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Uncertainty Modeling in Aeronautical System Testing Campaigns: An approach using Fuzzy Logic and Monte Carlo Simulation

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During an aircraft development, several tests are performed to assure the safety of flight and the compliance with certification requirements. These testing campaigns require significant resources, such as prototypes availability, technical staff and material resources. An effective planning is essential to avoid impact on the prototype schedule, and subsequent phases, including marketing and certification campaigns. This work proposes the combination between Fuzzy Theory and Monte Carlo Simulation (MCS) to evaluate the testing campaigns schedule and the risks associated with reducing the planning, through modeling the uncertainties. The Fuzzy Theory handles the subjective data and adverse conditions, while the Monte Carlo Simulation estimates temporal uncertainties, based on probabilistic models and data elicited with specialists.

Keywords: Elicitation, Fuzzy, Fuzzy Logic, Fuzzy Inference, Monte Carlo Simulation, MCS.

1. Introduction

During the development phase of an aircraft, an aeronautical prototype is built to perform ground and flight tests in order to validate and verify the systems implementation. According to SAE ARP-4754B (2023), ground and flight testing must be performed to confirm the required assumptions and analysis used during the safety assessment process and to ensure that the design safety issues are addressed. In this way, the prototype undergoes a series of ground and flight test campaigns. These testing campaigns evaluate handling qualities, operational performance, systems operation, and for certification purposes, the testing campaigns are undertaken to show compliance with the certification requirements.

Planning such testing campaigns requires a robust strategy to coordinate multiple departments and teams, secure the availability of essential resources, and, most importantly, accurately forecast the testing duration to minimize delays and optimize efficiency.

The testing campaigns are surrounded by uncertainties that impact the execution time of the tests, such as: the experience of the team, the complexity of the test execution, the initial condition of the aircraft (previous failures, limitations, and restrictions), physical conditions of the participants (availability, fatigue, exhaustion, stress, etc.), weather conditions, and more. These uncertainties must be taken into account during the planning phase to produce a more accurate and reliable schedule.

Faced with these uncertainties, traditional planning techniques are often insufficient to ensure the required level of accuracy (Kong et al. 2015). In this context, the combination of advanced methods, such as Fuzzy Theory and Monte Carlo simulation, emerges as a promising solution. Fuzzy Theory, by handling imprecise or subjective information—such as failure predictions and the interpretation of anomalous behaviors during tests—provides a robust approach to incorporating these uncertainties into the planning process, making it more adaptable and effective. Meanwhile, Monte Carlo simulation enables the modeling of variability and uncertainties present in the preparation and execution processes, offering a more realistic forecast of activity durations and resource utilization.

This article explores how the combined application of fuzzy logic and Monte Carlo simulation can optimize the planning of system integration test campaigns, supporting more informed decision-making. Monte Carlo simulation involves discretizing input data, while fuzzy logic accounts for the subjectivity and uncertainties of the data (Brandão 2008). By integrating simulation and fuzzy reasoning, it becomes possible to develop more flexible and accurate models that adapt more effectively to variations in the testing environment while minimizing the impact of uncertainties. This results in more efficient campaigns with reduced risk of delays.

The use of simulations, such as fuzzy inference and Monte Carlo, enables predictions of performance, test scenarios, and risk analysis, thereby mitigating uncertainties in the process. This integrated approach ensures a robust framework for managing complex test campaigns.

Based on this introduction, this article aims to (1) propose a method for predicting a more accurate schedule for testing campaigns using Fuzzy Theory and Monte Carlo Simulation; (2) apply the proposed method to a real-world case to evaluate the feasibility and risks associated with reducing the duration of a testing campaign; and (3) compare the results obtained with a maximum time allocated.

2. Literature review

Modeling uncertainties in test campaigns for aeronautical systems is a critical issue due to the complexity and risks inherent in the development of aeronautical prototypes. In planning these campaigns, traditional methods often prove insufficient to deal with uncertainties related to team experience, adverse conditions and variability in execution times. In this sense, the combination of advanced theories, such as fuzzy logic and Monte Carlo simulation, is emerging as a promising approach to improving the reliability and efficiency of schedules.

