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Enhancing Aviation Safety Analysis through FRAM-FDM: A Data-Driven Approach to Performance Variability

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Understanding how performance variability emerges within complex socio-technical aviation operations is critical for strengthening proactive safety management. While the Functional Resonance Analysis Method (FRAM) provides a structured framework for modelling such variability, its traditional use relies largely on qualitative judgment. This paper introduces a quantitative extension, FRAM-FDM, which integrates Flight Data Monitoring techniques to measure functional variability directly from operational flight data. By replacing subjective characterizations in FRAM's variability and aggregation steps with empirically derived metrics and regression-based modelling of functional couplings, the approach enhances analytical precision. The method is demonstrated through a case study focused on the landing-run phase of a jet aircraft fleet, using data from 110 landings. Results show that the FRAM-FDM framework augments traditional FRAM analysis by providing objective, data-driven insights, thereby supporting more robust pilot training, procedure refinement, and proactive safety strategies.

Keywords: Aviation, FRAM, Flight Data Monitoring.

1. Introduction

Complex socio-technical systems consist of diverse human, technological, and organizational components that interact in non-linear and often unpredictable ways across various domains. The Functional Resonance Analysis Method (FRAM) was developed to address the need for understanding and modelling how performance emerges in these dynamic systems, particularly focusing on the mechanisms behind everyday performance variability (Hollnagel 2012). Rather than interpreting outcomes through a predefined model, FRAM serves as a method-as-model—its primary aim is to construct representations of how things happen, enabling both qualitative and, more recently, quantitative analyses to assess risk (Reiser et al. 2023).

In the aviation sector, robust data collection mechanisms such as Safety Reporting Systems and Flight Data Monitoring (FDM) have been established under the Safety Management System (SMS) framework. Flight data, typically recorded via crash-survivable Flight Data Recorders (FDRs) or more accessible Quick Access Recorders (QARs), is routinely used in FDM programs to identify operational safety risks (Delhom 2014).

This paper introduces the third branch of FRAM-FDM—a quantitative approach that integrates FRAM with FDM to enhance the modelling and analysis of flight crew performance variability. FRAM provides a holistic framework for representing system behaviour, while FDM contributes empirical data to quantify variability in specific FRAM functions. These variabilities can be then aggregated through statistical modelling: (1) linear regression for risk assessment via Monte Carlo simulation (Reiser et al. 2022); (2) logistic regression to identify the most influential contributors to risk (Reiser et al. 2024); and (3) additional linear regressions to simulate operational scenarios using metadata in the FRAM Model Visualiser (FMV).

2. The Functional Resonance Analysis Method

FRAM 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, understanding what goes right when the daily work is carried out is as important as understanding what failed in the system (Hollnagel 2012).

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 trade-offs between being efficient and making sure the work can be completed as precisely as possible. These kinds of adjustments are named Efficiency-Thoroughness Trade-Offs (ETTOs). They are necessary and understandable; however, any changed system behaviour may raise variabilities in the system (Tian and Caponecchia 2020).

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 (Tian and Caponecchia 2020).

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 (Hollnagel 2012).

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 (Hollnagel 2012).

The modelling process consists of four steps, as follows.

2.1. *Functions Identification and Description*

FRAM's first step deconstructs the complex sociotechnical system into "functions", that represent an activity that is required to produce a certain outcome. The first step identifies the 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 (Fig. 1).

Fig. 1 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, assessing 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.

One way to assess the functions performance is to evaluate subjectively the outputs' variabilities. For instance, they could vary in terms of timing or precision. An output can occur too early, on time, too late or not at all. Regarding precision, it can be precise, acceptable, or imprecise. Note that precision is relative rather than absolute since it refers to the coupling between upstream and downstream functions. 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 one is something that is incomplete, inaccurate, ambiguous or in other ways misleading (Hollnagel 2012).

2.3. *Variability Aggregation*

FRAM's third step focuses on examining specific instantiations of the model to understand how the potential variability of each function can become resonant, leading to unexpected outcomes. 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 (Patriarca et al. 2017). It also may be addressed quantitatively like in Adriaensen et al. (2019), that used a method to identify critical functional couplings through the number of downstream dependencies for each function.

