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New Type of Aeronautical Risk Assessment: Performance of Kohonen Self-Organizing Maps in Identifying Brazilian Aircraft with Greater Associated Risks

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Abstract

The purpose of this paper is to present a new way of assessing aeronautical risk using a configuration of Kohonen Self-Organizing Maps (SOM) to identify the Brazilian aircrafts more likely to be involved in aeronautical accidents and the riskiest Brazilian aircrafts.

The technique described is classified as predictive for managing aeronautical risks, according to DOC 9859, and can be used both in the context of prevention and investigation of aeronautical accidents/incidents, as well as in the context of the insurance industry.

Using this technique, it was possible to identify the 147 Brazilian aircraft with the highest associated probabilities of occurrence of aeronautical accidents, and the 180 with the highest associated risks.

Five years after this identification, the respective percentages of aeronautical accidents/incidents were 34% and 27%.

The application of this technique can help achieve the objective of the aeronautical community in determining what, where, and when the next aeronautical accidents and/or incidents will occur.

Another aspect of the present work is to demonstrate that data collected by the national civil aviation agency in Brazil can be used to implement a predictive methodology for the management of safety in civil aviation.

Introduction

In 2020, air modal trade constituted 35% of international trade, had a share of 4.1% of global GDP, was one of the pillars of globalization [1], and was considered the safest transport mode worldwide.

According to the International Civil Aviation Organization [2], the civil aviation area is based on two pillars, the commercial pillar and the prevention of accidents pillar. Because of this, the continuous improvement of aviation safety is subjected to constant research by air service providers and by the civil aviation authorities in each state.

Based on those efforts, throughout the history of aviation, several studies have been developed to improve the models of aeronautical accidents, as well as their prevention and investigation.

The present work aims to contribute to those efforts by proposing a new means of modeling aeronautical risks, resulting in a better assessment of aeronautical risks associated with Brazilian aircraft.

Currently, Brazil has the second largest fleet of aircraft in the world, with several aeronautical industries, including Embraer, one of the largest manufacturers of commercial aircraft in the world, and Helibrás, a manufacturer of helicopters [3].

The Brazilian fleet comprises aircraft, which have been produced in various countries, and its aviation industry has a close relationship with the best practices in world aviation.

Contextualization

According to the International Civil Aviation Organization (ICAO), the history of operational aviation safety has had three eras, namely [4]: the Technical Era (until the 1960s), the Era of Human Factors (early 1970s until the mid-1990s), and the Era of Organizational Factors (from the 1990s onwards).

- Technical Era: in this era, accidents were faced with more emphasis on the failure of the equipment used;
- Era of Human Factors: in this era, the technologies adopted

in aviation were more mature, so the number of aeronautical accidents decreased significantly; however, to further reduce aeronautical occurrences, human failures and failures arising from human-machine interactions, human factors began to be studied and emphasized.
- Era of Organizational Factors: in this era, it was realized that a significant part of human failures in aviation resulted from failures in organizational processes, such as training, lack of adequate equipment, ergonomics, and so on.

Currently, all cited perspectives are used with the purpose of reducing aeronautical accidents in a complementary way.

It is important to highlight that at the beginning of the technical era, aeronautical accidents were mainly prevented through the investigation of aeronautical accidents. In this era, researchers Heinrich and Bird contributed with important researches [5].

Heinrich (1931) proposed the single cause theory where the accident was modeled as a result of a single cause that used to unfold linearly in time exploiting other deficiencies in the system [4]. Heinrich also created a pyramid that correlated the number of aeronautical accidents with the number of incidents (for each serious accident, there were 29 accidents with minor damage and 300 incidents that did not cause damage) [5].

In turn, Bird (1966) conducted a broader study and concluded that for each serious accident, there were ten prior accidents with minor damage, 30 accidents with damage to property, and 600 incidents [5].

Later, researcher James Reason (1997) proposed the theory of multiple causes in which the accident was not generated by a single cause, but by a linear combination of several latent conditions and active faults [4]. However, Reason did not contradict the relationships between accidents and incidents proposed by Heinrich and Bird. In fact, he expanded the scope of these relationships [4], as he considered all active failures and latent conditions of aeronautical systems that also routinely involved incidents as causes of accidents.