Expert elicitation is widely used to quantify uncertainties in scenarios where historical data is non-existent or insufficient. Pestana (2017) highlights the relevance of this method in reliability analyses, emphasizing that the combination of opinions from experienced experts and mathematical techniques, such as fuzzy logic, can result in a more realistic modeling of uncertainties. This approach ensures that planning incorporates expert judgment, leading to more accurate and reliable estimates. To enhance the reliability of expert opinions, it is essential to calibrate them by assigning weights to the elicited data. Several methods exist for this purpose, but weight assignment is a cognitively demanding task, subject to biases and influenced by the assessment method used and it is determined by procedural aspects (Riabacke, Danielson, and Ekenberg 2012).

Monte Carlo simulation is a computational technique that generates random sampling to estimate the probabilities of different outcomes in processes that involve uncertainty, based on historical data or expertise field (Takeshi 2013, Alzarrad 2020). It is widely used in fields such as engineering, finance, and project management to model the variability of complex systems and assess risks or forecast results.

Fuzzy logic stands out for its ability to deal with subjective and imprecise data. This technique is widely used in systems where variables cannot be modeled accurately, such as in handling uncertainties in construction projects that integrates risk management (Doungsoma and Pawan 2023, Marrouchi, Hessini and Chebbi 2024). Its application allows factors such as variability in environmental conditions or human performance to be incorporated into the planning model, promoting greater flexibility and adaptability.

Using fuzzy sets, linguistic variables and inference rules, it is possible to model systems with greater adaptability to the uncertainties of the environment. Work such as that by Marrouchi, Hessini and Chebbi (2024) demonstrates the effectiveness of fuzzy logic in resource optimization and planning problems in complex systems such as energy networks, highlighting its applicability in other operational contexts including the aeronautical sector.

Several studies highlight the benefits of Monte Carlo simulation in project scheduling, such as improving the accuracy of completion time predictions and identifying potential risks. Karabulut (2017) explores the integration of Monte Carlo simulation with project management techniques to enhance construction project planning, focusing on scheduling challenges and uncertainties inherent in project management. Kong et al. (2015) focuses on using Monte Carlo simulation to evaluate the risks associated with scheduling in construction projects. The method captures variability in project timelines by incorporating input data represented as probability distributions. Both studies demonstrate how probabilistic modeling can enhance decision-making in complex environments, emphasizing the importance of integrating risk assessments into schedule management to reduce project delays and budget overruns.

The integration of risk assessment techniques is a way to provide more comprehensive methods for decision-making in complex scenarios. Alzarrad (2020) proposes a hybrid approach to optimize resources planning and operation by combining probabilistic methods and fuzzy set theory to address both random and subjective uncertainties.

3. Method

This work proposes a method to forecast the duration of a testing campaign regarding the uncertainties inherent in this process, based on the specialist's opinion and using probabilistic methods and tools.

The process begins with an elicitation phase involving specialists with experience in similar test campaigns. In his case study, Pestana (2017) employed a structured scoring method to evaluate the expertise of specialists based on objective criteria, such as prior experience, academic background, and participation in similar studies. A similar approach is applied in this study, assigning scores to specialists according to their experience and expertise in test campaigns, based on the following criteria:

- Experience, regarding their tenure with company in this area of actuation;
- Number of test campaigns they had participated in.

In the next step, fuzzy logic is applied to model the variability and uncertainty inherent in the process. Linguistic variables and inference rules are defined to create a fuzzy system, which is then applied to the elicited data to adjust the time estimates provided by specialists. The defuzzification process converts the fuzzy results into numerical values using the centroid method (Mamdani model).

The numerical values obtained from defuzzification are aggregated across specialists for each test point, producing the mean and standard deviation (sd) that characterize a normal distribution for the adjusted duration of each test point.

In this work, Monte Carlo simulation is employed to predict the total duration of the process taking into account various factors, including the significant variability in setup and test execution times. The simulation is performed using a function designed to calculate the total testing duration based on the parameters involved in the process.

