A PROPOSAL OF A MIXED FUZZY LOGIC/ROUGH SETS FRAM MODEL FOR COMPLEX SYSTEMIC ANALYSES OF SOCIOTECHNICAL SYSTEMS

By

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FOREWORD

Pursuing a Ph.D. degree was a harder journey than anticipated! The idea of contributing to human knowledge in any shape or form was always attractive to me ever since I was in high school. It represented to me one of the honorable things that one could achieve in life. Now standing shortly before the end of this project, which started three and a half years ago, the journey was also more rewarding than ever expected!

For this project, I was granted a high level of freedom and autonomy by my supervisor to select the general direction of this study, for which I am very grateful. The topics covered by this thesis are subjects, about which I am very passionate. I tried to explain the ideas and concepts addressed in this dissertation thoroughly as much as the scope of this study allowed. I believe that the disciplines of fuzzy logic and rough sets can offer many advantages to the field of risk and safety management, especially when dealing with uncertain and incomplete information. Their usefulness has been demonstrated in many applications since their introduction in the second half of the 20th century and they enjoyed popularity in several fields such as control and automation, machine learning and decision-making. However, the leap into the domain of safety management remained limited and mostly did not extend beyond theoretical frameworks and specific contexts. This area of research could offer many innovative solutions and should therefore be studied more extensively. The results presented in this study are meant to be a pointer in that direction, to hopefully lead to more interest and initiate more similar projects in the future. From a personal perspective, this is just a first step that will hopefully lead to many other steps on my academic track.

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Une proposition d’un modèle FRAM combinant la logique floue et la théorie des ensembles approximatifs pour les analyses systémiques de systèmes sociotechniques complexes

Hussein SLIM

RÉSUMÉ

Les systèmes sociotechniques modernes se développent continuellement à un rythme rapide, ce qui entraîne une plus grande complexité et une plus grande interconnectivité entre leurs composants. La vision traditionnelle des méthodes bien établies d'évaluation des risques et de la sécurité a adopté une philosophie de cause à effet linéaire axée sur ce qui pourrait mal tourner (SAFETY-I). L'accent était principalement et simplement dirigé sur l'identification des erreurs, des causes profondes et des événements singuliers, qui pourraient directement causer des accidents et conduire à des résultats indésirables. Cependant, compte tenu de la complexité des systèmes sociotechniques actuels, les approches classiques pourraient ne pas être suffisantes pour couvrir tous les facteurs influents affectant leurs performances. Des approches différentes et innovantes capables de saisir une telle complexité sont donc nécessaires. Ces approches doivent adopter une perspective systémique et prendre en compte les différents facteurs d'un système sociotechnique complexe et leurs interactions (résonance). Cela permettra de comprendre comment des événements indésirables peuvent se développer et émerger de simples ajustements de performance et de la combinaison de la variabilité fonctionnelle systémique. En effet, le domaine de la gestion de la sécurité a été témoin d'un nombre important d'efforts de recherche pour aborder ces problèmes, ce qui a conduit à la proposition de plusieurs méthodes et approches novatrices adoptant de nouvelles perspectives. Le domaine de l'ingénierie de la résilience est l'une des disciplines récemment émergante à la suite de ces efforts proposant une nouvelle perspective SAFETY-II sur le thème de la gestion de la sécurité. Le principal outil proposé dans l'ingénierie de la résilience est la méthode d'analyse de résonance fonctionnelle (FRAM), qui servira d'outil principal dans ce projet.

Malgré les nombreux avantages offerts par ces nouveaux outils, ils sont encore limités à bien des égards et nécessitent davantage de recherche et développement pour mûrir et devenir plus normalisés et établis. L'utilisation d'échelles qualitatives dans des outils tels que FRAM permet de capter des relations complexes et dynamiques en utilisant le langage naturel. Cependant, cela induit d'autres limites pour les interprétations de l'importance et la détermination de l'ampleur précise des résultats produits. L'ajout de la quantification dans de telles approches sans sacrifier les caractéristiques distinctives de ces outils permettrait aux analystes de bénéficier des avantages offerts par les méthodes tant quantitatives que qualitatives. Une solution possible à cette limitation peut être proposée par la logique floue, qui facilite le calcul en langage naturel. Les avantages de la logique floue sont représentés dans la capacité à rendre compte des incertitudes dans les paramètres définis et l'ajout de la quantification à FRAM, qui repose sur des variables linguistiques. Grâce à la combinaison de la logique floue et de FRAM,

les avantages des deux approches peuvent être utilisés pour présenter un nouvel outil puissant pour l'évaluation des risques et de la sécurité.

L'intégration de la logique floue peut également faciliter la proposition d'un cadre normalisé pour tenir compte de la variabilité de FRAM et effectuer des évaluations prédictives en utilisant la base de règles du système d'inférence floue (FIS). Contrairement aux analyses rétrospectives des accidents, les évaluations prédictives de la sécurité doivent tenir compte des incertitudes et du flou découlant du manque de données ou de connaissances suffisantes sur la vraie nature et l'ampleur des concepts évalués. De plus, le processus de génération de base de règles dans le FIS est exhaustif et nécessite des efforts importants en cas de grand nombre de variables d'entrée. Cela conduit à son tour à la génération de grandes bases de règles lourdes en ressources informatiques et irréalisables en termes d'élicitation d'experts. Le cadre de la théorie des ensembles approximatifs (RST) peut fournir des solutions à ces problèmes en tant qu'outil d'exploration de données et de classification. Grâce à l'application de plusieurs algorithmes de recherche pour analyser les données d'entrée fournies par des experts ou des observations de terrain, l'approche RST permet une classification automatique des données (qu'elles soient quantitatives ou qualitatives) et par conséquent la génération de bases de règles réduites efficaces.

Le point de départ de ce projet de recherche a été l'analyse de l'environnement des opérations de dégivrage au sol des aéronefs, qui constitue un système sociotechnique complexe et dynamique. La performance optimale des procédures de dégivrage repose sur de nombreux facteurs tels que les conditions environnementales, la technologie, les aspects organisationnels et le facteur humain. L'objectif principal de ce projet de recherche est d'introduire une nouvelle approche pour l'évaluation de la sécurité des systèmes sociotechniques complexes, en particulier pour le contexte du dégivrage des aéronefs. Pour garantir l'intégrité des procédures de dégivrage / antigivrage et fournir le niveau de sécurité souhaité, une évaluation des facteurs influents est nécessaire. Les objectifs spécifiques sont de modéliser le système en place et d'effectuer une évaluation systémique en utilisant la méthode d'analyse de résonance fonctionnelle (FRAM) pour déterminer les facteurs influents qui affectent la performance des opérations de dégivrage; introduire une nouvelle approche systématique combinant la logique floue avec FRAM pour permettre une représentation plus standardisée de la variabilité des performances; et troisièmement, intégrer la méthode RST dans le cadre pour fournir les outils permettant de classer de grands ensembles de données et de générer automatiquement des bases de règles compréhensibles. Chaque phase de ce projet a fourni un scénario d'application inspiré des accidents d'avion réels liés aux opérations de dégivrage et les résultats obtenus ont finalement été comparés pour tirer des conclusions et valider les résultats d'un point de vue théorique.

Les résultats obtenus à chaque application ont fourni des nouvelles explications et éclairé certains domaines sous-étudiés concernant le dégivrage des aéronefs. L'analyse de l'accident scandinave SK751 a permis de modéliser le système de dégivrage en expliquant l'évolution de l'accident et en reliant les événements d'un point de vue fonctionnel. L'intégration de la logique floue a facilité le calcul de la variabilité des extrants de manière plus précise et a fourni un cadre systématique et normalisé pour tenir compte de la variabilité des performances.

L'approche RST telle que présentée dans les objectifs a permis la génération automatique de bases de règles réduites sans sacrifier la précision en utilisant des ensembles de données idéaux. Du point de vue de la disponibilité technologique, le modèle proposé en est encore à ses débuts et nécessite une validation supplémentaire à l'aide de données du monde réel et d'autres applications et optimisations. La portée et le calendrier de ce projet n'ont pas permis d'approfondir ces aspects ; cependant, on espère que ce projet encouragera l'émergence de nouvelles études et recherches sur les thèmes abordés par cette étude.

De plus, l'adoption de cadres comme la logique floue et les RST a été très limitée dans le domaine de la gestion des risques et de la sécurité. Ces outils offrent des approches innovantes et différentes pour faire face à l'incertitude et aux problèmes liés à la classification des données. Cela pourrait à son tour contribuer à améliorer les mesures de sécurité et à minimiser les risques afin de fournir de meilleures opérations de dégivrage / antigivrage au sol des aéronefs et une meilleure protection des humains et des machines. Les nouvelles perspectives offertes par ces outils pourraient à terme refléter positivement les aspects économiques, technologiques et organisationnels de l'industrie du dégivrage et de tout autre contexte industriel concerné par la gestion de la sécurité. En fin de compte, on espère que cette recherche fournira des réponses et ouvrira la porte à d'autres questions soulevées pour lancer en guise de conclusion d'autres études futures.

Mots-clés : systèmes complexes, ingénierie de la résilience, méthode d'analyse de résonance fonctionnelle, FRAM, dégivrage des aéronefs, logique floue, théorie des ensembles approximatifs.

A proposal of a mixed fuzzy logic/rough sets FRAM model for complex systemic analyses of sociotechnical systems

Hussein SLIM

ABSTRACT

Modern sociotechnical systems have been continuously developing at a fast pace leading to more complexity and interconnectivity among their components. The traditional view in well-established risk and safety assessment methods adopted a linear cause-effect philosophy focusing on what could go wrong (SAFETY-I). The focus was mainly and simply directed to the identification of errors, root causes and singular events, which could directly cause accidents and lead to undesired outcomes. However, considering the complexity of sociotechnical systems nowadays, classical approaches might not be sufficient to cover all influential factors affecting their performance. Different and innovative approaches capable of capturing such complexity are therefore required. Such approaches must adopt a systemic perspective and consider the various factors in a complex socio-technical system and their interactions (resonance). This shall provide an understanding of how undesired events might develop and emerge out of simple performance adjustments and the combination of systemic functional variability. Indeed, the field of safety management witnessed a significant amount of research efforts to address these issues leading to the proposition of several novel methods and approaches adopting fresh perspectives. One of these recently emerging disciplines is the field of Resilience Engineering adopting a new SAFETY-II perspective on the topic of safety management. The main method proposed in Resilience Engineering is the Functional Resonance Analysis Method (FRAM), which shall serve as the main tool in this project.

Despite the many advantages offered by these new tools, they are still limited in many ways and require further research and development to mature and become more standardized and established. The use of qualitative scales in tools such as FRAM allows for the capture of complex and dynamic relationships using natural language. However, this induces other limitations for the interpretations of the significance and for determining the precise magnitude of the produced outcomes. The addition of quantification into such approaches without sacrificing the distinguishing characteristics of these tools would allow the analysts to benefit from the advantages offered by both quantitative and qualitative methods. A possible solution to this limitation can be offered by fuzzy logic, which facilitates computing with natural language. The advantages of fuzzy logic are represented in the capacity to account for uncertainties in the defined parameters and the addition of quantification to FRAM, which rely on linguistic variables. Through the combination of fuzzy logic and FRAM, the benefits of the two approaches can be utilized to present a new powerful tool for risk and safety assessments.

The integration of fuzzy logic can facilitate as well the proposition of standardized framework to account for variability in FRAM and perform predictive assessments using the rule base of the Fuzzy Inference System (FIS). In contrast to retrospective accidents analyses, predictive safety assessments must deal with uncertainties and vagueness arising from the lack of

sufficient data or knowledge on the true nature and magnitude of the evaluated concepts. Additionally, the rule base generation process in the FIS is exhaustive and requires significant efforts in case of a high number of input variables. This leads in turn to the generation of large rule bases heavy on computing resources and unfeasible in terms of expert elicitation. The Rough Set Theory (RST) framework can provide solutions to these issues as a data mining and classification tool. Through the application of several search algorithms to analyze input data provided by experts or field observations, the RST approach allows for an automatic classification of data (whether quantitative or qualitative) and consequently the generation of efficient reduced rule bases.

The starting point for this research project was with the analysis of the environment of aircraft ground deicing operations, which constitutes a complex and dynamic sociotechnical system. The optimal performance of the deicing procedures relies on many factors such as environmental conditions, technology, organizational aspects, and the human factor. The main objective of this research project is to introduce a new approach for safety assessments of complex socio-technical systems, specifically the context of aircraft deicing. To ensure the integrity of deicing/anti-icing procedures and provide the desired level of safety, an assessment of influential factors is necessary. The specific objectives are to model the system in place and perform a systemic assessment applying the Functional Resonance Analysis Method (FRAM) to determine the influential factors that affect the performance of deicing operations; to introduce a new systematic approach combining fuzzy logic with FRAM to allow for a more standardized representation of performance variability; and thirdly, to integrate the RST method into the framework to provide the tools to classify large datasets and automatically generate comprehensible rule bases. Each phase in this project provided an application scenario inspired by actual airplane accidents related to deicing operations and the obtained results were compared eventually to draw conclusions and validate the results from a theoretical angle of view.

The results obtained from each application revealed new findings and illuminated some understudied areas concerning aircraft deicing. The analysis of the Scandinavian crash SK751 allowed for modelling the system of deicing providing an explanation for the development of the accident and linking events from a functional perspective. The integration of fuzzy logic facilitated the computation of the output's variability in a more precise way and provided a systematic and standardized framework to account for performance variability. The RST approach as declared in the objectives enabled the automatic generation of reduced rule bases without sacrificing accuracy using ideal datasets. From a technology-readiness perspective, the proposed model is still in the early stages and requires further validation using real world data and further applications and optimization. The scope and timeline of this project did not allow to dig deeper; however, it is hoped that this project shall initiate further research activities in the future addressing the tackled topics and issues.

Furthermore, the adoption of frameworks as fuzzy logic and RST has been very limited in the field of risk and safety management. Such tools offer innovative and different approaches to cope with uncertainty and problems related to data classification. This in turn could assist in improving safety measures and minimizing risks to provide better aircraft ground deicing/anti-icing operations and better protection for humans and machines. The new perspectives offered by these tools could eventually reflect positively on the economic, technological, and organizational aspects of the deicing industry and any other industrial context concerned with safety management. In the end, it is hoped that this research shall provide some answers and open the door for more arising questions to initiate as a conclusion further future studies.

Keywords: Complex Systems, Resilience Engineering, Functional Resonance Analysis Method, FRAM, Aircraft Deicing, Fuzzy Logic, Rough Sets.

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LIST OF ABREVIATIONS

AAF	Aircraft Anti-icing Fluid
ADF	Aircraft Deicing Fluid
AHP	Analytic Hierarchy Process
AMS	Aerospace Material Specification
APU	Auxiliary Power Unit
ASTM	American Society for Testing Materials
ATC	Air Traffic Control
ATM	Air Traffic Management
ATS	Automatic Train Supervision
BEA	Bureau d'Enquêtes et d'Analyses pour la sécurité de l'aviation civile
BN	Boundary Region
CASB	Canadian Aviation Safety Board
COG	Center Of Gravity
CPC	Common Performance Conditions
CREAM	Cognitive Reliability and Error Analysis Method
DSP	Deicing Service Provider
EPA	Environmental Protection Agency
EVF	External Variability Factor
FAA	Federal Aviation Administration
FIS	Fuzzy Inference System
FL	Fuzzy Logic

FMEA	Failure modes & Effects Analysis
FMV	FRAM Model Visualizer
FPD	Freezing Point Depressant
FRAM	Functional Resonance Analysis Method
FTA	Fault Tree Analysis
GIDS	Ground Ice Detection System
HMI	Human-Machine Interface
HSI	Human-Systems Interactions
HOT	Holdover Time
HRA	Human Reliability Analysis
ICAO	International Civil Aviation Organization
IS	Information System
ISO	International Organization for Standardization
IVF	Internal Variability Factor
LOUT	Lowest Operational Use Temperature
MSAW	Minimum Safety Altitude Warning
MTO	Man-Technology-Organization
NTSB	National Transportation Safety Board
OAT	Outside Air Temperature
PIC	Pilot In Command
PSF	Performance Shaping Factor
RAG	Resilience Analysis Grid
ROSETTA	Rough Set Toolkit for Analysis of Data

RST	Rough Set Theory
SAE	Society of Automotive Engineers
SHK	Swedish Accident Investigation Authority
SPC	Scenario Performance Conditions
STAMP	Systems-Theoretic Accident Model and Processes
TSB	Transportation Safety Board of Canada
WAI	Work As Imagined
WAD	Work As Done

INTRODUCTION

In simple terms, safety can be defined as the human need to be free of harm (Hollnagel, 2014). This need is an essential and inherent human characteristic, which was required from an evolutionary perspective to ensure human survival. Driven by this need, the general approach adopted in safety analysis, which is still dominant to this day, was to focus on hazard identification and the likelihood of risks. As we strive always to design and construct safer systems that function properly, we aim at eliminating any root causes that can produce adversity and inadequate outcomes. We therefore focus our attention on identifying what can go wrong and try implementing measures to mitigate and prevent such adversity. Modern sociotechnical systems are continuously and rapidly evolving and the contexts, in which they are designed and implemented, are introducing new challenges for safety and risk analysis methods. The fast advancement of technology has created new types of hazards and possibilities for accidents, while the rising demand for time- and cost-efficient processes has reduced the ability to predict and respond to potential hazards (Leveson, 2011). The increasing complexity manifests itself in modern sociotechnical systems in various forms. It can result from the interactions of system's components or from dynamic processes and environments (Hollnagel, 2012a). It can be nonlinear, in which causal relationships are not easily identifiable. The traditional way of risk and safety assessments depended primarily on determining linear causal relationships within the studied systems (Hollnagel, 2012b). The focus was simply directed to identifying root causes, failures or errors that might lead to accidents and adverse outcomes. This approach might have been adequate for simple systems in the past but is no longer sufficient today to provide adequate analysis of modern systems (Leveson, 2011). Considering the complexity of modern sociotechnical systems, different approaches are required (Leveson, 2011). Such approaches must consider the various factors in a complex sociotechnical system and their interactions (resonance) together and with the surrounding environment to determine the possibilities for undesired outcomes.

Safety is a top priority in aviation. Safe flying is a major concern for airlines, authorities and of course for passengers. Ensuring safe air travel is fundamental to avoid the drastic consequences of an airplane accident and to protect human lives. One of the critical problems that might compromise aviation safety is ice accretion and frozen contaminants' accumulation on the aircraft surfaces (Transport Canada, 2004). Accumulated ice or snow on the aircraft surfaces can degrade the aerodynamic characteristics of the aircraft and impact the functionality of its components (ICAO, 2000). Aircraft ground deicing/anti-icing procedures are crucial to maintain the safety of flight operations. Regulations and common practices require the deicing/anti-icing of aircrafts prior to takeoff in accordance with the « Clean Aircraft Concept ». The clean aircraft concept states that takeoff shall not be attempted if ice, frost, slush, or snow are present on the wings, control surfaces, engine inlets or any other critical area of the airplane body (ICAO, 2000).

Deicing operations are complex and dynamic by nature. "*The de/anti-icing operation is by its very nature a complex and fast paced environment with tight deadlines. All these factors together yield a higher than normal risk level and a higher potential for accidents to occur*" (Transport Canada, 2004). The optimal performance of deicing procedures relies on many interactive and dynamic factors such as environmental conditions, organizational aspects, and the human factor (Transport Canada, 2004). The weather conditions are variable by nature and forecasts are not always accurate. Adjustments are required continuously to cope with the variability of weather conditions. The different aircrafts' configurations, structures, build, and design require modifications in the application of deicing/anti-icing procedures (Transport Canada, 2005). The large number of individuals working together during deicing/anti-icing operations requires coordination, communication, policies, and regulations to ensure a successful operation and personnel safety (Transport Canada, 2005). The workload and time pressure associated with deicing/anti-icing operations are immense. Their influence on the mental and physical states of the deicing workers might degrade the performance quality. The continuous growth of air traffic (annual volume growth worldwide between 5.3 & 6.6% since 2011 as reported by the International Civil Aviation Organization (ICAO, 2020)) requires a continuous expansion and development of deicing/anti-icing operations, both in personnel and technology.

Generally, research on aircraft deicing from a human factors and systemic perspective is rare and with the continuous advancement and growth of air traffic, it becomes essential to study and analyze the context of aircraft deicing operations. To ensure the desired level of safety in such a complex sociotechnical system, a comprehensive understanding of the interactive influential factors is necessary. In this aspect, classical methods of risk analysis and safety assessment are no longer sufficient to provide a comprehensive and complete picture. Accidents and adverse events can no longer be viewed merely as direct results of singular failures or human errors. "*Accidents and incidents, whether understood as the unexpected and unwanted outcomes or the events that lead to them, can however occur in the absence of malfunctions and failures and be due, e.g., to performance variability or other transient phenomena*" (Hollnagel, 2012b). Therefore, different and new approaches are required in addition to the classical methods. The complexity and variability of the interacting systemic functions within the context of aircraft deicing/anti-icing operations has to be considered to provide a complete and comprehensive evaluation.

An interesting discipline that can offer a new perspective on systems' analysis is the lately emerging field of Resilience Engineering. Resilience Engineering offers a different perspective on safety assessment adopting a SAFETY-II approach and focusing on maintaining adequate performance conditions to construct resilient systems. The main tool in the field of Resilience Engineering is the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2004). FRAM was originally introduced by Erik Hollnagel in 2004 as an accident analysis tool (Hollnagel, 2004). It enjoyed a considerable level of attention in the research community and evolved over the years to a more mature safety assessment method (Hollnagel, 2012a; Patriarca et al., 2020). The distinctive characteristic of FRAM is the provision of a new understanding for successful and failed systemic performance. FRAM describes outcomes as a result of functional resonance arising from performance variability and normal local adjustments (Hollnagel, 2012a). The application of FRAM for system assessment goes beyond merely calculating error and failure probabilities. It provides a deep understanding of the system's functionality, which enables locating sources of variability and explaining how accidents and adverse outcomes can evolve within the studied context.

However, FRAM in its basic form is a qualitative method, which offers a conceptual framework for evaluation. Using qualitative scales, while advantageous in dealing with complex concepts and relationships, lacks the means to provide a more precise representation of the output's variability. This might result in difficulty to identify the extent or impact of variability on the outcome. Additionally, the perception of ordinal linguistic scales might differ between people. It would offer great benefits to quantify the magnitude of variability for the studied parameters. Quantification could be beneficial to present more intersubjective and comprehensible results. The dependence of FRAM on linguistic descriptors as input variables for analyzing the system is helpful in addressing complex and uncertain contexts, for which numerical measurements are not always available or possible. A possible solution to overcome this limitation can be achieved through the integration of Fuzzy Logic (Zadeh, 1965). Fuzzy logic was introduced by Lotfi Zadeh in 1965 as an approach to understand natural activities in terms of "*degrees of truth*" rather than absolute binary values. One of the main features of fuzzy logic is providing the possibility to account for vague and uncertain concepts in terms of linguistic variables (Zadeh, 1973). This approach resembles human reasoning more accurately than numerical measurements, since the human brain mainly relies on natural languages to assess and describe events and phenomena.

The integration of fuzzy logic into FRAM is faced still with several challenges and the majority of studies aiming at applying fuzzy logic within the framework of qualitative safety assessment methods did not move well beyond the theoretical foundation. Despite the existence of fuzzy logic since 1965, its validity was debated for a significant period of time to find later success in control applications and expand later to other fields. The nature of variables handled in such contexts such as control and automation can be somewhat easier to address as qualitative complex ones as presented in complex sociotechnical systems. Such variables are usually difficult to measure or express in terms of numbers in comparison to such variables as temperature or price for example. When faced with a high number of input variables, the size of the rule base extends significantly, and one is faced with the so-called rules' explosion problem. This results in large and exhaustive rule bases that can be challenging for analysts and experts to handle. Such rule bases would make the creation of the fuzzy inference system

(FIS) difficult and in many cases unfeasible. Additionally, the very nature of handled variables in complex contexts is often vague and uncertain by default, which results in many cases in the inability to determine the output of the rule. A solution to the above-discussed issues can be presented through the Rough Sets Theory (RST). RST provides a formalized mathematical framework suitable for the classification of incomplete, vague, and uncertain information. The indiscernibility principle of RST allows for discovering patterns and relationships in archived and historical data through the application of several search algorithms. RST allows for an automatic generation of reduced rule bases from large datasets, which are less demanding and easier on computing resources. The subjectivity can be herewith limited to the provided input data and the characterization of the classification method, not to the classification process itself.

In the following section, namely the critical review of literature, we will dig deeper to provide a better understanding and knowledge on the background of the above-mentioned topics. Given the interdisciplinary and exploratory nature of this project, an elaborative literature review is needed to describe and highlight the main features offered by each technique. The start will be in chapter one with a brief explanation of the followed search methodology to acquire needed knowledge and information on the different topics. A background on the definitions and characteristics of a complex sociotechnical system will be presented. A review of the Functional Resonance Analysis Method, Fuzzy Logic and Rough Sets Theory will be provided to reflect on their development over time and illustrate the relationships between them to address the issues stated above. Finally, a detailed description of aircraft deicing operations is presented from an operational and procedural angle to illustrate the complexity of the working environment. Accordingly, the objectives of this project and the designed methodology will be formulated and presented in chapter two of this thesis. Chapter 3 will consist of the first published journal paper addressing the first two objectives of this project extensively. Chapter 4 will be the second published journal paper focusing on the third objective, namely the integration of rough sets. Chapter 5 will present the third journal paper providing a reflection on the three phases and comparing the three models.

CHAPTER 1

CRITICAL REVIEW OF LITERATURE

1.1 Methodology of the Literature Review

The working environment of aircraft deicing presented a complex context for analysis at the beginning of this project. Upon searching scientific databases to identify relevant studies concerned with the human factors and a systemic perspective of deicing operations, the number of relevant studies was relatively small. Generally, for the search process, online scientific databases such as Google Scholar, Web of Science, Scopus, Compendex & Inspec, etc. were utilized. Most of the identified studies in such databases were concerned with operational and technical aspects of the deicing procedure. With the exception of our team and our partners, so far there is no other team worldwide conducting such a project to the best of our knowledge. Therefore, the main source to understand the human factors aspect of deicing operations and for designing our analysis model was the studies and findings published in recent years by our research team.

In addition, to demonstrate the danger and possible impact of icing on flight safety, realistic examples were needed to serve as models for our simulation. The Google search engine, websites of Transport Canada, the National Transportation Safety Board (NTSB) and the Federal Aviation Administration (FAA) were therefore scanned for relevant accident reports that can represent the consequences. The term "*ice airplane crash sensory components*" on Google lead to the detection of Air France Crash report (BEA, 2012). The term "*ice airplane crash ingested ice engine*" led to the detection of Scandinavian Airlines Gottröra crash report (SHK, 1993). For reviewing the specific details and issues of deicing/anti-icing procedures, keywords as "*deicing*" "*aircraft deicing*" "*anti-icing*" were used. The articles were found to mostly treat specific issues related to aircrafts icing without providing the needed details. This might be helpful to understand specific issues that can be solved with FRAM after applying the model. Therefore, the required details were searched for on other platforms. Guidelines of deicing/anti-icing procedures provided by aviation authorities and manufacturers were found to be more suitable to gather the required information. The details were studied mainly by reviewing the guidelines provided by Transport Canada (TP10643 & TP14052E). Other guidelines were also found helpful such as ICAO guidelines (Doc 9640-AN/940) or the guidelines of deicing fluids manufacturer DOW UCAR.

The story was different when it came to the other topics covered by this thesis. The amount of produced search results for the used keywords was significant. At first, the titles were reviewed to select the most relevant studies. Then, the abstracts of the selected studies were reviewed to narrow down the results. Additionally, the publications of the main contributors such as publications of the researchers proposing the utilized frameworks and models within this project as a starting point to identify relevant studies branching out from their projects and building on their results.

For providing a rationale for the research project, various books and articles on complexity and complex systems were reviewed. Keywords such as "*complexity*", "uncertainty" "*complex systems*" and "*sociotechnical system*" were applied. This part was relevant for understanding the characteristics of the system at hand and provide an overview of the evolution of systems' analysis and safety assessment methods over the last hundred years. Publications concerned with safety management and its evolution were reviewed and keywords such as "*human factor*", "*safety*", "*safety management*", "*risk analysis*", "*Resilience Engineering*" etc. were utilized to identify relevant studies.

The evolution of assessment methods in the field of safety management lead to the emergence of systemic analysis tools such as FRAM and consequently the field of Resilience Engineering in general. Since we identified FRAM as an appropriate tool for constructing our analysis model, an understanding its characteristics was needed. The publications of Erik Hollnagel, the father of FRAM, were the main reference for this project such as the website of FRAM (www.functionalresonance.com) (Hollnagel, 2020), the book "*FRAM: The Functional Resonance Analysis Method: Modeling Complex Socio-technical Systems*" (Hollnagel, 2012a) and a research report (2013:09) by Hollnagel (Hollnagel, 2012b), conducted for the Swedish

Radiation Safety Authority (SSM), were mainly reviewed in addition to other relevant scientific articles concerned with the application and development of FRAM such as Macchi, Patriarca et al. and Hirose & Sawaragi. For the various application fields of FRAM, keywords such as "*FRAM*", "*functional resonance*", "*functional resonance analysis*", "*hollnagel*", *"(functional resonance) AND (risk assessment)",* or *"(functional resonance) AND (assessment)"* were applied.

The efforts to improve and develop qualitative analysis tools are still faced with several challenges due to the complexity of the variables in question and the contexts at hand. An interesting approach to quantify natural language is provided through fuzzy logic (Zadeh, 1965), which is relatively under-utilized in the field of safety management. The majority of studies concerned with fuzzy logic in this aspect remained on the theoretical side and the proposition of practical applications is very limited. Select articles of Lotfi Zadeh, the father of Fuzzy Set Theory and Fuzzy Logic, were reviewed in this literature review to provide an overview of fuzzy logic and lay the foundations for our intended proposal. The article with the title "*Outline of a New Approach to the Analysis of Complex Systems and Decision Processes*" published in 1973 was especially relevant for our purposes, since it described the use of linguistic variables to account for fuzzy concepts. Other helpful and comprehensive studies by other authors were as well reviewed (Hirose & Sawaragi 2020; Konstandinidou et al., 2006). Search terms such as *"fuzzy logic", "linguistic variables", "decision making", "artificial intelligence" and "fuzzy rules"* were applied for the search process.

Lastly but not least, the issue with data classification was addressed within this project. Several issues were noticed with the use of systemic tools in conjunction with fuzzy logic during this project such as the complexity and vagueness of input variables, large and unfeasible rule bases in addition to the rarity and uniqueness of events that can be used for statistical and probabilistic tools. Solutions to handle these limitations can be provided through the framework of Rough Sets Theory (RST) (Pawlak, 1982). To this end, the proposed mathematical framework of RST was reviewed relying mainly on the publications of Zdzislaw Pawlak, the father of RST in addition to several other publications proposing software solutions for the utilization of RST such as Øhrn et al. and the ROSETTA research team. Scientific databases were scanned using keywords such as *"Rough Sets", "RST", Decision Tables", "Information System", "Reducts"* etc. Figure 1.1 presents a graphical representation of the literature review structure for this project. In the following section, an overview of complex systems and the evolution of safety assessment methods is presented at first.