Among the current methodologies for the investigation and prevention of aeronautical accidents, STAMP (System-Theoretic Accident Model and Processes) is noteworthy. This technique is based on the theory of electro-electronic systems [6]. According to this methodology, aviation safety can be seen and analyzed as a system control problem, and accidents occur when interactions between the components of these systems violate the control constraints, reflecting failures in the constraints of these interactions [6].

Since 2006, the ICAO has compiled the main studies cited, as well as many others in different editions of the DOC 9859 manual [2, 4]. The DOC 9859 manual contains the state of the art in the prevention and investigation of aeronautical accidents, including the analysis and management of aeronautical risks by civil aviation agents, such as aeronautical maintenance workshops and airline operators, as well as the civil aviation authorities of each country [2].

The aeronautical risk management methodologies cited in the second edition of DOC 9859 are listed as being [2].
- Reactive: following the occurrence of an aeronautical accident/incident, investigations and suggestion of improvements aim to ensure that other similar occurrences do not occur;
- Proactive: organizational work processes are continuously analyzed to mitigate aviation failures and avoid failures in aeronautical systems before accidents or incidents occur;
- Predictive: data from civil aviation systems are analyzed through statistical inference techniques or artificial intelligence and future failures in these systems are estimated to anticipate such failures and avoid the occurrence of aeronautical accidents/incidents.

Many of the current and innovative techniques in aviation are already established and popular in other engineering fields, as in the case of the System-Theoretic Accident Model and Processes (STAMP). This is also the case of the technique proposed in the present work.

According to the ICAO, the predictive management of safety is the most desirable philosophy since there is a complete anticipation of problems, incidents, and accidents in aviation and other areas [7].

As is well known, machine learning softwares can identify hidden patterns in a large mass of data [8]. In the present case, the proposed method was able to identify predictively unsafe patterns related to hidden unsafe conditions that generated accidents/incidents in the following years. Then, the technique described in this paper was classified as a predictive management technique for the assessment of aeronautical risks.

Previous Works

Despite the importance of the predictive management of safety, there is a problem related to the quantity and quality of data available in aviation since the amount of data inherent to aviation is very vast, and it is often difficult to collect [7]. Thus, the number of studies related to the predictive management of operational safety in aviation will be greater when the aforementioned problems can be solved [7].

In 1986, the Space Shuttle Challenger took off from the space station at Cape Canaveral and exploded shortly after takeoff [9, 10]. After investigation, it was found that the accident occurred due to a failure in the fuel sealing o'rings due to the strong cold weather conditions in the region at that time. It was shown that these o'rings failed when subjected to intense cold [9, 10]. The evidence of failure in these sealing o'rings was first obtained through a logistic regression between failures in these seals and ambient temperatures, and later also proven in a chemical laboratory [11]. Following this event, it was concluded that predictive analyses could identify future failure situations and support decisions that would avoid aeronautical accidents/incidents.

In 2009, Wong et al. presented a method which was able to infer aeronautical accident probabilities at US airports using the statistical inference of a logistic function and data from the United States Federal Aviation Administration's (FAA) Aviation Policy and Plans Office (APO), the Enhanced Traffic Management System Counts (ETMSC), and the National Oceanic and Atmospheric Administration's (NOAA) database [12]. This study strongly highlighted the importance of data from normal operations and cited other academic studies that had faced difficulties in acquiring normal operation data (NOD).

Despite such difficulties, the authors were able to obtain numerous normal operation data (NODs), but mainly related to risk assessment in the airport context. Indeed, this work was important as it was able to evaluate the probability of future accidents, and so on; however, it was limited to the context of airports, and did not consider more general events such as collisions with fauna.

All possible accidents or incidents were considered in the risk assessment of this work, including collisions with fauna. Some accidents and incidents with fauna occurred with aircrafts identified as the riskiest ones by the present work.