4. Development

4.1. Case study

In general, a planning of a testing campaign consists of: selection of test points, definition of a daily work schedule, identification of required support (technical staff, equipment and material resources), and the estimate of the testing campaign duration. It includes preparation time, breaks time, set-up time, and execution time for each test point.

Typically, a time slot is allocated for the test, accounting for general uncertainties. However, this allocated time may either be insufficient or excessive. In both scenarios, the schedule is negatively impacted, leading to delays or inefficient use of the prototype's availability.

In this work, the proposed method is applied to a real-world case to predict the duration of a testing campaign, aiming to create a more accurate schedule while reducing the predicted time and assessing the associated risks of this reduction.

4.2. Analysis

The elicitation process was conducted with a group of three engineers, each with experience in at least one test campaign. Table 1 and Table 2 outline the objective criteria used to assess their expertise, assigning a score to each level of proficiency. Based on these criteria, each specialist was evaluated and assigned a score. The individual scores were then summed and normalized, resulting in a weight for each specialist. The final weights are presented in Table 3.

Table 1: Score based on years of experience within the company

Experience	Points
0 to 5 years	1
6 to 10 years	2
11 to 15 years	3
16 to 20 years	4
21 years or more	5

Table 2: Score based on the number of test campaigns participated in

Number of test campaigns	Points
0 to 1	1
2 to 4	2
5 to 8	3
9 to 12	4
13 or more	5

Table 3: Weight obtained for each expert

Expert	Experience	Test campaigns	Total	Weight
A	27 years (5 points)	12 tests (4 points)	9	45 %
B	18 years (4 points)	2 tests (2 points)	6	30 %
C	6 years (2 points)	5 tests (3 points)	5	25 %

For the fuzzy inference in this case study, a fuzzy system was developed using defined linguistic variables and fuzzy rules. The linguistic variables are detailed in Table 4 for complexity, Table 5 for estimated time, and

Table 6 for adjusted time. The corresponding fuzzy rules are provided in Table 7.

Table 4: Linguist variable for complexity

Complexity (fuzzy triangle)	
Low	0, 2, 4
Moderate	2, 4, 6
High	4, 6, 8
Very high	6, 8, 10

Table 5: Linguistic variable for estimated time

Estimated time (fuzzy normal)	
Short	mean = 20, sd = 6
Medium	mean = 40, sd = 6
Long	mean = 60, sd = 6

Table 6: Linguistic variable for adjusted time

Adjusted time (fuzzy normal)	
Short	mean = 15, sd = 5
Medium	mean = 30, sd = 5
Long	mean = 45, sd = 5
Very long	mean = 60, sd = 5

Table 7: Fuzzy rules

Inputs		Output
Estimated time	Complexity	Adjusted time
Short	Low	Short
Short	Moderate	Medium
Medium	Low	Short
Medium	Moderate	Medium
Medium	High	Long
Long	Moderate	Medium
Long	High	Long
Long	Very high	Very long

Complexity is represented as a rating on a scale from 0 to 10 representing the challenges involved in executing the test procedures and verifying the expected results. The estimated time was derived from the elicitation process conducted with the specialists, while the adjusted time was obtained through fuzzy inference.

Fig. 1 presents the membership functions of the inputs (estimated time and complexity) and of the output (adjusted time) variables.

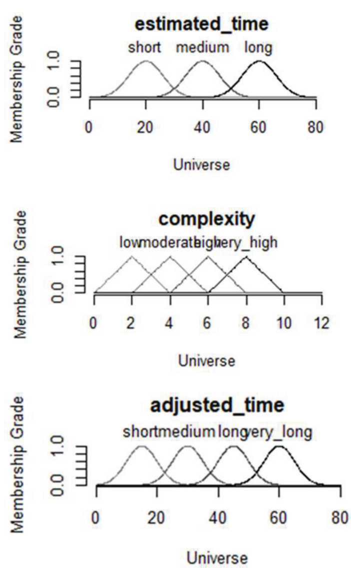

Fig. 1. View of fuzzy system membership function.