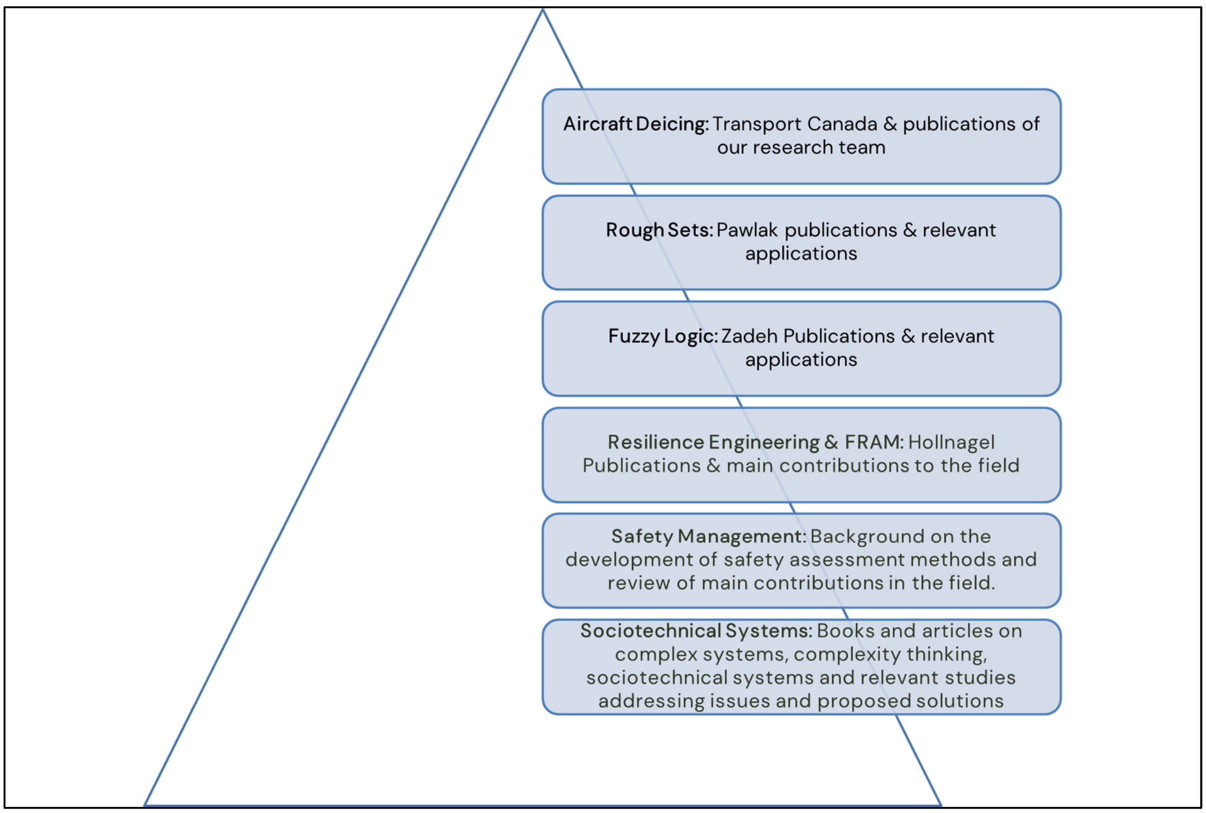

Figure 1.1 Structure of the literature review process

1.2 Context and Motivation

1.2.1 Complexity

Complexity is an inherent characteristic of the world around us and the understanding of complex systems' behavior is a key factor in the advancement of science and technology (Weaver, 1948). To be more specific, complexity can refer to different aspects of any given system based on its nature and constitution. Complexity can be related to the structure of a system such as molecular structures or neuronal networks of the brain (Érdi, 2008). Thus, one can say that structural complexity describes the relationships between the elements of the system (Érdi, 2008). Another concept of complexity is the dynamical complexity, which describes irreversible and periodic temporal processes such as neuronal oscillations and weather predictions (Érdi, 2008). Structural and dynamical complexities are not necessarily correlated or dependent on each other. In information theory, algorithmic information complexity refers to the length of an algorithm that describes a computable object, while cognitive complexity is related to personality theory (Érdi, 2008). And so on, depending on the field or discipline, complexity theory has manifested itself in various forms to address different issues and concepts.

The dominant view in science in the 20th century and before was that of mechanistic reductionism, which considered that any system, including the universe and life itself, can be reduced to its parts and understood in terms of mechanisms (Érdi, 2008). As suggested by complexity theory, this view is incomplete and fails to provide an understanding for the dynamic and emergent systemic properties, which arise from the interactions of the systemic parts (Érdi, 2008). Physical science before the 20th century was mostly concerned with simple problems, which involved two, three or four variables at most (Weaver, 1948). While this approach might be suitable in case of inanimate objects, it becomes inadequate once living things and social components are included. Living things present a much larger number of variables, which are uncertain, dynamic and interact in unpredictable ways (Weaver, 1948). In the 20th century, a paradigm shift happened in physical sciences, which resulted in developing powerful methods to include a large number of variables such as probability theory and statistical methods (Weaver, 1948). The new methods were suitable to address complexity problems with a large number of variables, whose individual behavior was unpredictable but collectively possessed analyzable average properties. Those problems are known as problems of disorganized complexity (Weaver, 1948). However, between the limited number of variables and the extremely large number of variables, there exists a region, in which the number of variables is moderate. The variables in the moderate region are considerably more than two variables and they behave in an organized manner. This group is known as problems with organized complexity (Weaver, 1948). In contrast to problems of disorganized complexity, problems of organized complexity "*involve dealing simultaneously with a sizable number of factors which are interrelated into an organic whole*" (Weaver, 1948). As an example for such problems, one might think of a study to analyze patterns of behavior for a specific group of people in a specific environment. Such problems are too complex for the simple methods and are untreatable by statistical methods since they possess organized behavior (Weaver, 1948).

Generally, systems are entities of defined components or organized elements, which act together cohesively to perform a common function (Bodenschatz, 2009). Systems themselves can be elements in larger and more complex systems as well. One can distinguish mainly between simple and complex systems.

1.2.2 Simple Systems

Simple Systems consist of a small number of components, which are organized together in an understandable manner (Bodenschatz, 2009). Simple systems are characterized by linear causal relationships and predictable behavior (Érdi, 2008). The system does not change over time or consist of subsystems with separate purposes or functions. Simple systems are closed or isolated systems and their performance is not easily affected by external influences. As an example for simple systems, consider an alarm clock (Lim & Wogalter, 2002) that consists of mechanical parts organized and related in an entirely understandable manner. The alarm clock serves the purpose of showing time and ringing at a specified time. The components of the clock perform as a whole to achieve a common function unaffected by the mental state of the owner or the environment. The alarm clock is a closed system that does not rely on external factors to perform. Another example of a simple but more complicated system is a water spray system, which can be used to extinguish fire (Nolan, 2011). The water spray system consists mainly of a water tank, pipes, nozzles, pumps, valves, smoke detectors or sensors, relays and electric circuits, etc. A water spray system is a closed system, which performs independently to achieve a specific purpose. The composition of a water spray system is known and understandable. The behavior of its components is predictable and the interactions among those components are linear and entirely analyzable. Simple systems are decomposable to their parts and can be well assessed and understood in the design phase. Therefore, they are well suited for analysis with traditional assessment methods.

1.2.3 Complex Systems

Complex Systems, on the other hand, consist of a large number of components, which interact to perform a common function cohesively (Bodenschatz, 2009). The function of a complex system emerges from the dynamic interactions of its components, which is known as self-organization or emergence (Bodenschatz, 2009). The majority of complex biological and social systems are open systems, which interact continuously with their environment (Érdi, 2008). To understand the functionality of complex systems, it is important to comprehend how the relationships and interactions among their parts produce the collective behavior of the entire system (Bar-Yam, 2002). The study of complex systems focuses on three main topics: formation of patterns of behavior, the space of possibilities and the formation and evolution of complex systems (Bar-Yam, 2002). The range of complex systems is not limited to a specific field or discipline; rather, it expands across all disciplines and fields of science and human knowledge (Bar-Yam, 2002).

Complex systems are non-deterministic (Pavard & Dugdale, 2006). Even if the functions of the individual components were known, the behavior of the system as a whole remains unpredictable. The relationships among the system components are mostly non-linear, in which the outcomes are not always proportional to the inputs (Érdi, 2008). This could mean that minimal changes in the inputs can cause disproportionate outcomes and effects. The sensitivity of dynamic systems to the initial conditions leads to producing significantly different outcomes for two adjacent initial values (Érdi, 2008). The sensitive dependence of the outcome on the initial conditions (The so-called butterfly effect) is a basic property of chaotic systems, which are dynamic complex systems (Érdi, 2008). Causal relationships in complex systems can be circular, in which the cause and the effect influence each other mutually, e.g., feedback loops (output feedback to input) (Érdi, 2008). Circular relationships and feedback loops can be found in natural, technological and social systems e.g., as in industrial and chemical processes, economics, decision making, etc. (Érdi, 2008).

Complex systems are irreducible (Pavard & Dugdale, 2006). This means that their characteristics cannot be simplified or reduced without losing their functional properties (Pavard & Dugdale, 2006). The structures of complex systems are dynamic and open for interactions with the surrounding environment. Thus, the functionality of the whole system as a cohesive unit cannot be understood from simply understanding and narrowing the focus on the functionality of its sub-parts decoupled from each other (Pavard & Dugdale, 2006).

Complex systems are distributed systems (Pavard & Dugdale, 2006). The structure of a complex system can be widespread and unlimited to one location. The resources necessary for the function of the system can be distributed to multiple sites or over a large area. The distribution of the system can be of physical or virtual nature. The virtual distribution refers to the inability to localize the physical location of the information (Pavard & Dugdale, 2006).

Complex systems are emergent and self-organized (Pavard & Dugdale, 2006). The principle of emergence refers to the relationship between the elements or parts of the system and the system itself (Bar-Yam, 2002). The main question here is how the properties of a given complex system emerge out of the properties of its elements or components. Separately, systemic components do not possess the same properties as the whole system. The collective behavior of the whole system emerges only when those components are put together to interact cohesively and perform their roles with or without external influence (self-organization).

Complex Systems are tightly coupled (Perrow, 1984), are more rigid and time-dependent and require more precision. Systemic components cannot be easily substituted and the failure of one component reflects significantly on the rest of the system. The elements or parts of a complex system are interdependent (Bar-Yam, 2002). The parts are interrelated, and the change caused by one part of the system can have effects on other parts of the system (resonance). The study of complex systems aims at understanding the relationships among the elements within the complex systems and how their interactions might cause indirect and unwanted effects. The causal relationships are not always obvious and easy to understand, which makes the behavior of complex systems unpredictable and challenging for system management and development.

In natural systems, the process of self-organization results in organized forms and patterns of behavior without any external control mechanism or agent (Bar-Yam, 2002). The initial condition of the system is disordered, and the local interactions among its parts lead to the formation of patterns and an overall order of the system. The evolution of the system over time leads to more complexity and organization, which appears to be a designed process. In designed systems, the purpose and positioning of each part is well known. The organized structure of the parts that build up the system serves the purpose of accomplishing specific goals. The behavior and performance of the system remains as designed in simple and closed technological systems. However, this idea does not apply in the case of complex sociotechnical systems. The local interactions among the systemic parts over time and the interactions with the environment change the behavior of the system and present a difference between work as imagined (WAI) and work as done (WAD) (Hollnagel, 2014). Human behavior in sociotechnical systems cannot be entirely predicted or explained in terms of design. The concept of self-organization applies to human behavior, which shows collective patterns arising from the systemic interactions as in economic and social systems (Bar-Yam, 2002). Understanding those patterns and mechanisms that define the behavior of complex sociotechnical systems and how the interactions among the systemic parts result in specific events (why things happen the way they happen) is essential to improve systems' engineering and safety management.

1.2.4 Sociotechnical Systems

The term "*sociotechnical system*" refers to any operational system with a defined objective, which comprises social and technical elements (Hettinger et al., 2015). The term dates back to the 1950's and was presented as a result of the research work performed by the Tavistock Research Institute in the British coal mining industry (Trist, 1981). The social aspect of a sociotechnical system refers to the human factor in form of individuals (personal characteristics of workers) and organizations (organizational structures, work environment, policies, etc.). The technical aspect represents any form of technology such as machines, electrical devices, simple tools, resources, or any equipment needed to execute the function. This concept of a sociotechnical system applies to the majority of modern systems in the world today and expands across all domains and fields such as education, healthcare, economy, etc. (Hettinger et al., 2015).

To specify the distinctive nature of sociotechnical systems, one can identify five key characteristics (Baxter & Sommerville, 2010):

- The systemic components or parts are interdependent;
- The objectives of the system adapt to the external environment;
- The whole system consists of internal separate but interdependent technical and social subsystems;
- Systemic objectives are achievable in multiple ways depending on the design choices;
- Successful performance depends on the joint optimization of human, organizational and technological factors (MTO) (Figure 1.2).

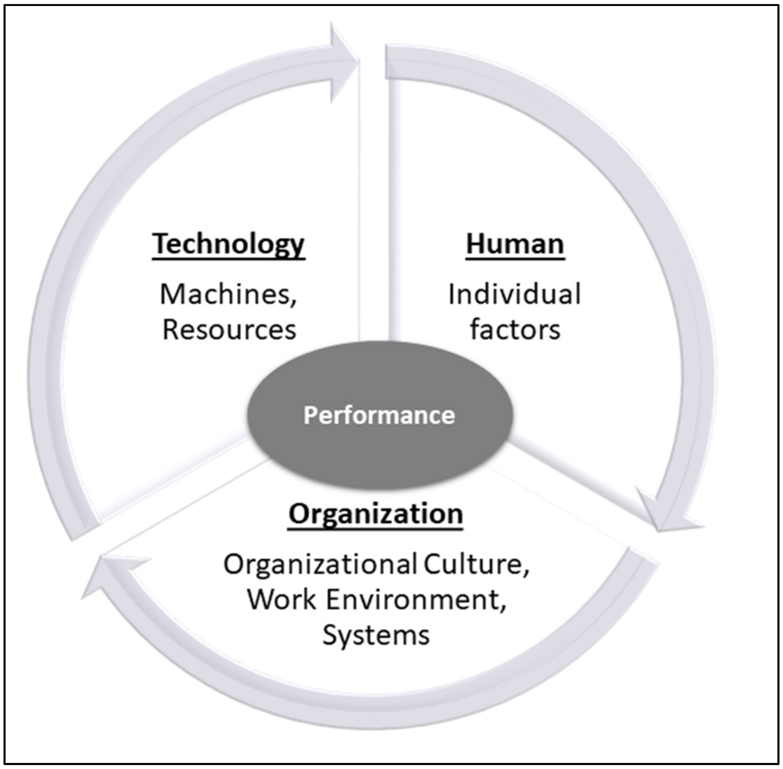

Figure 1.2 An illustration of the MTO classification method.

Sociotechnical systems are open systems embedded in their environment, which influences their behavior and performance significantly (Mumford, 2006). This means that their components interact with each other and with the surrounding environment in a decisive way for the quality of the system's performance (Carayon et al., 2015). The interactions in a complex system could be of linear nature and well understood in the designing process; or they could be non-linear and complex, which are mostly invisible and therefore possibly unpredictable. The success of the system here depends on the level of understanding for those relationships to better manage performance variability and unpredictability. Considering the above-mentioned characteristics, any design or assessment approach should consider the human and technical factors together (Mumford, 2006; Baxter & Sommerville, 2010). It would be advantageous to focus on the system as a whole and adopt a holistic perspective to provide a complete picture of the system status.

Leveson defines complexity as intellectual unmanageability (Leveson, 2011). This is reflected in the continuously growing complexity of modern systems, which in turn translates into more unpredictability and intractability (Leveson, 2011). The increasing complexity of systems and the introduction of new hazards resulted as well in adding up to the severity and cost of failures (Leveson, 2011). The large scale of modern systems raised the impact of accidents and failures on affected parties and environments (Leveson, 2011). Consequently, it becomes more imperative to provide adequate measures to prevent the occurrence of accidents and failures in the first place.

1.3 The evolution of systems' analyses: an argument for systemic perspective

Classical analysis methods starting with Heinrich's Domino model (Heinrich, 1931) adopted simple-systems-thinking. Classical safety approaches rely mainly on a linear cause-effect reasoning, which explains adverse outcomes as a direct result of errors, malfunctions, or component failures (Hollnagel, 2012a; Leveson, 2011). As described above, simple systems are predictable and the dominant relationships among components and interdependencies are well-defined and understood. Such an approach is very well suited for purely mechanistic and simple systems as explained earlier. However, to provide complete and comprehensive assessment of modern sociotechnical systems, the complex and emergent nature of the interactive social and technical factors must be considered (Hollnagel, 2012a; Leveson, 2011; Hettinger et al., 2015). Traditional assessment methods are insufficient to explain the performance of complex systems completely and the provision of alternative approaches becomes necessary.

The second half of the 20th century witnessed a rise in systems' complexity with the introduction of digital technology and the information revolution. As the adopted philosophy was a mechanistic one, the sixties saw the introduction of such tools as the Fault Tree Analysis (FTA) and the FMEA, which became well established and trusted in industrial applications. Such tools built on the traditional sequential thinking of older methods and were developed primarily to evaluate the reliability of hardware components in purely mechanical or technological systems. Such an approach considers the system in question to be decomposable to its parts and defines causal linear relationships among components and functions. This results on focusing on specific segments or level of the studied context and zooms in on operational aspects overseeing herewith the more holistic perspective and the resulting interactions of the system as a whole (Adriaensen et al., 2019). Traditional tools cannot cover the entire system or evaluate it as a cohesive unit and require therefore a combination of different methods to cover all technical and human-related factors. Focusing on one segment or a specific level in isolation from other systemic levels might result in overseeing risks and loopholes, from which adversity might emerge. Classical tools can be blind or insufficient when it comes to nonlinear combinations and overlapping of dynamic relationships.

The second aspect of complexity is focusing purely on technical aspects neglecting the human factor. Understanding that the main component of any sociotechnical system is the human or social component, it becomes imperative to develop and provide tools capable of including this factor and correctly and adequately capturing its implications on systemic performance. The majority of studies attributes around 80% of accidents to the human factor. Therefore, analyzing any system decoupled from the human factor would mean insufficient knowledge about its behavior. The human factor is the main driver or contributor to uncertainty and routine performance variability and local adjustments are the main reason why actual performance is continuously underspecified. Underspecified mean that actual work in reality is never carried out as imagined or prescribed in the design phase or the procedures. Performance variability is an inherent characteristic of any sociotechnical system and it could be beneficial mostly to ensure the resilience of the system. Therefore, the objective is always to manage variability by locating its sources within the system, strengthening the weak spots and maintaining conditions necessary for successful outcomes.

This understanding resulted in the emergence of more sophisticated human-factor-oriented tools and lead starting in the 1980s to the proposition of several epidemiological and organizational methods. Such tools adopted a more complex perspective on systems' analysis considering the human factor individually and collectively more deeply. The individual factor was considered here as the active component contributing at the sharp end to the formation of adverse events facilitated by latent organizational and environmental influences (Reason, 1990; Woods et al, 1994; Qureshi, 2008). Most notably here is Reason's Swiss cheese model, which describes accidents as emergent events resulting from loopholes in the defense mechanisms and barriers of the system (Reason, 1990). However, here again, the adopted philosophy remained a linear sequential one presenting a static snapshot of the system and ignoring its dynamic properties (Hollnagel, 2004). Rasmussen in the nineties proposed a systemic approach based on functional abstraction rather than structural decomposition (Rasmussen, 1997). Rasmussen defined six levels of a sociotechnical system: Government, Regulators/Associations, Company, Management, Staff and Work (Rasmussen, 1997). Rasmussen therefore proposed adopting hierarchical frameworks assessing interactive relationships between the several systemic levels in an interdisciplinary fashion (Rasmussen, 1997). The impact of variability or change on one level has to be evaluated in link to the other levels of the system. Again, the adopted philosophy was still sequential focusing on modelling influential factors on each level as an event chain or sequence of consequent events assuming the existence of a root cause (Leveson, 2011). The next leap in safety management was recorded with the introduction of systemic assessment tools with the beginning of the 21st century such as the Systems Theoretic Accident Model and Process (STAMP) (Leveson, 2011), the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2004) and the Resilience Analysis Grid (RAG) (Hollnagel, 2011). Leveson considered safety to be a control problem, which should be addressed by applying control mechanisms and constraints on the behavior of the system to ensure it does not fluctuate in an uncontrollable fashion (Leveson, 2011). In STAMP, a system is characterized as a control based hierarchical framework, which relies on adaptive feedback to identify loopholes and the potential of a system to produce negative outcomes. STAMP as a systemic assessment tool allows for retrospective and proactive analysis defining the system of interest as a causal model consisting of a set of control loops. Safety in STAMP is a control problem, which results from component failures, external influences, and malfunctions. Accidents therefore occur as a consequence of the failure of the control mechanisms that ensure an adequate outcome (Underwood & Waterson 2012).

Each system consists of control subsystems which ensure adequate performance and prevent accidents if constraints and barriers did not fail. STAMP therefore aims at identifying inappropriate components and characteristics of the system that could lead to a violation of the control mechanisms. As identified by Hollnagel & Speziali (2008), the elementary component is not an event in STAMP, rather a constraint. Therefore, the objective in STAMP is to limit systemic behavior and fluctuations to avoid and prevent the violations of the control mechanisms in place and ensure that the system maintains its performance within acceptable margins. The aim as can be seen is directed mainly at negative deviations in performance. STAMP is mainly an analysis method which lack a formal and structured formulation of the results (Hollnagel & Speziali, 2008). This can be beneficial in providing more flexibility to the analyst; however, it requires on the other hand in-depth knowledge of the system in question and would therefore by used by experienced users to provide reliable results (Hollnagel & Speziali, 2008).

Hollnagel on the other hand adopted the holistic perspective of functional abstraction representing the system in terms of functional couplings in the Functional Resonance Analysis Method (FRAM). FRAM functions are more objectives or tasks that constitute the whole system and accordingly can expand across systemic hierarchical levels. FRAM is not necessarily hierarchical unless the functions were to be defined as such. Despite the requirement of an initial learning effort at the beginning, the FRAM approach is simple and formally structured in well-defined five steps. It provides a graphical representation of the analysis context, which would allow for visual evaluation and understanding of the model. The characterization of the functions in FRAM follows the MTO classification approach rather than a structural or hierarchical one. The principles on which FRAM relies allow for describing dependencies and complex couplings among functions in contrast to causal and linear approaches. The concepts of emergence and functional resonance facilitate this type of understanding.

The very nature of complex systems is to grow and evolve. Continuous technological advancements in collaboration with social components will inevitably add to the complexity of such systems. As we stand at the doors of Industry 4.0 and its unstoppable expansion into all fields and domains, we are again faced with challenges to propose novel methods and improve the already existing tools if we do not wish to fall behind. The fourth industrial revolution will translate into a rise of systemic interconnection and the expansion of networks, more reliance on the data backup in online servers or clouds, the internet of things (IoT), Big Data, and continuously more reliance on human-machine interfaces all add up to more complexity and intractability. Technology mostly advances at a faster pace than policies and legislations. The importance of safety and performance assessments is therefore something that should be emphasized. As we continuously strive to design more efficient and reliable systems, safety has to be considered as a significantly influential factor that goes hand in hand with productivity. Realizing and understanding the previously described characteristics of complex systems, new types of unpredictable hazards and risks are inevitably about to emerge. Relying herewith on classical retroactive tools with focus on root causes and what goes wrong would undoubtedly result in insufficient results and overseeing risks, since such tools have not been updated or kept pace with technological advancements over time (Qureshi, 2008). The need for and lack of more innovative proactive methods well equipped for the upcoming industrial revolution becomes more noticeable.

Critical Sectors as nuclear power and aviation are high reliability systems, designed to perform safely and securely. The safety management of such systems is an important task done very rigorously. Much attention is directed to this process to eliminate any possibility of any adversity to avoid the severe consequences and dangerous impact of accidents in such environments. Thus, such critical structures became much secured performing with high reliability, which made the occurrence of accidents very rare and unique. This in turn resulted in a lack of sufficient statistics and data to apply probabilistic and statistical tools in a meaningful manner difficult even to draw meaningful and generalizable conclusions (systems with organized complexity). Classical tools here cover the majority of events and linear cascade effects within such systems. However, the type of accidents that can still slip through the barriers and defenses are of a complex nature and dynamic nature that cannot be anticipated with such tools. It would be therefore advisable to use a combination of different types of tools to cover all aspects of safety. Systemic tools using natural language can be helpful herewith to characterize such relationships that are difficult to express in terms of probability numbers and linear causal relationships. Since what can go wrong in such systems is very rare, it would be helpful here to look at what goes right (Figure 1.3) as well, especially since what goes right is the norm and is by far the outcome. This would provide more data and allow for looking at performance conditions that promote success. By maintaining such conditions, the system can be made resilient. This is mainly the principle of the newly emerging discipline of Resilience Engineering (Hollnagel, 2011; Hollnagel et al., 2015).

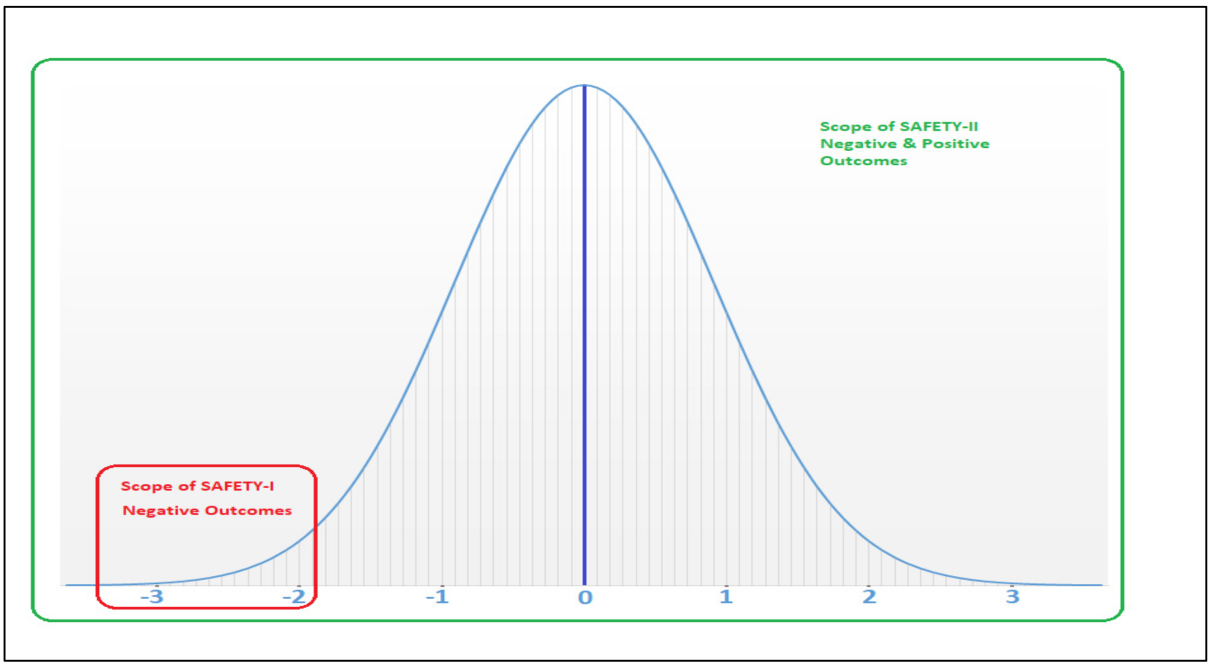

Figure 1.3 The focus of the two approaches SAFETY-I and SAFETY-II (Hollnagel et al., 2015)

Performance variability is here considered as a natural characteristic of any sociotechnical system required for making the system resilient i.e., adjusting performance to adapt with fluctuations and disturbances to maintain outcome within acceptable margins (EUROCONTROL, 2009). Resilience Engineering adopts a SAFETY-II approach, which in addition to what goes wrong looks at what goes right expanding the spectrum of analysis to cover the extremely negative and the extremely positive. Resilience Engineering has its roots deeply embedded in Human Factors and Safety Management adopting mainly the following four principles:

- Actual performance is continuously underspecified and there is a difference between WAI and WAD (Figure 1.4 & Figure 1.5);
- Variability in performance the main factor affecting the output and resulting in positive or negative deviations from expected values;
- Proactive analysis is needed in addition to retrospective analysis to be able to anticipate possible adversity;
- Safety goes hand in hand with productivity and to design and construct efficient and productive systems, safety management should be incorporated as a productivity precondition into the business planning and core processes.

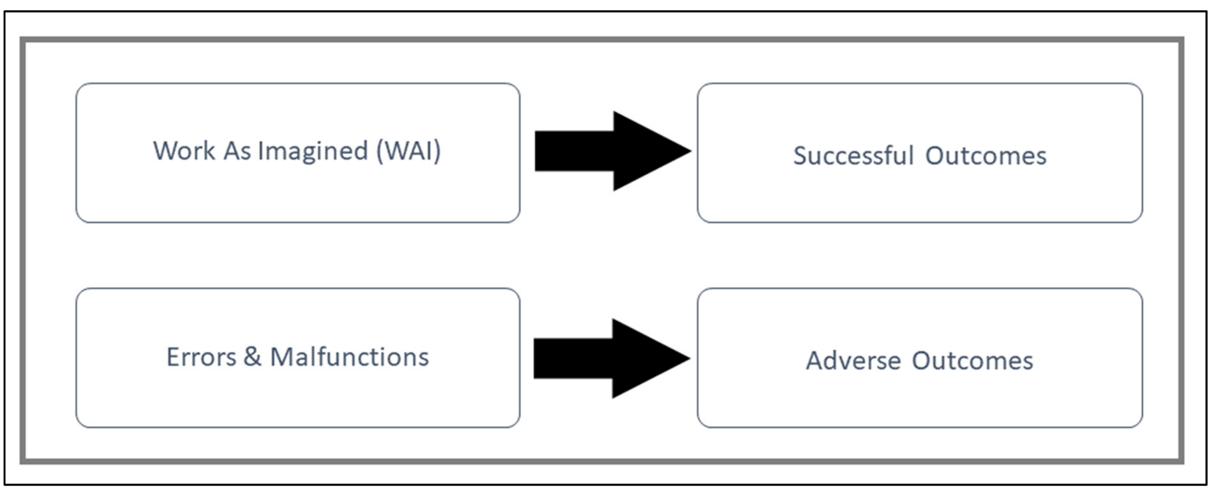

Figure 1.4 The classical view of successful and failed outcomes (Hollnagel et al., 2015)

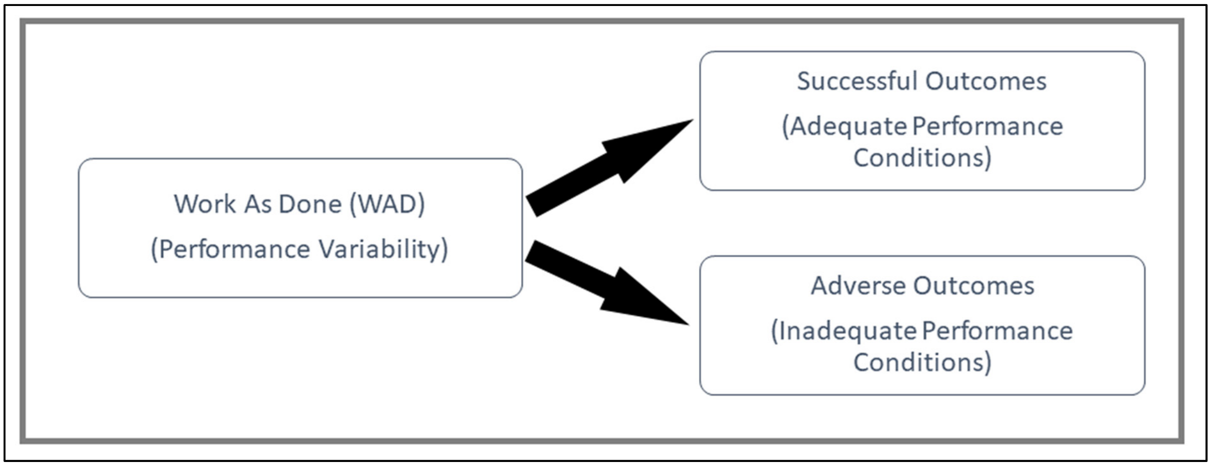

Figure 1.5 The Resilience Engineering view: equivalence of success and failure (Hollnagel et al., 2015)

The inclusion of complexity thinking marked a significant change in perspective and a move to systemic and more holistic approaches in systems' analysis. Rather than focusing on a singular event or malfunction, failure or adversity in complexity thinking is explained as a result of the interactions of several influential factors and the lack of resilience of the system to cope with the fluctuations and dynamic nature of the complex working environment. Adopting a systemic and holistic approach characterizing the dynamic nature of the studied context would be fundamental to designing and modelling sufficiently resilient systems. The Functional Resonance Analysis Method (FRAM) is most probably the most prominent tool in the field of Resilience Engineering, which attracted a lot of attention in recent years leading to a significant count of studies exploring its usefulness and applicability to different contexts. In the following section, FRAM will be presented and discussed more thoroughly.

1.4 The Functional Resonance Analysis Method (FRAM)

FRAM was introduced in 2004 by Erik Hollnagel (Hollnagel, 2004). "*The Functional Resonance Analysis Method describes system failures (adverse events) as the outcome of functional resonance arising from the variability of normal performance*" (Hollnagel, 2012b). FRAM is a systemic method that describes non-linear relationships and interactions between different systemic functions. It analyzes normal system activities taking into consideration functional variability and deviations from expected performance (Hollnagel, 2012a). These deviations are a normal part of any operation. The performance in a sociotechnical system is never applied as designed. It varies each time depending on the present conditions, environment, individual and collective human state and equipment. The performance in applying the same operation will be different each time, even if carried out by the same operator. FRAM will consider the variability in performance of different functions and study how it might resonate within the system to create unwanted events.

The principles, on which FRAM relies, can be therefore expressed as follows:

1. **Equivalence between success and failure:** success and failure are not considered opposites, rather both a result of the variability of normal performance. Performance adjustments are inevitable to cope with the complexity of the real world. Success can be considered as a result of the system's ability to adapt to changes and anticipate unwanted events before they occur, while failure is the absence of that ability (Hollnagel, 2012b; Macchi, 2010).