In [13] several different models of loss of control accidents (LOC) were evaluated using an object oriented belief network (OOBN) through the Hugin software. This study aimed to construct a generic model of loss of control accidents in flight (LOCAF). This generic model could be used to improve other OOBNs through the exportation of the entire subnets (e.g., the flight crew performance subnets). In this construction of a generic model of LOCAF, the authors used the National Transportation Safety Board (NTSB) dataset of accidents from 1987 to 2009 to categorize the types of accidents using three main root causes: human factors, system components, and external factors. Despite its importance in modeling LOCAF, and "lead(ing) to vulnerability discovery of emerging causal factors for which mitigations do not yet exist that then informs possible future R&D (research and development) efforts" this study was limited to the LOCAF context [14].

Valdés (2018) affirmed that [13] had a reactive perspective and instead, the author presented some Bayesian inference methods to forecast incidents in commercial fleets of aircraft. The Bayesian inference methods assessed by were used as prior probability functions: non-informative uniform, Jeffreys', and beta-binomial. Valdés (2018) also proposed three other hierarchical Bayesian inference methods:

- Model 1: used probability functions: beta, gamma, and binomial;
- Model 2: used probability functions: beta, gamma, and normal;
- Model 3: used probability functions: beta, gamma, and normal, but estimating more parameters than model 2.

The abovementioned Bayesian inference methods showed a good capacity for forecasting the future number of incidents in fleets of aircraft using past information. The study by has a striking similarity with the present study, however, it was not able to forecast or infer the density probabilities of aircraft accidents, while the present work does so implicitly in a nonparametric way [14].

Importantly, the study by [14] reported that: "there is limited available research (in the aviation context) that compares different predictive modelling approaches, identifies the most appropriate statistical models for forecasting safety events, or helps to predict safety performance". The present study aims to reduce such research gaps.

In 2017, a method was proposed for predicting future events from event logs in the context of the predictive maintenance of aircraft using a random forest machine learning technique [15]. This approach was aimed at forecasting in advance failures in aircraft. However, it is important to register that the majority of accidents that occur in aviation nowadays are related to human factors [16, 27].

Some years ago, the FAA Air Traffic Organization (ATO) and US Navy developed the Aerospace Performance Factor (APF) as a safety metric. The methodology has since been adopted in Europe, where several air navigation service providers (ANSPs) have worked together with EUROCONTROL in civil aviation risk assessments [17].

In 2018, two statistical techniques were compared to predict the future values of the APF [18], but this work still presented shortcomings in its incapacity to predict "what, where, and when the next incident will occur" [17].

It has previously been shown that the number of aeronautical incidents at a large airport in Brazil could be estimated one month ahead of the period of analysis using classical adaptive filters and data with a lesser impact on operational safety, such as foreign objects and near collisions on the ground [19].

In 2018, a deep learning model was used by [21] for traffic crash prediction. In this work, an unsupervised classification technique was used in combination with a supervised technique to predict the number of crashes in 635 roadway segments in Knox County. This work is similar to that of [12] of but used deep learning instead of logistic regression.

More recently, a combination of many prediction methods was used for forecasting civil aviation incident rates in China [20]. In this work, better estimations were obtained when using combinations rather than single estimations.

Predictive Methodologies

There are currently three main areas of knowledge responsible for supporting predictive analyses: statistics, digital signal processing, and machine learning.
Below are some of the techniques adopted by these areas of knowledge.
• Statistics [22].
• Frequentist techniques, such as classical statistical regression
• Bayesian techniques, such as Kalman filters
• Digital signal processing
• Adaptive filters [23, 19].
• Machine learning [8, 21].
• Neural networks,
• K-means.
• Deep learning.

The list of methodologies cited is not exhaustive and each of the techniques presented has its advantages and disadvantages; depending on the application, some techniques are more popular and widespread than others.

Kohonen Self-Organizing Maps

Professor Teuvo Kohonen proposed the Kohonen Self-Organizing Maps (SOM) in 1982; they were inspired by the functioning of the brain and designed to be computationally feasible [29]. Because SOMs were classified as a nonparametric methodology according to Duda Hart [8], the probability distribution functions of the variables are not evidenced, and thus it is only possible to determine the sets with higher risk probabilities than the other sets or clusters.