Fuzzy inference was conducted using RStudio (version 2024.04.2 Build 764)[a] with the "sets" package (version 1.0-20)[b], producing adjusted time based on test complexity, as assessed by specialist for each test point.

Following the fuzzy inference, the adjusted times were aggregated by integrating the weighted contributions of each specialist. The mean of the aggregated adjusted time was calculated using the weighted average formula shown in Eq. (1), and standard deviation (sd) was calculated using the formula shown in Eq. (2); where *i* is the *i*-th test point.

$$mean_i = \Sigma_i \left(weight_i \cdot time_{adjusted_i} \right) \tag{1}$$

$$sd_i = \sqrt{\Sigma_i \left(weight_i \cdot \left(time_{adjusted_i} - mean_i \right)^2 \right)} \tag{2}$$

The aggregated results are expressed as mean and standard deviation (sd).

For the Monte Carlo simulation, the parameter used to predict the total duration of the test campaign are presented in Table 8.

Table 8: Proposed case parameters

Number of test points	N = 20
Daily working hours per day	T_journey = 16h = 960 min (2 work shifts)
Preparation time	T_prep = 150 min
Break time	T_intervals = 180 min
Effective time per day	T_effective = 630 min
Set-up time	T_setup = Uniform distribution (5,180) / per teste
Allocated slot of time	5 days
Target time	3 days

Although preparation and break times are subject to variability and uncertainty; however, in this work, the mentioned times are considered fixed durations and are subtracted from the daily working hours, thereby determining the effective available time per day.

The set-up time refers to the time required to prepare the aircraft for the next test point. This includes resetting failure messages, returning systems to their normal configuration, setting parameters, and other necessary actions. It depends on the results of the previous test point and how it concluded. Additionally, any unexpected situation, involving the aircraft or not, such as weather condition, may affect the set-up time. Given the uncertainties and variability involved, the set-up time was modeled using a uniform distribution, ranging from 5 to 180 minutes.

The allocated time represents the available duration to complete the testing campaign, while the target time is the goal set to improve the efficiency of the testing campaign planning.

The equation used in the Monte Carlo simulation to calculate the total testing duration is presented in Eq. (3).

$$D_{total} = \frac{\Sigma_{i=1}^{N} \left(T_{test_i} \right) + \Sigma_{i=1}^{N} \left(T_{setup_i} \right)}{T_{effective}} \tag{3}$$

Monte Carlo simulation was conducted using RStudio (version 2024.04.2 Build 764)[a], generating the total testing duration results, after 10,000 simulation iterations.

The simulation results show that the mean duration of the testing campaign is 3.84 days, with a standard deviation of 0.36 days. Additionally, there is a 99.93% probability that the duration will be 5 days, while the probability to complete the testing campaign in 3 days is 0.96%.

Fig. 2 presents the probability density function and Fig. 3 presents the cumulative density function.

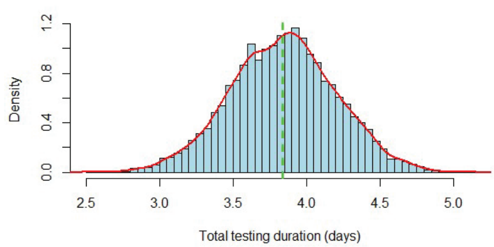

Fig. 2. Distribution of total testing campaign duration

[a] RStudio Team. *RStudio: Integrated Development Environment for* R. Version 2024.04.2 Build 764. Boston, MA: RStudio, PBC. Available at: https://posit.co/.

[b] Meyer, Matthias, and Florian Leisch. 2023. *sets: Set Theory, Generalized Sets, Customizable Sets and Intervals*. R package version 1.0-20. Available at: https://CRAN.R-project.org/package=sets.

