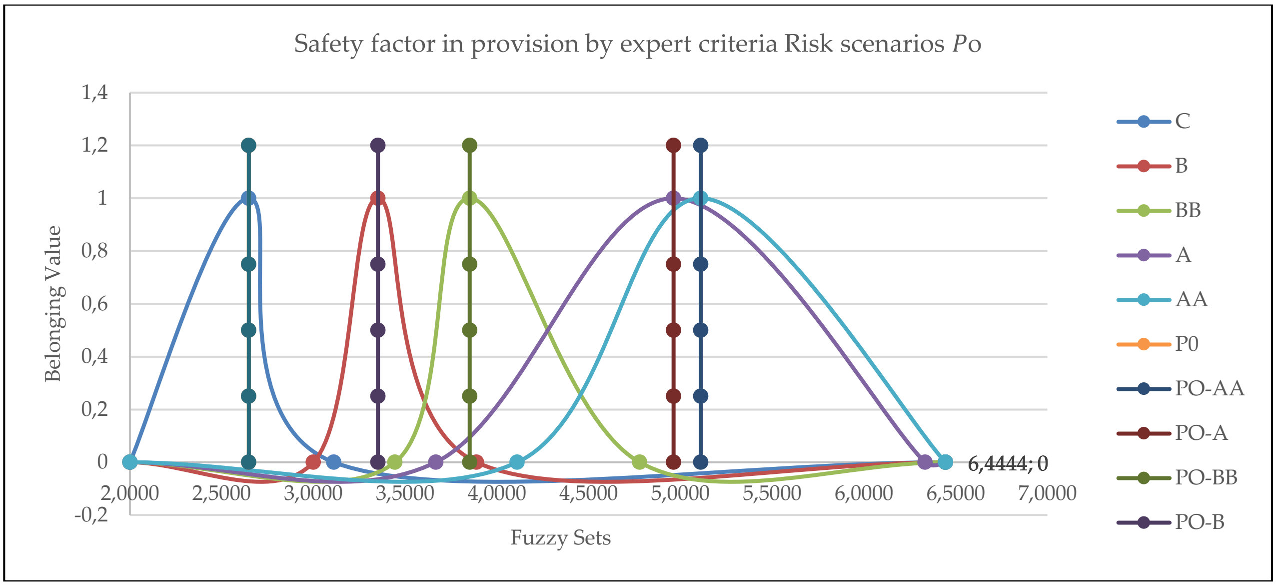

Figure 3. Safety factor in provision by expert criteria Risk scenarios P_0.

In the final stage, the results produced by the proposed model in comparison to the characterisation of three theoretical risk scenarios suggested by expert pilots (Low (L), Moderate (M), High (H)) demonstrate that the model was sensitive to different levels of risk during the approach and landing phase. The results indicate that, for the low-risk level (L), the proposed model yielded an AA risk scenario, where it could be identified within **Table 23** that the values tend to be very low in reference to Saaty's scale (**Table 3**), making it the least risky scenario. In the case of a moderate risk level (M), the model yielded a BB scenario where the predominant qualitative value in the expert survey rating was medium bad and good. Meanwhile, for the high-risk level, it produced a risk scenario in category C, tending to be a very low value in reference to the same Saaty scale, making it the riskiest scenario, as shown in **Figure 2**. The above illustrates the structural stability of the proposed model in relation to the characterisation of different risk scenarios based on criteria in the proposed scenarios according to the traditional model.

Table 23. Additional risk scenarios

Saaty scale	High	Medium	Low
EG	14	0	0
VG	11	2	0
G	10	12	0
MB	0	20	3
B	0	1	9
EB	0	0	23

After this, the analysis is carried out using the Fuzzy ELECTRE model, indicating the stability of said model, as shown in **Figure 5**.

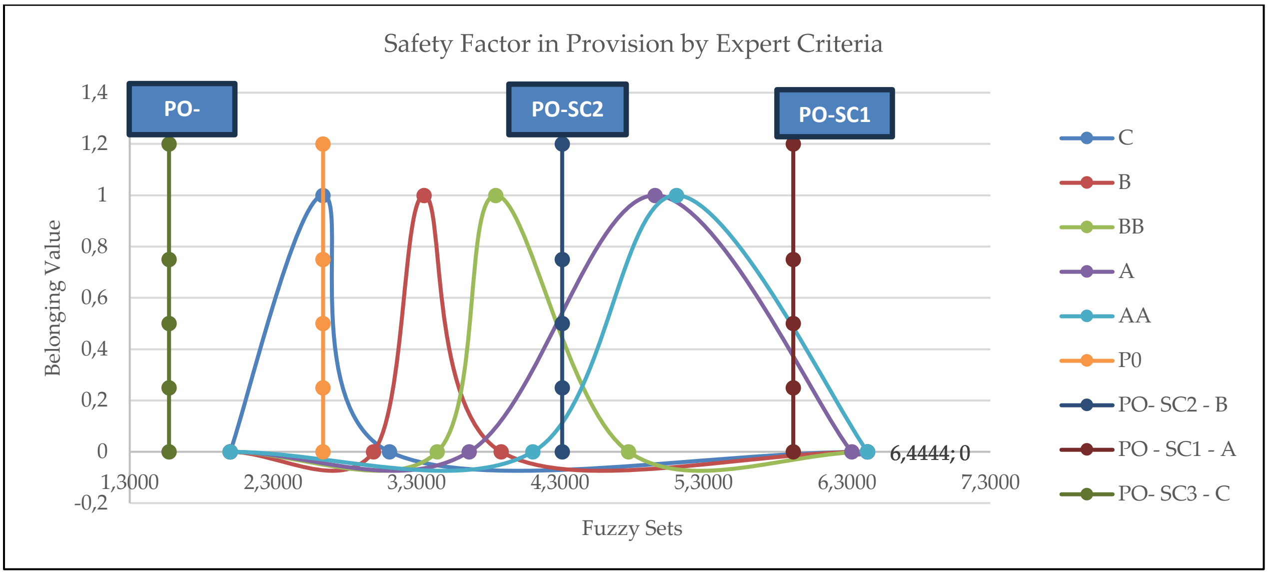

Figure 5. Safety factor in the provision based on expert judgment for additional risk scenarios

CONCLUSIONS AND RECOMMENDATIONS

The proposed model allowed the characterisation of the risk associated with aeronautical operations in the approach and landing phases according to the international risk regulations of the International Civil Aviation Organization (ICAO) through the participation of a group of expert pilots. Due to its conception, the model allowed the characterisation of each risk scenario according to the experience of each pilot and according to the criteria that define each scenario, thus shaping a set of recommendations for risk management in terms of each of the criteria defining a risk scenario.

Thanks to its dimensional stability, which allows it to identify a reference risk scenario automatically, and thanks to its structural stability, which allows it to recognise a scenario into five (5) standard risk categories automatically based on Basel II agreements, becoming the model as an ideal model for the evaluation of the associated risk, contributing to the operational safety management of the aeronautical sector as a proactive methodology in the early identification of the most common operational risks that may arise in the two most critical flight phases (approach phase and landing phase).

As future work, it is desired that the model incorporate into its structure the experience in years of each expert pilot, as well as a series of weights that reflect the importance of each risk criterion. It is also desired to incorporate the relevance for each of the criteria based on statistics provided by civil aviation regulatory bodies and the integration of quantitative information from flight data recorders to expand this study to all phases of flight. This will allow for improving the flexibility of the model in terms of the experience of the pilots and the importance that each aeronautical institution of the countries gives to each of the criteria that define each risk scenario and the accuracy of the data obtained from the operation of the aircraft.

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