It was later shown that SOMs represented a particular case of the generalized Lloyd algorithm of the vector quantization area [29].

A SOM has three steps [29]:

- Competitive step: in this stage, all neurons compete with each other in terms of being closer to the data sample;
- Cooperative step: in this step, the winning neuron determines the topological neighborhood of neurons that will be excited or adjusted by the data sample in question;
- Synaptic adaptation step: in this step, the winning neuron and its topological neighborhood are fitted by the data sample.

Although it is a relatively old algorithm, its variations continue to solve unsolved and current problems [30, 31]. Thus, the present work proposes a new form of aeronautical risk assessment, providing another unprecedented and essential example that shows the power of this technique.

The Attacked Problem

In 2016, Brazil had a total of 21,905 aircraft, but of these, only around 16,397 were licensed, that is, within the non-experimental category [24]. In 2020, the total number of aircraft was 22,409, but considering only the non-experimental category aircraft, this number becomes 16,674 [24], as shown in Table 1.

Table 1: Total Brazilian aircraft between 2009 and 2020 [24]

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Total of registered aircraft	18710	19769	20662	21438	21789	21905	22009	22189	22219	22409
Total of non-experimental aircraft	14236	15019	15704	16229	16631	16397	16421	16528	16554	16674

Considering the high number of aircraft, a smaller set of aircraft with bigger deficiencies in operational safety were identified.

The National Civil Aviation Agency (ANAC) has a series of data that are collected from regulated entities; the main channels for those data are the ADREPE (Accident/Incident Data Reporting), which deals with difficulties in service, and DCERTA (*Sistema Decolagem Certa*), which deals with the flight plans of nonregular aviation.

Difficulties on service data are data from public air transport operators (regular aviation) and aeronautical maintenance workshops voluntarily provided to the ANAC according to sections 121,703 of RBAC 121, 135,415 of RBAC 135, 145,221 of RBAC 145, or 21.3 of RBAC 21 [25].

DCERTA is a tool used for the inspection of general and executive aviation in Brazil providing flight plan analysts with information about the crew and aircraft associated with the respective flight plans. DCERTA not only provides information about crews and aircraft, but also collects data on non-regular air operations that occur in Brazil [26].

In addition to the data mentioned, which is owned by the ANAC, there are public data about accidents and incidents of Brazilian aircrafts released by the Aeronautical Accidents Investigation and Prevention Center (CENIPA), an agency linked to the Brazilian Air Force (FAB) [27].

Data from DCERTA and CENIPA were used with the objective of identifying risky aircrafts, since the data obtained through the in-service difficulty system were voluntary in nature, had many omissions and had little coverage of aircraft [28].

The data used by DCERTA were annual, starting in 2012, and consisted of:
• The number of pilots that operated the aircraft;
• Previous accidents or serious incidents involving the aircraft;
• If the aircraft had been flown any time by instruments or not;
• The number of flights;

• The number of flight routes;
• The number of flights with irregularities;
• The kinds of aircraft (single engine, multi-engine, and so on).

It is important to note that the DCERTA data meet the requirements of the ICAO's proposal regarding the acquisition of data to enable the predictive management of safety [7]. The parameters that are collected by DCERTA belong to the public domain, however, the data related to each aircraft prefix is confidential. For this reason, only the data that DCERTA collected are published in this study, and at no time are the mentioned data associated with aircraft prefixes.

Methodology, Part I

This section describes the Kohonen Map clustering technique adopted to identify the safety patterns present in the data, as well as some challenges found to design the algorithm.

Unlike in other predictive studies [20] [21], the data available for this study was not detailed or vast enough for any of the widely used machine learning and deep learning methods. Each aircraft had only three samples of information at most, one for 2013, another for 2014, and a third for 2015. At times, some aircraft only had one sample available.

It is important to highlight that the data used was not clean and reliable, since DCERTA allows simulations of flights, and while many aircraft fly mostly under DCERTA monitoring, other seldom do. For example, a commercial aircraft that used to mostly fly outside of DCERTA monitoring only flew a few times under DCERTA monitoring when it flew to get maintenance.