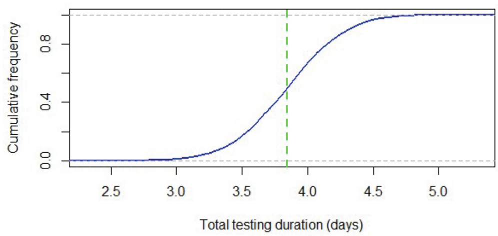

Fig. 3. Cumulative distribution of the total testing campaign duration

4.3. Discussion

The elicitation of specialists was conducted using a straightforward and traditional scoring method based on their expertise. While this approach may involve some degree of subjectivity, and no universal rule guarantees that specialist expertise always leads to optimal results (Pestana 2017), this method contributed to enhance consistency and reliability in the outcomes.

The Fuzzy Theory adjusted the estimated time provided by specialists taking into account the complexity involved in executing the tests, as defined by the established rules. In many cases, the adjusted time exceeded the estimated time, even when the complexity level is not so high. This phenomenon occurs due to the overlapping membership functions of the input (estimated time and complexity) and output (adjusted time) variables, as shown in Fig. 1, which simultaneously activate multiple fuzzy rules. The centroid method balances these influences, with a weighted average of contributions. As a result, the aggregation of outputs from these rules leads to a higher defuzzified value, reflecting the system's interpretation of the combined uncertainty and variability in the inputs.

Applying fuzzy inference separately for each specialist, prior to aggregation across them, captures their distinct perspectives and judgments, preserving variability and resulting in a more comprehensive model. In contrast, aggregating beforehand simplifies the process but sacrifices detail and precision.

Monte Carlo simulation can generate a vast number of scenarios by accounting for input variabilities, resulting in a distribution of values and their frequencies. This approach offers insights into the mean and maximum time durations, as well as the risks associated with reducing the duration of the testing campaign.

In this case study, the Monte Carlo simulation demonstrates that completing the testing campaign within the initially allocated 5 days is significantly more feasible, with probability of 99.93%, than achieving the target reduction to 3 days. As presented in Section 4.2, the probability of completing the campaign in 3 days is 0.96%, highlighting the high risk associated with such a reduction. Conversely, there is a 50% probability of completing the campaign in 3.86 days, indicating that the proposed target is overly ambitious and likely unrealistic within the constraints.

5. Conclusion

The aircraft testing campaigns are surrounded by uncertainties and variabilities that were modeled in this study through the use of the Fuzzy Theory and Monte Carlo simulation. These methods have proven effective to handle deviations in the process and collaborates to produce a more reliable planning. It provides decision-makers with the ability to reduce risk in the outcome and make a more well-founded decision.

Using only the Monte Carlo simulation on the elicited data would be feasible and provide a reasonable prediction, effectively addressing uncertainties and variabilities. However, the integration of fuzzy variables to account for the subjective nature of test complexity enhances the process. This fusion of methods represents a key advantage, combining quantitative precision with qualitative insights.

This study is grounded in a real-world case, with data elicited from specialists experienced in conducting testing campaign. Additionally, the information utilized, such as complexity, preparation time, set-up time, and other parameters, are also derived from practical scenarios, ensuring the analysis is both relevant and realistic.

Although the study focused on aircraft testing, the method shows potential to be adapted to other sectors facing similar challenges, such as construction and energy.

6. Future studies

For future studies, eliciting a larger number of specialists could enhance the reliability and representativeness. Other parameters, such as the complexity of the tests, may also be included in the elicitation process. Additionally, alternative elicitation methods, such as Cooke's method, Bayesian approaches, or Monte Carlo simulation, may be explored to incorporate probabilistic distributions and better manage uncertainty.

The method proposed in this work can be applied to a wider range of tests. Furthermore, it may incorporate other variables, such as weather constraints and equipment availability, to enhance the accuracy of the simulations and expand their scope.

To further enhance the risk analysis, the methodology could be complemented with failure assessment techniques, such as Failure Mode and Effect Analysis (FMEA) or Fault Tree Analysis (FTA), allowing for a more detailed and comprehensive view of the threats and uncertainties during the execution of the testing campaign.

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Appendix A. Data and Code Availability

The code used in this study was developed in RStudio and is available at the link below, providing full reproducibility of the analyses performed.

https://drive.google.com/file/d/15QF1lcLrKJHWSu9IXK7Y7aQbGNwLkbtv/view?usp=sharing

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