2. **Inevitability of approximate adjustments:** the performance variability of a sociotechnical system can be attributed to two factors. Firstly, real operating conditions are underspecified, and it is impossible to imagine them accurately in advance and secondly, operating conditions are variable and dynamic. Thus, instructions cannot be prepared precisely and are not to be followed with every detail to the letter. Rather, guidelines and procedures are to be provided along with extensive professional training to act properly and correctly. Variability is not a limited short-termed characteristic during system operations. Rather, it is an inherent condition, which exists permanently throughout the system operations. Therefore, performance adjustments are required and necessary to cope with the functional variability. The adjustments are approximate, since time and resources are limited and not infinite (Hollnagel, 2012b; Macchi, 2010).

3. **Emergence of consequences:** The performance variability of a single function in a sociotechnical system is not significant enough on its own to cause accidents or

malfunctions. The unexpected interaction between multiple functions might lead into the emergence of severe and large consequences. Both success and failure cannot be explained as results of the failures of specific system components, but as emergent non-linear outcomes of multiple interacting functions within the system (Hollnagel, 2012b; Macchi, 2010).

4. **Functional resonance:** FRAM introduces a systemic approach that focuses on the relationships between various functions within a system. It introduces the principle of functional resonance instead of the traditional cause-effect relationship. Functional resonance means that the variability of the different functions within a sociotechnical system might resonate and thus, produce large outcomes that exceed the normal limits, both in a positive or a negative way. Safety assessments are naturally concerned with the negative outcomes that might lead to malfunctions or accidents (Hollnagel, 2012b; Macchi, 2010).

Since its introduction, FRAM attracted a lot of interest in the research community and initiated several studies in different fields and disciplines to explore its applicability and benefits. At first, FRAM was mainly used as an accident investigation tool; however, it was soon after realized that the principles of FRAM allow for wider range of applications as a safety and performance assessment method. The method was applied in several fields such as healthcare, maritime, railway, industrial and manufacturing environments and most interestingly for our purposes in the aviation sector. In this review, we looked at some of the most interesting FRAM applications for our purposes to possibly draw parallels to the context of aircraft ground deicing/anti-icing operations.

FRAM was applied in the field of health care systems in a pilot study conducted in four National Health Service Scotland hospitals, where incident data was gathered and analyzed to understand variability in blood sampling activities (Pickup et al, 2016). The study identified two major factors that influence blood sampling: inaccuracy in sample labeling and inaccurate patient identification (Pickup et al, 2016). These two factors might lead to incidents, where wrong blood types are given to the patients. The consequences could be a delay in treatment and possible harm to the patient's life (Pickup et al, 2016). Most of the incident reporting systems are biased by the interpretation of gathered data and did not seem to identify accurately the reasons for the occurrence of these incidents (Pickup et al, 2016). These reporting systems did not capture the range of factors that influence human performance within a sociotechnical system (Pickup et al, 2016). FRAM was used as a systemic approach to analyze work as it is done in practice and to identify interactions between system functions and their variability (Pickup et al, 2016). The FRAM instantiation showed variability in the system's functions such as timing or accuracy. These were influenced by the work environment and conditions, equipment and resources (Pickup et al, 2016). It also showed dependencies and interactions among many functions in the blood sampling activity leading to vulnerabilities in the system (Pickup et al, 2016). Some functions affected more functions at once, while other functions depended on or were influenced by several functions together. FRAM provided an understanding for how practitioners adjust their performance and modify their practices on a daily basis to cope with their dynamic work environment. FRAM showed the need to optimize four aspects of the blood sampling procedures: design of equipment and technology, reliability of the technical systems, resources management and finally, monitoring, reporting and feedback (Pickup et al, 2016).

Another application of FRAM found place in a manufacturing environment (Albery et al, 2016). The main objective of the study was to investigate whether an application of FRAM as a risk assessment tool can overcome shortages related to traditional assessment methods such as the Risk Matrix (Albery et al, 2016). The study evaluated four systems within one manufacturing environment (Albery et al, 2016). The research methodology defined four specific objectives: Work as imagined (to understand how work is defined), Work as done (to understand how work is actually performed), Risk Matrix Approach and FRAM approach (to evaluate both methods and compare them) (Albery et al, 2016). Accordingly, four manufacturing systems were selected whereas the output of system 1 feeds system 2 and the output of system 3 feeds system 4 (Albery et al, 2016). "*The defining attribute of systems with low process control was high variability, which meant that workers had to engage in more physical and mental activity to complete the task within the allotted timeframe. Comparatively,* *systems with a high level of control required a lower degree of mental and/or physical engagement from workers to achieve objectives due to timed automation*" (Albery et al, 2016). Systems 1 & 2 were highly controlled, while systems 3 & 4 were low controlled. The results of questionnaire one (objective: work-as-imagined) showed the level of control for each system, which found to be as specified. The results of questionnaires two & three (objectives: work-as-done & Risk Matrix) showed that workers had introduced hidden functions, i.e., uncontrolled hazards, to maintain the success of operation in all four systems (Albery et al, 2016). Building on the findings of the first three questionnaires, questionnaire four (objective: FRAM) determined instantiations of the four systems and the sources of variability within them. These variabilities introduced risks and exposed the workers to the danger of being injured. They affected the productivity and caused interruptions and delay. The coupled systems (1 with 2 & 3 with 4) were affected by the variability within either system, i.e., upstream and downstream effects (Albery et al, 2016). FRAM provided a perspective that enabled a better understanding of the system's goals. It showed the effect of performance variability within one system and the effects between coupled systems. By using FRAM, the potential sources for variability could be determined and thus by adding further control mechanisms, the system's performance could be optimized, and the risks of hazards minimized. The benefits of applying FRAM in comparison to the Risk Matrix method were demonstrated. FRAM also benefited from the application of the other method and provided conclusions that might have not been reached if it was applied separately, which promotes and supports the idea of using FRAM as a complementary tool in addition to classic tools.

An additional FRAM study in the field of railway traffic focused on analyzing the impact of the Automatic Train Supervision (ATS) system on the safety of the railway system (Belmonte et al, 2011). To study the influence of human and organizational factors, a Human-Machine-System approach was adopted over a machine-centered approach (Belmonte et al, 2011). Human-Machine-System approaches integrate the human and organizational aspects in the analysis and study their interactions with the integrated technology. Machine-centered approaches were found to be insufficient to deal with the complexity of a sociotechnical system (Belmonte et al, 2011). FRAM was selected for having the ability of modeling human, organizational and technical aspects of a system in accordance with the MTO classification (Belmonte et al, 2011). In FRAM, a function represents the means necessary to carry out a specific task (Hollnagel, 2012a). It can be a human or an organizational activity. It can represent an automated operation of a technical system or the product of the collaboration of humans, organizations, and technology (Hollnagel, 2012a). Railway systems have become nowadays more automated in regard to operation, control or monitoring (Belmonte et al, 2011). The framework of the study was the application of a modern Automatic Train Supervision (ATS) system to control and monitor railway traffic (Belmonte et al, 2011). Despite the high level of automation, human intervention is still necessary to avoid incidents, modify schedules or set routes (Belmonte et al, 2011). The case study, in which FRAM was utilized here, was about a scenario involving the locking of a switch to protect maintenance teams while present on sections of the track (Belmonte et al, 2011). The ATS system was linked to a railway simulator, which can simulate situations involving incidents (Belmonte et al, 2011). The application of FRAM showed differences between the strategies followed by ATS operators to deal with equipment failures (Belmonte et al, 2011). These differences among operators showed a potential for inadequate decisions resulting from functional resonance (Belmonte et al, 2011). Consequently, high variability in the required time for incident or accident detection was the result (Belmonte et al, 2011). An inadequate monitoring strategy would lead to a late incident detection creating time pressure on the diagnostic operational unit (Belmonte et al, 2011). Time pressure in turn would result in taking the wrong choices by recovery actions. It would hinder the prevention of an accident or the reduction of the damage resulting from it (Belmonte et al, 2011). The study showed the significance of interactions between humans and machines. It showed that even operators, who received the same training working under the same conditions, apply different strategies to perform their tasks. The technology involved here had less variability and performed mostly as designed. The high variability here is a direct result of the human factor. The study results showed possible enhancements to be applied to the ATS HMI to improve the performance of operators and thus minimize chances for incidents. The study was performed in a simulated and controlled environment. The simulated environment simplified the complexity of the system. In reality, problems could occur from other parts of the system such as communication routes or servers or other maintenance teams.

The influences of working conditions such as workload, shift durations and times, network size and traffic and the number of individuals collaborating to perform various tasks simultaneously, etc., add to the complexity and thus need to be included.

FRAM found application as well in the construction industry as an occupational risk-assessment tool (Rosa et al, 2015). The construction environment is a complex one, which requires the collaboration of many groups of workers, contractors, and equipment. On site, the working conditions are dynamic due to the use of different resources, replacement and employment of temporary workers, safety conditions etc. (Rosa et al, 2015). Workers are performing their routine tasks under continuously changing conditions, which exposes them to hazards and threatens their safety. FRAM was selected for being justifiable, traceable, repeatable and verifiable (Rosa et al, 2015). The applied methodology in the study by Rosa et al. was a combination between FRAM and the Analytic Hierarchy Process (AHP), which marked a development of the FRAM framework adding a sort of quantification using weights. The work activities exposed workers to many risks such as noise, vibration, dust, thermal overload, postures, and occupational accidents (Rosa et al, 2015). Eight functions were identified and through the application of FRAM, the resonance between those functions and possible risks were determined. Through the addition of new control mechanisms, the risks were minimized, and the process was enhanced. The FRAM model provided insights about potential loss of control in the process and allowed for the proposition of indicators for monitoring (Rosa et al, 2015). The questionnaires were used to obtain value judgments from a group of experts: a supervisor and two operators (Rosa et al, 2015). The questionnaires were based on the AHP, which aims to provide a numerical ranking (ratio scale) by directly comparing pairs of criteria (Rosa et al, 2015). The results were presented in tables showing the weights of variability and couplings among functions. Even though the subjectivity in determining variability and couplings among functions was reduced through the application of the AHP, the fact remains that the initial data input is still subjective since it represented only the operational aspect by including two operators and one supervisor only. Additionally, the AHP approach is not very well suited for handling the vagueness in expert judgements and translating linguistic scales into numerical scales (Ishizaka, 2014).

To the best of our knowledge, FRAM has never been applied to analyze aircraft ground deicing/anti-icing activities. However, FRAM was applied on multiple occasions in the field of aviation. For example, the application of FRAM as an assessment model for the Minimum Safety Altitude Warning system (MSAW) (Macchi et al, 2009). As far as we can tell, Macchi's study was the first study to propose an improvement to the FRAM framework (Macchi et al., 2009). Three limitations were tackled by Macchi, namely the representation of variability as a result of local performance adjustments; the distinction between three types of performance variability in accordance with the MTO (huMan-Technology-Organization) classification method; and finally, the generation of a simplified and aggregated numerical representation of the output's variability using the list of the Common Performance Conditions (CPC) as indicators (Macchi, 2010). The quality classes of the classical FRAM phenotypes "*precision*" and "*timing*" were combined into a single quality score of the output. Performance conditions in the form of the CPCs were rated using an ordinal scale on a spectrum between −3 for highly variable and +3 for highly dampening. The numerical output was calculated as the median value. The proposed approach was then used to evaluate a case study simulating a landing approach in Stuttgart after the introduction of the Minimum Safe Altitude Warning (MSAW) system to Air Traffic Control (ATC). The MSAW system is a safety system that alerts Air Traffic Control (ATC) about deviations from approach path and potential controlled flights into terrain or obstacles (Macchi et al, 2009). The human factor here was the main focus of the study, since the organizational and technological functions were considered stable (Macchi et al, 2009). To induce variability, two functions were performed inaccurately. The application demonstrated the possibility for the identification of risks resulting from normal performance variability (Macchi et al, 2009). Based on the assumptions for the chosen scenario, FRAM showed performance degradation of the monitoring function, which was performed later than expected. One issue was that that the proposed method by this study simplified the functions' potential to induce variability by using ordinal values or medians as aggregators. "*The simplification done by using the set of ordinal values is compensated by the advantages to have a methodology that can be used for safety assessment the same potential impact on performance variability, i.e. that a degraded input has the same effect as a degraded control* *or precondition*" (Macchi, 2010). The proposed method simplifies reality significantly as acknowledged by Macchi; however, it can be efficient in practical applications. Despite the practical benefit, the issue with this approach is the oversimplification of the functions' potential to dampen or amplify variability by using ordinal values to characterize the functional aspect or median values as aggregators for the functional outputs (Macchi, 2010). Moreover, the distinction between internal and external variability sources is not clearly formulated. Additionally, this approach considers all functional aspects to possess the same impact on the output's variability, which is again another oversimplification of reality (Macchi, 2010). The impact of an aspect on the execution of any given function depends on the nature of the function in question and the significance or weight of each aspect for its execution. Furthermore, the adopted MTO classification approach considers the impact of the CPC's to be the same for all functions of the same type; for example, a given CPC such as "Availability of Resources" affects human and technological functions only. The quality of the CPC "Availability of Resources" as all CPC's is evaluated in terms of a linguistic scale (adequate, inadequate and unpredictable) (Macchi, 2010). The impact for the three qualities of the CPC is small, noticeable and high respectively (Macchi, 2010). As it can be seen, this characterization considers the impact of said CPC to be the same for affected functions. The impact of "inadequate" resources is "noticeable" for human and technological functions. It does not distinguish between human and technological functions or between functions of the same type with different characteristics. The ignorance of the weights of each variable for each function could lead to assigning more impact for non-significant variables or less impact for more significant ones. This might result in expecting adverse outcomes, where none should be, or overseeing the actual ones. The assignment of weights for each variable and for each function separately is therefore necessary to ensure the validity of the obtained results. The characterization table might be thought of as a sort of guideline (since the approach is a generalized one and no specific scenario is being analyzed) and might not necessarily imply that the analyst has to follow it literally. However, a clear and standardized procedure for the analyst to follow in evaluating the CPC's and determining a more precise value is still lacking. Additionally, the proposed approach assumes that the functional aspects possess the same impact on the output. Fuzzy logic can address these limitations and offer solution, which shall be discussed later in this thesis. Nonetheless, Macchi's model was an important first step for advancing research on FRAM.

Following the contributions of Macchi (2010) and Rosa et al. (2015), several studies aimed consequently in the following years to improve FRAM and provide a wider scale of applications. Many studies therefore proposed combining FRAM with other methods to allow for a more standardized representation of variability. Slater (2017) proposed a probabilistic approach constructing a FRAM model as a Bayesian network of functions (Slater, 2017). Lee and Chung (2018) as well designed a FRAM model to assess and quantify the effect of performance variability in human–system interactions (HSI) (Lee and Chung, 2018). Patriarca et al. provided several contributions proposing several forms of applications and improvements of FRAM (Patriarca et al., 2017 & 2018 & 2019). The study that affected our project significantly aimed at improving the representation of variability through quantification by combining FRAM with the Monte Carlo Simulation to generate probability distributions and represent the output's variability (Patriarca et al., 2017c). The FRAM phenotypes "*precision*" and "*time*" were scored to determine the output's variability as the product of the two scores (Patriarca et al., 2017c). The dependencies among functions through upstream and downstream couplings were accounted for using for each coupling two amplifying factors for the two phenotypes ($a < 1$ amplifying; $a = 1$ neutral; $a > 1$ dampening). A specific status of the present performance conditions defines an instantiation of the model, for which an impact factor was defined as well ($b = 0$ for no impact; $b < 1$ for moderate impact; $b = 1$ for high impact). The set of possible analysis scenarios or instantiations is represented by a matrix to represent their total effect and determine the resulting conditional variability. The proposed framework was applied in this case for the evaluation of the Air Traffic Management (ATM) system as well. The advantage for using probability distributions instead of static scores can prevent misrepresenting of the status and dynamic behavior of the system in question. The generated outcome by this approach presents as well a distribution of possible outputs with respective probability values. This approach is better suited for uncertain contexts and variables and allows for better predictive assessment. The model proposed by Patriarca et al. marks another significant contribution and promotes further the use of FRAM in a new way. For some contexts such as high reliability systems, in which statistics data is not provided sufficiently, such an approach might be difficult to implement. The applied Monte Carlo simulation is unidirectional since the sampling process is random. The size of the required data samples for producing the probability distributions is significant to allow for running a high number of iterations. This might not be provided in such systems as deicing operations, in which statistics are generally rare and the variables in question are vague and uncertain by nature. Such variables are better represented using natural language, which makes the application of such tools as fuzzy logic and rough sets a more appropriate approach. Relying on natural language is preferred and might even be the only possible route in those cases, when the input data is too imprecise to allow for the use of numbers (Zadeh, 1996). The tolerance for imprecision could be even exploited to produce better outcomes (Zadeh, 1996).

Finally, in this section, many applications of FRAM in different fields using different methodologies were reviewed. It was possible to see the benefits and limitations of FRAM as shown by the selected examples. The proposed improvements are important first steps and provide first indicators for future work to further develop FRAM. Another approach to accomplish a more standardized and systematic framework to quantify the output's variability can be achieved with Fuzzy Logic.

1.5 Fuzzy Logic: A quantification tool for natural language

Human knowledge is shaped by our perception of the world. Humans rely on their senses and reasoning skills to understand and classify perceived information into labels and sets. The limited spectrum of human perception and reasoning skills forms a true barrier for forming a certain knowledge base (Sivanandam et al., 2007). Before we proceed with designing our model, we have first to define what is meant with the term "uncertainty" to gain an understanding on how it is employed in this project. The term "uncertainty" has a broad spectrum and can refer to different types of uncertain information. There is admittedly a continuous debate on the exact meaning of "uncertainty" in literature (Njå et al., 2017) and the different types of uncertainty are sometimes used interchangeably; however, it is important to specify exactly the aspects, to which are referred in the context of this study since these concepts refer to different types of uncertainty. It is also worth mentioning that different definitions of uncertainty can be used depending on the field or discipline of study. Therefore, we would focus here mainly on defining how these terms were used in relation to our study supported of course by formal definitions in the literature.

Generally, uncertainty refers to an epistemic situation involving unknown aspects or imperfect information about a concept, an object, or an observed instance (Njå et al., 2017). The lack of certainty represents a state of limited knowledge, where it would not be possible to precisely define the outcome. Uncertainty can be of different types depending on its different sources: randomness, ignorance or lack of knowledge, inability to measure the phenomena, ambiguity, vagueness or as often used in the context of fuzzy logic, fuzziness (Cox, 1994).

Inexactness or imprecision refers to the ability to precisely measure phenomena of interest i.e., the lack thereof, which leads to compromises in the precision of measurements due to either the inadequacy of the used measurement tools or due to the intrinsic characteristics of the observed variable itself (Cox, 1994). Whether quantitative or qualitative, the ability to quantify or qualify a specific value is challenged due to imprecision in the measurement methods such as quality of input data, subjectivity & bias, inadequate scales, and measurement tools etc. Accuracy on the other refers to the degree, to which a provided measurement is representative of the standard value of the measured variable. This can be as well a result of issues related to measurements. Fuzzy logic usually addresses intrinsic imprecision of the measured variables and their properties rather than imprecision resulting from the inadequacy of measurement tools (Cox, 1994). Additionally, the imprecisions in human knowledge can be due to the vagueness and ambiguity of the observed context itself (Dernoncourt & Métais, 2011).

Ambiguity on the other hand is another type of uncertainty related to the phrasing or definition of the variable, which is not explicitly defined leaving the space open for interpretations (Klir, 1987). The intended meaning of the used term or expression is not clearly stated, well-defined or cannot be definitely resolved from the provided information.

Vagueness usually refers to concepts that are hardly quantifiable by nature. Vagueness is one of the main uncertainty types addressed in the context of fuzzy logic since fuzzy logic provides a mathematical framework to quantify linguistic variables and try to minimize the vagueness produced using words and linguistic scales as “adequate”, “late” or “short”. Vague concepts have a borderline region, and it would be difficult to make sharp distinctions for them (Klir, 1987). The transition between what can be considered a member or not member of the class is not sharp or crisp but rather gradual and fuzzy. Consequently, the precise magnitude of such labels can be perceived differently by different parties since the perceptions of people are different and they can associate different meaning with words.

Finally, variability in our context refers to the variations and deviations in performance due to adjustments from norms and prescribed guidelines. A process that is executed in reality is never carried out as imagined (WAI & WAD) leading consequently to changes and deviation in the produced output from the nominal value.

Generally, fuzzy logic addresses two main types of uncertainty, namely vagueness and ambiguity with the possibility to address other types as well if intended. Fuzzy logic is not a fixed structure and is rather a mathematical tool that can be utilized to address different types of issues. In this project, uncertainty is used as a general term referring to uncertain information introducing challenges to specify the output of a given task. Vagueness, as defined above, refers to the fuzziness of the used linguistic scales, which can make the classification of a decision difficult.

Real world systems are complex, and the relationships of their components are not linear or easily understandable. The degree of clarity is proportional to the degree of complexity, i.e., the more complexity a system possesses, the more vague and fuzzy it becomes. Humans managed over the years to develop advanced measurement tools that are capable of measuring phenomena beyond the spectrum of human senses. Regardless of how accurate these instruments might become, inaccuracy of measurements is always a present factor

(Sivanandam et al., 2007). The human mind approximates the perceived information; and even relying on the most accurate and advanced measurement instruments, human knowledge remains imprecise, incomplete and uncertain (Sivanandam et al., 2007). To cope with the complexity and uncertainty, the construction of approximate models of the real systems is the only way given the limitations and lack of precision in human knowledge and perception. The approximate models are simplifications of reality, in which linear or clear relationships between systemic components are drawn. Based on those models, rules and laws are designed to provide and maintain functionality of the designed systems.

Another factor affecting human understanding is relying on natural language to describe, formulate and communicate knowledge. By using words to describe phenomena and things, the true nature of those described things becomes approximated and is consequently reduced to have specific limited meanings (Zadeh, 1973). The general meaning of words can be the same for different humans, but specifically, they can have different meanings depending on the context and person's perception. For example, the word "*tall*" is known to describe people, who have a greater height than the average person does. However, depending on the context, the required height to be considered "*tall*" might be different from a specific group of people to another. The word "tall" provides a general idea of the concept of "*tallness*", but not a precise measure to classify "*tall*" people from "*not tall*" people. The word "*tall*" is simply vague and fuzzy. Linguistic descriptors capture the relative but not the precise magnitude of the measured value. They are subjective, imprecise and vague (Shepard, 2005).

To determine and measure phenomena more objectively, mathematical analyses and quantification methods become necessary. However, not all phenomena and contexts are easily quantifiable (Zadeh, 1973). The determination of a precise magnitude for qualitative variables and uncertain contexts is difficult and, in some cases, not achievable in terms of discrete mathematics. The problem with using traditional methods to analyze vague and uncertain contexts is the inability to collect precise data and provide quantifiable analysis results (Zadeh, 1973). Qualitative analysis methods are descriptive by nature and rely mainly on the use of natural language to capture and evaluate the studied context.

Fuzzy logic can be an appropriate method to quantify linguistic variables and vague contexts (Zadeh, 1965). Fuzzy logic resembles human reasoning, which means approximating reason and the ability to capture and deal with vague and ambiguous concepts (Zadeh, 1973). Fuzzy Set Theory was introduced by Lotfi Zadeh in 1965 (Zadeh, 1965), which built on theory of many-valued logic to propose a generalization of classical set theory. In classical set theory, objects are either elements of a given set, or they are not i.e., they are either true or false (Sivanandam et al., 2007). Elements in fuzzy set theory on the other hand can belong to a given set with a certain degree of truth or membership (Sivanandam et al., 2007). The membership function defines the value for the degree of truth of an element in a fuzzy set on a spectrum between zero and one. The curve of the membership function could have many shapes depending on the nature of the variable in question (triangle, trapezoid, S-shape, etc.) (Shepard, 2005).

To better understand fuzzy set theory, we start with some definitions in classical set theory (Shepard, 2005; Dernoncourt & Métais, 2011):

Let *A* be a crisp set, in the domain *U*, with a characteristic function

$$fA(x) = \begin{cases} 1, if\ and\ only\ if\ \ x \in A \\ 0, if\ and\ only\ if\ \ x \notin A \end{cases} \tag{1.1}$$

If we define *A* as a set of elements greater than *a*, for $x \in R$, then the characteristic function will be

$$fA(x) = \begin{cases} 1, & x > a \\ 0, & x \leq a \end{cases} \tag{1.2}$$

The curve of the characteristic function of a crisp set *A* looks as in Figure 1.6 below.

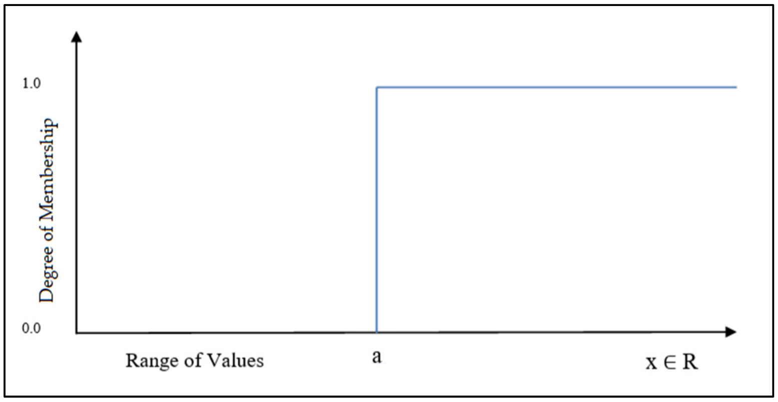

Figure 1.6 An example for membership in classical set theory

To define the characteristics of fuzzy sets, the usual characteristics of classical sets have to be redefined.

Let A be a fuzzy set of U and μ_A is the membership function characterizing the fuzzy set A. $\mu_A(x)$ is the membership degree of x in A.

A then can be defined as: $A = \{(x, \mu_A(x)) \mid x \in A, \mu_A(x) \in [0,1]\}$ *with* $\mu_A: X \rightarrow [0,1]$

A fuzzy set A is therefore a collection of ordered pairs $(x_i, \mu_A(x_i))$, where $\mu_A(x_i)$ is the degree of membership of x_i in A.

For example, a fuzzy set of tall people (above 185cm), which consists of four people, could look as follows: A = {(176,0.1), (180,0.5), (183,0.8), (188,1.0)}

Where the first value in the brackets is the measured height of each element (person) of the set A and the second value is the membership value i.e. the degree of truth concerning the defined margin of "*tallness*" at "*above 185 cm*". If we define A now as a fuzzy set of elements greater than a, then each $x > a$ belongs to A with a degree of membership and the membership function then looks as in Figure 1.7 below.

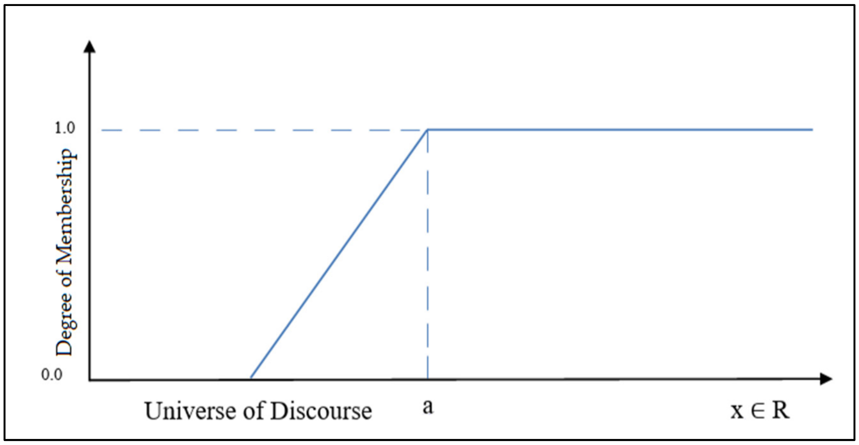

Figure 1.7 An example for membership in fuzzy set theory.

The transition between membership and non-membership in fuzzy sets is gradual as can be seen in the illustrated membership function above. Some basic operations of fuzzy sets are listed below as follows:

- Union of two fuzzy sets:

$$C = A \cup B = \mu_C(x) = max[\mu_A(x), \mu_B(x)] \tag{1.3}$$

- Intersection of two fuzzy sets:

$$\mathrm{C} = \mathrm{A} \cap \mathrm{B} = \mu_C(\mathrm{x}) = \min[\mu_A(\mathrm{x}), \mu_B(\mathrm{x})] \tag{1.4}$$

- Compliment of a fuzzy set *A:*

$$A' = 1 - \mu_A(x) \tag{1.5}$$

The concept of many-valued logic was introduced at the beginning of the 20th century by the Polish philosopher Jan Lukasiewicz (Pelletier, 2000). Lukasiewicz introduced the infinitely valued logic, in which truth-values can be any real number in the interval between zero and one (Hájek, 1998). Lukasiewicz' work initiated multiple studies over the years to follow, which further developed and elaborated the concept of many-valued logic (Hájek, 1998). In 1965, Lotfi Zadeh then presented a formalized definition of many-valued logic and laid the foundations of Fuzzy Set Theory and Fuzzy Logic in an article called "*Fuzzy Sets*" (Zadeh, 1965). The positions on fuzzy logic in the scientific community have been divided since its introduction (Pelletier, 2000). While some advocated fuzzy logic and considered it to be groundbreaking and a more accurate representation of reality, others questioned its validity and correctness (Pelletier, 2000; Hájek, 1998). The mathematical and logical justifications for the correctness of fuzzy logic are irrelevant in our case and beyond the scope of this study. The interesting aspect for our purposes is the provision of an applicable approach to quantify vague and imprecise linguistic concepts, which are not easily quantifiable with classical logic and mathematical methods. Fuzzy logic works and it provides a method to model vague concepts, which even if not completely accurate (accurate in the sense of reality representation) is still accurate enough to provide reliable and representative results. Fuzzy logic is easy to implement, therefore it became preferable and found application in many fields over the past decades.

The article published by Zadeh in 1973 introduced a new approach to analyze complex systems relying on three main features: the use of linguistic variables, the characterization of simple relationships through fuzzy conditional rules, and thirdly fuzzy algorithms (Zadeh, 1973). Zadeh argued that humanistic systems could not be analyzed with classical tools as mechanistic systems. The application of conventional quantitative methods for system analyses is inappropriate in the case of humanistic systems due to the principle of incompatibility. The ability to understand the behavior of any given system in a precise manner decreases when the degree of complexity increases (Zadeh, 1973). Humanistic systems, i.e., economic, societal, and political or any other systems are characterized by dynamic and unpredictable behavior (Zadeh, 1973). The new approach presented by Zadeh allowed for the use of linguistic variables instead of purely relying on numerical data. Human reasoning does not resemble machine processing and relies on natural language and non-discrete logic with continuous functions. It approximates and summarizes information in form of labels, words and sentences (Zadeh, 1973). This tolerance for imprecision can be utilized to elicit only relevant information and design an analysis model that resembles the true nature of the system (Zadeh, 1973). The three main features distinguish the approach presented by Zadeh (Zadeh, 1973) are as follows:

The use of linguistic variables: A linguistic variable is a variable, whose possible values are words (Zadeh, 1973). They represent classes of objects and serve as labels for fuzzy sets, in which the membership degree of elements is determined by the membership function (0,1) (Zadeh, 1973). For example, a variable "*height*" can have the following values: *"short", "not short", "not tall", "tall" and "very tall"*. The values of a fuzzy variable can be one word as in the case of "*short*" or more than one word as in "*not tall*". These values are in the same time labels of fuzzy sets. For example, a fuzzy set "short" contains people who have a height below average human stature. It can be noticed the term "*short*" is vague, since the definition of "*shortness*" differs depending on the context, therefore it is fuzzy. It would be certainly more precise in the above-given example to measure height quantitatively in meters. However, the use of linguistic variables and fuzzy logic is more suitable for complex systems, in which quantitative measurements are not possible or useful (Zadeh, 1973).

The characterization of simple relationships through conditional fuzzy rules: The conditional rules are simple IF-THEN statements and have the following form*: If x, then y*; where x and y are two linguistic variables (numerical values are also acceptable) (Zadeh, 1973). For example, *IF input is precise, THEN output is on time.* The input and output are two linguistic variables, which have the values "*precise*" and "*on time*" respectively. The two values are labels for two fuzzy sets with the same name (fuzzy sets "*precise*" and "*on time*" in *U*). The conditional statement or rule describes a simple relationship between the two variables "*input*" and "*output*".

The characterization of complex relationships through fuzzy algorithms: Fuzzy sets, fuzzy functions, fuzzy relationships and any fuzzy construct by nature can be better defined by fuzzy algorithms than simple conditional statements (Zadeh, 1973). A fuzzy algorithm is a sequence of instructions that may contain labels of fuzzy sets, which are at the same time the values that the linguistic variables can take (Zadeh, 1973). For example:

IF input is late, THEN output is late

IF resources are imprecise, THEN output might be imprecise IF preconditions are not provided, THEN stop output

Despite the vagueness and imprecision in the above statements, they still provide an effective method to describe complex systems in an approximate but nonetheless adequate manner.