Other problems that can be mentioned include: the provision in the flight plan of aeronautical licenses data that belong to other pilots, and agricultural aircraft that rarely fly under DCERTA monitoring. Therefore, a clustering software based on the Kohonen SOM algorithm was adopted for the identification of these aircraft; since the safety patterns of the aircraft are shared in the algorithm, SOM can overcome the problem of the limited amount of data.

Another feature of the clustering algorithms is the identification of infraction behaviors common to several operations of different aircrafts, when those infraction behaviors imply in similar DCERTA data.

Here, the SOM aimed to associate all aircraft contained in the DCERTA data in clusters, using all parameters, including aeronautical accident data. A training set and test set were selected during this procedure. The training set was used to train the clustering algorithm, while the test set served to adjust the parameters to maximize the generalization ability of the clustering algorithm. In the training step, the cluster that had the highest parameter associated with accidents was considered the critical cluster.

Following this stage of training and identification of the critical cluster, the test step aimed to evaluate which of the aircraft in the critical cluster had accidents or serious incidents in the test set. Each aircraft in the critical cluster that had been involved in an aeronautical accident or serious incident was considered a hit and evidence of a good generalization capacity.

The hyper parameters in this SOM that had to be tuned for better performance were the:

- Number of neurons (NN);
- Interneuron training decay rate (TD);
- Decay rate of the topological neighborhood centered on the winning neuron (T);
- Parameter that represents whether there was any operation flight by instruments (ROP) in the considered year;
- Parameter that represents the occurrence of an accident or serious incident (ROC);
- Learning rate (α).

Each new sample of the data vector was represented by *X(t)*, where *t* was the index of samples with integer values ranging from 1 to NMA (the total number of samples). In the training step, there was a nearest neuron (NT_1) for each *X(t)*, as well as other neighboring neurons (NT_i) close to *X(t)* that also had to be evaluated.

The distance measure adopted was the Manhattan distance, according to Equation 1.

$$d_i = \|X(t) - NT_i\|_0$$

In addition to the nearest neuron, other neurons in the topological neighborhood of that nearest neuron were also fitted by *X(t).*

Here, the definition of the number of nearby neurons trained for each *X(t)* was represented by RT, according to Equation 2.

$$RT = (NN-1)e^{\frac{-t}{NMA.T}} + 1$$

When RT had fractional values, it was approximated to the nearest integer.
The fittest neuron and its neighborhood were adjusted by *X(t)*, according to Equation 3.

$$NT_i(t+1) = NT_i(t) + \frac{\alpha}{i^{TD}}[X(t) - NT_i(t)]$$

The parameter i was the identifier index of the fitted neurons. The neuron corresponding to the index equal to 1 ($i = 1$) was the neuron closest to X(t), the second closest had an index equal to 2 ($i = 2$), and so on. In this way, the neurons in the topological neighborhood of the winning neuron were also fitted, but the fit was inversely proportional to the distance to the winning neuron.

Many other forms of training were tested; this stands out from the stability of the results, because even with the randomness of the initial weights of the neurons, the results were always the same at the end of the training. This characteristic was of fundamental importance for the adjustment of the parameters by the genetic algorithm, since the initial parameter data of SOMs are random in the genetic algorithm.

After training, the aircraft contained in the cluster associated with the critical neuron were verified, and it was counted how many of these aircraft were actually involved in accidents or serious incidents (aeronautical occurrences) in the test set. Using this metric, the ratio between the number of occurrences and the critical aircraft (precision - RC), and the ratio between the number of occurrences and the total number of aircraft in the test set (AC) were evaluated.

Methodology, Part II

This section describes the technique used to adjust the parameters of the SOM to maximize its ability to classify safety patterns and generalize them. This technique was a genetic algorithm that used championships and mutations [35]. The genetic algorithm had a population of ten individuals, each championship was held between two individuals, the mutation rate was 5% of the genes, the genes were numerically valued, and the adjusted parameters had already been already cited.

