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LONG TOUCHDOWN THROUGH A SAFETY-II PERSPECTIVE

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Abstract

Safety-II assumes that individuals and organizations habitually adjust their performance to match current demands, resources, and constraints to compensate the incompleteness of procedures and instructions. It suggests that everything happens basically in the same way, regardless of the outcome. This work aims to analyze the aircraft touchdown procedure through this perspective, focusing on the everyday performance and the consequent variability. The Functional Resonance Analysis Method or FRAM provides a way to explain outcomes using the idea of resonance - an activity is described through a pool of functions and the outcomes arise from their day-by-day variability. To characterize the functions' variability, Flight Data Monitoring (FDM) techniques are here used. To examine specific instantiations of the model and understand how the potential variability of each function can become resonant, the application of Monte Carlo Simulation (MCS) is proposed. To apply the MCS, a linear regression is performed in order to capture the relationship between the functions' outputs and their inputs. This method is applied to the touchdown of 288 flights. The outcome is a model to assess the risk of a long touchdown of the current sample, including the organizational, human, and technological aspects of the complex aeronautical system. Note that long touchdown is a runway overrun precursor.

Keywords: Safety II, FRAM, Runway Overrun, Risk Analysis

1. Introduction

Progress in safety management made flying one of the safest ways to travel, reaching a rate of less than 0.5 commercial jets accidents per 1 million flights (Figure 1) [1].

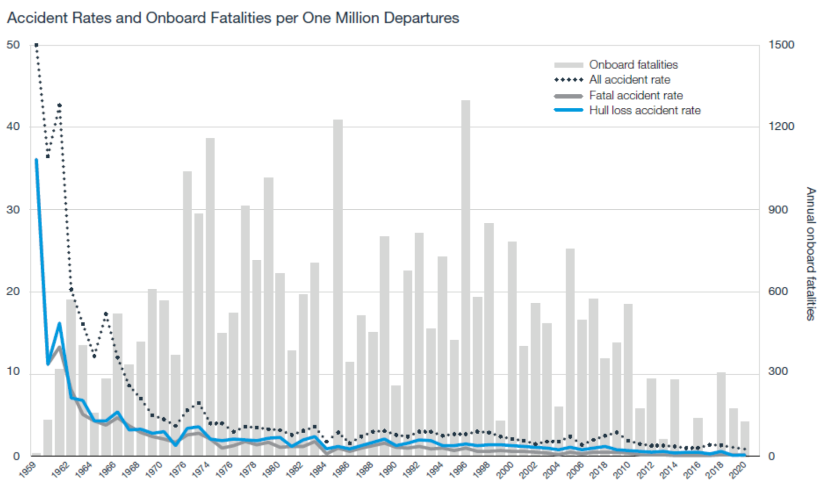

Figure 1 - Evolution of the Number of Accidents and Fatalities [1]

The aircraft accidents rate reduction was substantial only until the 1980s in the so-called age of technology, in which safety concerns focused on guarding machinery, stopping explosions, and preventing structures from collapsing. The focus on technology as the main – or even only – source of both problems and solutions in safety was successfully maintained until 1979, when the accident at the Three Mile Island (TMI) nuclear power plant demonstrated that safeguarding technology was not enough. The TMI accident brought to the fore the role of human factors and made it necessary to consider human failure as a potential risk. Seven years later the loss of the space shuttle Challenger, reinforced by the accident in Chernobyl, required yet another extension, this time by adding the influence of organizational failures and safety culture to the common lore [2]. Safety began to be viewed from a systemic perspective and to encompass organizational factors as well as human and technological factors during the mid-1990s. The notion of an "organizational accident" was introduced. This perspective considered the impact of such things as organizational culture and policies on the effectiveness of safety risk controls. Additionally, routine safety data collection and analysis using reactive and proactive methodologies enabled organizations to monitor known safety risks and detect emerging safety trends. These enhancements provided the learning and foundation which led to the current safety management approach. The "organizational accident" paradigm assists by identifying the latent conditions on a system-wide basis, rather than through localized efforts, to minimize active failures by individuals [3].

Safety-I management focus on aviation is to analyze the events from latent circumstances to the flight crew errors, monitoring the potentially unsafe conditions in the daily operations. Latent circumstances are often related to deficiencies in organizational processes and procedures. Flight crew errors may be a result of an ineffective management due to, for example, deficient trainings, unspecific policies, or even airline pressures. In other words, the so-called Safety-I approach promotes a bimodal or binary view of work and activities, considering acceptable and unacceptable outcomes as two distinct and different modes of functioning: things go right because the system functions as it should and because people work as imagined, things go wrong because something failed (Figure 2). It is then possible to achieve safety only minimizing, or even blocking, the transition from normal to abnormal functioning [2].