2.4. Variability Management

Fourth, performance variability is monitored and managed. This last step 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 most fruitful 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 happening.

3. Flight Data Monitoring Programs

Flight data is the information coming from aircraft sensors, onboard computers and other instruments that are recorded into an FDR and occasionally also into a QAR. For most aircraft, FDR and QAR file format follows the ARINC 717 standard, composed of a continuous stream of bits.

ARINC 717 divides data into subframes and frames. A subframe is one second long and contains anywhere from 64 12-bit words, up to 2048 12-bit words, depending on the aircraft. A frame is comprised of 4 subframes (Fig. 2). Every frame contains exactly the same information (i.e., the same parameters distribution). The four subframes within each frame are not identical. Some parameters may be found in every subframe (even multiple times), while others may appear only once per frame (ARINC 2011).

Given the FDR file in an ARINC 717 format and the map with the parameters location as stated by the aircraft manufacturer, some commercial tools can convert the raw data into a table as shown in Fig. 3. The process in which the flight data is converted into engineering units is called decoding. Schwaiger and Holzapfel (2021) proposes a method for the decoding of binary ARINC 717 recorder files.

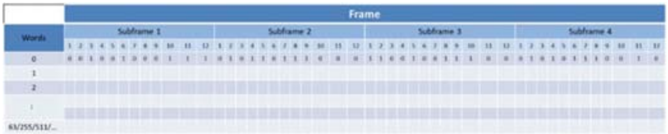


Fig. 2 ARINC 717 Structure.

Time	UTC Time	Air/Ground Transition	Groundspeed (knots)	Airspeed (knots)	Pressure Altitude (feet)	Latitude (deg)	Longitude (deg)	Gross Weight (Kg)	Pitch Attitude (deg)	Longitudinal Acceleration (g)
947577.5	14:15:26								0.5	-0.046
947577.6		1	84							
947577.8									0.5	-0.052
947577.9										
947578						-12.91048243			0.5	-0.038
947578.1				88	-180					
947578.2							-38.33194906		0	-0.07
947578.4										
947578.5	14:15:27								0	-0.062
947578.6		1	83							
947578.8									0	-0.072
947578.9										
947579						-12.91048243			0	-0.054
947579.1				86	-182					
947579.2							-38.33155994		-0.5	-0.068
947579.4										
947579.5	14:15:28								-0.5	-0.07
947579.6		0	82							
947579.8									-0.5	-0.074
947579.9										
947580						-12.91039642			-0.5	-0.108
947580.1				85.5	-182			4400		
947580.2							-38.33121997		-0.5	-0.126
947580.4										

Fig. 3 FDR Raw Data Converted into a csv File.

The decoded aircraft parameters represent the entry point and are used for measurement calculations, which may be analysed by means of distributions or directly compared with a threshold to produce events (EASA 2022). The distributions and events are investigated to highlight any trend that could show a latent or potential risk. FDM programs are applied reactively through analysis of incidents or accidents; proactively through analysis of the airline's activities; and predictively through data gathering to identify possible adverse future outcomes (Delhom 2014).

The EASA Guidance for the Implementation of Flight Data Monitoring Precursors (2022) introduces algorithms to mitigate hazards across four key risk areas: Runway Excursion (RE), Loss of Control in Flight (LOC-I), Controlled Flight into Terrain (CFIT), and Mid-Air Collision (MAC). These algorithms rely on predefined thresholds and operate independently, leaving the overall fleet risk uncertain since interactions among hazards are not assessed.

While some airlines have also begun analysing flight data without thresholds—examining distributions of routine operational data to gain a broader understanding of performance—the algorithms themselves remain isolated from one another.

4. An Introduction to FRAM-FDM

The FRAM-FDM approach extends the traditional FRAM framework by introducing enhancements to Steps 2 and 3 (Fig. 4).