One can distinguish between two types of fuzzy sets: Type I and Type II (Shepard, 2005). Type I fuzzy sets represent the degree of membership of a number in a fuzzy set to quantify the subjective terms that apply to said number (Shepard, 2005). This number can be any counted quantity or measured value such as population count, air traffic or distances, which in that case are better represented in terms of linguistic variables such as "*too long*", "*very large*", "*acceptable*", etc. The second type of fuzzy sets, namely Type II, allows for the quantification of pure linguistic variables such as "*imprecise*", "*significant*" "*too late*" etc., which in that case represent vague and uncertain terms and concepts (Shepard, 2005). Such variables are not easily measured and can be quantified through the application of a suitable scale and membership function shape (Shepard, 2005). The scale to measure those vague concepts and the suitable shape of the membership function can be determined through the collaboration with field experts. The selection process of a suitable scale and membership function shape does not have to follow specific rules other than representing the true nature of the variables in question as adequately as possible. The more the experts agree on the selected scale and shape, the better the choice is to represent the variables in question. The second type of fuzzy sets is more relevant and important for the application in a FRAM analysis, which deals mostly with vague concepts that are not easily measurable in terms of numeric scales.

Upon searching the scientific databases for articles on fuzzy logic, thousands of relevant papers were found. The search for the term "*fuzzy logic*" in the Web of Science database provided 12948 results. Since its introduction in 1965, Fuzzy Logic has matured and was further developed and improved over the years to find applications in various fields and domains (Shafaei Bajestani et al., 2017). In 1975, Professor Mamdani at the London University designed the first fuzzy controller for a steam engine, which was applied successfully in a cement plant in Denmark (Garrido, 2012; Negnevitsky, 2005). The Mamdani fuzzy inference method became the most commonly applied method for performing the inference process (Negnevitsky, 2005). Many of the early and notable applications of fuzzy logic took place in Japan, where several research groups from Japanese universities improved and applied fuzzy logic in many mechanical and industrial processes (Garrido, 2012). The interest in fuzzy logic applications was awakened in the eighties. Hitachi used a fuzzy controller for the control of the high- speed Sendai train in 1987, which represented an innovative jump in the use of fuzzy controllers (Garrido, 2012). In 1993, Fuji used a fuzzy controller for the first time for the control of water treatment plants (Garrido, 2012). The applications of fuzzy logic controllers by major companies in their electric products such as wash machines, cameras, elevators, video games, etc. increased rapidly (Garrido, 2012). Fuzzy models have been applied numerous times in medical research, e.g. in the research on diabetes (Shafaei Bajestani et al., 2017). To indicate the degree of pain or disease in clinical research, linguistic terms are used such as high, low, etc. (Shafaei Bajestani et al., 2017). The fuzzy logic approach was improved through the integration of statistical analysis methods such as regression analysis to cope with uncertain and vague data obtained on diabetes (Shafaei Bajestani et al., 2017). The application fields of fuzzy logic are numerous and extend from business and finance, health care and medicine to power plants and industrial processes to automation and computer network etc. (Sivanandam et al., 2007).

The most interesting application possibility of fuzzy logic in our case is the application in Decision-Making and risk analyses to deal with uncertain contexts (Sivanandam et al., 2007). The reliance on linguistic variables allows for the quantification of qualitative expert knowledge in the form of natural language and consequently the provision of more precise outcomes. To better understand the development and formation of accidents and adverse outcomes, Human Reliability Analysis (HRA) methods had to address and predict the variability of human performance (Hollnagel, 1998). The analysis of human performance in first generation HRA methods remained limited due to the lack of clear classifications and structure, explicit modeling, and accurate representation of dynamic systemic interactions (Konstandinidou et al., 2006). The impact of Performance Shaping Factors (PSF) on human performance was poorly considered and represented (Konstandinidou et al., 2006). The second generation of HRA methods shifted the focus of safety assessments from calculating error probabilities to analyzing the influence of contextual factors and work conditions on human performance (Hollnagel, 1998). Hollnagel redefined the PSF's and presented nine Common Performance Conditions (CPC) as part of the Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998). The main difference to classical PSF's lies in the application of the CPC's at the beginning of the analysis to characterize the whole context rather than simply determining probability values for singular events or functions (Konstandinidou et al., 2006). While the PSF's are independent, the CPC's are interrelated and depend on each other (Yang et al., 2013). The effect of a given CPC can change positively or negatively through the dependencies on other CPC's, if the status of those CPC's has changed i.e., interrelated CPC's might affect each other and accordingly change their influence on the system (Yang et al., 2013).

Fuzzy logic has been used in conjunction with the CPC methodology in an effort to quantify the influential factors that affect systemic performance. Konstandindou et al. (2006) developed a fuzzy classifier based on the CPC methodology (as part of CREAM) to estimate the probability of erroneous human actions. The developed model used the CPC's as input variables and associated fuzzy sets and membership functions to characterize the impact of each input. The Mamdani Inference Method was applied to calculate failure probability of human actions. The number of fuzzy rules generated for the nine CPC's was 46656 rules, which required a significant effort for manually correlating an output to each rule. The developed model was validated through evaluating five independent and different industrial contexts (Konstandindou et al., 2006). The article did not specify whether the fuzzy sets and membership functions were assigned relying on expert elicitation or merely on the expertise of the research team. The main objective of this study was to construct a quantitative CREAM model integrating fuzzy logic and to demonstrate how it can be applied. Therefore, the issue of using expert elicitation or using literature and own judgment is probably less critical in this pilot study. Additionally, the analyst would have to specify for each scenario the respective fuzzy sets and membership functions considering the characteristics of the studied context. In the study at hand, the fuzzy sets and membership functions were defined in advance and applied to all five scenarios. The specific characteristics and settings of the selected scenarios are not further presented to determine if contextual differences would imply methodological differences as well. The number of generated rules for nine CPC's was significantly large. If we consider a FRAM model consisting of more input variables than the above-mentioned study, then the rule base could expand to include hundreds of thousands of rules. The feasibility of said approach should be evaluated as well to present a practical and useful model.

The link between fuzzy logic and FRAM was made as well by Hirose & Sawaragi, who noted that FRAM provides only a conceptual framework and requires therefore further extensions and implementations. Accordingly, they proposed an extended FRAM model integrating fuzzy logic and based on the principle of cellular automation (Hirose & Sawaragi, 2020). The extended FRAM model was based on a previously proposed fuzzified CREAM model, which provided a numerical definition for performance variability in FRAM (Hirose et al., 2017). The FIS for the CPC's in CREAM was constructed to determine the control modes considering different weights for the CPC's. The fuzzy CREAM model is applied consequently to the FRAM functions to determine the influential mechanism driving performance variability. The FRAM model represents accordingly a network of fuzzy CREAM mechanisms acting within each function. The numerical representation of variability shall account herewith for the influence of the working environment or the context on the execution of the required tasks. The eleven CPC's provide the labels that summarize said influence. Thus, the obtained scores for the CPC's in fuzzy CREAM represent the dynamic change in variability of the working environment. Consequently, the variability of the FRAM functions is modelled as the dynamic transition of the CPC's scores as well. This allows for identifying dependencies among functions and how variability of an upstream function for example can affect a downstream function. The propagation of variability between functions is herewith represented in the change of the calculated scores for the CPC's.

To summarize, FRAM mostly deals with complex concepts that are of qualitative nature and are not easily quantifiable. It relies on linguistic variables, which do not provide a precise magnitude of the produced values. In fuzzy logic, variables can have multiple values at the same time. A linguistic variable can belong with a certain degree of truth or membership to a fuzzy set, which represents a label or a class of objects with specific characteristics (Zadeh, 1973). The transition between membership and non-membership is gradual and not abrupt as in classical logic. It is this aspect of fuzzy logic, which is most interesting in our case since the FRAM analysis will mainly rely on linguistic variables as input data. The application of a rule-based fuzzy logic methodology to quantify the qualitative values of FRAM is an adequate approach to address the earlier mentioned limitations in the CPC-based FRAM. The approximate reasoning is achieved through the establishment of a set of fuzzy rules (IF-THEN-Rules), which then forms the base for the fuzzy inference process. This approach allows working directly on the linguistic variables and the qualitative concepts of human knowledge without the need to provide precise quantitative points to account for risk factors. The set of fuzzy rules resembles human reasoning and is either determined by domain experts or through a data mining process. The quality of the inference process outcomes depends on the quality of input data and the quality of the fuzzy rules, i.e. the more sophisticated the rules are, the better the outcomes are. In the following section, we provide an overview of the Rough Set Theory (RST) approach as a data-mining tool that can be used in conjunction with fuzzy logic.

1.6 Rough Sets: An approach for data classification

The application of fuzzy logic into the field of safety management has not been without challenges so far and consisted mostly of theoretical studies that are specific to the context of application. Further research would still be therefore needed to address these limitations and provide more generalizable and standardized approaches. One of the issues facing the implementation of fuzzy logic is the so-called “Rules’ Explosion” problem. In the presence of a large number of variables and classes, the number of generated rules can be significant, which would make any proposed model difficult to implement. This difficulty arises from the need for high computing and human resources to accomplish such a task. Decision-makers in practice prefer more efficient and timesaving tools. The expert elicitation in the presence of thousands of rules can be difficult and unfeasible. In other instances, depending on the nature of the variables in question, the consequent part of many rules cannot be determined using natural language due to the vague and uncertain nature of the variables themselves. For example, it would be difficult to specify for a given function, if a "too late" input would necessarily cause any variability in the output or determine how this variability would be translated i.e., as late output or imprecise output.

The application of data-mining tools can offer here a solution to the above-described problems by allowing the analyst of using historical and archived data to predict outcomes and generate rule bases. Such solution can be offered by the RST method (Pawlak, 1982). RST is a mathematical framework proposed by Zdzislaw Pawlak in 1982 for the classification of data sets and reaching approximate decisions given a defined set of attributes (Pawlak, 1982). RST provides tools for processing imperfect data sets in the presence of uncertainty, inconsistency, and incompleteness of information. Data is organized in the form of two-dimensional matrices called information systems (Pawlak, 2004). Each row in the matrix represents an object, while the columns represent their attributes (Pawlak, 2004). The values then of each attribute are assigned for each object with the final column being the decision class (or several rows if more than one decision is derived). The information system can then be represented as IS = (U, A, V, D), where IS is then called a decision system after adding a decision class D ($d \notin A$) (; U is a finite set of objects; A is a finite set of attributes; V is the set of assigned values, and D is the decision class (Pawlak, 2004).

The principle of RST assumes that with every object in the universe of discourse some information can be associated. Objects can be indiscernible if they possess the same information or attribute values, which makes the classification of the output or decision difficult. The indiscernibility relation is a binary relation, which represents the set of objects that cannot be discerned from each other given a specific array of attributes' values. The set of indiscernible objects forms accordingly an equivalence class (Pawlak, 1982). The principle of indiscernibility is the foundation, upon which the mathematical framework of RST is built. In classical set theory, sets have clear boundaries and elements either belong or do not belong to the set. In RST, a set is defined by a pair of crisp sets, namely the upper approximation and the lower approximation. The lower approximation contains all elements that certainly belong to the main set, while the upper approximation contains the elements that can possibly belong to the main set. The difference between the two is then the boundary region. The main set is defined as a rough set if the boundary region was not empty i.e., some elements do belong to the upper approximation but not necessarily to the lower approximation. The decision class is called rough, when it cannot be represented uniquely by the provided input data for the respective attributes. This method can be advantageous to approximate decisions using the indiscernibility principle and the concept of approximation (upper and lower approximation) to identify equivalence classes of indiscernible objects and determine a set of reducts that can be used to generate conditional rules and classify outcomes.

This concept of approximations allows for computing reducts in data tables, which is one of the main features of the RST method. Reducts give the ability to reduce original sets using the principle of indiscernibility. They are reduced subsets of the original sets, which can contain the same accuracy and essential information as the complete dataset (Øhrn, 2000). The values of the attributes are scanned through an algorithm to identify only core attributes needed to discern the decision class. The equivalence classes are used to construct the discernibility matrix, which is then used to define the discernibility functions for the equivalence classes. A discernibility function (true or false) is used to identify the reducts for each object by identifying all attributes' combinations that discern an object with a different decision class from other objects in the original dataset (Hvidsten, 2010). Each logical product in the minimal disjunctive form defines accordingly a reduct of the attributes. This filters the original dataset and reduces its size by keeping only the necessary attributes that can discern the decision class. Thus, the generated rule base can be minimized in size significantly, which would translate into less requirements on resources and effort. The RST method presents a powerful tool for data mining, classification of information and detecting hidden patterns. This approach allows for reducing input data and computing minimal datasets (data reduction) to generate a set of accurate decision rules (Hvidsten, 2010). The obtained set of rules written in natural language is comprehensible and allows for an easy interpretation of the provided results.

Instead of then evaluating a complete dataset to generate the rule base, the generated set of reducts can be used instead to produce the decision rules, which are constructed as IF-THEN statements similar to the FIS rule base (Øhrn, 2000). The antecedent is the conditional part (IF part) is derived from the values of the attributes, while the consequent part (THEN part) is the obtained decision for the rule. The set of reducts possess the same accuracy as the original set depending on the quality of the gathered data and its size. Attributes can be redundant and can therefore be removed as a classification criterion to maintain only a minimal set of attributes sufficient to classify the decision. The support, accuracy and coverage of the generated rules is evaluated to ensure the provision of an adequate and reliable rule base (Hvidsten, 2010). For further details on the rough set process, the reader is advised to consult to Chapter 4 (section 4.2) in this thesis.

The attributes for a given set of objects or functions in the case of FRAM can be defined as a set of performance conditions to reach conclusions on the state of those functions. To this end, the principles of indiscernibility and equivalence are utilized to compute a reduced set of rules, which can help in the classification of output and provide an efficient rule base for computing. Generally, probabilistic and statistical techniques were mainly utilized for the construction of predictive assessment models over the years. While such techniques can be most helpful in the presence of large data sets and for systems with disorganized complexity, qualitative evaluation is still needed and is present in the form of expert judgement and the analyst's input and subjective decisions. The human factor here is decisive for understanding the influential relationships and dependencies among variables and for interpreting the results. The subjectivity is always present in the form of human judgement. The RST approach can provide a mathematical framework adequate for the classification of imperfect and uncertain information by discovering patterns and relationships in archived and historical data. By classifying archived data, the expert input can be abandoned in the rule generation process and would only be needed at the time of data recording and observation. The archived data does not require expert judgement to construct the rule base since the algorithm in the RST software would overtake this task. The expert input would be needed for defining what factors or attributes are to be considered for the data table, what accuracy threshold is valid to ensure the validity of the generated rules and for the validation process of the generated rules afterwards. However, it would not be needed for the reduction, the rule generation or classification process itself, since the algorithm would do this on their behalf by scanning the data set for patterns using the principles of RST. The classification and reduction process can be entirely performed applying several search algorithms to analyze input data provided by experts, operators, and even technological systems. The RST approach would scan the provided data automatically and the quality of the provided rules would depend on the quality of the initially provided dataset. The subjectivity can be herewith limited to the input data provided by humans and to the selection or characterization process performed by the analyst and not the classification or rule generation process itself.

The RST approach despite being newer than fuzzy logic has been heavily studied and found applications in several fields and domains; especially in the fields of Artificial Intelligence (A.I.) (Jelonek et al., 1995), Data and Knowledge Engineering (Parmar et al., 2007), Pattern Recognition (Swiniarski & Skowron, 2003) and Health Care (Komorowski & Øhrn, 1999) etc. Applications in Risk Management and Decision-Making are more interesting for the purposes of this study, which allow for deriving decision rules from archived and historical data (Alisantoso et al., 2005). Such applications propose solutions to problems similar to the ones we are trying to address in this project, which would allow for drawing parallels and to deduce a way to utilize the RST approach to address some of the limitations faced with our prototyping model. More on the merits of rough sets and the integration into FRAM is provided in Chapter 4 of this thesis. A significant number of studies was dedicated to the relation between fuzzy logic and rough set theory as well. Many studies on fuzzy logic and rough sets addressed mathematical and theoretical issues of both concepts and aimed to either compare or combine both methods (Dubois & Prade, 1990; Anderson et al., 2000). From our point of view, the practical aspect is more interesting, since the objective is to provide a useful and comprehensible method for practical applications in safety and performance assessments. Fuzzy logic and rough sets are two different approaches to address uncertainty. The development and extensive research work on both methodologies lead to the introduction of new methods and techniques, which address many uncertainty issues. However, generally speaking, fuzzy logic and rough set theory address different types of uncertainty: while fuzzy logic is advantageous for handling fuzziness and vagueness of data, rough set theory is mainly advantageous for handling inconsistency and incompleteness of data (Yao, 1998). This does not imply that fuzzy logic and rough set theory are restricted methods that can only be applied in a specific way. Similar to Boolean logic and crisp set theory, fuzzy logic and rough set theory are mathematical constructs, whose benefits and limitations depend on the direction and form of application. Fuzzy set theory and rough set theory extend classical Boolean logic through the gradual membership and degrees of truth of fuzzy logic and through the boundary region analysis of rough set theory (Pawlak, 1982). The principle of approximation is fundamental to rough set theory to handle and process uncertainty in contrast to fuzzy logic, which relies on the membership function and numerical values [0, 1] to define the degree of truth or membership (Greco et al., 1999). The two methods do not conflict with each other; rather they complement each other and were combined to address both vagueness and incompleteness in the form of rough fuzzy sets and fuzzy rough sets (Dubois & Prade, 1990; Anderson et al, 2000).

The discussion on the relationship between the different theories, especially in relation to probability theory is controversial. Many misunderstandings could have been avoided if communication between the protagonists were better (Dubois & Prade, 1993). The mathematical and logical discussions on the “correctness” of fuzzy logic and rough sets are irrelevant in our case. The important aspect for this study is the provision of a practical and useful model to quantify vague and imprecise linguistic concepts, which are not easily quantifiable with classical logic and mathematical methods. Fuzzy set theory and rough sets are consistent frameworks and the relationship to probability despite the distinctions is present in the form of possibility theory (Dubois & Prade, 1993). Possibility theory is an extension of fuzzy set theory and was introduced by Zadeh in 1978 (Zadeh, 1978). Possibility theory complements probability theory and differs in addressing types of uncertainty by measuring the possibility and necessity of a variable on a scale between 0 and 1, ranging from impossible to possible and unnecessary to necessary, respectively. Possibility distributions present a graded semantics to statements expressed in natural language (Zadeh, 1978). The three concepts of probability theory, rough set theory and fuzzy set theory, present three different approaches to manage different types of uncertainty (Nurmi, 2009). They are non-contradictive and can be rather complementary to each other (Nurmi, 2009). It is up to the analyst to judge which methodology is more adequate to handle the issue at hand depending on the objective and the context specified for the analysis i.e., performance conditions, type and quality of available data, aspired results, and type of application etc.

1.7 Aircraft Ground Deicing Operations: A complex sociotechnical system

1.7.1 The impact of icing on aviation safety

The issue of icing is a critical one, which caused since the dawn of aviation many accidents, severe damage and loss of human lives. The impact of icing on the integrity of aircraft manifests itself in various forms. The accumulated ice, frost or snow on the aircraft wings can change the aerodynamic characteristics of the aircraft. It can disturb the airflow over the wings and add up to the total weight of the airplane. This will cause a reduction in the lift force and increase the drag force, which in turn will make the takeoff a more difficult procedure with unpredictable consequences. An example to demonstrate the consequences of such an event is provided through the Air Ontario Flight 1363 crash (Moshansky, 1992). On the 10th of March 1989, Air Ontario Flight 1363 carrying 65 passengers and four crew members, crashed shortly after takeoff in Dryden, Canada, killing 21 passengers and three crew members (Moshansky, 1992). The aircraft was a Fokker F-28 Mk1000 registered as C-FONF (Moshansky, 1992). The Canadian Aviation Safety Board (CASB) stated in its final report that "*the immediate cause of the crash is attributable to the contamination of the aircraft lifting surfaces at the time of take-off*" (Moshansky, 1992). The aircraft was not deiced prior to takeoff and was heavily loaded. This accident was the reason for major changes in Canadian Aviation Regulations including deicing procedures.

Accumulated ice on the aircraft control surfaces (flaps, stabilizers, ailerons, etc.) might disturb their functionality severely. As a result, it will reduce the controllability and stability of the plane (ICAO, 2000). On the 31st of October 1994, American Eagle Flight 4184 crashed while in holding pattern before landing in Roselawn, Indiana, USA, and descending to an altitude of 8000 feet. The aircraft was an ATR-72 model and was carrying 64 passengers and four crewmembers (NTSB, 1996). The National Transportation Safety Board (NTSB) stated in its accident report that "*the probable causes of this accident were the loss of control, attributed to a sudden and unexpected aileron hinge moment reversal that occurred after a ridge of ice accreted beyond the deice boots*" (NTSB, 1996). All passengers and crewmembers died in the crash.

Another adverse consequence of accumulated ice might be the disturbance of the functionality of the sensory components such as the Pitot tubes or the angle of attack vanes (ICAO, 2000). This might result in providing wrong information to the air data systems (ICAO, 2000). On the 31st of May 2009, Air France flight AF 447 crashed into the Atlantic Ocean while heading from Rio de Janeiro to Paris (BEA, 2012). The aircraft was an Airbus A330-203 registered F-GZCP and was carrying 216 passengers and 12 crewmembers (BEA, 2012). The Bureau of Enquiry and Analysis for Civil Aviation Safety (BEA) stated in its final report that "*Temporary inconsistency between the airspeed measurements, likely following obstruction of the Pitot tubes by ice crystals that, in particular, caused the autopilot disconnection and the reconfiguration to alternate law*;"(BEA, 2012). The crew failed to diagnose the situation correctly and to react properly and the airplane stalled and crashed killing all passengers and crewmembers (BEA, 2012).

Additionally, ice on the airframe might breakup during takeoff and rush into the engines damaging the turbine blades and causing engine failure (ICAO, 2000). On the 27th of December 1991, Scandinavian Airlines Flight 751 took off from Stockholm/Arlanda Airport and crashed into a field near Gottröra (SHK, 1993). The aircraft was a McDonnell Douglas MD-81, registered as OY-KHO, and was carrying 123 passengers and 6 crewmembers. The Swedish Accident Investigation Board (SHK) stated in their accident report that "*The aircraft took off with clear ice on the wings. In connection with liftoff clear ice came loose and was ingested by the engines. The ice caused damage to the fan stages of the engines which led to engine* *surging. The surges destroyed the engines.*" (SHK, 1993). All passengers and crewmembers survived. The aircraft was completely destroyed (SHK, 1993).

The above-mentioned cases provide just a few examples for the severity of icing on flight safety. Effective and efficient deicing/anti-icing procedures are imperative. Regulations and common practices were developed over the years to prevent accidents and maintain safety. These procedures continuously require improvement to cope with the growing complexity of air traffic.

1.7.2 An overview of Aircraft Deicing Operations

This section provides an overview of deicing operations to describe and clarify the process, so that the reader can gain an understanding of the complexity of the system and is capable of understanding the characterized functions in the proposed model later. Deicing is the removal of ice, frost, slush or snow from the aircraft surfaces. Anti-icing is a precautionary procedure that follows the deicing process to protect the cleaned aircraft surfaces against the formation of ice and snow for a limited period of time (Holdover Time) (Transport Canada, 2004). Currently, on-ground deicing/anti-icing is mainly achieved through the application of deicing/anti-icing fluids. The Pilot-In-Command (PIC) is responsible for deciding whether deicing/anti-icing procedures are to be applied. He/she inspects the aircraft closely prior to takeoff to determine if all surfaces are clear. In addition, the pilot considers many other aspects before deciding if deicing/anti-icing is needed, such as weather conditions (temperature, humidity, precipitation, wind speed, etc.) or the remaining time for takeoff. Even if ice is not present on the airplane surfaces, the possibility of ice accretion in the remaining time due to precipitation or fog is considered (Transport Canada, 2004).

Deicing/Anti-icing fluids consist typically of freezing point depressants (ethylene glycol or propylene glycol), water, corrosion inhibitors, wetting agents and dye. Propylene glycol is more applied and common than ethylene glycol since it is less toxic and harmful (EPA, 2000). Deicing fluids are abbreviated as ADF (Aircraft Deicing Fluids) and the anti-icing fluids as

AAF (Aircraft Anti-icing Fluids) (Transport Canada, 2004). The main acting component of the ADF/AAF is the freezing point depressant (FPD) (Transport Canada, 2004). The FPD lowers the freezing point of freezing precipitation and delays the accumulation of ice, frost or snow on the aircraft surfaces. Deicing/anti-icing fluids must be manufactured in accordance with the specifications of the International Organization for Standardization (ISO) and the Society of Automotive Engineers (SAE) (Transport Canada, 2005). Transport Canada only recognizes the latest SAE specifications, since the ISO specifications are extracted from the SAE specifications (Transport Canada, 2005). The SAE specifications are mainly: SAE Aerospace Material Specification (AMS) 1424 "*Aircraft Deicing/Anti-icing Fluid SAE Type I*" and SAE AMS 1428: "*Deicing/Anti-icing Fluid SAE Type II, III and IV*" (Transport Canada, 2005).

Deicing/Anti-icing fluids are classified into four groups as determined by the Society of Automotive Engineers (SAE) (Transport Canada, 2005):

- Type I (Orange Color): This type has low viscosity and is used mainly for deicing. It is usually diluted with water to achieve the optimal freezing point for application. Additionally, it is heated before application and sprayed with high pressure on the aircraft surfaces to achieve better deicing capability. The Holdover Time after the application of Type I fluids is short-termed, since they flow off the airplane surfaces quickly after their application (Transport Canada, 2005; ICAO, 2000).
- Type II (Colorless): This type contains a thickening agent and has a high viscosity. It is usually applied for anti-icing on a clean surface after the application of Type I. The fluid remains on the wings until takeoff. During takeoff, the viscosity will be reduced due to exposure to wind shear forces and the fluid flows off the wings. Experiments, performed by aircraft manufacturers, show that Type II fluids flow off the aircraft surfaces at rotation speed (V_r). Some aircraft suffer from aerodynamic performance degradation during takeoff, therefore Type II fluids should only be used on airplanes with rotation speed higher than 100 knots (Transport Canada, 2005; ICAO, 2000). Rotation speed is the speed at which the airplane during takeoff changes its ground attitude and rotates along its lateral axis causing the airplane nose to lift up (Swatton, 2000).

- Type III (Yellow Color): This type can be considered a diluted Type II or IV. It is used mainly for airplanes with lower rotation speed (V_r lower than 100 knots) at takeoff such as turbo-propeller airplanes (Transport Canada, 2005; ICAO, 2000).
- Type IV (Green Color): This type has similar fluid characteristics and functionality as Type II but provides a longer holdover time, which is the main reason why it has become more commonly used than Type II (Vasilyeva, 2009).

Holdover Time (HOT): is the time that the deicing/anti-icing fluid remains effective after its first application on the aircraft surfaces until the reformation of ice on that surface (Transport Canada, 2004). Holdover time guidelines are published yearly by Transport Canada. The approved ADF/AAF's are tested to determine their characteristics and their appropriate HOT values for the yearly guidelines (Transport Canada, 2005). These guidelines assist the flight crew in estimating the length of time or the duration of the fluids' effectiveness (Transport Canada, 2004). Many factors affect the performance of the ADF/AAF's and the length of the holdover times such as outside air temperature, airplane skin temperature, precipitation rate, deicing fluid temperature and strength, relative humidity, wind speed and direction (ICAO, 2000; Transport Canada, 2004). The PIC may always adjust the times according to weather conditions or one of the above- mentioned factors. To determine the right HOT, the precipitation type and rate are to be determined firstly. Then, the fluid type, manufacturer and the fluid dilution percentage are to be determined. The Outside Air Temperature (OAT) is to be recorded. This information can then be used to determine the appropriate time range based on the tables provided in the HOT guidelines (Transport Canada, 2004). Holdover times are not generated for extremely low temperatures or for extreme conditions such as heavy freezing rain or heavy snow or in case of ice pellets (Transport Canada, 2004). The factors to be considered for the determination of the right HOT are many and this can be deceptive in case one aspect was neglected. The dynamic nature of the operations and the surrounding environment adds up to the complexity of the process, which requires a high level of caution and awareness.

Application: Before deciding whether deicing/anti-icing is necessary, the airplane is inspected carefully, both visually and tactually. In some cases, the visual inspection is not sufficient to detect ice contamination such as the formation of clear ice (Eyre, 2002). Tactile inspection with bare hands is required therefore to ensure that all surface are clean (Eyre, 2002). The aircraft should be checked systematically focusing on the critical areas such as the wings' surfaces, the horizontal and vertical stabilizers, probes and angle of attack sensors, static ports, general intakes and outlets, control surfaces (slats, flaps, rudder), engines, fuselage, and landing gear (Transport Canada, 2005). If ice contaminations are detected, then deicing, anti-icing or deicing/anti-icing are to be applied (Transport Canada, 2005). The inspection takes place before deicing and after deicing to make sure that the aircraft is clean and airworthy. The inspection process usually takes place in extreme weather conditions and in a hectic environment, which might affect the capabilities and awareness of the person performing the inspection (Transport Canada, 2004).

The deicing/anti-icing procedure is applied shortly prior to aircraft takeoff. The time between the fluid application and takeoff should be kept as short as possible (Transport Canada, 2005). Thus, it is recommended to place the deicing areas near the departure runways (Transport Canada, 2005). If the aircraft waits for a longer period of time after deicing/anti-icing, especially in difficult weather conditions, then the fluids might fail, and deicing/anti-icing must be applied again (Transport Canada, 2005). Anti-icing fluids (Type II, III or IV) must never be applied on contaminated surfaces. Deicing must be applied first to remove contamination and then anti-icing (Transport Canada, 2005). Fluids must be applied only by properly trained personnel using specialized equipment as per aircraft manufacturer's specifications and SAE standard regulations (ARP4737). It is important to apply the fluids as recommended by the fluid's manufacturers. The settings and recommendations provided by the manufacturers, such as pressures or temperatures, will ensure an optimal and effective fluid performance (Transport Canada, 2005). The fluids are to be sprayed symmetrically onto the aircraft surfaces for aerodynamic reasons (Transport Canada, 2005). The following aircraft areas should be avoided during spraying: cockpit windows, aircraft brakes, engine inlets and openings, door handles, APU inlets, open vents, open air conditioning valves, open baggage compartment doors, pitot heads & static ports, angle of attack vanes, air data sensors and any other areas specified by the aircraft manufacturer (Transport Canada, 2005). The cabin windows also should not be sprayed directly, rather the fluid should be sprayed above the windows and it will flow down washing the windows (Transport Canada, 2005).

The term "*Deicing/Anti-icing*" means the combination of both the deicing process and the anti-icing process, and this procedure is classified into two types:

- **One-step deicing/anti-icing:** Applied in case active precipitation is not present and it is not expected to occur before aircraft takeoff. Both deicing and anti-icing are achieved in one step through the application of heated fluids to remove ice and provide protection against the reformation of ice. All fluid types can be used for this procedure, but the anti-icing protection provided by Type I fluid has a shorter holdover time than Type II, III or IV. The freezing point of Type I fluids applied for the one-step procedure must be at least 10°C below the ambient temperature (ICAO, 2000; Transport Canada, 2004 & 2005).
- **Two-step deicing/anti-icing:** Applied in case of active precipitation and contaminated aircraft surfaces. Deicing and anti-icing will be carried out in this case separately in two different steps. Firstly, deicing will be performed mostly through the application of heated Type I fluid (60-82°C or 140-180°F) to remove contamination from the airplane surfaces (Transport Canada, 2005). The freezing point of the used solution in the first step must be more than 3°C above the ambient temperature. Then, anti-icing protection will be provided through the application of Type II, III or IV on the cleaned surfaces to prevent the reformation of ice before takeoff. If Type I fluids are to be applied for anti-icing in the second step, then the fluid's freezing point must be at least 10°C below the ambient temperature (Transport Canada, 2005). The second step must be applied and finished quickly within 3 minutes after the first step to prevent the contamination of the deiced areas (Transport Canada, 2005). It is advisable to divide the aircraft surfaces into areas and apply the complete two steps procedure area by area, i.e. to finish one area completely before moving to the following one. The second step fluid will wash the first step fluid off the surfaces and a thick layer of fluid remains on

> the surfaces to provide anti-icing protection for a specific period of time (HOT). If the fluid fails and freezes before takeoff, the deicing/anti-icing procedure must be repeated starting with the first step. The anti-icing fluids (Types II, III & IV) may have a temperature limit until -25°C when applied. Otherwise, if the temperature limit is below -25°C, then a safety buffer of 7°C between fluid's freezing point and ambient temperature must be maintained. Additionally, the aerodynamic acceptance test results must show that the fluids will perform as intended with such temperatures (ICAO, 2000; Transport Canada, 2004 & 2005).