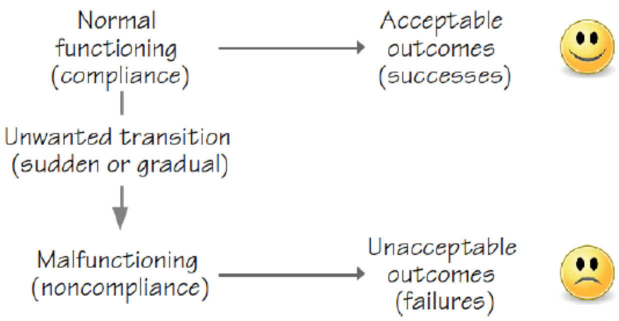

Figure 2 - Safety-I Basis [2]

Although this conception paved the way to outstanding improvements in safety research, they seem to be not so effective for socio-technical systems: that are incompletely understood, whose descriptions can be complicated, and that changes are frequent and irregular rather than infrequent and regular [4]. Safety-II aims to fill this gap by assuming that everything basically happens in the same way, regardless of the outcome (Figure 3). This concept accepts that individuals and organizations habitually adjust their performance to match current demands, resources, and constraints in order to compensate the incompleteness of procedures and instructions. Following Safety-II, the definition of safety shifts to consider not only the adverse outcomes, but also positive and negative events, to achieve a holistic view of the system and in-depth understand its functioning. Safety-I aims to limit performance variability, whereas Safety-II requires it to be proactively managed, rather than simply constrained [2].

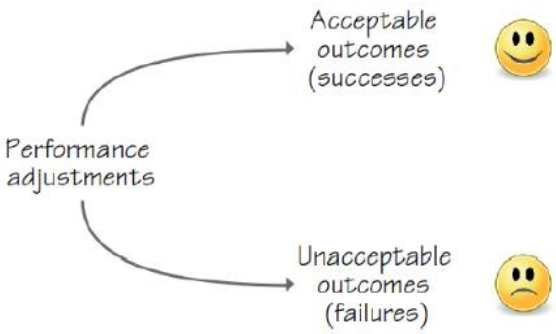

Figure 3 - Safety-II Basis [2]

The Functional Resonance Analysis Method or FRAM [5] provides a way to describe outcomes using the idea of resonance arising from the variability of everyday performance [6]. The purpose of this work is to apply a customized FRAM for operational risk assessment related with an aircraft landing procedure - the touchdown.

2. Methodology

FRAM is a method-sine-model, whose purpose is to build a model of how things happen rather than to interpret what happens in the terms of a model. It is built over the following four principles. First, failures and successes are equivalent in the sense that they have the same origin. In other words, things go right and go wrong for the same reasons. Thus, to understand what goes right when the daily work is carried out is as important as understanding what failed in the system.

Second, the everyday performance of socio-technical systems, including humans individually and collectively, is always adjusted to match the conditions. Workers usually need to make some tradeoffs between being efficient and to make sure the work can be completed as precisely as possible. These kinds of adjustments are named as efficiency-thoroughness tradeoffs (ETTOs). They are necessary and understandable; however, any changed system behavior may raise variabilities in the system [7].

The third principle states that many of the outcomes we notice – as well as many that we do not – must be described as emergent rather than resultant. To be more specific, minor variabilities always exist in normal system operations and do not affect system safety. Nevertheless, a particular external environment may integrate variabilities and magnify their influence to generate an undesired outcome [7].

Fourth, the relations and dependencies among the functions of a system must be described as they develop in a specific situation rather than as predetermined cause–effect links. This is done by using functional resonance [5].

FRAM does not imply that events happen in a specific way, or that any predefined components, entities, or relations must be part of the description. Instead, it focuses on describing what happens in terms of the functions involved. These are derived from what is necessary to achieve an aim or perform an activity, hence from a description of work-as-done rather than work-as-imagined. But functions are not defined a priori nor necessarily ordered in a predefined way such as hierarchy. Instead, they are described individually, and the relations between them are defined by empirically established functional dependencies [5].

However, notwithstanding the potential value of FRAM in system modelling and safety, researchers have suggested integrating quantitative approaches to FRAM to enhance its strengths. Patriarca et al (2017) presented a semi-quantitative application of FRAM by integrating Monte Carlo Simulations (MCS) [4]. Kaya et al (2021) used this semi-quantitative approach to FRAM and a criticality matrix to explore how the system-based perspective would enrich the quantified risk-orientated analysis in a tram operating system [8].

The following paragraphs present the four (4) steps to perform our customized and quantitative FRAM analysis, applied to a risk assessment. Figure 4 illustrates this methodology.

Step 1: Identify the functions and their aspects.

↓

Step 2: Estimate the probability distribution of each functions' aspect variability.

↓

Step 3: Aggregate the functions' aspect through a Linear Regression for Monte Carlo Simulation, taking the variables dependence in consideration.

↓

Step 4: Manage the functions' variability.

Figure 4 - Customized FRAM Steps

2.1 Functions Identification and Description

FRAM's first step deconstructs the complex sociotechnical system into "functions", that represent a task or an activity that is required to produce a certain outcome. The first step identifies these functions that are needed for everyday work to succeed and characterized by six different aspects as follows. Aspects are traditionally placed at the corners of a hexagon, which represents the function itself (Figure 5).

Figure 5 - A Hexagon Representing a Function

The Input (I) activates or starts a function and/or is used or transformed by the function to produce the Output (O), which is the result of the function. The output can be either an entity or a state change and serves as input to the downstream functions. Preconditions (P) are mandatory conditions that must exist before carrying out the function. They do not necessarily imply the function execution. The function needs the Resource (R) when it is carried out, or consumes it, to produce the output. Controls (C) supervise, regulate, or monitor the function. They are exemplified by guidelines, regulations, or even social expectations. Temporal requirements or constraints of the function, regarding both duration and starting point, are given by Time (T).

2.2 Performance Variability Characterization

The idea of the second step is to characterize the variability of the functions that constitute the FRAM model. One way to do that is to distinguish among different types of functions, for instance technological, human, and organizational. Technological functions are carried out by various types of 'machinery'. Since they are designed to be highly predictable and reliable, the default assumption of the FRAM is that they do not vary significantly during the scenario that is analyzed.