Regarding the data itself, the information on whether an accident happened or not was binary, one or zero, as was the information on whether there was an operation per instrument (IFR) in the considered year. The best representations of these two parameters were also adjusted by the genetic algorithm, so that the nonoccurrence continued to be represented by zero, while the occurrence was represented by a number between zero and one, which was obtained by the genetic algorithm.

The objective function (OF) of the genetic algorithm considered RC (55%) and AC (45%). Although AC maximization was important in terms of increasing hits in the test set, it was understood that RC was more important, since an aircraft wrongly considered as critical could generate great losses for the operators of those aircrafts.

In this way:

$$OF = 0.55RC + 0,45AC$$

In the genetic algorithm used, the OF had multiple *criteria* as shown in Equation 4 and was heavily penalized when the critical cluster had less than 120 or more than 180 aircraft.

The present methodology was used both to identify the aircraft with the highest associated probability of being involved in aeronautical accidents and the aircraft with the greatest associated risks.

Risk was defined as the product between the probability of occurrence and the associated consequences.
To overcome the lack of availability of probability density functions in SOMs and their consequent multiplication by the associated consequences, the consequences were added in the cost function of the genetic algorithm responsible for identifying this set of aircraft with the highest associated risks. The aircrafts identified as having the highest probability of being involved in aeronautical accidents were listed as LAP and the aircrafts with higher associated risks were listed as LAR.

As already stated, to identify the aircraft most likely to be involved in future accidents, Equation 4 with high penalization when the number of aircrafts were bigger than 180 and lower than 120 was enough. However, to identify the riskiest aircraft, the consequences associated with each aircraft had to be estimated; for example, for airplanes equipped with one conventional engine (L1P), the estimated consequence factor (ESF) was 5, while for an airplane equipped with two jet engines (L2J), the estimated consequence factor was 1000.
Table 2 shows the estimated consequence factor values used for each type of aircraft.

Table 2: Consequences Associated With the Types of Aircraft in Brazilian Aviation

	L2J	L2T	H1T	L1T	H2T	L1P	L2P	H1P	A1T	A1P	L3J	L00	L4J	S1P	G1P
ESF	1000	500	200	50	250	5	10	50	50	6	1000	1	1000	30	5

Note: L2J – plane with two jet engines; L2T – plane with two turbojet engines; H1T – helicopter with a turbojet engine; L1T – plane with a turbojet engine; H2T – helicopter with two turbojet engines; L1P – airplane with a piston engine; L2P – airplane with two piston engines; H1P – helicopter with one piston engine; A1T – plane with a turboprop engine; A1P – aircraft with a piston engine; L3J – plane with three jet engines; L00 – glider plane; L4J – aircraft with four jet engines; S1P – seaplane with one piston engine; G1P – gyrocopters with a piston engine

These ESFs were adopted by the genetic algorithm to identify the LAR aircraft inferring the consequence values associated with each aircraft cluster. The cluster with the highest associated consequences was selected as the most fitted.

The ESF of the critical cluster (β) was averaged by the number of critical aircraft (γ) and multiplied by 0.1. Then, it was summed to the combination of previously related RC and AC.

In this case of risk criteria, the OF was generated by the following formula:

$$OF = 0.55RC + 0,45AC + 0.1\frac{\beta}{\gamma}$$

Thus, for LAR, the OF of the genetic algorithm was selected as the most fitted cluster, i.e., the cluster that met the following criteria:
• Had a number of aircraft greater than 120 and less than 180;
• Had a number of accidents or serious incidents of aircraft classified as critical in the test set (the clusters that were most likely to have future accidents);
• Had greater associated consequences, only for LAR.

Results

It is important to emphasize that the results obtained are not the result of simulations, as in most academic studies related to the predictive management of aeronautical risks, but were and are being observed in practice.

Another important issue regarding the results obtained is that, similarly to what was observed in aviation as a whole, most accidents/incidents that occurred with LAR and LAP aircraft were caused by human errors, and only a minority were caused by equipment failures.

To begin this section of results, Table 3 presents the parameters used to obtain the LAR, after being tuned by the genetic algorithm.