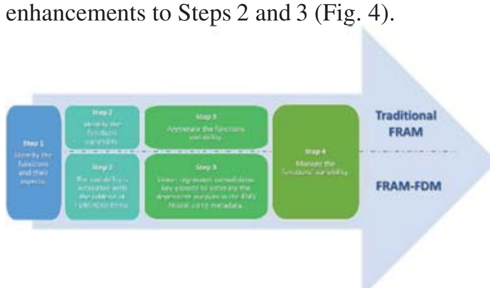


Fig. 4 Steps of FRAM compared to FRAM-FDM.

Rather than assessing function variability subjectively in Step 2, FRAM-FDM applies FDM techniques to quantify system variabilities—using algorithms similar to those referenced in EASA Guidance. Unlike event-based approaches that count threshold crossings, the goal here is to understand the system's everyday behaviour and estimate how each function fluctuates in real-world conditions.

Instead of qualitatively assessing function variability in Step 3, this approach uses regression analysis to quantify and predict certain function outputs based on their inputs. Regression analysis is a statistical method that estimates the expected output (Y) as a linear function of one or more input variables (**X**). When multiple input variables are included, the model is referred to as a multiple regression model, as illustrated in Eq. (1) (Montgomery and Runger 2003).

$$Y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_n \cdot x_n + \varepsilon$$
$$\mathrm{Y} = \mathbf{X}.\beta + \varepsilon \quad (1)$$

The FRAM model, along with its measured and estimated variabilities, can be integrated into the FRAM Model Visualiser (FMV). This application enables building and exploring FRAM models to understand how function couplings shape system behaviour. Its evolution introduced the FRAM Model Interpreter (FMI), which simulates models in real time, validates structure, and visualizes results. FMI also supports metadata—user-defined key–value pairs that can store descriptive or quantitative data, including dynamic values computed during interpretation and propagated through aspect couplings, enabling structured quantitative analysis (Hill and Slater 2024).

5. Case Study

The methodology described in Section 2 and 4 was applied to the landing run of a sample fleet, starting at the aircraft touchdown. A total of 110 landings were analysed.

5.1. *Functions Identification and Description*

In Step 1, the landing-run procedure is deconstructed into 7 functions, as shows Fig. 5. Functions shaded in grey are performed by the pilots, those in green represent the aircraft's response to pilot inputs, and those in pink denote environmental conditions.

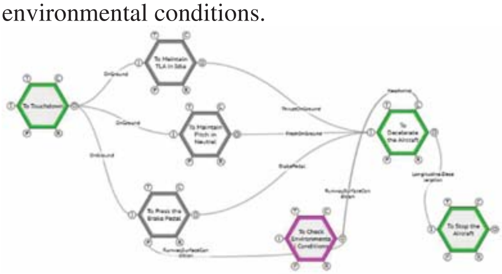


Fig. 5 FRAM Model.

The function 'To Touchdown' initiates the analysis as soon as the aircraft transitions from air to ground. Its output, OnGround, triggers the subsequent functions responsible for decelerating the aircraft—namely, "To Press the Brake Pedal", "To Maintain Pitch in Neutral", and "To Maintain TLA in Idle". The fleet examined does not employ ground spoilers, thrust reversers, or autobrake systems.

The function "To Press the Brake Pedal" represents the flight crew's application of the brake pedal, which varies throughout the landing run. As groundspeed decreases, the effectiveness of the normal wheel brakes increases due to the progressive loss of lift and the resulting rise in the load over the wheels. Consequently, the brake pedal output is defined as the brake pedal application normalized by groundspeed, expressed as their arithmetic mean (Eq. (2)).

$$BrakePedalOutput = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{BrakePedal}{Groundspeed} \quad (2)$$

The landing run should be performed with pitch command in neutral position and the TLA in idle as stated by the "To Maintain Pitch in Neutral" and "To Maintain TLA in Idle" functions, respectively. A pitch down command moves the load distribution from the main landing gear to the nose one, diminishing braking efficiency and affecting the aircraft deceleration. An increase in the TLA position accelerates the aircraft via an expansion of the engine thrust.

The "To Decelerate the Aircraft" function uses three inputs: the brake-pedal application normalized by groundspeed, and the arithmetic means of pitch and TLA. The resulting output of this function is the aircraft longitudinal deceleration, which is also influenced by environmental factors such as wind and runway surface condition.