Human functions are carried out by humans, either as individuals or in small groups. In a FRAM analysis it is important to recognize that the frequency of human performance variability is high, and that its amplitude is large. High frequency means that performance can change rapidly, sometimes even from moment to moment. Large amplitude means that differences in performance can be large, sometimes dramatically so – for better or for worse. The variations in both frequency and amplitude depend on many different things, including working conditions.

Organizational functions are carried out by groups of people, where the activities are explicitly organized. For a FRAM analysis, the frequency of organizational performance variability is typically low but that its amplitude is large. Organizational performance changes are slow, as exemplified by alterations to rules, regulations, or policies; the differences in performance, that is, the amplitude, can be large.

Having considered some of the possible sources of variability, the next question is how performance variability will show itself – either in the sense of how it can be observed or detected – or in the sense of how it may affect downstream functions. A simple solution to describe the consequences of performance variability is to note that the Output from a function can vary in terms of timing and precision. It can occur too early, on time, too late or not at all. Regarding precision, it can be precise, acceptable, or imprecise. Since it refers to the coupling between upstream and downstream functions, precision is relative rather than absolute. If the Output is precise, it satisfies the needs of the downstream function. An acceptable Output can be used by the downstream function but requiring some adjustment. An imprecise Output is something that is incomplete, inaccurate, ambiguous or in other ways misleading.

Instead of evaluating functions variability in a subjective way, this work uses Flight Data Monitoring (FDM) techniques to estimate the variabilities. The FDM program, also known as Flight Data Analysis (FDA) or Flight Operation Quality Assurance (FOQA), is designed to enhance flight safety by identifying an airline's operational safety risks and taking the necessary actions to reduce these risks. When a safety event is highlighted by the program, statistical analysis will assess whether it is isolated or part of a trend. Appropriate corrective action is then taken if necessary [9].

Essentially, information coming from aircraft sensors, onboard computers and other instruments are recorded into a crash-survivable Flight Data Recorder (FDR) and occasionally also into easily accessible Quick Access Recorders (QAR). They are able to record over 3,000 parameters as binary raw data files, which are sequenced in frames and subframes. Each subframe is divided into a number of "words", each one with a fixed number of bits. A parameter is recorded on one or several bits of one or more words. To save memory space, a parameter value is generally not recorded as such, but converted using a conversion function defined by the aircraft manufacturer [9].

When the aircraft arrives at the gate, data are either extracted by maintenance staff via optical disc or Personal Computer Memory Card International Association (PCMCIA) card, or automatically via a wireless link. To transcribe the recorded parameters into useful values, raw data must be processed to recover the actual values. Events are automatically weighted according to risk with fine-tuned algorithms. Analysts look for all high deviation magnitude events to assess any serious safety concern and take appropriate corrective action. All reliable events are stored into the database and are investigated on a regular basis to highlight any trend that could show a latent or potential risk [9].

The FDM program is applied reactively through analysis of past incidents or accidents; proactively through analysis of the airline's activities; and predictively through data gathering to identify possible negative future outcomes or events [9]. Still, it is employed through a Safety-I perspective – looking for specific deviations.

The functionalities of this technique are here used to characterize the variability of the FRAM functions, understanding how the system works on a daily basis and estimating how each function varies in the "real world". In this work, FDR raw data from a typical jet is processed into Comma-Separated Values (csv) files and analyzed via R functions. R is a programming language and free software environment for statistical computing and graphics [10].

FDR parameters like latitude, longitude, altitude, airspeed, and groundspeed are used, which is performed in an eight samples per second (8 sps) basis. Parameters that are recorded in a smaller sampling rate are interpolated. Some of them are linearly interpolated to enhance their precision and others remained constant until the next sample.

2.3 Variability Aggregation

FRAM models the potential couplings among functions, not showing the effects of a specific scenario. This step focuses instead on examining specific instantiations of the model to understand how the potential variability of each function can become resonant, leading to unexpected results, as stated by the functional resonance process. It is therefore necessary to identify the functional upstream-downstream couplings. The variability of a function results as a combination of the function variability itself and the variability deriving from the outputs of the upstream functions, depending on the function type and the linked aspects type.

This step may be addressed qualitatively, based on potential for dampening performance variability ranges from +1 to +3 and for increasing performance variability ranges from -1 to -3 [4]. However, this step is addressed quantitatively here, through a statistical coupling between the functions' outputs variabilities.

MCS is a useful tool for modelling phenomena with significant uncertainty (or variability) in inputs and has a multitude of applications, including risk analysis. It is a fairly simple mathematical procedure, with random inputs and random outputs: $y = f(x_1, x_2, \cdots, x_n)$, where the input values are sampled and the output values are recorded and analyzed as illustrated in Figure 6 ([11],[12]).