The ratio of the FPD to water is a significant factor in determining the deicing strength of the fluid. Depending on weather conditions and air temperature, the fluid strength can be adjusted to achieve the desired holdover time. FPD fluids come either diluted with water by the manufacturer or they can be later diluted by the user. They undergo many laboratory tests such as aerodynamic acceptance tests or endurance time tests to ensure quality and meet performance specifications (Transport Canada, 2004 & 2005). It is very important to determine the freezing characteristics of the FPD fluid before application. These characteristics are provided by the manufacturer's specifications and can be tested through quality control inspections as provided by the manufacturer (Transport Canada, 2004). ADFs and AAF's can be used in various forms and ways to provide specific deicing needs. For example, Type I fluids are generally used in larger quantities than Type II or IV, so if snowfall is expected, then AAFs Type II or IV can be used in advance to prolong the time needed for ice to form or snow to accumulate (Vasilyeva, 2009). This way, the use of Type I ADF later will be reduced, which is cost effective and healthy for the environment.

Cold-soak effect: In some cases, ice even forms if the outside air temperature (OAT) is above freezing point (0°C or 32°F). This happens as a result of tanking the airplane with very cold fuel or after landing from a flight at high altitudes. The cold fuel lowers the skin temperature of the upper and lower wing surfaces to below freezing point. If precipitation falls or the relative humidity were high, then clear ice would form on the wing surfaces above and under the fuel tanks at ambient temperatures between -2°C and +15°C. This phenomenon is known as the "*Cold-soak effect*" (ICAO, 2000; Transport Canada, 2004). The cold soaking of the wing surfaces and the accumulation of freezing precipitation are affected by many factors, mainly by: ambient temperature and relative humidity, temperature and quantity of the fuel in the fuel tanks, precipitation type and intensity, wind speed and direction, quantity of the fuel in the fuel tanks, and duration of flight at high altitudes. The formed clear ice can be invisible to the eye and might be overlooked during inspections (Transport Canada, 2004). Therefore, a tactile inspection by bare hand or with the help of the ground ice detection system (GIDS) is required (Transport Canada, 2004). Clear ice can be especially problematic, if it forms at airports at above freezing weather conditions where there is normally no need for deicing.

Properties of Deicing/Anti-icing Fluids: It is imperative to consider the properties of the ADF/AAF's to apply them correctly and perform safe deicing operations. The Determination of the fluid freezing point is important for the application of ADF/ADF's. The freezing point will be appointed by the American Society for Testing Materials (ASTM) D1177 method. The freezing point will be the temperature, at which the first ice crystal forms. ADF/AAF's are generally used in combination with water. The freezing point will be measured for various concentrations of the fluids starting from 0 % (glycol solution percentage) upwards. As the concentration of the fluid is increased gradually, the freezing point will decrease. As the fluid concentration comes closer to the 100%, the freezing point increases (Transport Canada, 2005). Since the freezing point is correlated with the glycol concentration and the glycol concentration is related to the refraction of the fluid, the freezing point can be determined by measuring the index of refraction. The American Society for Testing Materials (ASTM) applies standardized tests using a refractometer, a laboratory device to measure the index of refraction, to measure the freezing point of glycol-based fluids (Transport Canada, 2005). This method is difficult to apply in the field. In the field, the freezing point can be monitored by measuring the refraction (magnitude) through portable refractometers. A correlation chart between freezing point and refraction index is provided by fluid manufacturers to determine the freezing point. To avoid errors resulting from wrong readings of the charts or temperature variations, a safety freezing point calculation buffer is added (Transport Canada, 2005). The approved Lowest Operational Use Temperature (LOUT) to apply ADF/AAF's is higher than the lowest temperature, at which the fluid will maintain its aerodynamic acceptance and flow properly off the aircraft surfaces; and secondly, the actual fluid freezing point plus its safety buffer (10°C for type I & 7°C for types II, III & IV) (Transport Canada, 2005). If the outside air temperature is lower than the LOUT, the fluid must not be used (Transport Canada, 2005).

Types II, III & IV possess, as stated earlier, high viscosity. During the application of these fluids, their viscosity can be reduced due to pumping through the nozzles. This will reduce the expected HOT of the fluid (Transport Canada, 2005). A viscosity range for the fluids is defined that each manufacturer shall maintain for their product. If the viscosity exceeds the range (higher), then the aerodynamic performance will suffer. If the viscosity drops below the range, then the HOT values will be reduced. That is why, after pumping, it is important to check the viscosity of the fluids to see if it meets the required specifications (Transport Canada, 2005).

Fluids of Type II, III and IV stay after application on the aircraft surfaces to provide anti- icing protection. As the temperature drops, the viscosity increases, which might affect the aerodynamic performance of the aircraft negatively (Transport Canada, 2005). Usually, the fluids should flow off the aircraft wings and surfaces during take-off after exposure to airflow (shear stress), which reduces the fluid's viscosity. The fluids flow off the aircraft depending on the speed during take-off. Aerodynamic performance is tested by determining the coldest temperature, at which the fluids would flow off the aircraft surfaces. Additionally, the fluids can be affected if exposed to UV light for example: color fading (DOW, 2004). Specially, fluids stored in site gauges are exposed to UV light (Transport Canada, 2005). The fluids are to be stored as specified by the fluid manufacturer to protect against UV degradation, e.g. avoid storing in ultraviolet light transparent vessels (DOW, 2004).

The handling, transportation and storing of the fluids is a delicate matter and must be performed as specified by the fluid's manufacturers and the SAE specifications (ARP4737, AMS1424 & 1428) (Transport Canada, 2005). The transfer vessels and storage tanks should be fabricated out of fluid compatible materials. Incompatible materials might change the fluids characteristics and lead to performance degradation. The fluids should be routinely tested to assure that they maintain their characteristics (Refraction Tests, Viscosity Tests, Suspended Matter Tests, etc.) (Transport Canada, 2005). The fluids should be protected against contamination by using dedicated equipment (Transport Canada, 2005). The used containers and equipment, whether for storage or transport, should be always internally inspected. The tanks should be sealed properly, and the covers should be weatherproof (Transport Canada, 2005). In addition, all tanks, vessels, valves or any other equipment should be labeled correctly and clearly to identify the fluid in question and provide necessary details (Transport Canada, 2005).

1.7.3 The characteristics of the Deicing Work Environment

The working environment for deicing operations is characterized by dynamicity and complexity (Transport Canada, 2004). The many influential factors are variable, which might affect the performance quality and cause severe consequences. Deicing is usually required, whenever the weather conditions are at or below freezing temperatures. Meteorological conditions are variable by nature, and they require caution from all actors involved with the deicing process to ensure the integrity of the deicing procedures. The holdover times for extreme weather conditions such as freezing rain or heavy snow have not been evaluated yet, which prevents aircraft from flying in those conditions (Transport Canada, 2005). Heavy weather conditions require attention and adjustments if necessary, e.g., repetition of inspections, time schedules' amendments, fluid type to be applied, etc. (Transport Canada, 2005).

Deicing operations can be applied at the gate or in special reserved areas and centralized deicing pads (Günebak et al., 2015). In Canada, deicing operations are carried out today in centralized deicing pads (Günebak et al., 2015). Centralized deicing pads facilitate the deicing of multiple airplanes simultaneously in one place. This operation demands good coordination and clear communication between the flight crew, Air Traffic Control (ATC), the deicing team and the deicing tower (Günebak et al., 2015). Communicating is necessary to coordinate the movement of the airplanes, the deicing trucks, and any vehicle into the deicing pad and in the surrounding environment. Adequate communication is imperative to comply with temporal constraints and avoid operational imprecisions and incidents on the ground, e.g., the accident of Royal Air Maroc in 1995 at the Montreal (Mirabel) International Airport, Quebec (Transport Safety Board, 1995).

The PIC is ultimately responsible for ensuring that the aircraft is clean prior to takeoff. He/she must consider many factors whenever deicing procedures are to be applied. The PIC decides whether deicing is required after inspecting the aircraft surfaces visually and tactually. The pilot as well inspects or assigns another party to inspect the aircraft after the conclusion of deicing/anti-icing operations to ensure a clear state for take-off. Otherwise, the pilot would request the re-application of deicing until the airplane is clear for takeoff. He/she should be aware of the requirements of the aircraft (fluid type, application of fluid, safety precautions, etc.) and communicate this to the service provider (Transport Canada, 2005). The PIC communicates and monitors the operations to ensure that all steps are executed in accordance with the rules and regulations. He/she is to be aware of the surrounding environment, review meteorological data and HOT tables, and eventually make the decision whether the aircraft is clean and airworthy for takeoff (Transport Canada, 2005). The above-described tasks are only a simplified representation of the aspects that the PIC should consider and perform. The decision-making process for the PIC and his first officer is complex and requires the highest level of awareness and knowledgeability.

The provision of deicing services can be provided either by the airlines themselves or by specialized deicing contractors (Landau et al., 2017). The deicing staff work mostly on a temporary seasonal basis. Their job as deicing technicians require the performance of dynamic and heavy-duty tasks, which require mental readiness and impose physical stress (Landau et al., 2017). The work environment for deicing technicians is tough and dynamic, in which they are constantly exposed to several physical and chemical influences such as noise, vibrations, glycol solutions, extreme weather conditions, etc. (Landau et al., 2017). Working for long hours in shifts and overnight can cause behavioral disorders and disturb the circadian rhythm of the workers (Boivin & Boudreau, 2014). The performance of deicing activities under heavy workload for several hours under such circumstances imposes high levels of fatigue and stress on the workers (Torres et al., 2016). Additionally, the employment as a deicing technician imposes several health and safety issues on the workers such as risks of falls, accidents with vehicles, contact with propellers, etc. (Landau et al. 2017). Despite the harsh conditions, deicing service providers prioritize performing the procedures with high accuracy and strive to execute the operations in a very reliable manner. However, the aspects of the deicing environment should still be further assessed and improved, where possible, to provide adequate safety measures and protect the workers.

The influential factors that affect deicing operations are not simply limited to the operational factors. Organizational and technological factors are very much influential and should be considered as well (Torres et al., 2013). Providing adequate instructions, equipment and technology is imperative for an appropriate execution of the procedures. Inadequate guidelines and equipment could affect the quality of operations significantly and could prevent workers from performing their tasks as designed, who would then be forced to adjust their performance to cope with the variability, e.g., the earlier-mentioned Scandinavian Airlines flight 751 crash in 1991 (SHK, 1993). The absence of adequate instructions and equipment influenced the inspection process and the mechanic performing the inspection adjusted his actions accordingly, which resulted along with other factors in overseeing the accumulated clear ice on the wings (SHK, 1993). The organizational climate is very important as well and it can contribute to the formation of accidents if not considered. Adequate management and monitoring of operations ensure the correct execution of procedures as prescribed. Organizational factors such as training programs, salary systems, planning of working and rest hours, etc. all affect the quality of the deicing operations (Torres et al, 2013).

To summarize, this review explored as much procedural details as possible in this report to draw a relatively representative picture of the deicing context. The main message that we can take away from this section is that deicing operations are demanding, complex and important. The number of influential factors is significant and presents an interdependent and dynamic context for analysis that requires attention. Research from a human perspective has been rarely conducted to study the context of deicing operations.

CHAPTER 2

OBJECTIVES AND RESEARCH METHODOLOGY

2.1 Research Problem and Objectives

The main conclusions that we were able to draw from the literature review summarize the following three issues that need to be addressed in research endeavors to make the next leap in the field of risk and safety management:

Firstly, the noticeable expansion of safety management and its applications across different disciplines and fields require the proposition of new tools and techniques as well that are suitable to address the challenges and specific characteristics of the modern systems of today. With the advent of Industry 4.0 and the inevitable and continuous growth of sociotechnical systems into very complex structures, innovative tools providing a fresh perspective adopting complexity-thinking are needed. Such tools should look at the system as a whole considering its animate and inanimate components together.

Secondly, while applying a qualitative assessment method could provide a better representation of the dynamic and complex relationships, the provision of more inter-subjectively comprehensible and reliable results could be more difficult due to the vagueness and uncertainty of the analyzed context. The magnitude of qualitative scales could be differently perceived by different parties, which could result in different evaluations and decisions as a consequence. Therefore, the proposition of more standardized methodological frameworks to reduce subjectivity and present more comprehensible results should be sought.

Thirdly, the limitations and scarcity of significant data and statistics on accidents due to the high reliability of critical systems and the rarity of such events make the collection of meaningful data and statistics somewhat difficult. Often, the lessons learned are hardly generalizable to other contexts due to the unique nature of such events. Incidents could provide indicators and lessons can be learned to anticipate possible accidents in the future. The question whether an event constitutes an accident or incident is irrelevant in FRAM, since the focus of the analysis is not directed towards only singular events or root causes. Therefore, incidents can be used, and even day-to-day routine operations can be analyzed to evaluate the performance of the system as a whole. This is main concept behind Resilience Engineering. Other times, the amount of generated data sets is immense (Big Data) and require an exhaustive filtration and classification process. Additionally, it is sometimes difficult to collect meaningful data on instances or variables that are vague and uncertain by default. It makes the assignment of a quality score an uncertain mission as well. It is therefore advisable to investigate and propose adequate and efficient data collection and classification tools capable of handling such challenges.

The main objective of this research project will be to introduce a new systemic approach for the assessment and analysis of complex sociotechnical systems generally and aircraft on-ground deicing/anti-icing operations specifically.

Accordingly, the specific objectives can be listed as follows:

- **Phase I:** To provide a new approach for modelling and analyzing the system of aircraft deicing operations from a systemic perspective through the application of the Functional Resonance Analysis Method (FRAM);
- **Phase II:** To construct a systematic and standardized framework for FRAM distinguishing between external and internal variability factors and introducing quantification tools by combining fuzzy logic with FRAM to allow for numerical representation of performance variability;
- **Phase III:** To integrate RST as a data-mining tool for the classification of data and to automatically generate efficient and reduced rule bases to be implemented in the FIS of the FRAM functions.

Generally, each phase would result in a model for analysis of complex systems. Each model will adopt the principles of Design Science Research Steps (Vaishnavi & Kuechler, 2015). Firstly, the problem to be addressed will be formulated as a result of the literature review in the contexts of sociotechnical systems and safety management generally and aircraft deicing specifically. The objective of each phase will be formulated accordingly, and a possible solution will be proposed. Consequently, in the next step, a first application as in Phase I or a prototype as in Phases II & III will be designed and introduced. The results obtained for each model will be afterwards discussed, evaluated, and validated by comparison of the three phases. At this stage, the main concern of this project will be to formulate an initial model adopting the recommended frameworks and provide a proof of concept. Moving forward, in future research projects, further validation and optimization will be needed using expert judgement and field data. Finally, results and conclusions will be drawn to provide feedback and insights for future work. The steps as recommended by Design Science are illustrated in Figure 2.1.

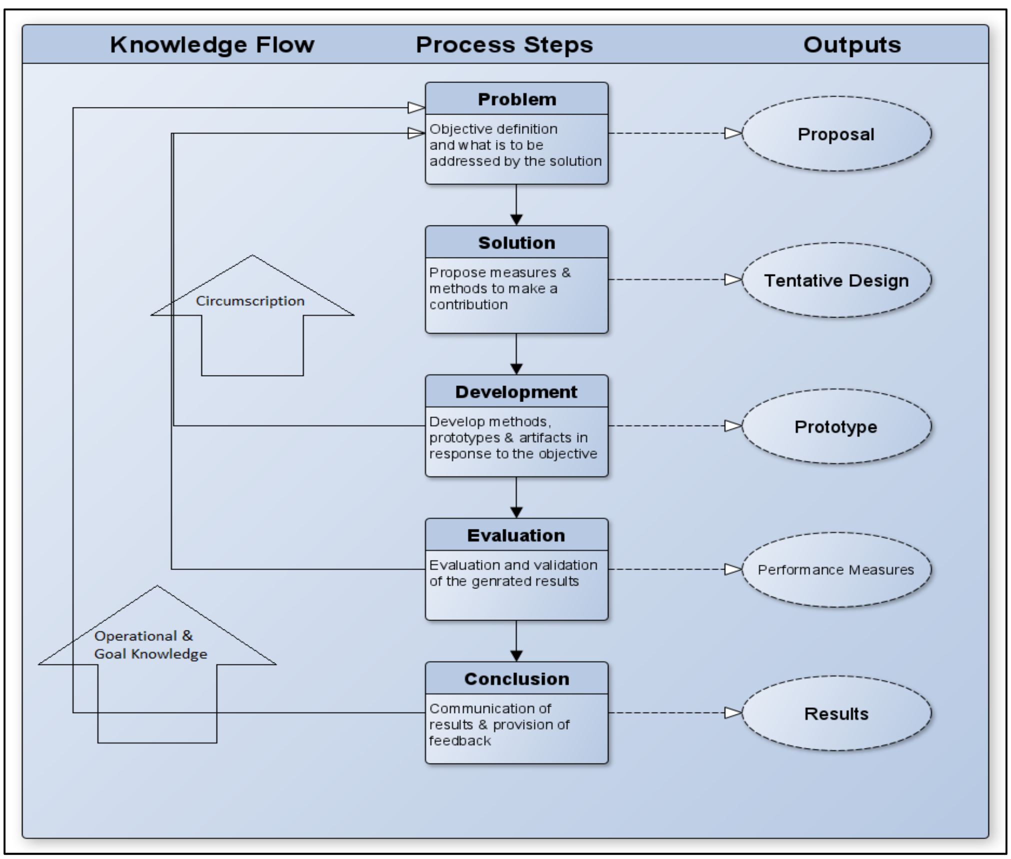

Figure 2.1 Design Science research steps for each phase

Figure 2.2 provides an illustrative overview of the entire research methodology for the three phases of this project.

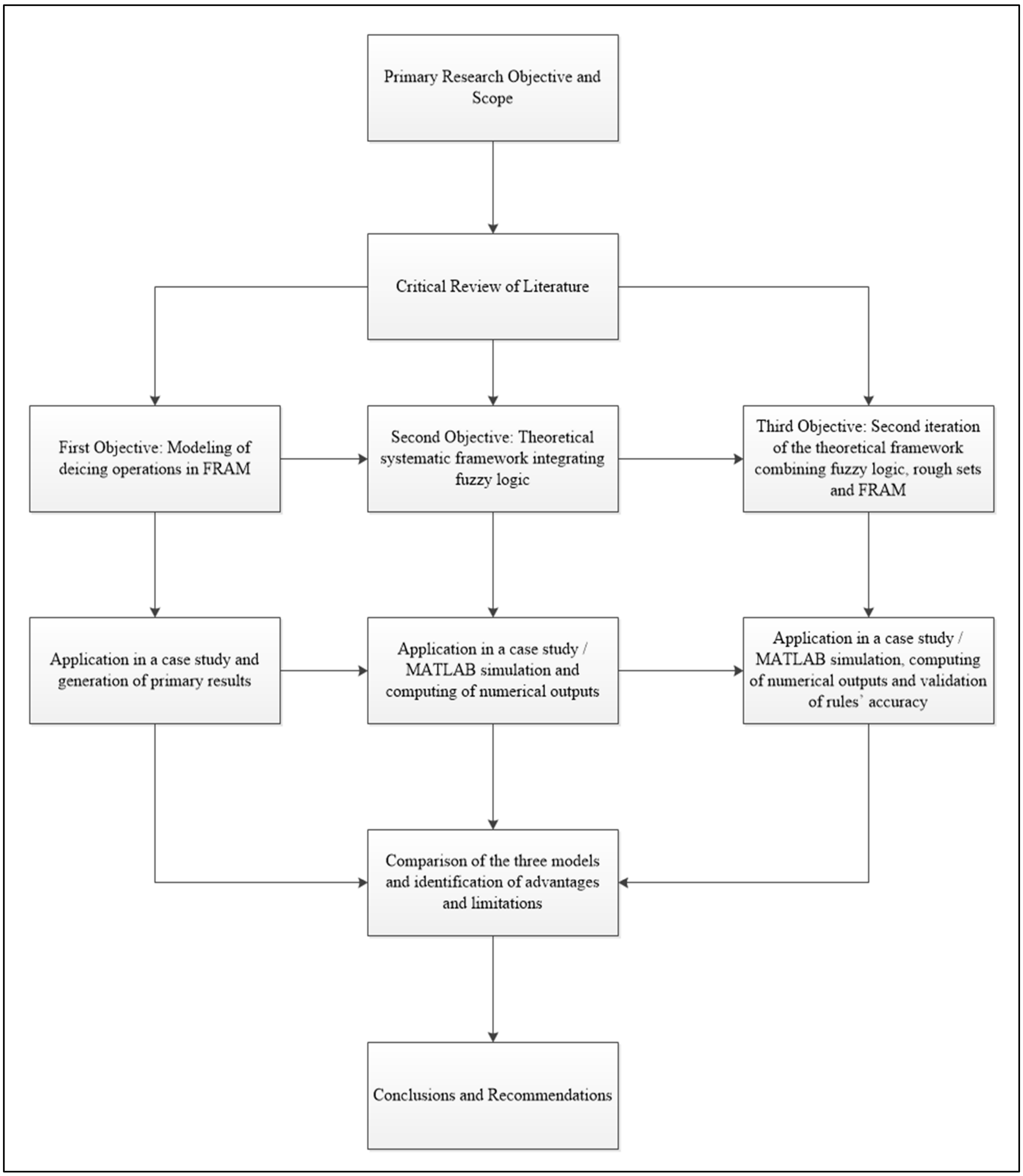

Figure 2.2 General structure of the entire research methodology

2.2 Research Methodology

2.2.1 Phase I: A FRAM Model of Aircraft Deicing Operations

The context addressed by this study is the working environment of aircraft ground deicing operations. The FRAM approach shall differ from traditional models and analyze the context of deicing operations from a more functional and systemic point of view. FRAM allows for the analysis of normal system activities taking into consideration functional variability and deviations from expected performance i.e., the difference between Work-As-Imagined (WAI) and Work-As-Done (WAD) (Hollnagel, 2012a). The merits of FRAM in comparison to other occupational risk assessment tools is addressed in detail in the second section of Chapter 5. The performance adjustments in the execution of functions and the inner and external systemic interactions will be studied to identify possible sources of variability. To the best of our knowledge, FRAM was never applied for the assessment of aircraft ground deicing/anti-icing operations. The analysis will rely primarily on the research results (papers and technical reports) produced by our research team and on official reports published by aviation authorities on accidents related to deicing or on operational procedures and specifications. The basic FRAM model is constructed following the next five steps as proposed by Hollnagel (2012a):

Step Zero - The determination of the objective for applying FRAM: Usually, the question to answer here is, whether FRAM will be applied as an accident investigation tool or as a risk and safety assessment model. Even though the FRAM procedure is the same in both cases, the difference lies in the type of information needed for the two applications. In the case of an accident analysis, the event has already occurred and the required information for FRAM like the circumstances of the accident or the sequence of events are mostly known i.e., the analysis is retrospective. In the case of safety assessments, an analysis scenario can be constructed inspired or based on historical and archived data to predict and anticipate events that might occur in the future i.e., the analysis is proactive (Hollnagel, 2012a). In our case, the objective of the FRAM analysis is to provide a risk and safety assessment for aircraft deicing operations. Accidents and near miss events can provide suitable and realistic case studies for risk and safety assessments to model the system at first and demonstrate in a tangible manner what can go wrong or right and how.

From a practical point of view when it comes to the context of deicing, the type of data available for a FRAM analysis is mostly of qualitative nature. If only quantitative data were permitted, then the analysis of deicing operations as a complex sociotechnical system would be very difficult. Rather, the relationships of the system would have to be linearized and simplified and the focus would be directed to a specific part of the system, which would make the analysis of the dynamic and emergent properties therefore not possible. For example, if we were to evaluate a function with the name "*Deicing*" in terms of quantitative measures, then the inputs and outputs of the function would have to be quantified. If the function had as an input "*adequate resources*", then the list of the required resources would be long and to quantify each aspect or type would be a very difficult endeavor. The quality of the applied deicing liquid as an example is a factor of adequateness for the provided resources. We can measure temperature, time, consistency, pressure of spraying, amount, etc. but this would not cover all factors that can affect the quality of the liquids. We can notice that the factors that must be considered for one aspect are too many, which would result in a very excessive and complicated model. Secondly, other influential factors on the quality of liquid might not be quantifiable and can only be expressed in qualitative form such as handling of liquids, behavior of operators, contextual and external influences, etc. Such factors are better represented in qualitative form using linguistic descriptors. Moreover, some factors cannot be expressed in terms of numerical values at all. For example, for the same function "*Deicing*" we assume another input "*adequate instructions and procedures*". Such an input cannot be simply evaluated in terms of quantitative measures for obvious reasons. Now, if we were forced to simplify things, zoom in on a part of the system, and apply only quantitative measures, then the analysis of complex interactions of the system as a whole would become very difficult. Therefore, a holistic approach is needed to analyze the system as a cohesive unit, in which adverse events are emergent due to the combination of several influential factors. These factors can be classified according to the MTO classification method as human, organizational and technological factors in addition to environmental or contextual factors.

Step One - Identification and characterization of system's functions: A FRAM function is any systemic activity or task, which is relevant and important to the state of the system and has consequences on other actions in the system (Hollnagel, 2012a). Systemic here means the conservation of systemic properties i.e., addressing the complex relationships maintaining their dynamic and non-linear properties. To this end, the relationship between input and output must consider the holistic nature of the system i.e., not just the performance of its parts rather the system taken as a whole considering its emergent properties as a cohesive unit. A non-systemic or simple relationship on the other hand draws a linear relationship between input and output, which provides a predictable output and zooms in on tasks to linearize these relationships. These can be as well included in the FRAM characterization and the question here remains how much sense it would make for the objective of the analysis. The identification of functions happens in three sub-steps (Hollnagel, 2012a):

- Firstly, the overall functionality, which will be the focal point of the analysis, is to be determined (Hollnagel, 2012a).
- Secondly, the system's boundaries are to be defined i.e., the set of relevant background functions are to be determined. Background functions are not variable, and they serve merely as the boundary of the identified system i.e., their outputs are invariable. FRAM functions do not have physical characteristics as humans or machines do. They are rather structures without natural boundaries. These boundaries must reflect the scope of the study and its focus. The boundaries are flexible, and it is up to the analyst to determine which functions do belong into the scope of the study within these boundaries. The foreground functions do possess incoming values from upstream functions, and they represent the focus of the analysis i.e., their outputs can be variable. The analyst determines the set of functions based on a commonsense perspective. Functions can be added into the scope or removed from it at a later point in time, if deemed necessary or helpful (Hollnagel, 2012a).
- Thirdly, the degree of resolution and level of details to describe the system's functions is to be identified. The level of details can be determined from a pragmatic point of view considering the activity to be performed. It is important to choose a level of details

that enables the examination of the impact of function's variability on the performance of the system without sacrificing the holistic perspective (Hollnagel, 2012a). If a high level of details were to be incorporated into the characterization of a given function, then the model might become complicated and demanding. On the other hand, if a zoomed-out perspective and a low level of details were chosen, then the issue might become the provision of a trivial and unnecessary analysis. There is a trade-off to be considered here between the level of details and adequacy of the analysis that should be considered in the characterization process. The analysis should be useful and should make sense.

Following the above-mentioned three steps, the functions for the FRAM model can be identified. The main criteria for identifying the functions, is the need to describe the normal functionality of the system. The focus should be on describing the normal activities carried out by the system without considering the quality or accuracy of their outputs. The accurate and correct identification of the system's functions is very imperative to achieve the desired quality of the analysis model.

Functions are characterized in terms of six aspects (Hollnagel, 2012a):

- Input (I): the parameter that initiates and is processed by the function.
- Output (O): the result of the function, which can be a specific value, a product, or a change of status.
- Preconditions (P): conditions that must be fulfilled to enable the execution of the function.
- Resources (R): personnel, data, technology, equipment, etc. needed and required by the function to produce results.
- Time (T): temporal limitations or constraints on the execution of the function, e.g., duration, starting and finishing times.
- Control (C): monitoring and control mechanisms for the function. (Figure 2.3)

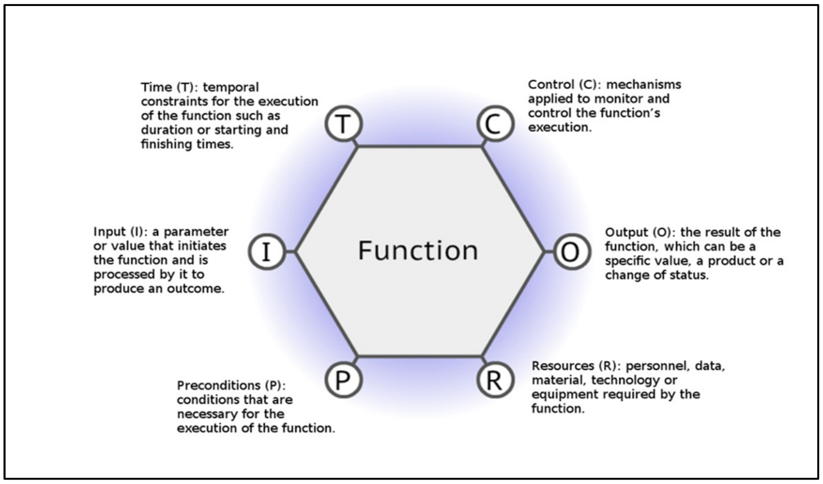

Figure 2.3 A graphical representation of a FRAM function with its six aspects

The definition of the relationships among functions determines the type and nature of the incoming aspect from upstream functions. For example, if work instructions are to be defined as a control for one function, it would be needed as an output from an upstream function. The description and characterization of the functions is accomplished by using a simple table format (Figure 2.4). This table includes the above-mentioned six parameters or aspects of the function with their descriptions (Hollnagel, 2012a). The simple table is not the same as the graphical representation of FRAM, which serves as a visualization tool and consists usually of hexagons representing the functions and their couplings. An instantiation represents a specific case or analysis scenario with defined performance conditions and is not the same as the model in its general form. The simple tables of the functions constitute the FRAM model. The functions are classified according to the MTO classification method and in terms of their relation to the context of analysis and to the other functions (Figure 2.5).

Name of function	
Description	
Aspect	Description of Aspect
Input	
Output	
Precondition	
Resource	
Control	
Time	

Figure 2.4 A simple characterization table of a FRAM function

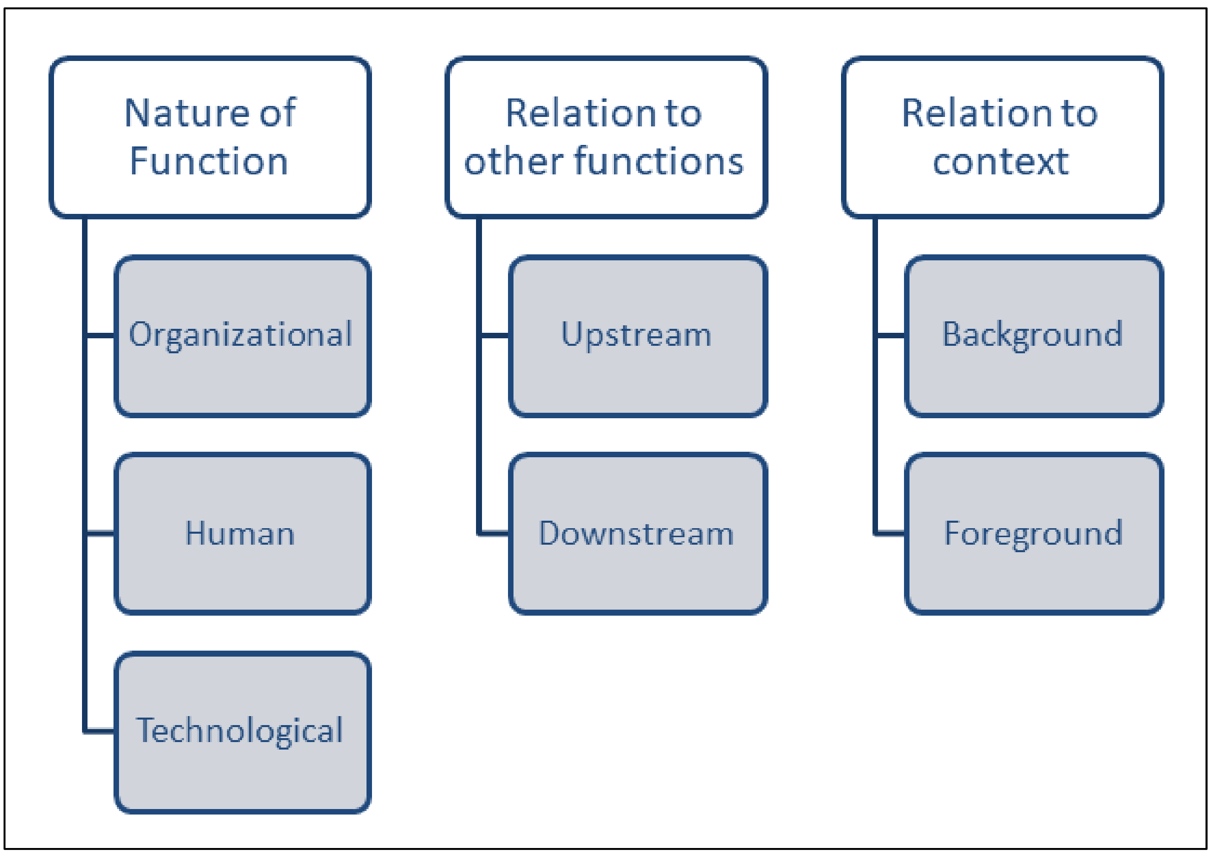

Figure 2.5 Types of FRAM functions according to three criteria

After the identification and characterization of the system's functions, the relationships or couplings between the functions can be determined. The descriptions of the six aspects inside the simple table contain the couplings between the functions. These couplings are defined by the six aspects of each function and reflect the dependencies among the functions, how the aspects of the functions relate to each other and affect each other. The FRAM model is the set of all functions with all potential iterations of variable performance. On the other hand, the FRAM instantiation is a specific analysis scenario describing actual variability of specific functions, which can be visualized using the graphical representation (Figure 2.6). The positions of the functions in the graphical representation do not reflect an order or a sequence of events. The couplings do not reflect cause-effect relationships between the functions. The instantiation can be used as the basis to study the variability for the specific case study and the impact of functional resonance on the performance of the system as a whole (Hollnagel, 2012a).