5.2. *Performance Variability Characterization*

For Step 2, FDR raw data from a typical jet is converted into csv files and analysed using R. R is a programming language and free software environment for statistical computing and graphics (R Core Team 2024).

Based on an 8 sps sampling rate, the analysis in R functions begins by interpolating the selected parameters to fill the gaps caused by lower sample rates. Continuous parameters are linearly interpolated to enhance their precision (e.g., brake pedal position), while positional and discrete parameters remain constant until the next sample (e.g., thrust lever angle and air ground transition, respectively). The data is then split into flights, identified by the engines start/stop, and used to compute the FRAM functions outputs for each flight cycle.

Aircraft air-ground transition, brake-pedal position, groundspeed, pitch attitude, and thrust-lever angle are recorded parameters, along with wind speed and direction. The longitudinal wind component is then estimated using Eq. (3).

$$Headwind = WindSpeed \cdot \cos(WindDirection - TrueHeading) \quad (3)$$

The runway surface condition is assessed using an index (Eq. 4) that reflects the interaction between the aircraft and runway through anti-skid actuation. It compares actual brake pressure with the expected value based on brake pedal input, which is typically reduced by anti-skid action influenced by friction, tire condition, speed, and wheel load. Values near 1 indicate optimal conditions, while lower values denote poor interaction.

$$Runway\ Surface\ Index = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{BrakePressure}{ExpectedBrakePressure} \quad (4)$$

Fig. 6 illustrates a subset of the 110 analysed landings, with each line representing a distinct instantiation.

Flight	Brake Pedal (Normalized)	Pitch OnGround	Thrust OnGround	Headwind	RunwaySurface Condition	Longitudinal Deceleration
1	1.33	-0.88	0.15	2	0.46	-0.27
2	1.50	-1.98	0.15	-5	0.37	-0.30
3	0.94	-0.90	0.20	-4	0.81	-0.21
4	1.29	-0.89	0.16	0	0.34	-0.21
5	1.23	-0.94	0.17	-5	0.52	-0.25
6	1.31	-1.21	0.32	-6	0.49	-0.24
7	0.82	-1.42	0.15	4	1.00	-0.26

Fig. 6 Some Analysed Landings.

5.3. *Variability Aggregation*

The functions "To Decelerate the Aircraft" indicate the aircraft response to the pilots' inputs and environmental conditions. Its output (i.e., the longitudinal deceleration) may be measured through FDR data (Fig. 6) but also estimated to exercise different inputs from the flight crew.

The longitudinal deceleration function was derived using a linear regression implemented with the 'lm' function from R's stats package (R Core Team, 2024). Table 1 lists the input variables and corresponding coefficients. The model demonstrated a satisfactory fit, with an adjusted R^2 of 0.8135—a measure of how closely the data aligns with the regression line, where values range from 0 (no explanatory power) to 1 (perfect fit).

Table 1 Summary of the Linear Regression.

Inputs	Coefficients	p-Value
BrakePedal-	0.2230432	< 2e-16
PitchOnGround	-0.0249746	0.000303
ThrustOnGround	-0.0317916	0.284041
Headwind	-0.0004438	0.245712
RunwaySurfaceCondition	0.1372878	3.77e-10
-	-0.1093121	8.08e-05

5.4. *Variability Management*

The FRAM model is imported into the FMV for simulation under varying conditions, combining fixed and variable outputs. Longitudinal deceleration (LONGDECEL) is treated as a variable output within the 'To Decelerate the Aircraft' function (Fig. 7).

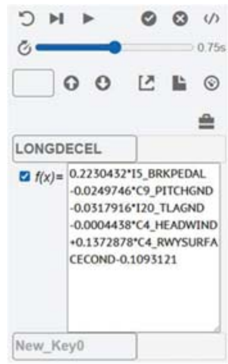
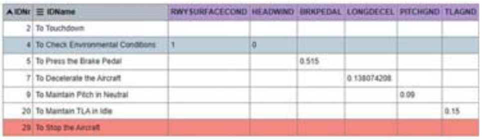


Fig. 7 Metadata of the "To Decelerate the Aircraft"

The normalized brake pedal (BRK-PEDAL), the pitch and thrust on ground (PITCHGND and TLAGND), the longitudinal component of the wind (HEADWIND) and the runway surface condition (RWYSURFACE-COND) are treated as fixed variables, as exemplified by Fig. 8.