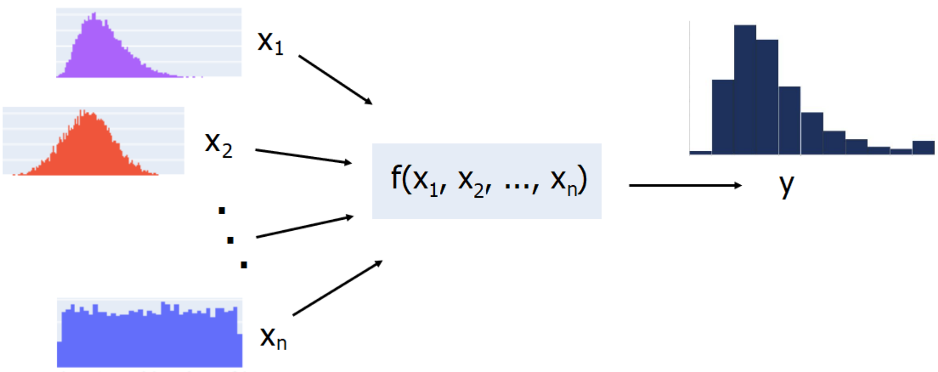

Figure 6 - Simplified Monte Carlo Simulation Procedure

The main advantage of the MC method is the low level of complexity. Another important advantage is the ease of comprehension by decision-makers. 'What-if' scenarios and the sensitivity of the outputs to input assumptions can be quickly analyzed. The disadvantages of using MC include computational intensity, especially with complex models requiring large numbers of simulation runs, although with growing computing power, this becomes less of a problem. Another potential drawback is that MC implicitly assumes that all the input parameters are independent, which may not be the case, especially with complex models [11]. Correlated inputs must be identified in advance and simulated as such.

This step is accomplished through the following stages. First, a linear regression between the function output and its inputs is performed. Many problems in engineering and science involve exploring the relationships between two or more variables. Regression analysis is a statistical technique that is very useful for these types of problems by assuming that the expected value of the output (Y) is a linear function of the input(s) ($\mathbf{X}$ or regressor variable(s)). When the model contains more than one regressor variable, it is called a multiple regression model as shows Equation (1) [13].

$$Y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_n \cdot x_n + \varepsilon \quad (1)$$

$$\mathrm{y} = \mathbf{X}.\beta + \varepsilon$$

The second stage consists of refining the model regressor variables selection. An important problem in many applications of regression analysis involves selecting the set of regressor variables to be used. Even with the use of previous experience or theoretical considerations to specify the regressor variables to use in a particular situation, sometimes not all these candidate are necessary to adequately model the response Y. In such a situation, it is interesting to screen the candidate variables to obtain a regression model that contains the “best” subset of regressors [13]. Several criteria may be used for evaluating and comparing the different regression models obtained. A commonly used one is based on the value of R^2 or the value of the adjusted R^2, R^2_{adj}. This criterion is a statistical measure of how close the data are to the fitted regression line, varying between 0 (the output cannot be explained by the inputs) and 1 (the output is perfectly explained by the inputs). In general, the higher the R^2, the better the model fits your data.

Third, the correlation between the regressor variables is checked using the Pearson Method. Correlation is a dimensionless quantity that can be used to compare the linear relationships between pairs of variables in different units [13]. Pearson’s correlation coefficient is the test statistics that measures this statistical relationship, or association. It assigns a value between -1 and 1, where 0 is no correlation, 1 is total positive correlation, and -1 is total negative one.

Based on the Pearson’s correlation coefficient, the multivariate probability distribution of the inputs is modeled by a copula. For a continuous random variable x_1 with distribution function F_{X1}, the random variable $U=F_{X1}(x_1)$ is uniformly distributed. For two continuous random variables x_1 and x_2, the distribution of the vector $(F_{X1}(x_1), F_{X2}(x_2))$ is supported on the unit square and has uniform marginals. Any such distribution is called a (bivariate) copula. This notion may be extended to as many dimensions as necessary. There are many kinds of multi-dimensional copulas ([14],[15]). In this work, the normal copula, which is one of the most common copulas, is employed.

Finally, Monte Carlo integration is conducted to estimate the final probability. This approach capitalizes on the data from small sample, extrapolating it to a big one.

2.4 Variability Management

This last step is not addressed here. It consists of monitoring and managing the performance variability, identified by the functional resonance in the previous steps. Performance variability can lead both to positive and negative outcomes. The best strategy consists of amplifying the positive effects, i.e., facilitating their happening without losing control of the activities, and damping the negative effects, eliminating, and preventing their occurrence.

3. Case Study

Runway overrun is a type of runway excursion in which the aircraft departs the end of the designated runway once it is unable to stop within the runway limit. It can occur on takeoff or landing [16]. During landing, its precursors have been identified under a Safety-I perspective as adverse weather, wet or contaminated runway surface, deficiencies in airport facilities, and flight crew operational deviations such as:

- **Unstable approaches:** an approach during which an aircraft does not maintain at least one of the following variables stable - speed, descent rate, vertical/lateral flight path and in landing configuration, or receive a landing clearance by a certain altitude.
- **Long touchdowns:** occurs when an aircraft touches the ground too far away of the aiming point, which is usually 1,000 feet from the runway threshold. RBAC (*Regulamento Brasileiro da Aviação Civil*) nº154 defines that the runway aiming point must be between 500 and 1,300 feet, depending on the runway’s length or Landing Distance Available (LDA) [17].

- **Inadequate or late use of deceleration devices**, such as ground spoilers, engine thrust reverser, normal or even emergency brakes.

This work contemplates the long touchdown precursor, analyzing the touchdown point and its correlated functions through the Safety-II perspective.

3.1 Functions Identification and Description

Figure 7 shows a diagram with the functions considered relevant to explain the performance variability of the “To Touchdown”, whose output is the focus of the current analysis. The diagram was drawn using the FRAM Model Visualiser.