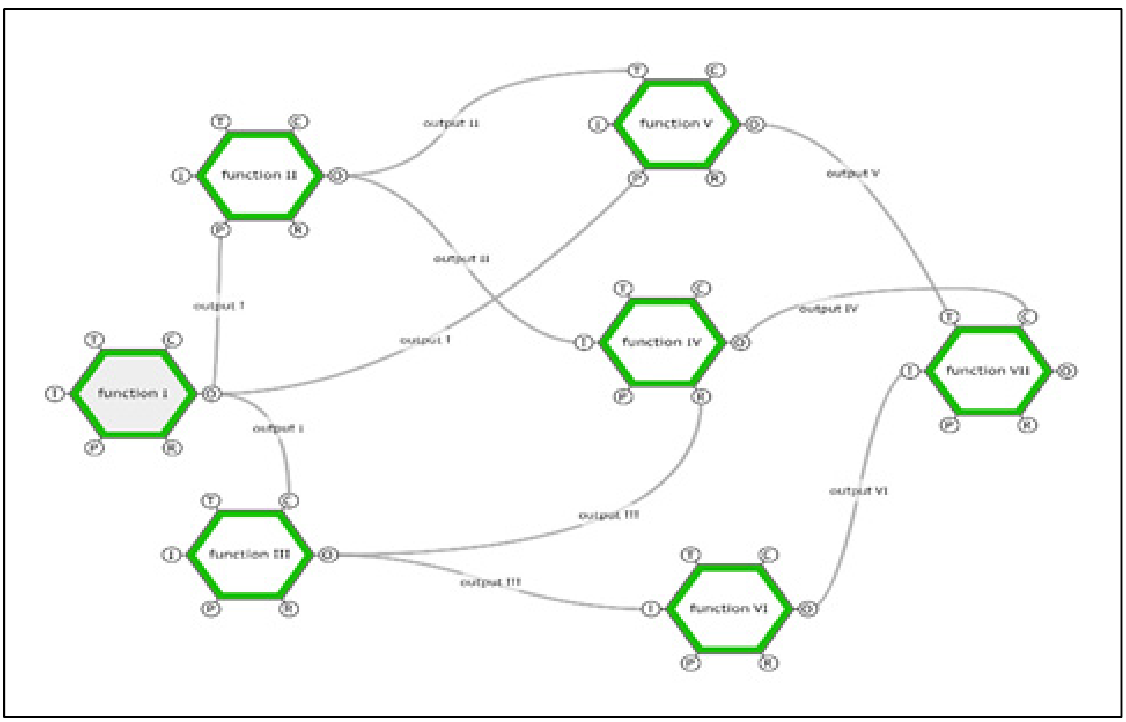

Figure 2.6 An example of a graphical representation of a FRAM model in FRAM Model Visualizer (FMV)

Step Two - Identification and characterization of functional variability: Functional performance variability is necessary and is required for the sociotechnical system to function properly. The conditions and rules, which specify how performance should be executed, are usually underspecified, and do not cover all practical aspects of reality. Through adjustments to real work conditions and problems faced in practice, the sociotechnical system can function successfully. These intentional adjustments are necessary for success, but variability results also unintentionally, which might have negative influences on the system's functionality and lead to its failure (Hollnagel, 2012a). According to Hollnagel, variability can be attributed to three sources (Hollnagel, 2012a):

- Internal potential sources due to the nature of the function itself;
- External influence imposed by the context of the function;
- Finally, functional upstream-downstream couplings i.e., variable outputs of the upstream functions influence the downstream functions.

According to Hollnagel (Hollnagel, 2012b), the main six influential factors for human and organizational performance variability are:

- Human physiological and psychological factors e.g., fatigue, attention span.
- Organizational factors e.g., temporal constraints, demands on quality and quantity.
- Higher-level psychological factors e.g., incapability to be creative and adapt with underspecified conditions.
- Social psychological factors e.g., meet the expectations of colleagues and managers.
- Work conditions variability e.g., humidity, noise.
- Work environment variability e.g., weather, high traffic, technical problems.

Hollnagel defines the effect of work conditions on the performance using the set of Common Performance Conditions (CPC) (Hollnagel, 1998; Macchi, 2010):

1. **Availability of Resources:** resources are primarily personnel, equipment and material required and necessary to perform the tasks. The shortage of resources might produce variability in the performance.

2. **Competence:** adequate training of working staff and level of experience are necessary to perform correctly.
3. **Communication Quality:** refers to the equipment and technology used for communication and to human interaction. The quality of communication is important to ensure transparency and observability of the system.
4. **Human/Machine Interaction (HMI):** interface design and other forms of operational support.
5. **Availability of Procedures and Plans:** needed in both normal and emergency operation conditions. The availability of adequate procedures ensures stability and accuracy of performance.
6. **Work Conditions:** can affect performance positively or negatively e.g. noise, lighting, temperature.
7. **Number of Goals and Conflict Resolution:** excessive workload and the demand to work on many tasks simultaneously can affect the performance negatively and lead to its degradation.
8. **Available Time:** the pressure to finish tasks without sufficient amount of time can cause psychological stress for humans and thus degrade performance.
9. **Circadian Rhythm and Stress:** lack of sleep and asynchronism with the current time can lead to performance degradation.
10. **Team Collaboration:** work climate, trust and good collaboration among colleagues are necessary for a team to perform effectively and properly.
11. **Organizational Support:** refers to the quality of roles and responsibilities of team members, safety culture, management, instructions and guidelines, etc.

These common performance conditions do not affect each function in the same degree. The degree of influence on each function has to be rated and categorized. The rating can then be used to determine the potential performance variability of the functions (Hollnagel, 2012a). The variability in the basic form of FRAM as proposed by Hollnagel is characterized in terms of timing and precision using ordinal three-classes linguistic scales (Table 2.1). The magnitude of the ratings provided by the linguistic scales can mean different things for the outputs' variability depending on the nature of the function in question. In our first application, the FRAM model will be applied as proposed in its basic form following the above-described criteria for characterizing functions and performance conditions (Please see ANNEX I).

Table 2.1 Variability in FRAM

Characterization of Output's Variability in	
Precision	Imprecise
	Acceptable
	Precise
Time	Too early
	On time
	Too late

Step Three - Identification of functional resonance: According to Hollnagel, there are two ways, in which performance variability can affect the system (Hollnagel, 2012b):

- **Variability of the function's output:** the actual output can differ from the expected output. The affected output of a function in turn will affect the other functions e.g., if an operation has consumed more time than intended, then the following functions will have less time to perform their tasks on time (Hollnagel, 2012b).
- **Variability of the common conditions:** performance variability might cause changes into the common conditions e.g., consumption of more resources or time than intended (Hollnagel, 2012b).

Following these two criteria, the couplings and dependencies among functions can be evaluated to identify the impact of variability (whether positive or negative) and its combinations or resonance on all foreground functions of the system.

Step Four - Management and identification of effective countermeasures: The final step would be to implement measures to minimize or eliminate the sources of negative variability and strengthen the sources for positive one. The ways, in which functions are performed, has to be studied to localize sources of variability. Afterwards, ways to enhance performance and reduce the variability of the functions should be proposed (Hollnagel, 2012b). However, this study will not go into detail on how to eliminate risks and enhance systems. This would be out of the scope, which is the provision of a new approach and examples on how to use FRAM. The selected scenario would not be sufficient to make recommendations on a large scale to improve all possible aspects of the system. Rather, recommendations based on the received results of the analysis would be provided to show how the analysis results could be used to improve the system in place.

2.2.2 Phase II: The Introduction of Fuzzy FRAM

The list of the Common Performance Conditions (CPC), which was originally proposed for CREAM, was used in conjunction with the basic version of FRAM to evaluate performance variability (Hollnagel, 2004; Macchi, 2010).

Table 2.2 The affected FRAM functions by each CPC according to the MTO classification (Macchi, 2010; Hollnagel, 2004)

Common Performance Conditions	Human	Technological	Organization
Availability of resources	X	X	
Training & competence	X		
Quality of communication	X	X	
HMI and operational support		X	
Availability of procedures and plans	X		
Work conditions		X	X
Number of goals and conflict resolution	X		X
Available time and time pressure	X		
Circadian rhythm and stress	X		
Team collaboration quality	X		
Quality and support of the organization			X

The impact of the CPC's is not the same for all the FRAM functions (Hollnagel, 2004). It depends on the nature of the function and its relation to each CPC. The MTO framework (huMan-Technology-Organization) is utilized here to identify how each CPC affects each function type (Macchi, 2010). The impact of the CPC's according to the MTO classification framework is presented in Table 2.2 and Table 2.3 (Macchi, 2010).

Table 2.3 The performance variability as a function of the CPC impact (Macchi, 2010)

Common Performance Conditions (CPC)	**Impact of each CPC**		
	Adequate	**Inadequate**	**Unpredictable**
Availability of resources	Small	Noticeable	High
Training & competence	Small	High	High
Quality of communication	Small	Noticeable	High
HMI and operational support	Small	Noticeable	High
Availability of procedures and plans	Small	Noticeable	High
Work conditions	Small	Noticeable	High
Number of goals and conflict resolution	Small	High	High
Available time and time pressure	Small	High	Very high
Circadian rhythm and stress	Small	Noticeable	High
Team collaboration quality	Small	Noticeable	High
Quality and support of the organization	Small	Noticeable	High

Thus, each function in FRAM is assigned to a function type of the MTO classification system. However, the above-described methodology accounts only for the contextual factors affecting functional performance. The impact of the inherent functional characteristics is not considered and there exists a lack of a standardized approach to account for the internal variability of each function. Macchi (2010) addressed three limitations of the CPC-based methodology: representation of variability as a result of local adjustments and functional couplings, distinction of heterogeneity of the functions and the lack of aggregated representation of variability (Macchi, 2010). The first limitation was addressed by characterizing the quality of the functional aspects in terms of timing and precision (Macchi, 2010). The heterogeneity of the functions was taken into account by introducing the notion of foreground and background functions and using the MTO framework to determine the possibility of functional performance variability (Macchi, 2010). Finally, an aggregated variability representation was achieved by assigning simplified numerical values for the aspects' qualities and calculating their median value as an output (Macchi, 2010).

To provide a more precise representation of the output's variability, we propose the integration of fuzzy logic as a quantification tool into FRAM. The idea is to fuzzify the functional aspects and produce numerical outputs for all the functions. The boundary of the model is defined as the outputs of the background functions, which are not variable. Therefore, all outputs of the background functions will produce perfect or ideal outputs i.e., the quality of the output is at 100%. The outputs are linked as previously discussed as functional aspects to the downstream functions, which are the foreground functions. The foreground functions are the focus of the analysis and therefore are possibly variable. However, if all received aspects were ideal (100%), then the outputs accordingly would be also ideal or non-variable. Therefore, the idle state of the model represents an ideal scenario, in which all outputs are ideal as well and no variability is present. Of course, this is not realistic when it comes to practical applications. This state describes "*work-as-imagined*", as specified in the procedures and theoretical documents. To account for variability, we have to define, first of all, the sources of variability from within the functions, which we named the Internal Variability Factor (IVF). Hollnagel defines three sources for variability in FRAM: internal, external, and functional resonance (Hollnagel, 2012a). The latter is accounted for in the above-described case through the functional couplings and is the result of the first two sources. However, since no variable outputs are present in the idle state, no resonance will be present as well. The first two sources of variability are the ones that introduce variability into the system. We have to distinguish between the External Variability Factor (EVF) imposed on the function from the outside and the Internal Variability Factor (IVF) that comes from within. The IVF will account for the inherent characteristics and the potential of the function itself to produce variability driven by the state of the present performance conditions at the time of execution. Such factors can be the different human characteristics as emotional states, personality traits, attitude, knowledge (not training), physiological and psychological factors, technological features and functionality, organizational climate, etc. The EVF in our model is represented in the influence of both the functional couplings and the performance conditions. The IVF comes from within the function; however, it is important to note here that influential factors that drives its variability are both internal and external. The performance conditions can be also here expanded to include the impact of other external sources such as the environment or sudden unexpected events. This extension would rely greatly on the context of analysis and what would be needed to perform the analysis in a reliable and representative way. In principle, the definition of the performance conditions should be evaluated building on field observations to provide a more representative list. A ten-point numerical scale will be used to assign a quality value for each CPC and the numerical product will be used as an additional aspect that affects the quality of the functional output. The fuzzy rule base allows through the characterization of the relationships between inputs and outputs using natural language to assign different weights to each aspect, class and factor. This depends on the nature of the function in question. Additionally, each rule can be assigned a different weight in the rule base. In our model here however, the weights for all functional aspects and CPC's will be kept the same for simplicity reasons and to allow for a more efficient modelling process.

Steps of the fuzzy logic method: The fuzzy logic methodology consists of the following three steps: Fuzzification, Inference Process and Defuzzification (González Dan et al., 2017). The following steps are intended to describe qualitatively the aspects of FRAM that were modified by adding fuzzy logic and provide an explanation how this was achieved. An illustrative and mathematical representation of the model is provided in the methodology section in Chapter 3 (Article 1).

1. **Fuzzification:** In the first phase of this project (first objective), we constructed a FRAM model of the deicing working environment. The functions were identified, and their aspects were characterized. The input values for those functions can vary in terms of timing and precision applying linguistic variables to describe the respective outputs. The first step in the FIS is the fuzzification of the input values. This is achieved by defining the fuzzy sets and determining the membership functions of the linguistic variables to each set. The fuzzy sets in our model are the partitions of the universe of discourse that a CPC or a functional output can have. For each CPC, two classes were defined: "*inadequate, adequate*", which extend on a ten-point scale. The rationale for selecting two classes derives from the need to minimize the number of the resulting rules in the rule base. Two levels would be sufficient to represent performance variability since the numerical scores would serve as a more accurate representation. If three classes were to be defined, the resulting number of rules in case of human functions would have been immense deeming the project unfeasible. This is known as the "*rule explosion*" problem. Additionally, the two classes partitioning makes sense given that any performance condition is more adequate and less inadequate if the input value was closer to the perfect score and vice versa. The output of the internal FIS is the IVF, which can be linked as an additional aspect to the other functional aspects. For the functional aspects, the regular classes are for timing: "*too early, on time, too late*" and for precision: "*imprecise, acceptable and precise*". In addition to the rules' explosion problem here as well, it was noticed in the rule generation process that it was not always possible in a predictive assessment to determine how the variability of the output would be manifested in reality. For example, it was not always obvious or possible to determine, whether a "*too late*" input would result in a "*on time*", "*too late*" or even "*imprecise*" output. In contrast to retrospective analyses, in which events are well defined and the outcome is already known, predictive or proactive analyses must anticipate the outcome providing educated assumptions based on historical lessons or scientific findings and observations. It was therefore preferable to aggregate the representation of the output's variability and merge the two phenotypes "*time*" and

"*precision*" into one class, namely "*variability*". The IVF and the functional aspects would therefore have the following three classes: "*non-variable*", "*variable*" and "*highly variable*" on a scale between 0 and 1.5. One here is a non-variable output, while any output below one is negatively variable and any value above one is positively variable. One was chosen here as a neutral point which means variability of the output remains unchanged in relation to the provided inputs. It would serve as the input for the downstream function. Then, to account for the dampening effect, we had to go above one or 100 percent. However, the dampening effect beyond the neutral point of one is smaller, since the potential of the functions to dampen is considered less in our model given the high requirements of reliability in aviation. High reliability systems do not allow for a high tolerance for negative variability due to the severe consequences. We wanted to represent this fact by increasing the sensitivity of the provided input values to sufficiently represent output variability and clarify that the dampening effect is smaller since these systems already possess high requirements for adequacy and reliability. Each term of these labels represents a class or a fuzzy set. The linguistic variables, which can belong to these fuzzy sets with a certain degree of membership, are the functional outputs. Each input for any FRAM function is an output of another upstream function, until the boundaries of the model are reached, where the background functions are providing only non-variable outputs. The membership functions for linguistic variables will be calculated and the membership degree of those linguistic variables in one of the fuzzy sets will be determined. The FRAM functions will be modelled with the MATLAB software defining the functional aspects as variables and the shapes of their membership functions. The appropriate shapes and overlaps will be determined through a sensitivity analysis process to obtain the best results possible. A more detailed and structured representation of the steps is provided in Chapter 3.

2. **Inference Process:** After fuzzifying the CPC's and the functional outputs, the link between the incoming inputs to a FRAM function and its output is to be determined. This is achieved through the inference process applying fuzzy rules. The set of fuzzy

rules for each function will be in the form of "*IF-THEN*" rules. Experts from the fields of risk analysis and fuzzy logic can be consulted here as well to weight, generate the rules, and validate the proposed model. In our case, we relied on our expertise in the field and on the technical reports provided by Transport Canada in addition to the accident reports used to construct our analysis scenario. The rule generation was done automatically in Microsoft Excel using an ordinal scale to qualify each class in the antecedent part of each rule. An example of the dataset and the MATLAB code were published in the supplementary file of Article 2 (Chapter 4 in this thesis). The decision for each rule was done manually based on the values of each class in the antecedent part. Two FIS were defined for each function: a lower order internal FIS to generate the IVF and a higher order FIS to determine the total numerical output of the function. Each FRAM function has five incoming aspects (Input, Preconditions, Resources, Control and Times). The inputs or antecedents will be linked to each other applying the fuzzy logical operators *"AND", "OR" or "NOT"*. In case of the "OR" operator, the union or maximum operation will be used (e.g., max[μA(x), μB(x)]). In case of the "AND" operator, the intersection or minimum operation will be used (e.g., min[μA(x), μB(x)]). In our model, the *"AND"* operator was used solely since we accounted for all possible combinations. The "AND" logical operator is used in the antecedent part and the "MIN" function is used to determine the implication of the same rule in the consequent part. The "MIN" function does employ the "AND" operator to determine the intersection of the input values. The obtained implications will be then aggregated to provide one implication for the output in the form of a fuzzy set. For the aggregation process, there can be chosen between two calculation methods: the maximum operation (MAX function) and the summation method (SUM function) (González Dan et al., 2017). The maximum method collects the highest areas in the fuzzy sets of the results' implications, while the summation method simply adds up all the received areas for the implications (González Dan et al., 2017) (Figure 2.7).

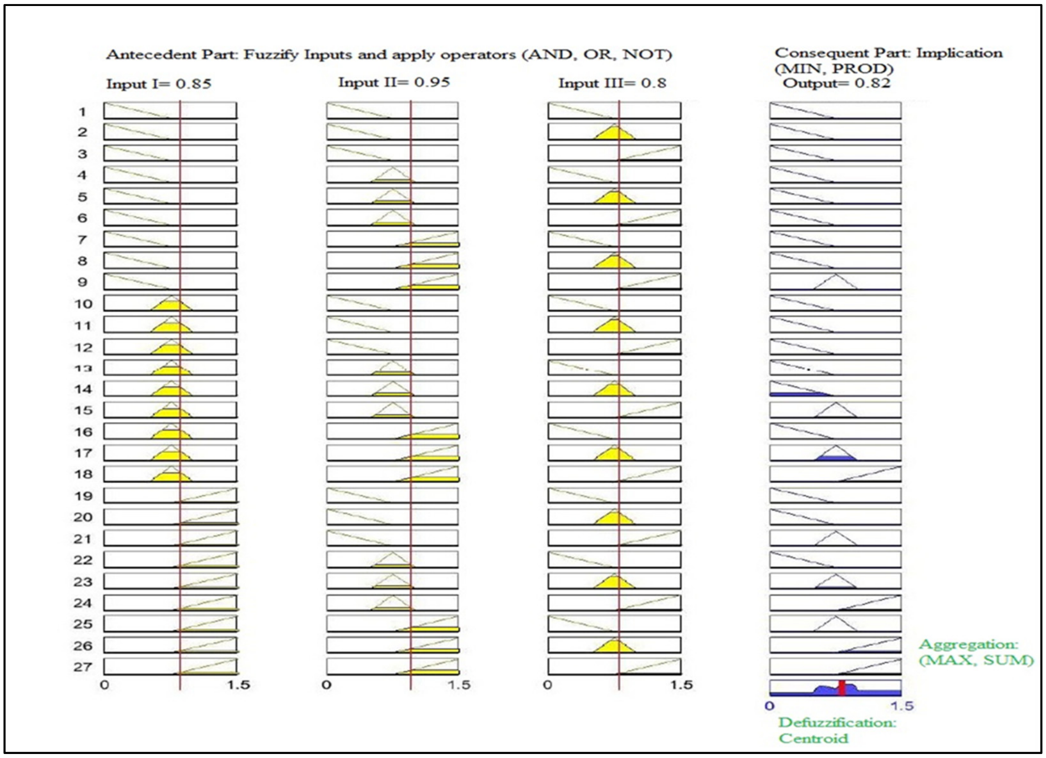

Figure 2.7 An example of the FIS as represented in MATLAB

3. **Defuzzification:** The final step in the FIS is the defuzzification, which means transforming the fuzzy output into a crisp value. To achieve this purpose, the center of gravity method is used. The center of gravity method simply finds the point where a vertical line would cut the obtained area into two equal masses (Negnevitsky, 2005). The calculated numerical value will present a quantification for the quality of the functional output. With the third step finished, the fuzzy FRAM model would be ready for application to analyze the deicing operations (Figure 2.8).

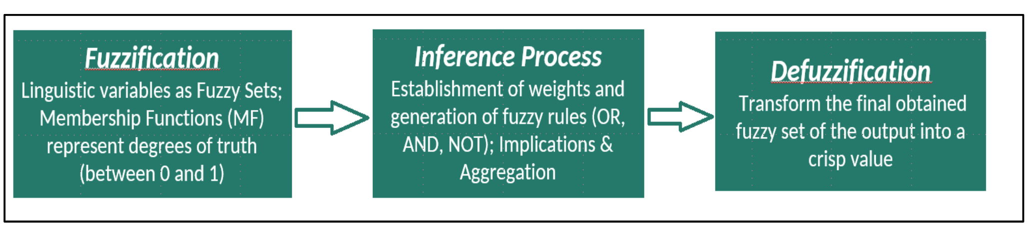

Figure 2.8 The steps of the fuzzy logic-based methodology

2.2.3 Phase III: A mixed RST-Fuzzy FRAM Approach

The third objective is aimed at exploring a possible solution to overcome the limitations in the number of input variables and output's classification. A possible solution here was presented in the form of the RST method (Pawlak, 1982). Using the indiscernibility relation in RST, search algorithms can be utilized to scan the provided data set to classify outputs, identify reducts and automatically generate the rule base. The expert input herewith would be limited to the design of the RST approach itself, however not to the classification process and the results. The five steps of FRAM would then be modified as follows:

Step Zero: The first step, which is concerned with defining the objective of the analysis, remains unchanged.

Step One: The characterization of the set of functions follows the same principle as in the first two phases with one significant change. The FRAM functions will be defined as RST information systems as well i.e., the data would be entered into a two-dimensional matrix consisting of the functions as objects and their aspects as attributes. For the IVF, the list of the CPCs will serve as attributes and the IVF would be accordingly the produced decision class. Each cell in the matrix or table contains a value assigned to the function in the same row with regards to the attribute in question. The data here can be obtained from real word observations and archived data. This would minimize the need for a manual rule generation process consequently. The discernibility matrix can be used to discern functions, which provide different outcomes for the same values. This would allow consequently to compute the reducts, which means a minimal but sufficiently accurate rule base. A formalized mathematical representation of these definitions is provided in Chapter 4 (Article 2).

Step Two: The variability characterization in this step takes place over two stages as achieved in the Fuzzy FRAM model as well: the IVF characterization and the EVF characterization. The starting point is to identify for each function the IVF using the CPC list. The CPC list can be used to record the performance conditions for each iteration of the function in a real-world observation and their values can be entered into the decision table. After completing the table, the RST approach can be used to identify the reduced set of necessary attributes (reducts) to preserve the same classification information as the original set. Here again, the CPC's are classified as either "*adequate*" or "*inadequate*". The two classes serve here first as possible values that the RST attributes can possess and later serve as the two partitions in the FIS for determining the IVF. The accuracy of the RST method depends greatly on the quality and quantity of collected data i.e., the larger and more representative the data set is, the more accurate the results would be.

The output is as mentioned above the IVF, which can take three possible values: *"non-variable", "variable", or "highly variable".* The collected data can be split into two groups: training data and testing data. The split factor can be determined by the analyst as deemed appropriate using a trial-and-error approach to find the most suitable split point. The training data can be used to train the model using a searching algorithm to identify the reducts and generate the rules. For each row in the discernibility matrix, the logical operators "*AND*" or "*OR*" can be used to link the antecedent part (IF-Part) or the consequent part (THEN-Part) if more than one decision is required. The generated rule base can then be tested for coverage, accuracy and support by classifying the testing set. The rule base can be validated and checked for inconsistencies and the final approved rule base can then be migrated into the internal FIS for the function and used in the FRAM instantiation to calculate the IVF for each function. The FIS characterization remains the same as in phase II. A more detailed and formalized representation of these definitions is provided in Chapter 4 (Article 2).

The second stage in the variability characterization is to characterize the external variability (EVF) produced by the IVF in addition to the incoming functional couplings. The same process is repeated here as with the IVF (internal FIS); however, in the higher order FIS, the functional aspects serve as attributes in addition to the IVF and the output would be the decision class. The functional aspects are inputs originating from upstream functions. The IVF of the next downstream functions receiving only inputs coming from boundary function would be identical to the main output of the function, since all aspects are providing non-variable inputs.

Therefore, the aspects possess as the IVF three classes: "*non-variable*", "*variable*", or "*highly variable*". The aspects are represented as the attributes in the RST table, which are assigned different values for each object and the decision class in the table represents the obtained class for the final output of the function. All other settings in the FIS are kept the same as in phase II to allow for a better comparison and validation of the results. A flow diagram illustrating the many steps of the modified FRAM model combining fuzzy logic and rough sets is provided in Chapter 4 (Figure 5.5).

The final two steps of the FRAM process (**Step Three & Four**) stay the same as well: identification of functional resonance and management of variability. The model will be used to evaluate a specific analysis scenario in the context of aircraft deicing. As mentioned earlier, the scenario is not the model; rather, it represents a defined set of performance conditions and circumstances for the execution of deicing operations. Several iterations can be run of the scenario making minimal changes every time. The FRAM model on the other hand is the total sum of the functions that constitute the system generally. To model the context of deicing, FRAM was applied in phase I as an accident investigation tool to evaluate the Scandinavian Airlines SK751 crash. The analysis scenario for phase II and III kept identical settings maintaining the same characterization of variables, classes, membership functions etc. to allow for a better comparison of the results. The detailed explanation of these applications will be presented in Chapters 3 & 4.

CHAPTER 3

ARTICLE 1: A PROPOSAL FOR A PREDICTIVE PERFORMANCE ASSESSMENT MODEL IN COMPLEX SOCIOTECHNICAL SYSTEMS COMBINING FUZZY LOGIC AND THE FUNCTIONAL RESONANCE ANALYSIS METHOD (FRAM)

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Abstract

Modern sociotechnical systems exhibit dynamic and complex behavior, which can be difficult to anticipate, model and evaluate. The perpetually evolving nature and the emergent properties of such systems require a continuous re-evaluation of adopted safety and risk analysis methods to comply with arising challenges and ensure successful performance. One of the interesting methods proposed in recent years is the Functional Resonance Analysis Method (FRAM). FRAM adopts a systemic perspective to model sociotechnical systems characterizing non-linear relationships and quality of outcome arising from performance variability and functional resonance. This paper aims to further improve the framework and expand the spectrum of features provided by FRAM through the integration of fuzzy logic. Fuzzy logic offers adequate mathematical tools capable of quantifying qualitative concepts and uncertain information applying comprehensible inference systems based on human judgement. An example of a possible application scenario is included through a simulation of aircraft onground deicing operations. The preliminary results of this project present an approach to generate numerical indicators for the quality of outputs, which can allow for a more comprehensible representation

of potential performance variability. The presented model however requires further validation and optimization work to provide more representative and reliable results.

3.1 Introduction

The dominant view in science before and at the beginning of the 20th century was that of mechanistic reductionism, which considered any system to be reducible to its parts and understandable in terms of mechanisms (Érdi, 2008). While this approach might be valid in case of inanimate objects, it becomes inadequate as soon as living objects are involved (Weaver, 1948). The term "*sociotechnical system*" refers to a complex operational system, which consists of interactive social and technical components (Hettinger et al., 2015). The social aspect of a sociotechnical system refers to humans as individuals or organizations. The technical aspect on the other hand refers to any form of technicalities such as technological systems and devices, tools, resources or any equipment needed to execute the systemic functions. As a result of this definition, the concept of a sociotechnical system applies to the majority of complex systems in the world today and cuts through all domains and fields such as education, healthcare, economy, etc. (Hettinger et al., 2015). Such systems are too complex for evaluation by simple methods and are hardly treatable by statistical methods since they possess organized behavior.

Modern sociotechnical systems are open systems embedded in their environments (Mumford, 2006). They consist of a large number of interactive components; whose behavior collectively characterizes the emergent properties of the whole system. The interactions among the system components and between the whole system and its environment are determinant for the success or failure of the system performance (Carayon et al., 2015). Those interactions can be linear causal relationships, which are mostly considered in the designing process; or they are non-linear and dynamic complex relationships, whose implications are difficult to predict in the designing process. Diagnostic problems, lack of information and the inability to determine theoretically how the different system parts would interact can result in overlooking possible risks and adverse implications (Nadeau, 2003). The behavior of individuals or groups can change in response to emergent conditions. The emergence of successful performance depends on the level of understanding and the capability to manage variability and uncertainty (Nadeau, 2003).

The work environment of aircraft ground deicing/anti-icing operations forms such a complex sociotechnical system, in which man and machine collaborate to perform a specific task. The influential factors that affect the quality of the system's performance are variable. Operations are conducted in a dynamic and fast-paced environment under strict temporal constraints and in harsh meteorological conditions (Transport Canada, 2004; Günebak et al., 2016). The workload can be demanding and might affect workers psychologically and physiologically (Torres et al., 2013 & 2016; Le Floch et al., 2018; Landau et al., 2018). Human factors as age, sex, physical strength, knowledge level, experience and others are significant factors that characterize the performance of workers (Torres et al., 2016). Organizational factors as providing adequate guidelines and resources are essential for an appropriate execution of the procedures in force (Nadeau & Morency, 2017). Inadequate equipment and instructions might prevent the workers from performing their tasks correctly who then tend to adjust their performance to cope with the shortage, e.g., the Scandinavian Airlines flight 751 crash in 1991 (SHK, 1993). The provision of adequate management and monitoring processes ensures the execution of the procedures as designed. The provided training programs, salary systems, planning of working and rest hours, etc. are all among the factors that might have an impact on the deicing operations (Torres et al., 2013). Precision and caution are continuously required. Coordination and communication between many parties across different organizational hierarchies and departments are necessary in a clear manner (Günebak et al., 2016). Imprecise communication can cause loss of time, affect performance, and might even cause accidents on the ground, e.g., the accident of Royal Air Maroc in 1995 at the Montreal (Mirabel) International Airport, Quebec (TSB, 1995). Those and many more factors shape the working environment of deicing operations to be a highly dynamic and complex one.

As is the case in aviation generally, deicing operations are high reliability organizations. Operational procedures are formulated and executed in a strict manner to ensure safe operations. The number of accidents and incidents is low in aviation in comparison to other systems. The trend in aviation over the years shows a continuous improvement in performance and safety measures. In Canada, most deicing operations at large airports nowadays take place in centralized deicing pads (Günebak et al., 2015). The utilization of centralized deicing pads facilitates the simultaneous deicing of multiple airplanes, which requires precise coordination and clear communication between the flight crew, Air Traffic Control (ATC), the deicing team and the deicing tower (Günebak et al., 2015). Most incidents related to inadequate ground deicing activities occurred in the takeoff and climb to cruising altitude phases (Aventin et al., 2015). The most critical period, in which incidents happened, was between December 10 and January 10 (Aventin et al., 2015). Despite having the largest air traffic volume in Ontario, only 5.3% of the incidents occurred there (Aventin et al., 2015). The highest rate of incidents occurred in Quebec and British Columbia (each 26.3%) (Aventin et al., 2015). Smaller airports and smaller aircraft types are more frequently involved with ground deicing accidents or incidents than larger airports and larger aircraft (Aventin et al., 2015).