Table 3: Parameters used to obtain the LAR

	NN	TD	T	ROP	ROC	α
Values	22	0.60	0.62	0.90	0.24	0.35

The author does not have the corresponding parameters used to obtain the LAP because he was a victim of a hacker attack that tried to destroy all the scripts used here, as well as damaging the machine used in this study.

The LAP and LAR are all Brazilian civil aircraft types, but since the ANAC categorizes Brazilian civil aircraft into experimental and non-experimental, it was important to verify the number of experimental aircraft in LAP and LAR. In LAP, the number of experimental aircraft was 1, and in LAR it was 11.
Category In Tables 4 and 5 describe the aircraft.

Table 4: Aircraft Categories in LAP

	PRI	TPP	SAE	TPX/SAE	TPX	TPR	PET/PEX	ADE/ADF	Total
Aircrafts	115	21	7	0	0	0	1	3	147

Table 5: Aircraft Categories in LAR

	PRI	TPP	SAE	TPX/SAE	TPX	TPR	PET/PEX	ADE/ADF	Total
Aircrafts	58	48	18	12	19	1	11	13	180

Note: PRI – instruction aircraft; TPP – private aircraft; SAE – special services aircraft, aerial survey for example; TPX/SAE – aircraft that are operated for non-regular public transport and special services at the same time; TPX – aircraft that are operated for non-regular public transport; TPR – aircraft that are operated for regular public transport; PET/PEX – experimental aircraft; ADE/ADF – aircraft operated by the State

The overall performance of the two groups of critical aircraft between 2016 and 2021 was:
• LAP: a set of 147 aircraft identified in 2016, using data up to 2015. Between January 2016 and December 2021, there were 50 accidents/incidents involving 38 aircraft, one of which was fatal.
• LAR: set of 180 aircraft identified in 2017, using data up to 2016. Between January 2017 and December 2021, there were 30 accidents/incidents with 27 aircraft, two of which had fatalities.

Considering only non-experimental aircraft, the overall performance was:
• LAP: a set of 146 aircraft identified in 2016, using data until 2015. Between January 2016 and December 2021, there were 50 accidents/incidents with 38 aircraft, one of which was fatal.
• LAR: set of 169 aircraft identified in 2017, using data until 2016. Between January 2017 and December 2021, there were 29 accidents/incidents with 26 aircraft, two of which had fatalities.

In annual terms, the occurrences (accidents or incidents) per year for the list of aircraft with the highest associated probability (LAP) are described in Table 6, while the occurrences for the list of aircraft with the highest associated risk (LAR) are described in Table 7.

Table 6: Occurrences of Aircraft in LAP

Year	Number of occurrences (accidents or incidents)
2016	17
2017	8
2018	8
2019	4
2020	7
2021	6

Table 7: Occurrences of Aircraft in LAR

Year	Number of Occurrences (Accidents or Incidents)
2017	3
2018	6
2019	9
2020	6
2021	6
2021	6

Some comparative performance analyses are provided next.
To estimate the probability of an aeronautical occurrence in the LAP, LAR, or even in the general aviation set, the statistical frequency of the event called "aeronautical occurrence" in these three sets was measured according to Equations (6) and (7), where C is the cardinality of the set in question.

$$P(occurrences = k) = \frac{\binom{C}{k}}{\sum_{j=0}^{C}\binom{C}{j}}$$

$$\binom{C}{j} = \frac{C!}{j!(C-j)}$$

However, this calculation involved the factorial operation of very high numbers, making it difficult to obtain these probabilities. To estimate this probability for the total set of Brazilian aircraft in 2016, it was necessary to at least calculate the number (21,789 – 387)!. The difficulty in working with factorial numbers of large magnitude is not new, and indeed, the mathematician Stirling proposed an approximation for the calculation of large factorial numbers [33]:

$$n! \approx \sqrt{2\pi n}\left(\frac{n}{e}\right)^n$$

For example, using the online calculator for large numbers [34], the approximate value of (21,789 – 387)! is:

$$21,402! \approx \sqrt{2\pi 21,402}\left(\frac{21,402}{2.7183}\right)^{21,402} \approx 1,124e20,850$$

Due to the immense magnitude of the numbers related to the problem in question, the calculations of exact probabilities extrapolated the computational resources available to the author. To overcome this problem, an approximate comparison between the quantities was proposed.