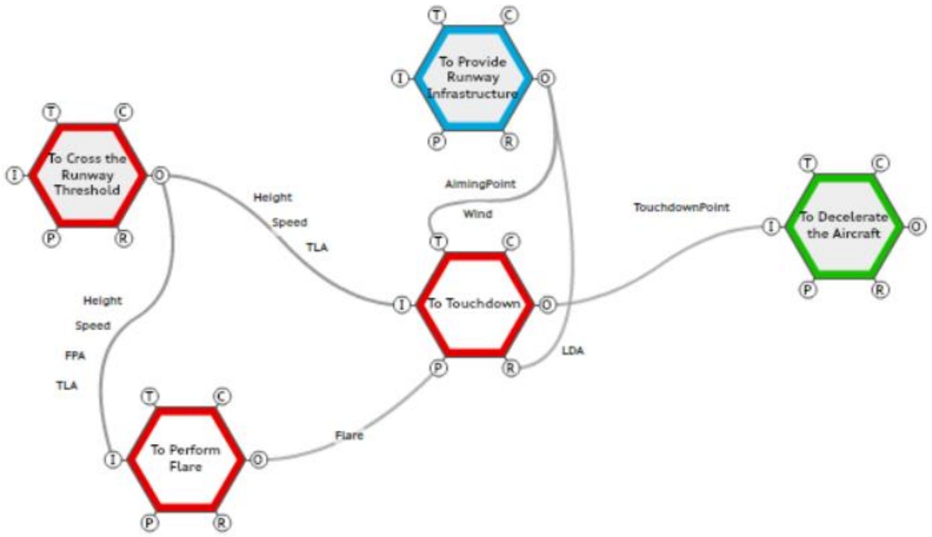

Figure 7 - FRAM Diagram for Touchdown

“To Provide Runway Infrastructure” is an organizational and background function. It represents the external environmental of the aircraft landing procedure, whose variabilities may integrate and magnify the foreground functions’ variabilities generating an undesired outcome. The flight crew uses a runway to land the aircraft, whose characteristics like length, aiming point and typical wind may influence the touchdown point.

The designated runway is intercepted by the minimum distance between the aircraft position at 50 feet Above Ground Level (AGL), provided by its linearly interpolated latitude and longitude, and its threshold, given by an external database. This database contains circa of 23,000 runways, specified by their airport ICAO Code, direction, length, aiming point position, width, altitude, threshold latitude and longitude.

Regarding the wind, some fleets are equipped with inertial and air data (barometric) systems. Thus, the values for the wind vector are computed on board and the result may be recorded. Its components, Headwind and Crosswind, are then given by Equations (2) and (3), respectively. Note that the barometric part of this calculation may be affected by the ground effect resulting in values for wind that are affected by noise. Despite this fact, the recorded values are the best an analyst can have for wind component values [18].

$$Headwind = WindSpeed \cdot cos(WindDirection - TrueHeading) \quad (2)$$

$$Crosswind = WindSpeed \cdot sin(WindDirection - TrueHeading) \quad (3)$$

“To Cross the Runway Threshold” is a human function that initiates the analysis as soon as the aircraft crosses the runway threshold. Theoretically, this crossing is performed at a height of 50 feet in landing configuration with the reference speed (v_{ref}) after a stabilized approach. An approach is stabilized when some criteria are met.

First, the aircraft must be on the correct flight path, normally given by a three-degree approach path [19]. The flight crew usually assumes the aircraft control at the Decision Altitude (DA) in a precision approach or Minimum Descent Altitude (MDA) in a non-precision approach, using the control column and the thrust lever to guarantee the correct flight path. They perform a visual approach and may use the runway markings as a navigation aid, which is, sometimes, non-standard. ICAO Annex 14 as well as RBAC nº154 contains recommendations regarding the runway markings, like aiming point and touchdown zone indication.

Second, the aircraft speed should not be more than v_{ref} + 20 knots indicated airspeed and not less than v_{ref} [19]. Still, the airspeed must be equal to v_{ref} at the runway threshold to ensure the estimated Unfactored Landing Distance (ULD). This is the distance used by an aircraft in landing and braking to a complete stop (on a dry runway at sea level) after crossing the runway threshold at 50 feet with the reference speed (v_{ref}) in landing configuration [20]. It is determined during certification flight tests with maximum brake application and without the use of thrust reverser. Corrections for airport elevation, aircraft weight, wind and icing conditions are available at the Aircraft Operating Manual (AOM).

Third, the aircraft must be in the correct landing configuration [19]. The flight crew must extend the landing gear and set the Slat/Flap position to obtain the correct configuration.

Thus, "To Cross the Runway Threshold" outputs are aircraft height, speed, and Flight Path Angle (FPA) at the runway threshold, whose references are respectively 50 feet, v_{ref}, and -3^{o}. The thrust is also an output, as idle must be established at runway threshold. This function's outputs are captured at the minimum distance between the aircraft position, provided by its linearly interpolated latitude and longitude, and the already identified runway threshold.