Improving a high reliable system that really works well can be difficult, since the possibilities for things to go wrong are limited and not immediately obvious. High reliability translates into a limited amount of data for analysis due to the rarity of adverse events that can provide conclusions and data for analysis and evaluation. Despite the high safety standards and high reliability of such a system, the need to evaluate and improve does not diminish. The continuous developments of applied technologies and the evolving nature of complex systems necessitate continuous evaluation of the state of the system to maintain desired reliability and safety levels. New perspectives become necessary to cope with changes and relying on traditional analysis methods solely could be insufficient. To the best of our knowledge, research in the area of aircraft deicing from a systemic perspective considering human factors (individual and organizational) is rare (Eyre, 2002; Landau et al., 2017; Le Floch et al., 2018). Studies mostly aim at determining optimal operational conditions and technical requirements for maintaining and advancing deicing procedures. Classical safety and risk analysis methods reduce the scope of the analyses to simple basic tasks to identify problems in specific parts of the system and evaluate the reliability of its components. However, understanding that sociotechnical systems are emergent and complex by nature, a more holistic approach becomes necessary to understand the system's performance in its entirety. Knowing that most accidents are caused by the human factor, this aspect cannot be neglected or assigned less significance than technical and operational aspects.

Adopting a systemic approach would require the consideration of the above-mentioned factors, which is easier said than done. First, the scope of the analysis must be wide enough to allow for a systemic evaluation, which increases the amount of considerable variables and thus the complexity of the analyzed context. Secondly, such factors can hardly be measured quantitatively and are best represented in terms of qualitative linguistic values. The high reliability and the low number of accidents and incidents in aviation generally, and in deicing specifically, makes the composition of quantitative analyses more difficult. Some evaluation parameters and factors in the deicing context can be difficult to quantify. Linguistic scales present only an approximate evaluation of the observed variables, which results in imprecise and uncertain analysis results. Humans can have different concepts of the same linguistic terms and might therefore evaluate the significance of the measured variables accordingly.

This study is part of a years-long research program (Nadeau, 2003; Torres et al., 2013 & 2016; Aventin et al., 2015; Günebak et al., 2015 & 2016; Melanson & Nadeau, 2016; Nadeau & Morency, 2017; Le Floch et al., 2018; Slim et al., 2018a). The Functional Resonance Analysis Method (FRAM) is recommended in this paper as an adequate systemic analysis method, which can provide a fresh perspective in complement to classical analysis tools. In section 2, we discuss two approaches to safety (Safety-I & Safety-II) and argue why adopting a Safety-II approach is necessary for the assessment of complex systems. The principles and steps of FRAM are shortly presented in section 3 to illustrate its features and advantages. In section 4, a review of several recent studies proposing improvements to the framework of FRAM is presented. The focus in this paper is mostly directed to the theoretical aspect and the main objective is to propose a possible approach for the integration of fuzzy logic into FRAM as a means of quantification. A brief overview of fuzzy logic and its features is provided in section 5 and the proposed methodology is presented in section 6. In section 7, an application example is presented by modelling and simulating the aircraft deicing context in the FRAM Model Visualizer (FMV) and MATLAB. The influential factors were evaluated on a scale between 0 and 10 to anticipate possible variability in performance. The results of the simulation presented numerical quantifiers for the quality of functional performance, which can point to possible variability sources in the analyzed system. Finally, the obtained results are discussed to evaluate what conclusions one might draw and reflect on possible future research to improve and validate the proposed model. In the following section, we make the case why adopting a systemic approach is necessary to ensure safety in aircraft deicing or any form of sociotechnical system.

3.2 From Safety-I to Safety-II: The case for FRAM

Safety can be defined as "*the system property or quality that is necessary and sufficient to ensure that the number of events that could be harmful to workers, the public, or the environment is acceptably low*" (Hollnagel, 2014). Historically, the focus in traditional risk and safety management aimed at identifying what can go wrong and lead to adverse outcomes. Accident analyses and annual statistical reports concentrate on what went wrong (losses in lives and material, root causes, adverse conditions, etc.) and as a result measures to prevent the occurrence of such events in the future are adopted. The dominant view in safety management to focus on adversity comes from the human need for certainty, to feel free of harm (psychological) and to be free of harm (practical) (Hollnagel, 2014). This approach proved to be successful so far considering that, the number of accidents and fatalities is continuously declining on a yearly basis (Hollnagel, 2014). However, as the number of accidents and incidents continues to decline, the way ahead into the future to maintain desired safety levels and further reduce the number becomes more difficult (since what goes wrong would also decline). Further insights might be needed to further improve the designed systems and maintain acceptable safety levels.

As a consequence of the human need to be free of unacceptable risk, safety was defined as a "*dynamic non-event*" (Hollnagel, 2014) and was therefore evaluated as a result of its absence rather than as a quality itself (Patriarca et al., 2017c). The occurrence of an unwanted event was explained in terms of linear causal relationships, which defined the outcome as the direct result of errors, failures or inadequate circumstances. This philosophy defined what is known as the Safety-I approach.

Safety-I takes a simple-system approach in analyzing systems. Simple systems are characterized by linear causal relationships and predictable behavior (Érdi, 2008). Systems in Safety-I are decomposable to their parts and the relationships among those parts are well defined and understood (Patriarca et al., 2017c; EUROCONTROL, 2009). The design process accounts for any type of risks that might occur and work is usually executed as imagined. However, upon examining the characteristics of complex systems, one would inevitably conclude that the above-mentioned characteristics do not apply.

Complex systems are self-organized distributed systems, which are open to their environments (Érdi, 2008). The behavior of a complex system as a whole is non-deterministic and can be difficult to anticipate (Pavard & Dugdale, 2006). The relationships among the system components are mostly non-linear, which can cause the outcomes to be unproportional to the inputs (Érdi, 2008). Complex systems are irreducible to their parts without losing their functional properties (Pavard & Dugdale, 2006). The elements or parts of a complex system are interdependent, and any change caused by one part of the system can have effects on other parts of the system. The elements of a complex system separately do not show the same properties as the complex system as a whole. Only when put together, the collective behavior and properties of the whole system emerge due to the interactions of those elements with or without external influence (self-organization). Due to this dynamic and fluctuating nature, the function of the whole system cannot be understood from simply and solely understanding the functions of its subparts (Pavard & Dugdale, 2006). The result is the inability to precisely predict and analyze the behavior of complex systems, which presents a barrier in the face of system management and development.

Successful systemic performance depends on the level of understanding of the relationships among the components and the capability to manage variability. Focusing on one aspect or analyzing each aspect separately without considering the emergent and complex properties of a sociotechnical system would not provide a complete picture of the system status. Systems have become so complex nowadays that only domain experts are still capable of understanding their aspects and behavior (Leveson, 2011). The large scale and increased complexity of modern systems along with the introduction of new types of hazards and risks resulted as well in adding up to the severity and cost of failures (Leveson, 2011). Relying on traditional analysis methods, in which accidents and adverse outcomes are explained in terms of single errors, component failures or root causes, would not be sufficient to explain the behavior of complex sociotechnical systems entirely (Leveson, 2011; Hollnagel, 2012a). The scope of such an analysis would be limited to evaluating causal and linear relationships, while the emergent properties of a complex system and the resonance of dynamic non-linear relationships would not be covered. New systemic and holistic approaches are required considering social factors in addition to mechanistic relationships. Those approaches shall consider non-linear and dynamic relationships in addition to linear and sequential ones. Only by considering the properties of a complex sociotechnical system and looking at it holistically, a complete and comprehensive evaluation can be provided. Adopting such an approach would allow for a better understanding of the characteristics and behavior of the system in question, which is necessary whether for design and development purposes, performance evaluation or safety and risk management.

An alternative approach would be to focus additionally on "*what goes right*" i.e., the conditions of the system in question that ensures risk-free and optimal outcomes (Hollnagel, 2014). Changing the definition of what composes an event, safety can be defined as a dynamic event as well (Hollnagel, 2014). Just as an adverse outcome is an event, a successful outcome is an event as well. Things that go right to ensure that a task is carried out as intended should be considered. Upon examining actual performance and evaluating why things work out in practical applications, one eventually notices that the actual execution deviates from the foreseen procedures. This is the difference between "*work-as-done*" and "*work-as-imagined*"

(Hollnagel, 2014). The task specifications from the theoretical or procedural end prescribes what and how things should be done, while actual applications differ depending on the context of the application. Local adjustments are necessary each time to ensure that a function is executed successfully. This is due to the underspecified and partial understanding of reality at the procedural end (Patriarca et al., 2018a). Human thinking approximates and summarizes information in form of labels, words, and sentences to extract relevant information for the intended purposes (Zadeh, 1973). The approximation of reality misrepresents its true nature, however, for human purposes, such approximations are sufficient to perform most of the tasks and functions that do not require high degree of precision (Zadeh, 1973). The human brain exploits this tolerance for imprecision and acquires only relevant information, which can construct a model that resembles the true nature of the phenomenon in question and describes the required features that are necessary to perform required tasks (Zadeh, 1973). The brain thus limits the amount of information received through the human senses to a level, at which it can process the acquired information. Traditional analysis methods fail to capture the fuzziness of human reasoning and behavior. They are therefore inadequate to analyze humanistic systems (Zadeh, 1973). A shift in perspective is necessary and adopting a more holistic and systemic approach is required. The flexibility and local adjustments in performance are an essential factor for the success of applications. Performance variability is natural and even required to comply with real world conditions that were not covered in the procedures. The shift in perspective requires therefore looking proactively at what goes right in addition to what goes wrong. This approach is known as Safety-II (Hollnagel, 2014).

In summary, to avoid falling behind and cope with the growing complexity of modern sociotechnical systems, a shift in perspective is needed. Complex systems have to be considered as a whole to better understand the functional relationships of the systems in question. In addition to looking at what goes wrong (Safety-I), one should look at what goes right as well (Safety-II), especially in the case of highly reliable systems and the absence of statistics and sufficient data.

3.3 The Functional Resonance Analysis Method (FRAM)

FRAM was introduced by Erik Hollnagel in 2004 as a systemic accident investigation method. "*The Functional Resonance Analysis Method describes system failures (adverse events) as the outcome of functional resonance arising from the variability of normal performance*" (Hollnagel, 2012b). The performance of a sociotechnical system is never carried out in reality as imagined or designed. Operational deviations from procedures are normal and are sometimes required to perform successfully. The variability of performance depends on the contextual conditions present at the time of execution, which results in altering the application each time the same procedure is carried out. FRAM analyzes systems in terms of functions and examines how the functional variability can resonate within the system to produce successful or failed outputs. The advantage in contrast to classical analysis methods is the capability to analyze dynamic nonlinear relationships and provide a more holistic approach. FRAM relies on four principles:

- Equivalence of success and failure
- Inevitability of approximate adjustments
- Emergence of consequences
- Functional resonance

The reader is advised to consult the website of FRAM for a more detailed presentation of the features of FRAM (http://www.functionalresonance.com/).

The application of FRAM consists of five steps: Objective, Functions' Identification, Variability Characterization, Functional Resonance and finally Variability Management. The five steps will be discussed briefly in the following subsections.

3.3.1 Step Zero: Objective

The objective of the FRAM application has to be determined, whether the objective is to perform an accident investigation (reactive) or a safety and performance assessment (proactive).

3.3.2 Step One: Identification of Functions

The functions that compose the system have to be defined and characterized. FRAM functions are objectives or tasks to be achieved by the system in question. They are characterized in terms of six aspects: input, preconditions, time, control, resources and output (Figure 3.1). The characterization of the functional aspects defines the functional couplings and potential variability among the functions through linking the outputs of upstream functions as inputs for the downstream functions.

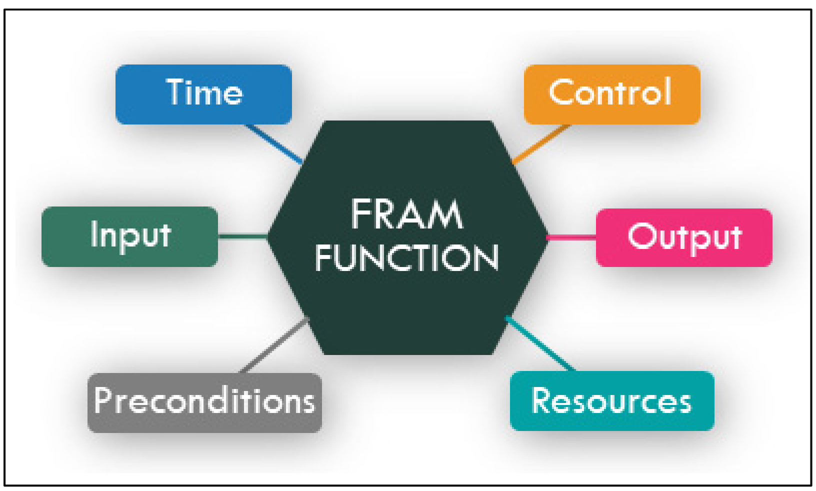

Figure 3.1 A graphical representation of a FRAM Function (Hollnagel, 2012a)

3.3.3 Step Two: Variability Characterization

The performance variability of the functional outputs has to be identified. The basic FRAM model characterizes variability in terms of time and precision using a qualitative three-point scale for each attribute (Table 3.1).

Table 3.1 Characterization of variability using linguistic labels (Hollnagel, 2012a)

Characterization of Variability			
Precision	Imprecise	Acceptable	Precise
Timing	Too early	On time	Too late

3.3.4 Step Three: Identification of Functional Resonance

A specific analysis scenario or instantiation can be used to evaluate the influence of variable functions on other functions and the overlapping or resonance of those influences through functional couplings to result in adverse or successful outcomes (Figure 3.2).

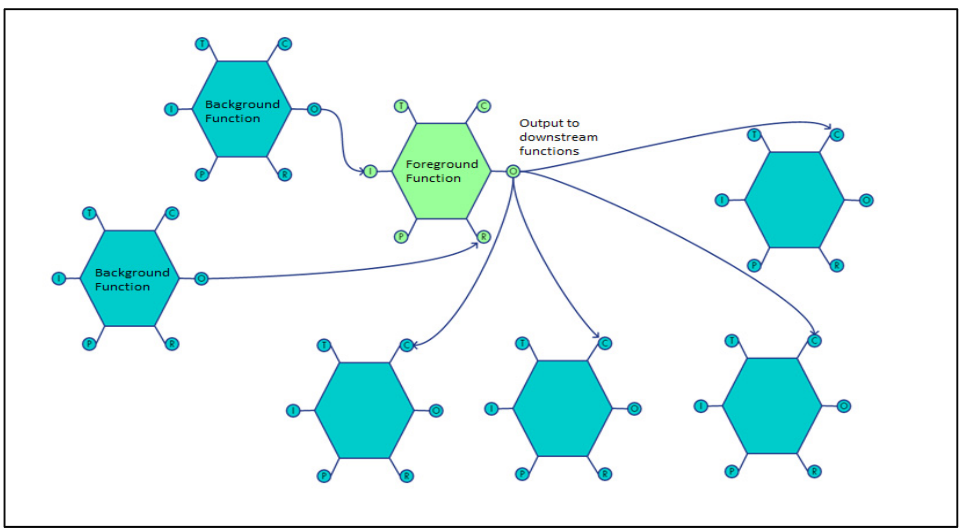

Figure 3.2 A graphical representation of a FRAM model depicting different function types (Hollnagel, 2012a)

3.3.5 Step Four: Management of Variability

The final step in FRAM is to identify countermeasures for variability management to design a more resilient system, ensure adequate performance and provide desired outcomes.

3.4 FRAM's Applications and Evolution

Since its introduction, FRAM's usefulness was demonstrated through many applications in many fields as in construction (Rosa et al., 2015), manufacturing (Albery et al., 2016), healthcare (Pickup et al., 2016), railway systems (Belmonte et al., 2011), and mostly in aviation (Sawaragi et al., 2006; Nouvel et al., 2007; Hollnagel et al., 2008; De Carvalho, 2011) etc. The early applications of FRAM mostly were conducted in a retroactive manner as an accident investigation method, which was indicated in the original naming of FRAM as the "*Functional Resonance Accident Model*" (Hollnagel, 2004). In retroactive analyses, real events are usually evaluated. The parameters and data for the event in question are known (Cacciabue, 2000). Existing work conditions can be monitored to evaluate the state of the system and lessons from past events can be learned to improve safety measures (Cacciabue, 2000). Proactive applications are different in so far that they require creative thinking and imagination to anticipate what might happen and estimate the likelihoods for the occurrence of desired or undesired outcomes (Cacciabue, 2000). Due to the capability of FRAM to provide an understanding for the evolution of accidents and therefore the possibility for proactive applications, the acronym "*FRAM*" was redefined and changed to the "*Functional Resonance Analysis Method*".

FRAM is beneficial when dealing with contexts that are of qualitative nature, which can be difficult to quantify. The main advantage of FRAM remains the ability to account for complexity in the studied systems and to analyze nonlinear dynamic relationships among functions. Precise data for such contexts can be lacking due to their inherent complexity and the nature of the evaluated factors. The reliance on qualitative linguistic scales enables the analyst to evaluate contexts, in which data are missing or uncertain or the variables are hardly measurable numerically. However, one issue of this approach is that it does not provide a precise magnitude of the examined variables. The perceptions and definitions of the same linguistic scales as "*imprecise*" or "*too late*" can differ from one person to another. Adding quantification tools would allow for a more comprehensible representation of variability in terms of numerical values. As remarked by Hollnagel, in order to realize safety objectively and practically, it is important to validate the existence of safety through "*intersubjective verification",* i.e. different parties should be able to confirm that their definitions and understanding of safety are matching (Hollnagel, 2014). This can be achieved through quantification. People have different interpretations for the meanings of such expressions as "*harmful*" or "*low*" and these differences become significant when it comes to qualitative safety and risk assessments. It is important to define what is meant with the used expressions and terminology to ensure conformity in the understanding of the provided results.

The basic FRAM method evolved over the years and many improvements were proposed to provide more precise analysis results. Many studies addressed several limitations of FRAM related to the absence of quantification means. One of the first studies to propose an improvement to the framework of FRAM was conducted by Macchi (Macchi, 2010). Macchi addressed three limitations of FRAM: the representation of variability as a result of local adjustments in performance to comply with requirements; the differentiation between performance variability of heterogeneous functions according to the MTO (huMan-Technology-Organization) classification method; and finally, the generation of a single numerical representation to aggregate the scores of the eleven Common Performance Conditions (CPC) into one value (Macchi, 2010). Macchi (2010) combined the qualities of the "*precision*" and "*timing*" phenotypes to produce a single quality of the functional output. The impact of the nine possible qualities on performance was rated numerically applying an ordinal scale between -3 for highly variable and +3 for highly dampening. A median value is then calculated to generate a single numerical quality value for the output. The improved methodology was then applied to evaluate a landing approach in Stuttgart examining the impact of the introduction of the Minimum Safe Altitude Warning (MSAW) system to Air Traffic Control (ATC). The proposed methodology applying an ordinal scale and calculating a median value for the output simplifies reality as acknowledged by Macchi, which can be efficient in practical applications. The proposed model was an important first step for the improvement of FRAM. Another limitation of the proposed methodology is assuming that the impact of the functional aspects on the output is the same. We believe that those limitations can be addressed appropriately using fuzzy logic.

Rosa et al. (2015) proposed a methodology merging FRAM with the Analytic Hierarchic Process (AHP) relying on experts' knowledge. Questionnaires were directed at the experts to provide a numerical ranking (ratio scale) based on comparisons between pairs of criteria (Rosa et al., 2015). The AHP and the pairwise comparison approach has the disadvantage for not handling the vagueness in judgments for transforming linguistic scales into numerical scales very well (Ishizaka, 2014).

A recent and significant study for the evolution of FRAM was published by Patriarca et al. (Patriarca et al., 2017c) proposing a different approach. Patriarca et al. proposed a semi-quantitative approach based on the Monte Carlo simulation (Patriarca et al., 2017c). Numerical scores were assigned to each performance state of the two criteria: precision and timing. A higher score indicated a higher variability. The variability of the output of a given function was defined as the product of the two scores. To determine the effect of the couplings between upstream and downstream functions, two amplifying factors in terms of timing and precision was defined for each coupling separately (a<1 amplifying; a=1 neutral; a>1 dampening). The effect of the performance conditions (abbreviated SPC) for each scenario or instantiation of the analyzed system was considered as well defining a factor on a rating scale between 0 and 1 (b=0 for no impact; b<1 for moderate impact; b=1 for high impact). A matrix consisting of the set of possible scenarios of the system in question and their respective effect was constructed and the resulting conditional variability e_j of any output was formulated as $e_j^z = \max\ \{1; \frac{\sum_{k=1}^{m} SPC_z^k . b_j^k}{m}\}$.

The variability for each coupling (VPN_{ij}^z) therefore was calculated as the product of the output's variability (Timing Variability V_j^T & Precision Variability V_j^P), the amplifying factor for each coupling (a_{ij}^{T}& a_{ij}^{P}) and the conditional variability e_j^z and the formula looked as follows: $VPN_{ij}^{z}= V_j^T \,.\, V_j^P \,.\, a_{ij}^T .\, a_{ij}^P .\, e_j^z$

To avoid misrepresenting the status and behavior of the system by using static scores, discrete probability distributions were instead utilized to provide a better representation of functional variability. Accordingly, the resulting product in the final formula above becomes through the Monte Carlo simulation a probability distribution as well. The developed methodology was then showcased through the application on a case study evaluating the Air Traffic Management (ATM) system. The proposed framework by Patriarca et al. marks an important development in the evolution of FRAM towards validation as a complementary tool to classical analysis methods. Rather than simply providing a simple numerical output, probability distributions are provided to assess variability. The applied Monte Carlo method relies on statistical data analysis to generate those distributions, which usually requires large data samples to run a large number of iterations. This makes the generation process of those values unidirectional since the sampling process is random.

A different approach to add quantification to FRAM can be achieved through the integration of fuzzy logic and the creation of a rule-based fuzzy inference system. The relationships between inputs and outputs can be characterized through the If-Then rules. Different weights and impacts can be associated with each quality class for each variable. The concept of fuzzy granulation and use of linguistic variables is a unique feature of fuzzy logic (Zadeh, 1997 & 2015). Relying on linguistic variables becomes necessary when the "*available information is too imprecise to justify the use of numbers*" or there is a tolerance for imprecision, which can be exploited for better outcomes (Zadeh, 1996). The reliance on linguistic variables allows for the quantification of qualitative expert knowledge in the form of natural language and consequently the design of comprehensible analysis models.

In this article, we explore a possibility to address this issue through the integration of fuzzy logic into FRAM as proposed by Hollnagel (2012a).

3.5 Fuzzy Logic

Fuzzy Logic is based on the Fuzzy Set Theory (Zadeh, 1965), which is a generalization of classical set theory. In classical set theory, elements either belong to a set or do not belong; they are either true or false (Sivanandam et al., 2007). In fuzzy set theory, elements can belong to more than one fuzzy set with a certain degree of membership or truth (Sivanandam et al., 2007). The characteristics of fuzzy sets are defined through the generalization of the usual characteristics of classical sets:

Let *A* be a fuzzy set and μ_A is the membership function characterizing the fuzzy set *A*.
A then can be defined as: $A = \{(x, \mu_A(x) \mid x \in A, \mu_A(x) \in [0, 1]\}$ *with* $\mu_A: X \rightarrow [0,1]$
A fuzzy set *A* is therefore a collection of ordered pairs (x, μ_A(x)), where μ_A(x) is the degree of membership of *x* in *A*.

Some basic operations of fuzzy sets are listed below as next:

- Union of two fuzzy sets:

$$C = A \cup B = \mu_C(x) = max[\mu_A(x), \mu_B(x)] \tag{3.1}$$

- Intersection of two fuzzy sets:

$$\mathrm{C = A \cap B} = \mu_C(\mathrm{x}) = \min[\mu_A(\mathrm{x}), \mu_B(\mathrm{x})] \tag{3.2}$$

- Compliment of a fuzzy set *A:*

$$A' = 1 - \mu_A(x) \tag{3.3}$$

The application of the fuzzy logic methodology consists of three steps: Fuzzification, Inference and Defuzzification (González Dan et al., 2017).

3.5.1 Fuzzification

A linguistic variable in fuzzy logic can belong with a certain degree of membership to a fuzzy set, which represents a label or a class of objects with specific characteristics (Zadeh, 1973). The range of values that a linguistic variable can possess is defined as the universe of discourse, which is partitioned to multiple linguistic classes i.e. fuzzy sets (González Dan et al., 2017). The first step is to fuzzify the input data through the assignment of membership degrees to the defined linguistic variables (González Dan et al., 2017). The transition between membership and non-membership is gradual and not abrupt as in classical logic. The degree of membership for an element in a fuzzy set can be any value between zero and one. The degree of membership is determined with the help of a curve called the membership function, which can have many shapes depending on the nature of the variable (triangle, trapezoid, S-shape, etc.) (Shepard, 2005) (Figure 3.3).

3.5.2 Inference Process

The most used fuzzy inference processes are the Mamdani Inference model (Mamdani & Assilian, 1975) and the Sugeno Inference model (Sugeno, 1985). The Mamdani model is more interpretable and adequate for handling qualitative knowledge and generating fuzzy rule-based expert systems, while the Sugeno model is more adequate for mathematical analysis. In this study, the Mamdani model will be used, since it is more intuitive and suitable for human input. After defining the linguistic variables and the respective membership functions and ranges of values, a rule base has to be generated. The conditional rules (IF-THEN rules) shall characterize the relationships between the inputs and the outputs. The rules are comprehensible since they are written in natural language. For example, IF input is precise, THEN output is on time. The input and output are two linguistic variables, which have the values "*precise*" and "*on time*" respectively. The two values are labels for two fuzzy sets with the same name. The conditional statement or rule describes a simple relationship between the two variables "*input*" and "*output*". The number of rules depends on the number of variables and respective classes. Different weights can be assigned to the rules depending on their significance and influence on the output. The inputs or antecedents will be linked to each other applying fuzzy logical operators such as AND, OR, or NOT. After the formulation of the rules, the implications for each rule will be determined. In the implication process, the results for each fuzzy rule will be transformed in an area value in the membership function of the output. The calculation method of the implication area in the output function will depend on the selected operator (AND or OR). In case of the "*OR*" operator, the union or maximum operation will be used (e.g. max [$\mu_A(x)$, $\mu_B(x)$]). In case of the "*AND*" operator, the intersection or minimum operation will be used (e.g. min [$\mu_A(x)$, $\mu_B(x)$]). The obtained implications will be then aggregated to provide one implication for the output in the form of a fuzzy set. For the aggregation process, two calculation methods are mainly utilized: the maximum operation and the summation method. The maximum method collects the highest areas in the fuzzy sets of the results' implications, while the summation method simply adds up all the received areas for the implications (Figure 3.3).

3.5.3 Defuzzification

The final step of the fuzzy methodology is the defuzzification, which means transforming the fuzzy output into a crisp value. Many methods exist for defuzzification, from which one can be selected depending on the characteristics of the needed output (Figure 3.3) (González Dan et al., 2017). The center of gravity (COG) method is most common and the output can be determined using the following formula:

$$\mathrm{COG}\mu_A(x) = \frac{\int \mu_A(x).x dx}{\int \mu_A(x) dx}. \tag{3.4}$$

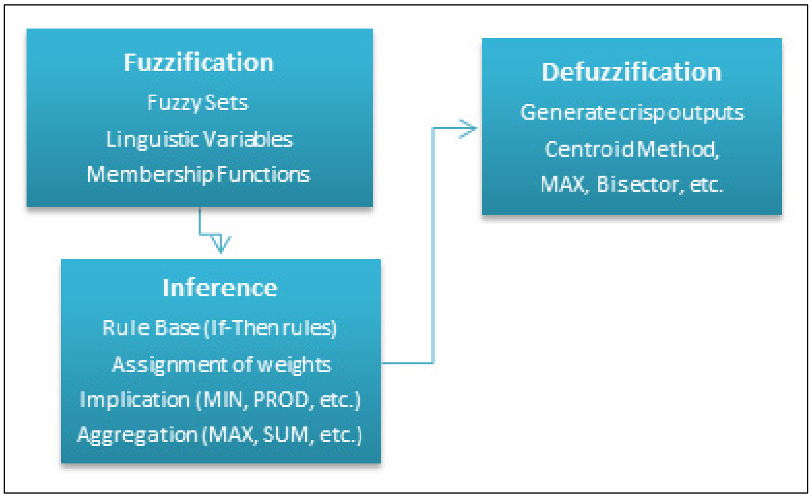

Figure 3.3 The three steps of a fuzzy inference system (González Dan et al., 2017)

Fuzzy logic can be an appropriate method to quantify uncertain and vague contexts, in which linguistic scales are the only possibility to measure the variables of interest (Zadeh, 1965). Human reasoning does not rely primarily on numbers, rather on linguistic variables, whose possible values are words or sentences in natural language (Zadeh, 1973). Zadeh argued that, due to the principle of incompatibility, the application of traditional methods to analyze humanistic and complex systems could not be successful as with pure technical or mechanistic systems. The principle of incompatibility states that whenever the complexity of a given system increases, the ability to understand its behavior in a precise manner decreases (Zadeh, 1973). In contrast to theoretical idealistic concepts, realistic processes in real life situations are characterized by ambiguity and vagueness. Real life conditions and processes are never as imagined and even in the most precise applications of procedures and regulations; operations and performance always deviate from the norms and defined standards. This deviation is what Hollnagel defines as the difference between Work-As-Imagined (WAI) and Work-As-Done (WAD) (Hollnagel, 2014). The deviation from the theoretical procedures is not exceptional or abnormal; rather it is an inherent characteristic of real life conditions. The quantification of the qualitative values in FRAM can be achieved through the fuzzification of the functional aspects and the application of a rule-based Fuzzy Inference System (FIS) to produce numerical outputs for the functions.

3.6 Methodology

The MTO classification of functions in FRAM distinguishes between three categories of functions: huMan, Technological and Organizational (MTO) functions (Hollnagel, 2012a). This classification serves a practical purpose of simplifying things for the analyst and allows for defining the potential functional variability depending on the type of each function (Macchi, 2010). As noted by Patriarca et al., the implication of this approach is assuming that functions of the same type have the same variability, since the evaluation of variability occurs in a qualitative manner relying on linguistic scales (Patriarca et al., 2017c). In reality, the performance of the different types of functions differs depending on their individual characteristics (Patriarca et al., 2017c). For example, assigning an "*imprecise*" quality to the output of two "*human*" functions does not differentiate clearly how the variability of the two functions is different. There is no obvious distinction between the magnitudes of the two outputs. Additionally, while the expert performing this analysis might understand how the variability of the two functions is manifested in reality, other parties might have different perceptions for the magnitude of the label "*imprecise*". The same label might mean different things to different people. Another additional issue is that most functions in reality are not purely technological, human or organizational. Most functions are a combination of the three aspects. A mostly technological function can still have a human aspect, just as a human function can partly be technological. Assigning a function to one category is a generalization, which might limit the consideration of the influential factors on performance.

Despite the drawbacks of this approach, it remains practical and useful. Capturing the precise nature of complex systems is difficult. Our perception of reality as humans is simplified and fuzzy. Simplifications are necessary for modeling reality and providing means of evaluation and control. Therefore, improvements to the current framework of FRAM could overcome the above-described issues without sacrificing the practical advantages of this approach. Fuzzy logic as a mathematical approach capable of computing with natural language and quantifying words can resolve the ambiguity of the outputs and present more comprehensible results. In the following section, we will present a detailed description for the integration of fuzzy logic into FRAM to present a possible approach for the addition of quantification.

The first two steps (step zero and step one) in FRAM remain unchanged: the identification of the analysis purpose and the identification and characterization of the functions. In step two, the performance variability has to be characterized. We can distinguish between two types of variability with respect to the identified functions: an exogenous variability, which is imposed on the function from external sources (other functions) through the functional couplings; and an internal variability, which comes from within the function in question and depends on the characteristics and nature of that function (Hollnagel, 2012a). The functional couplings describe the relationships among functions and depict the possible impact of an upstream function on a downstream function. However, there is no clear path to account for how the internal variability manifests in the quality of the function's output. Therefore, the first step would be to introduce an internal variability factor (IVF), which shall account for the internal variability of each function. The IVF can account for the inherent characteristics and the potential of the function to produce variability affected by present performance conditions, while the external variability is imposed on the function through the couplings with the other functions. Such factors can be the different human characteristics as emotional states, personality traits, attitude, knowledge, physiological and psychological factors, technological features and functionality, organizational climate, etc. In our case here, to determine the internal variability for each function, the Common Performance Conditions (CPC) will be applied to calculate a numerical output. The CPC list can be used to evaluate the influence of the contextual influences on performance (Table 3.2).