Considering Set I with δ aircraft, Set II with ξ aircraft, where $\delta > \xi$; there were ζ aeronautical occurrences in both Set I and Set II. In this case, it was possible to confirm that the probability of aeronautical occurrences in Set II was greater than in Set I, because even with a lower cardinality it presented the same number of occurrences. This can be expressed by Equation 10:

$$\frac{\zeta}{\xi} > \frac{\zeta}{\delta}$$

Thus, this comparison metric was used to compare the probabilities of aeronautical occurrences between different sets.

In 2016, there were 387 accidents and/or aeronautical incidents, in a context with around 21,789 active aircraft, representing a proportion of 1.78% (=387/21,789). Considering only aircraft of categories other than experimental categories, the proportion becomes 2.10% (=345/16,397). During that same year, there were 16 aeronautical accidents and/or incidents in a set of 147 aircraft in the LAP grouping, translating into a proportion of 10.88% (=16/147). Considering only aircraft of categories other than the experimental category, the proportion becomes 10.95% (=16/146).

Since this proportion was around five times bigger than the global proportion considering all aircraft in 2016, it can be said that the probability of aeronautical accidents in this set in 2016 was much higher than the probability of accidents considering the entire Brazilian aviation.

In 2017, there were 31 accidents with fatalities, that is, aeronautical accidents where people inside or outside these aircraft died due to the operation of these aircraft. Such scenarios generated a proportion of accidents with fatalities of 0.14% (= 31/22,009). Considering only aircraft of categories other than the experimental category, the proportion becomes 0.19% (=31/16,421). In that same year, two fatal accidents were also observed among the LAR group, and the respective proportion was 1.11% (=2/180). Considering only aircraft of categories other than the experimental category, the proportion becomes 1.18% (=2/169).

Since the proportion of accidents with fatalities in LAR was considerably higher than the proportion observed in all of Brazilian aviation in 2017, it can be said that the risk level of LAR in 2017 was higher than in Brazilian civil aviation as a whole.

Finally, according to page 11 of the 2017 Operational Safety Report (RASO 2017) [35], the number of accidents per million of takeoffs in Brazil in 2017 was 83.10. Considering only fatal accidents, this number was 22.93. In 2017, the number of accidents per million of takeoffs at LAR was 190.08. Highlighting the fact that those accidents were fatal too, this number can be compared with the overall number of accidents per million takeoffs as well as with the context considering only fatal accidents. Thus, it is clear that the risk level in LAR in 2017 was much higher than the risk level in Brazilian civil aviation as a whole, especially regarding fatal accidents.

Figures 1, 2, and 3 show some accidents involving LAP and LAR aircraft. The aircraft were properly defaced to preserve the privacy of those involved, as well to ensure that the purpose of this study is strictly academic.

Figure 1: Accidented Aircraft

Figure 2: Accidented Aircraft

Figure 3: Accidented Aircraft

Conclusions

Tuned through a genetic algorithm, the Kohonen Self-Organizing Maps technique can identify a set of aircraft with high associated probabilities of being involved in aeronautical accidents and to identify a set of aircraft with high risks associated with good adherence to reality, not simulations.

The identification of aircraft with higher associated probabilities of being involved in aeronautical accidents and/or associated risks using this type of statistical approach is new to the aeronautical sector.

Another important aspect of this study was to demonstrate that DCERTA data can be used for the predictive management of aviation safety. This mitigates the problems faced by several countries regarding which data to collect from their regulated civil aviation providers [7].

This methodology can be considered of great value in the assessment of aeronautical risks, as it can considerably improve accident prevention and inspection activities if used with government data. In addition, the use of this methodology with private data could improve the prevention of aeronautical accidents, as well as refining the pricing of risks by insurance companies.

Finally, the presented methodology could bring the aeronautical community closer to its objective of determining "what, where, and when the next incident will occur", which has been its main aim when developing metrics such as the Aerospace Performance Factor (APF).

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