Once the threshold cross point is determined, height is given by the Radio Altitude, or the Pressure Altitude corrected by the runway altitude. Speed increment (Δv_{ref}) is given by actual airspeed minus v_{ref}, which depends on ice conditions, aircraft gross weight and flap position. FPA may be given by Equation (4). The difference between the pitch attitude and the angle of attack is not used to avoid the effect of wind on the descent performance estimation [21]. Thrust is given by the Thrust Lever Angle (TLA) position, which is zero (0) at idle.

$$FPA = atan\left(\frac{VerticalSpeed}{Groundspeed}\right) \tag{4}$$

"To Perform Flare" is a human function, given by the descent rate reduction to accomplish a smooth landing. It is normally performed near to the ground (less than 50 feet AGL) through the increase of aircraft pitch attitude simultaneously with the reduction of engine thrust. The detection of the point where the flare was initiated is the major challenge to evaluate this function as it is highly dependent on the aircraft handling and can be well pronounced or smoothly driven. A proposal is to monitor the time it takes during landing from 50 feet to the touchdown point [18].

Flare reflects this time, being a consequence of the "To Cross the Runway Threshold" outputs as well as its internal variability, given by the pitch attitude increase ($\Delta\theta$) and the thrust reduction (ΔTLA). $\Delta\theta$ is measured by the difference between the maximum pitch attitude before touchdown and the pitch attitude at 50 feet AGL. ΔTLA is determined by the difference between the TLA at the maximum pitch attitude before touchdown and the TLA at 50 feet AGL.

"To Touchdown" is a human function that follows the "To Cross the Runway Threshold" and uses the "To Perform Flare" as precondition. Regarding the "To Provide Runway Infrastructure", the flight crew lands the aircraft using the runway markings as reference and consuming the runway length (LDA). Its output, the touchdown point, is given by distance between the runway threshold and the aircraft position at the first air-ground transition. It starts the functions that decelerate the aircraft.

3.2 Performance Variability Characterization

A total of 288 flights were analyzed. The functions' outputs were captured for each flight and fitted to the most adequate probability distribution, using the skewness-kurtosis plot as proposed by Cullen and Frey (1999) as reference [22]. This step used the “fitdistrplus” R package [23].

One of the “To Cross the Runway Threshold” output is height. Normally, the aircraft crosses the runway threshold under 50 feet. Figure 8 reveals a box plot of this output, and the density plot of each fitted distribution with the data’s histogram. Figure 9 exposes its skewness-kurtosis plot. The sample has a median around 37 feet and some outliers under 10 feet as well as over 70 feet. The outliers over 70 feet touched more than 300 feet after the aiming point. Height is fitted to a Weibull distribution with a shape (β) of 3.087609 and a scale (α) of 42.966164.

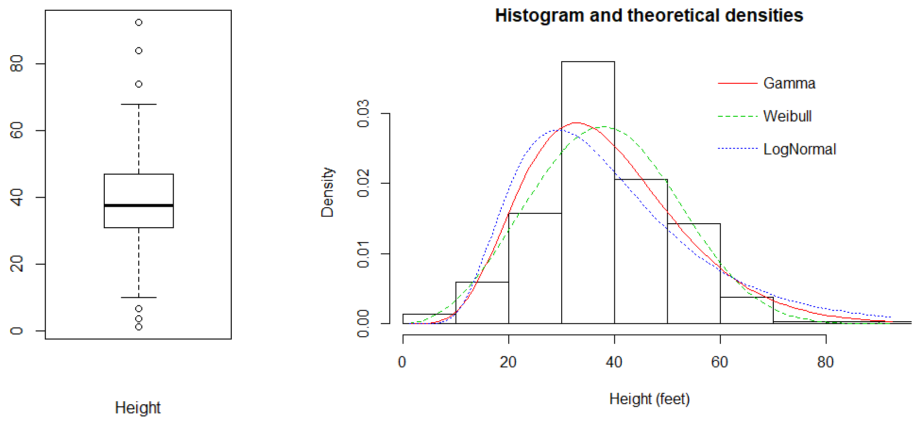

Figure 8 – Aircraft Height at the Runway Threshold (Boxplot and Histogram)

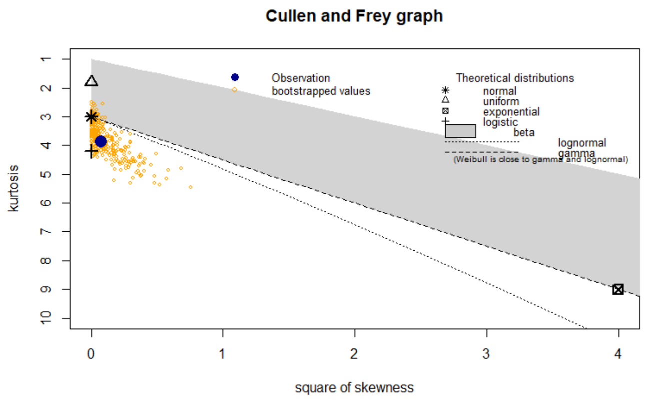

Figure 9 - Aircraft Height at the Runway Threshold (Skewness-Kurtosis Plot)

Similar analysis is then performed to each functions’ output in order to characterize their variabilities. Outputs that are restricted to positive values are fitted to distributions like Weibull, Gamma or Lognormal. The “non-positive” outputs are fitted to Normal or Logistic.

Regarding the touchdown point, the sample has a median of almost 1,500 feet and some outliers touching the ground more than 3,000 feet past the runway threshold. The outliers are a result of a shallower approach angle followed by a high and overspeed landing. However, none of them were outliers of the other functions’ outputs. In other words, the touchdown point’ outliers emerged from the combination of upstream functions’ outputs minor variabilities.