Fig. 8 Metadata of the "To Check Environmental Conditions".

When the FMI interpretation begins, the entry and background functions provide their metadata—represented as key–value pairs—through their couplings to the downstream functions' aspects, when applicable. In the subsequent FMI cycles, the foreground functions deliver their own key–value pairs to their downstream functions as they become active. The interpretation ends once the exit functions have been reached. The outcome of each instantiation is then presented in a table, as illustrated in Fig. 9.



IDNr	IDName	RWYSURFACECOND	HEADWIND	BRKPEDAL	LONGDECEL	PITCHGND	TLAGND
2	To Touchdown						
4	To Check Environmental Conditions	1	0				
5	To Press the Brake Pedal			0.515			
7	To Decelerate the Aircraft				0.138074208		
9	To Maintain Pitch in Neutral					0.09	
20	To Maintain TLA in Idle						0.15
29	To Stop the Aircraft						

Fig. 9 Example of the Metadata Output of an Instantiation

To simulate additional scenarios, the fixed variables must be adjusted. These adjustments can be applied individually or combined with repeated activations of the entry functions. Repetition is achieved by entering a value in the text box beneath the O control, which generates new outputs (Fig. 10). Scenario variation can then be introduced by applying mathematical functions to the fixed variables, such as *rndi(a,b)*—which returns a random integer between a and b—or *xref(,)*, which retrieves cross-referenced values from a .csv file.

Fig. 10 Repetitive Activation of the "To Touchdown" function

The FRAM model within the FMV enables the exploration of emergent behaviours across different scenarios, thereby enhancing the understanding of specific instantiations. Once the points of attention for the analysed fleet are identified, they can be addressed through recurrent flight crew training, reinforced during safety meetings, or incorporated into updates to standard operating procedures.

Table 2 consolidates the functional architecture of the FRAM model developed for the case study, specifying each function's classification (entry, foreground, background, or exit), its corresponding output, and whether that output is treated as a fixed or variable key–value metadata element within the FMV framework.

Table 2 Summary of the Case Study FRAM Model

Function	Type	Output	Type
To Touchdown	Entry	OnGround	-
To Press the Brake Pedal	Foreground	BrakePedal	Fixed key-value
To Maintain Pitch in Neutral	Foreground	PitchOnGround	Fixed key-value
To Maintain TLA in Idle	Foreground	ThrustOnGround	Fixed key-value
To Decelerate the Aircraft	Foreground	LongitudinalAcceleration	Variable key-value
To Stop the Aircraft	Exit	-	-
To Check Environmental Conditions	Background	RunwaySurfaceCondition	Fixed key-value
		Wind	Fixed key-value

6. Conclusions

The current study demonstrates that integrating the Functional Resonance Analysis Method (FRAM) with Flight Data Monitoring (FDM) provides a robust, data-driven approach for examining performance variability in complex socio-technical aviation operations. By quantifying the variability of selected FRAM functions using flight data and applying statistical modelling—particularly linear regressions—the proposed FRAM-FDM framework overcomes the limitations of purely subjective assessments traditionally used in Steps 2 and 3 of FRAM.

Integrating these quantified variabilities into the FRAM Model Visualiser (FMV) and

Interpreter (FMI) enabled the simulation of multiple operational scenarios, enhancing the ability to explore emergent behaviours and identify conditions under which performance variability may become resonant.

Overall, the FRAM-FDM approach enhances the understanding of coupled system behaviours and offers a structured pathway to improve training and procedures.

Future research may extend the FRAM-FDM framework by applying it to additional flight phases—such as approach, flare, or go-around—to evaluate whether the variability patterns identified in the landing-run phase hold across broader operational contexts.

Expanding the analysis to larger and more diverse fleets, and comparing results across different aircraft types, operating environments, or airline procedures, would further enhance understanding of resilience patterns in routine operations. Such developments would also support the validation of the method's scalability and strengthen its contribution to proactive safety management and training.

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