3.3 Variability Aggregation

To accomplish this step, the function to be used at the MCS must be estimated and refined. The “olsrr” R package [24] is used to build the linear regression model. The correlation between the output and its predictor variables (inputs) is then checked using the Pearson Method via the “corrplot” R package [25]. In the sequence, correlated random numbers are generated from a normal copula function via the “copula” R package ([26], [27], [28], [29]) and the simulation is conducted.

The focus of this work is the touchdown point, for which the following predictors variables are proposed: height, Δv_{ref}, FPA, TLA, flare, $\Delta\theta$, ΔTLA, LDA, headwind and crosswind. Note that the tailwind is given by a negative value of headwind, being considered a runway overrun precursor as usually increases the landing distance. The absolute value of the crosswind is employed as the wind direction, in this case, is irrelevant.

The stepwise build regression method removed the FPA, ΔTLA and headwind from the touchdown point model. $\Delta\theta$ is also excluded due to its intrinsic relationship with flare. The function obtained for the simulation is given by Equation (5). The model fitted well to the dataset as the R^2_{adj} is 0.9043 (Figure 10).

$$TouchdownPoint = \begin{matrix} 19.00073 \cdot Height + 10.25366 \cdot \Delta v_{ref} + 3.66572 \cdot TLA + 136.14892 \cdot Flare \\ +0.02538 \cdot LDA - 8.68695 \cdot |Crosswind| \end{matrix} \tag{5}$$

```
> model <- lm(TouchdownPoint ~ Height + Deltavref + TLA + Flare + RunwayLength + Crosswind, data = finalresults)
> summary(model)

Call:
lm(formula = TouchdownPoint ~ Height + Deltavref + TLA + Flare +
    RunwayLength + Crosswind, data = finalresults)

Residuals:
    Min      1Q  Median      3Q     Max
-497.35  -86.00  -16.63   66.07 1184.71

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -8.484e+02  5.677e+01 -14.945  < 2e-16 ***
Height        1.900e+01  9.084e-01  20.917  < 2e-16 ***
Deltavref     1.025e+01  2.748e+00   3.731 0.000231 ***
TLA           3.666e+00  1.380e+00   2.657 0.008335 **
Flare         1.361e+02  5.018e+00  27.130  < 2e-16 ***
RunwayLength  2.538e-02  6.924e-03   3.666 0.000295 ***
Crosswind    -8.687e+00  2.962e+00  -2.933 0.003638 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 167 on 280 degrees of freedom
Multiple R-squared:  0.9063,    Adjusted R-squared:  0.9043
F-statistic: 451.6 on 6 and 280 DF,  p-value: < 2.2e-16
```

Figure 10 - Model's Summary

Figure 11 shows the correlation between the touchdown point and its predictor variables. It has a positive high degree association with the height and TLA at the runway threshold as well as with the flare and LDA (Runway Length); a positive moderate association with Δv_{ref} (DeltaVref); and a negative low degree with the crosswind. Namely, flare is the most relevant input of the model.

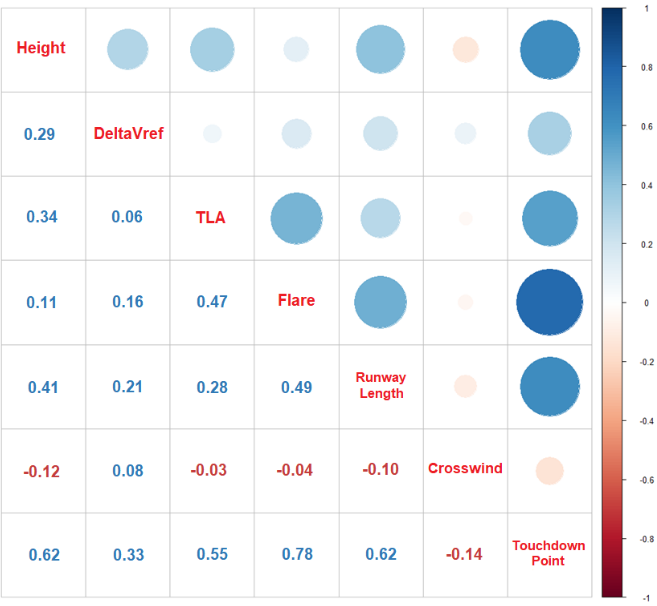

Figure 11 - Correlation by Pearson of the Touchdown Point Model

The influence of the LDA over the touchdown point may be unexpected at a first moment. Nevertheless, it is related with the runway aiming point position, that is a visual indication for the pilot and a reference for the glideslope.

Based on the initial 288 flights predictor variables probability distributions and correlation, 10,000 random numbers were generated (Figure 12). These numbers were then used for the MCS in accordance with Equation (5). Figure 13 shows the density plot of each fitted distribution with the data's histogram as well as the cumulative distribution plot. Note that 50% of the simulated flights touched the ground after 2,340 feet and only distances over circa of 3,750 feet are considered outliers.

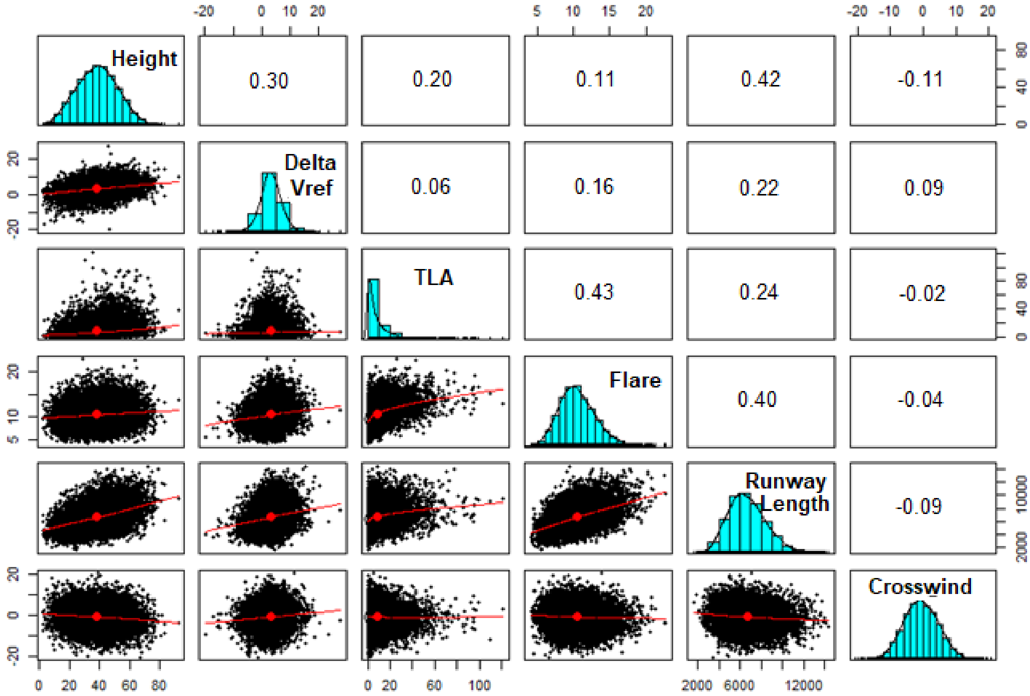

Figure 12 - Correlated Random Numbers of the Touchdown Point Predictor Variables

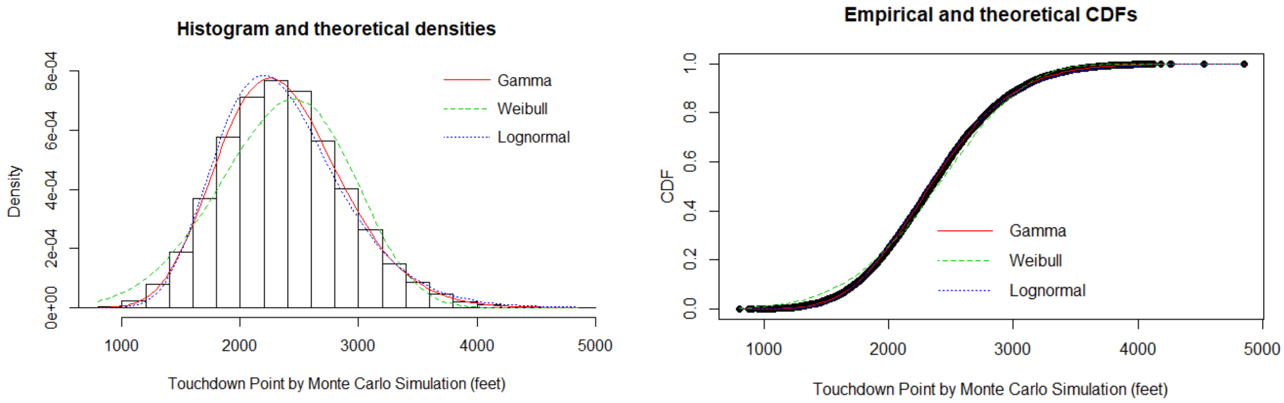

Figure 13 - The Touchdown Point Simulated through Monte Carlo

Figure 13 represents the “long touchdown” current risk of the sampled fleet, which comes from comparing the obtained values with the aiming point or, in a more elaborated way, with length of the runway. If acceptable, it can be monitored. If unacceptable, it can be managed. Through the model, it is possible to exercise mitigation actions and simulate their influence in the final output – the touchdown point.

4. Conclusions and Perspectives

This work analyzes the touchdown through the Safety-II perspective, focusing on the everyday performance and the consequent variability. The outcome is a model to assess the risk of a long touchdown during normal operation including the organizational, human, and technological aspects of the complex aeronautical system. The model uses the FRAM to have a clear description of the system functions, studying their interactions rather than the single probability of failure.

First of all, this work defines a quantitative framework which aims to enhance traditional FRAM. It proposes the use of FDM techniques to characterize the functions’ variability, and a Monte Carlo basis to define quantitatively the system resonance. Considering the variability of each function aspect, the model is able to highlight which outputs have larger influence in the final outcome – the touchdown point. It identifies potential sensitive areas in the system's functioning to take mitigating actions. Eliminating the hazard, if possible, or introducing barriers are the traditional ways to manage this variability.

Secondly, the model offers the opportunity to properly understand the real operating scenario. The risk of an unexpected or unwanted situation, like a long touchdown, in a typical operation may be estimated. Based on this risk, it is possible to evaluate the necessity of a damping strategy for the variability. Note that the model is valid for further operating scenarios, but the variables statistical distribution, copulas and functions must be calibrated to the reality under analysis.

Further research will model the "Unstable Approach" as well as the "Inadequate or Late Use of Deceleration Devices", covering the runway overrun precursors related with the flight crew operational deviations.

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6. Copyright Statement

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