Table 3.2 Common Performance Conditions & their influence on different function types (Macchi, 2010)

Common Performance Conditions (CPC)	Human Functions	Technological Functions	Organizational Functions
Availability of resources	X	X	
Training & competence	X		
Quality of communication	X	X	
HMI and operational support		X	
Availability of procedures and plans	X		
Conditions of work		X	X
Number of goals and conflict resolution	X		X
Available time and time pressure	X		
Circadian rhythm and stress	X		
Team collaboration quality	X		
Quality and support of the organization			X

The MTO classification method can be used here to determine which factors affect which functions. Originally, the quality of the CPC was evaluated on a three points scale: Adequate, Inadequate and Unpredictable (Macchi, 2010). The impact of adequate CPCs is small, of inadequate CPCs noticeable to high and of unpredictable CPCs high to very high (Macchi, 2010). In our case, the quality of the factors will be evaluated in two classes as "*adequate*" or "*inadequate*", while the quality "*unpredictable*" will be represented in the fuzzy rule base. The quality "*unpredictable*" means that a statement about the status of the CPC in question cannot be presented due to the lack of information or the dynamic nature of the condition itself i.e. a numerical score cannot be assigned. Since a numerical value cannot be plotted for unpredictable factors, adding the class "*unpredictable*" in this case is not useful. Rather, in case of dynamic or ambiguous conditions, the rule base can be designed in a manner to account for the unpredictability e.g. the quality "*none*" in the Fuzzy Logic Designer in MATLAB can be selected to represent an unpredictable variable. Additionally, limiting the number to two classes would allow for the limitation of the number of rules. A numerical scale between zero and ten will be used to assign a quality value for each factor (Figure 3.4). The IVF will be calculated as an internal function for each function applying a fuzzy inference system to produce the numerical output as a result of the quality of present Common Performance Conditions (CPC). The range of the generated IVF will be between 0 and 1.5. Values between 0 and 1 account for negative variability that impairs performance, while values between 1 and 1.5 account for variability dampening and performance-enhancing impact (Figure 3.5). The IVF is then linked to the function as an additional aspect next to the other incoming five aspects from upstream functions, which will be fuzzified to determine the output's quality (accounts for internal and external variability) of the function.

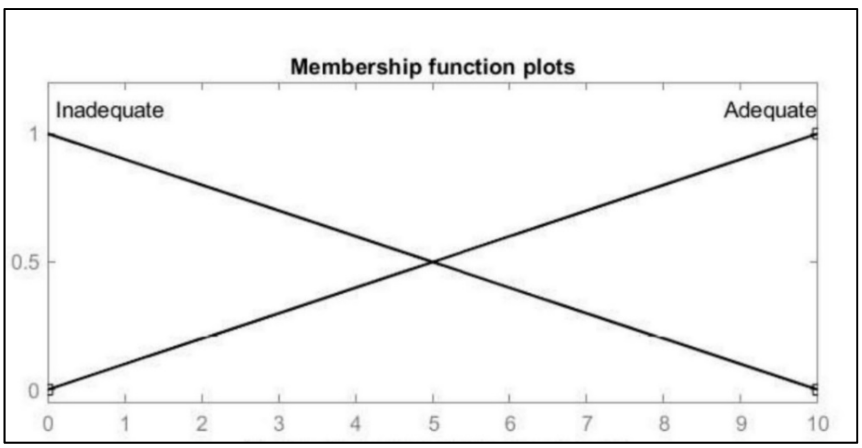

Figure 3.4 Membership functions of the IVF function in MATLAB

Macchi (2010) addressed the limitations of the CPC methodology stating that "*the use of the CPCs seems to be inadequate*" to evaluate performance variability due to local adjustments. The CPCs reflect the influence of the context on performance and relying solely on them cannot account for the resonance of variability among functions through their couplings.

However, the aim here is to anticipate potential sources of internal variability that comes from within the functions. The impact of the context here is essential and added to the variability due to local adjustments, both internal and external variability can be represented. The list of the influential factors is not necessarily limited to the CPC list. The analyst can adopt any list of factors that he/she deems most relevant for the performance of the function. The list of performance shaping factors in Human Reliability Analysis is long and depending on the context of the analysis, a set of influential factors can be selected.

The second type of variability is the external variability, which can be characterized through the couplings among functions. The outputs of the background functions are invariable, which means a stable output at 100% or one. The output of the foreground functions, which are the direct downstream functions to the background functions will receive only stable incoming aspects from the background functions. The outputs will be classified into three classes relying on the classification method of Macchi (Macchi, 2010). Macchi combined the accuracy and timing characteristics to determine nine possible quality classes for the outputs (Macchi, 2010). He then plotted the classes graphically to determine the degree of impact on the functions whether it was inducing or dampening variability (Table 3.3).

Table 3.3 Characterization of the output's quality (Macchi, 2010)

Characterization of variability		**Time**		
		Too early	**On time**	**Too late**
Precision	**Precise**	A: Dampening	B: Highly dampening	C: Low dampening
	Appropriate	D: Low dampening	E: Dampening	F: Slightly variable
	Imprecise	G: Slightly variable	H: Variable	I: Highly variable

Five classes were found to dampen variability (A to E) and four to increase or induce variability (F to I). At this stage of scientific developments, we need to limit the number of classes further to avoid the problem of rules explosion and present a simplified and practical model. Since highly controlled environments as aviation require high accuracy and all functions are to be executed as perfectly as possible, then we hypothesize and consider any dampening output as "*Non-variable*", which shall account for positive or neutral impact. The outputs with low and medium variability will be combined and classified as "*Variable*". The outputs with high variability will be classified as "*Highly Variable*". This would simplify the classification of the outputs and limit the number of rules for the downstream functions significantly. The simplification is not an issue for the interpretation of the output's quality, since an accurate numerical value for the output is provided (Table 3.4).

Table 3.4 Simplified characterization of the output's quality

Characterization of variability		**Time**		
		Too early	**On time**	**Too late**
Precision	**Precise**	Non-variable	Non-variable	Variable
	Appropriate	Non-variable	Non-variable	Variable
	Imprecise	Variable	Variable	Highly variable

Note that "*Variable*" in this context refers to the negative deviation of the output from the desired outcome, which is ideally one. A "*Non-variable*" label accounts for possibly positive impact on performance (Figure 3.5).

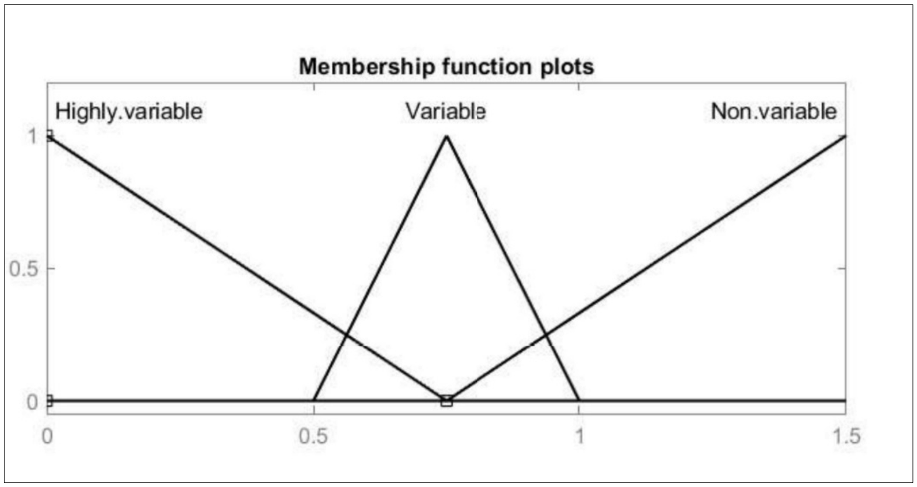

Figure 3.5 Membership functions of the function's output in MATLAB

Then, a second higher-order fuzzy inference system relying on the rule base that characterizes the relationships between the incoming functional aspects in addition to the IVF of the function and the output is designed to produce the numerical output for the output's quality of the function. The number of rules depends on the number of variables and respective classes. To keep the number of rules reasonable, many solutions can be adopted such as hierarchical fuzzy systems, or the use of genetic algorithms to design the rule base, etc. This would further complicate the design process and would make the application of FRAM difficult and exhaustive at this stage. In our case here, we tried to simplify the model to a degree that allows for the construction of a helpful model with reasonable effort. The simplification however shall not lead to the trivialization of the model. The rule base is helpful in overcoming another issue of FRAM, which is the assignment of weights to the different functional aspects. Different weights can be assigned to the rules depending on their significance and influence on the output. Additionally, weight scores can be assigned to the different labels in the antecedent part of the rule base to determine the implication of each rule and determine the respective consequent label. In our case, the applied implication method was the "*MIN*" method, and for aggregation, both the "*MAX*" and the "*SUM*" methods were applied.

The final step is to defuzzify the output to produce a numerical output. The applied defuzzification method in our case was the centroid method. The calculated numerical value presented a quantifier for the quality of the functional output. The fuzzy FRAM model is now ready for the simulation of deicing operations.

3.7 Aircraft Deicing Simulation: a case study

Looking at "*work-as-imagined*", all performance conditions are optimal, and the outputs of the functions are non-variable. To provide an application example in our case, a hypothetical scenario was constructed inspired by two deicing-related accidents, namely the Scandinavian Airlines flight 751 crash in 1991 (SHK, 1993) and the Air Maroc accident in Mirabel in 1995 (TSB, 1995). For our simulation, we will assume the following:

- An international flight is scheduled to take off at a North American airport for a Trans-Atlantic flight provided by an international airliner;
- The pilots of the aircraft to be deiced are not very familiar with deicing procedures;
- Airliner instructions and guidelines provided for the flight crew do not specify clearly communication protocols and inspection procedures;
- The aircraft is to be taxied from the gate to the deicing pad, where two deicing trucks are positioned to perform the deicing operations;
- The weather conditions: temperature around 0°C and snow showers were present;
- The flight crew was under temporal constraints: the flight was delayed due to weather conditions;
- The organizational performance conditions are not optimal, especially the provision of adequate training and instructions by the Airliner to its flight crew;
- The human or individual performance conditions for the flight crew are impaired: availability of resources, airliner procedures and plans, competence and time pressure.

The five steps for our FRAM model are then as follows:

3.7.1 Step Zero: Objective Identification

The first step in FRAM is to identify the purpose of the analysis. Our objective is to present an example for a possible way to construct and run a FRAM model integrating fuzzy logic as a quantification method. The selected context for analysis is the context of aircraft deicing operations. The model will be of predictive nature and will not focus on simple basic activities such as move from point A to point B. Rather, the focus will be on more complex tasks to allow for a wide systemic perspective.

3.7.2 Step One: Definition of Functions

The functions of the model are to be identified. To keep the number of functions, variables and respective rules reasonable, the scope of the analysis will be limited to the de-icing activities conducted by the deicing service provider at the deicing pad. The functions will be identified based on knowledge gained through literature review of deicing reports and research work conducted by our team over the previous years. The background functions will form the boundaries of the model and will provide invariable outputs. The foreground functions will be the focus of the analysis and can produce therefore variable outputs. Totally, there are four background functions and 13 foreground functions. Table 3.5 presents a list the functions and their characteristics.

Table 3.5 The list of defined functions that constitute the deicing model

No.	Function Name	Type	Description
1	**Review Meteorological Data**	Background	Review of weather conditions for preflight planning and inspections
2	**Aircraft Specifications**	Background	Aircraft technical and operational information provided mainly by manufacturer
3	**Regulations and Supervision**	Background	Supervision and regulations provided by governmental agencies

Table 3.5 The list of defined functions that constitute the deicing model (continued)

No.	Function Name	Type	Description
4	**ATC Supervision**	Background	Clearances provided by the ATC to navigate aircraft on the airport grounds
5	**Resources and Equipment**	Organizational	Resources and equipment provided for the inspection and deicing operations
6	**Training**	Organizational	Training provided to the deicing personnel
7	**Airliner Instructions & Guidelines**	Organizational	Guidelines provided by the airliner for the flight crew and deicing personnel
8	**DSP Instructions & Guidelines**	Organizational	Guidelines provided by the Deicing Service Provider (DSP) to its personnel
9	**Preflight Planning**	Human	Flight planning performed by the pilot and the flight dispatcher
10	**Flight Crew Supervision**	Human	Supervision provided by the pilot and flight crew to monitor and control operations
11	**Deicing Tower Control**	Human	Supervision provided by the deicing tower or the bay-lead to monitor and control operations
12	**Pre-deicing Inspection**	Human	Inspection of the aircraft to decide if deicing/anti-icing is required
13	**Taxi Aircraft to Deicing Pad**	Human	Taxi aircraft from gate to the deicing pad
14	**Deicing**	Human	The application of deicing fluids and removal of contamination
15	**Post-deicing Inspection**	Human	Inspection after deicing to ensure all surfaces are clean
16	**Anti-icing**	Human	The application of anti-icing fluid to keep aircraft clean until take-off
17	**Taxi to Runway**	Human	Taxi aircraft from deicing pad to runway for takeoff within the specified holdover time

3.7.3 Step Two: Variability Characterization

The variability of the functions is to be characterized. We start by characterizing the internal variability for each function using the CPC list as explained above. Each CPC is evaluated on a scale between zero and ten to plot its membership to the fuzzy sets "*adequate*" or "*inadequate*". The detailed assignment of scores to each performance condition is listed in Tables 3.6 & 3.7. In practice, the evaluation of each CPC should occur based on expert judgement and in-depth knowledge of the conditions for executing the functions in question. Each CPC can be viewed as a set of influential factors as well. The list of influential factors can be selected based on the analysis context to determine the criteria for assigning the numerical score. For example, the CPC "*conditions of work*" can include a list of factors that define what constitutes adequate or inadequate conditions. The internal FIS is used to produce the IVF for each function.

Table 3.6 The numerical characterization of internal variability for the organizational functions

No.	**Function Name**	Conditions of work	Number of goals & Conflict resolution	Quality & support of the organization	**IVF**
1	**Resources and Equipment**	**9**	**9**	**9**	**0.969**
2	**Training**	**7**	**9**	**5**	**0.859**
3	**Airliner Instructions & Guidelines**	**8**	**9**	**4**	**0.845**
4	**DSP Instructions & Guidelines**	**8**	**8**	**9**	**0.93**

Table 3.7 The numerical characterization of internal variability for the human functions

No.	Function Name	Availability of Resources	Goals & conflict resolution	Quality of Communication	Availability of procedures and plans	Training & Experience	Available time	Circadian Rhythm and Stress	Team Collaboration	IVF
1	**Preflight Planning**	**9**	**10**	**8**	**8**	**8**	**8**	**9**	**10**	**0.985**
2	**Flight Crew Supervision**	**6**	**10**	**6**	**6**	**6**	**6**	**9**	**10**	**0.815**
3	**Deicing Tower Control**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**
4	**Pre-deicing Inspection**	**8**	**10**	**8**	**8**	**8**	**8**	**9**	**10**	**0.985**
5	**Taxi Aircraft to Deicing Pad**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**
6	**Deicing**	**10**	**10**	**7**	**7**	**7**	**7**	**10**	**10**	**0.891**
7	**Post-deicing Inspection**	**10**	**10**	**7**	**7**	**7**	**7**	**10**	**10**	**0.891**
8	**Anti-icing**	**10**	**10**	**8**	**8**	**8**	**7**	**10**	**10**	**0.968**
9	**Taxi to Runway**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**

3.7.4 Step Three: Identification of Functional Resonance

The functional resonance is to be determined. The numerical outputs of the upstream functions will serve as incoming aspects for the downstream functions. The incoming aspects will be fuzzified in addition to the internal IVF and their impact on the down-stream functions will be determined through the output's Fuzzy Inference System (FIS) of each function (Table 3.8).

Table 3.8 The numerical scores for the output's quality

No.	Function Name	Output's Score
1	Review Meteorological Data	**1.0**
2	Aircraft Specifications	**1.0**
3	Regulations and Supervision	**1.0**
4	ATC Supervision	**1.0**
5	Resources and Equipment	**1.08**
6	Training	**0.885**
7	Airliner Instructions & Guidelines	**0.867**
8	DSP Instructions & Guidelines	**1.0**
9	Preflight Planning	**0.916**
10	Flight Crew Supervision	**0.933**
11	Deicing Tower Control	**1.18**
12	Pre-deicing Inspection	**0.925**
13	Taxi Aircraft to Deicing Pad	**1.22**
14	Deicing	**0.932**
15	Post-deicing Inspection	**0.689**
16	Anti-icing	**0.849**
17	Taxi to Runway	**0.866**

3.7.5 Step Four: Variability Management

The final step would be to analyze the received results according to the selected scenario and examine what measurements can be taken to improve the quality and resilience of the examined system (Figure 3.6).

The modelling of the system's functions in the FMV happens in the form of tables characterizing the purpose of the defined functions and their aspects according to the FRAM structure. The FMV enables the generation of a graphical representation of the designed model depicting a sort of a map of the system. This graphical representation provides an illustration of the relationships among functions, which allows for understanding how the functions affect each other and how variability can combine throughout the system. The numerical values of the IVF (representing the potential variability of the functions) and the outputs (representing the combined impact of internal and external variability on the output's quality) were plotted in the graphical representation for illustrative purposes. Functional resonance is to be determined.

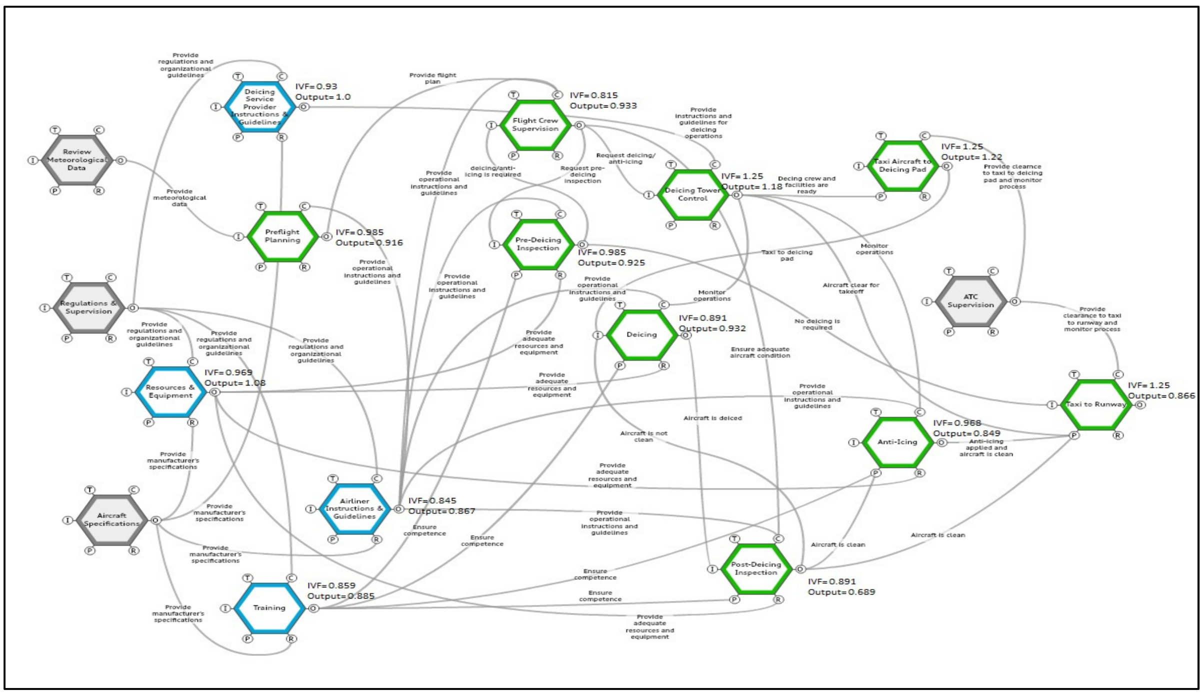

Figure 3.6 A graphical representation of the generated FRAM model with numerical outputs

The formulated assumptions in our case here present a scenario, in which the airliner did not provide adequate training and adequate instructions to its flight crew. The flight was delayed due to weather conditions and a stressed flight schedule. This impacted negatively the performance conditions for the functions: Training, Airliner Guidelines and Instructions, Planning, Flight Crew Supervision, Pre-deicing Inspection, Deicing, Post Deicing Inspection, Anti-icing and Taxi to Runway. The functions with an output's quality of one or higher are not variable in an adverse manner and has the potential to dampen variability in the downstream functions. The maximum output that can be achieved is 1.25 due to the selected defuzzification method i.e. the center of gravity method. The minimum quality output is 0.25. The numerical outputs showed a negative deviation from the ideal value (one or more) for the above-mentioned functions. The lowest result was received for the output of the function "*Post-deicing Inspection*" due to the principle of resonance of variability.

Based on the characterized functions and performance conditions, the analyst would be able to construct a map of the system in question. The relationships and dependencies between the performance conditions and the quality of the outcome can be described to identify which conditions promote success and which ones impair performance. This map describes how the functions are linked and how they can possibly affect each other's performance. The numerical outputs can provide more precise and intersubjective representation of the variability magnitude. Using this map, the analyst would be able to locate potential sources for variability within the system. It is then possible to propose and implement measures to strengthen weak points and enforce conditions that ensures successful outcomes.

3.8 Discussion

The application of FRAM can provide interesting and helpful results to keep up with the fast pace of technological developments and the dynamic nature of complex sociotechnical systems. This is not to say that FRAM can replace traditional analysis tools; rather, FRAM is complementary to the established methods and can present a different perspective on safety management and performance evaluation (Melanson & Nadeau, 2016). FRAM enables the analyst to examine dynamic and complex relationships to present a holistic perspective of the studied system. Through the evaluation of the contextual conditions, FRAM allows for characterizing operations in terms of coupled functions to determine possibilities for positive or negative performance variability.

In contrast to retrospective analyses, in which events and their consequences can be described in a more precise manner, proactive or predictive studies lack certainty. Through the integration of fuzzy logic into the framework of the classical FRAM, the advantages of both approaches can be utilized for the provision of systemic analyses. Applying probabilistic methods relying on statistical data analysis may not always be possible. Fuzzy logic can be more suitable in the absence of sufficient quantitative data or the presence of vagueness and information imprecision (Zadeh, 1996). The reliance on linguistic scales allows for the incorporation of approximate human judgements of experts to handle contexts, which are of qualitative nature and are not easily quantifiable. The representation of variability as a result of local adjustments to comply with performance requirements and the differentiation between the heterogeneous natures of functions as recognized by Macchi (2010) can be realized through the fuzzy rule base. The IF-THEN rules describe the relationships between inputs and outputs and facilitate the assignment of different weights and significance for each variable. The addition of fuzzy logic facilitates the production of numerical results, which present more comprehensible and precise results without sacrificing the advantages for using linguistic labels.

The construction of the simulated model (characterization of functions, relationships, selection of membership functions, etc.) and the analysis were performed based on knowledge gained from studying deicing operations. Additionally, the characterization of the simulated deicing functions was performed relying as well on literature findings, accident reports and technical reports published by governmental agencies around the world. Through the formulation of some assumptions over performance conditions, a proactive analysis model was constructed. The simulation was run in the FRAM Model Visualizer and in MATLAB using the Fuzzy Logic Designer to demonstrate a possible approach for the realization of a fuzzy-logic-based FRAM model. The evaluation scale was selected between zero and ten, which can be used either as a discrete or as a continuous scale. However, it is important to note that human judgement can be less accurate on a continuous scale. While different scales may be more suitable for different applications, the test-retest reliability for rating scales with 11 response categories or more tends to decline in comparison to a 7-point, 9-point or 10-point scale

(Preston & Colman, 2000). On the other hand, the reliability of scales with fewer response categories (2, 3 or 4) is much lower also than scales with 7, 9 or 10 response categories (Preston & Colman, 2000). It is important to select a scale that allows for the elicitation of experts' judgement maintaining valid and reliable results.

The aggregated numerical output does not translate into a definite membership into one class of quality. Rather, the numbers can be seen as indicators for the potential of positive or negative variability based on the designed functions and their respective membership functions, quality classes and performance conditions. The model is flexible i.e., the functions can be redefined and recharacterized if needed, new functions can be added, or existing ones subtracted and relationships can be redefined as deemed appropriate. The influence of the different CPCs and the different functional aspects on the output can be weighted in the rule base. Each function depending on its nature can be examined separately to determine the weights in the rule base and account for the different influences on the output. In our case study, same weights were attributed to the different aspects and to all rules in the rule base of each function, which simplified the construction process of the rule base and allowed for a more efficient and feasible execution of the simulation. After all, the objective is to demonstrate how such an application can be executed and the focus is mostly directed to the theoretical aspect. Applying this approach to a real case study must be done with caution, since the proposed model at this stage is still a prototype in need of further improvements.

Admittedly, the simulation in the proposed case is a simplification of reality. The representation of influential conditions and the characterization of functions were simplified to facilitate the simulation process, which requires high computing resources. To avoid the "*rules explosion*" problem, the number of inputs was limited to a maximum of six. A higher number is possible of course; however, the size of the rule base would increase exponentially with each added variable, which can amount to a very exhaustive process. The validity and reliability of the numerical outputs depend greatly on the defined model characteristics for this simulation and the formulated assumptions. This means that the results are not necessarily generalizable to other contexts, which is not the point of this simulation anyway.

The continuous improvement of safety in aviation and the declining number of accidents year after year make it difficult to collect sufficient data to generate meaningful statistics (Roelen & Klompstra, 2012). The establishment of adequate databases and performance indicators for aviation maintenance generally and deicing specifically can be very helpful to construct accurate and meaningful fuzzy inference systems. The proposed model in this paper is a first step, which requires further validation and optimization work to present more representative and reliable results. Further validation is still required to define a more realistic model of deicing operations. Nonetheless, the results presented here are promising and provide a possible approach for the integration of quantification means into FRAM, which can be beneficial to assess complex sociotechnical systems.

3.9 Conclusions

To keep up with the fast pace of evolving modern sociotechnical systems, a continuous re-evaluation of applied safety and risk management tools is advised. A paradigm shift in the way we look at adversity is needed, namely the shift from a SAFETY-I to a SAFETY-II perspective. In addition to looking at what goes wrong and aiming at simply identifying causes and errors, looking at what goes right becomes necessary, especially when there is a lack of sufficient or precise data. The Functional Resonance Analysis Method (FRAM) is proposed in this paper as an adequate method to address these challenges in addition to classical assessment methods. The principles of FRAM allow for a fresh and different perspective on system analysis characterizing nonlinearity, complexity and performance variability. The main objective of this paper was to propose a possible improvement to the framework of FRAM through the integration of fuzzy logic as a quantification tool. In an effort to produce more intersubjective results, a fuzzy-FRAM model of the aircraft ground deicing operations was constructed relying on literature and findings of our research team over recent years. The context of deicing operations was simulated in the FRAM Model Visualizer and in MATLAB to present a first application of the proposed model. The preliminary results are promising and allow for a more comprehensible representation of potential performance variability. The presented model is still at this stage a prototype and requires further validation and optimization work going forward to provide more representative and reliable results.

CHAPTER 4

ARTICLE 2: A MIXED ROUGH SETS/FUZZY LOGIC APPROACH FOR MODELLING SYSTEMIC PERFORMANCE VARIABILITY WITH FRAM

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Abstract

The task to understand systemic functioning and predict the behavior of today's sociotechnical systems is a major challenge facing researchers due to the nonlinearity, dynamicity and uncertainty of such systems. Many variables can only be evaluated in terms of qualitative terms due to their vague nature and uncertainty. In the first stage of our project, we proposed the application of the Functional Resonance Analysis Method (FRAM), a recently emerging technique, to evaluate aircraft deicing operations from a systemic perspective. In the second stage, we proposed the integration of fuzzy logic into FRAM to construct a predictive assessment model capable of providing quantified outcomes to present more intersubjective and comprehensible results. The integration process of fuzzy logic was thorough and required significant effort due to the high number of input variables and the consequent large number of rules. In this paper, we aim to further improve the proposed prototype in the second stage by integrating rough sets as a data-mining tool to generate and reduce the size of the rule base and classify outcomes. Rough sets provide a mathematical framework suitable for deriving rules and decisions from uncertain and incomplete data. The mixed rough sets/fuzzy logic model was applied again here to the context of aircraft deicing operations keeping the same

settings as in the second stage to better compare both results. The obtained results were identical to the results of the second stage despite the significant reduction in size of the rule base. However, the presented model here is a simulated one constructed with ideal data sets accounting for all possible combinations of input variables, which resulted in maximum accuracy. The same should be further optimized and examined using real-world data to validate the results.

4.1 Introduction

Resilience Engineering is a discipline concerned with designing and constructing resilient systems i.e. systems with the ability to cope with complexity and adapt with unforeseen changes and performance variability (Patriarca et al., 2018a). Classical approaches are no longer sufficient in the age of complexity to provide a complete and comprehensive picture and a trend shift occurred in recent years leading to the introduction of innovative methods to present a systemic perspective in system's analysis. One of the main methods in Resilience Engineering is the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2004 & 2012a). The principles (Figure 4.1), on which FRAM rely, allow for understanding complex systemic behavior as a result of performance variability and its combinations. The idea in systemic approaches is that undesired outcomes are not simply and entirely explainable in terms of singular components' failure, errors or sequential events. The natural deviation in performance from prescribed procedures and routines is an inherent characteristic of any system and is even necessary sometimes to cope with unexpected changes in performance conditions (Patriarca et al., 2018a). This is what Hollnagel defines as the difference between Work-As-Imagined (WAI) and Work-As-Done (WAD) (Hollnagel, 2014). This new understanding for the development of undesired outcomes lead to the redefinition of what constitutes safety. Instead of simply looking at "*what goes wrong*", one could look at "*what goes right*" as well to better manage performance variability and provide resilient systems (Hollnagel, 2014). The main advantages is represented in the fact that what goes right occurs more often than what goes wrong, which is especially rare in high-reliability systems such as aviation. This new approach to safety is known as SAFETY-II in contrast to the classical approach known as SAFETY-I (Hollnagel, 2014).

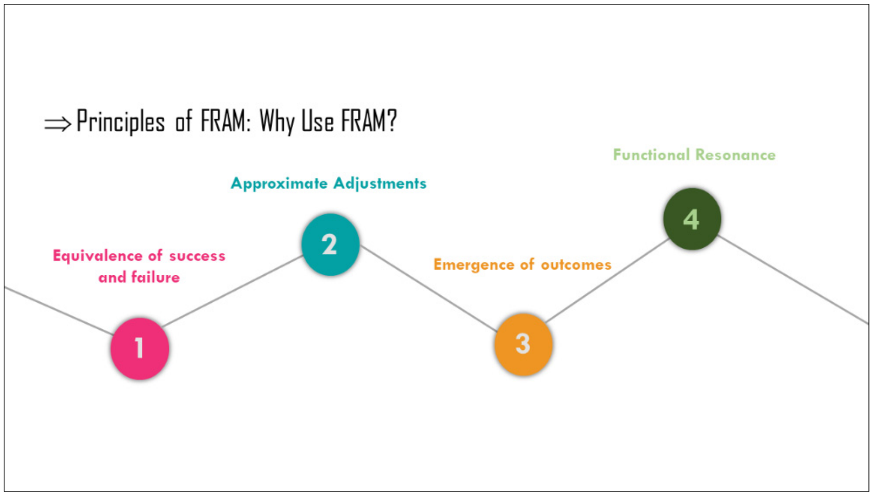

Figure 4.1 The four principles of FRAM (Hollnagel, 2012a)

In the study of complex systems, assessing instances of interest in quantitative terms might become difficult and sometimes even not possible. One might be forced to rely in many cases on qualitative measures to assess the magnitude of such instances, which might not be adequate or precise to a sufficient degree. Especially in the case of imperfect and vague data, estimating and determining the values of such variables become a difficult objective to achieve. Generally, people find it more difficult in such cases to express their evaluation in terms of numbers and prefer to use natural language (García-Lapresta & Pérez-Román, 2016). Qualitative tools such as FRAM can prove helpful in such cases maintaining a systemic perspective and enabling the analyst to evaluate such complex instances using words. The rising popularity of FRAM in recent years has translated into a significant body of research addressing several forms of applications across different fields and disciplines such as aviation (De Carvalho, 2011; Nouvel et al., 2007; Patriarca, 2018), construction (Rosa et al., 2015), healthcare (Pickup et al., 2017; Patriarca et al., 2017d & 2018c), education (Slim et al., 2018b) etc. Despite the many advantages offered by FRAM, there still exists room for improvement and development to apply FRAM in a more standardized and reliable manner. One issue with qualitative scales generally can be attributed to the ambiguity and vagueness of the used scales, which might result in different perceptions of the associated magnitudes (Hollnagel, 2014). People can perceive the magnitude and meaning of the same words and terminology differently. Additionally, it is not always easy to determine the outcome of an evaluation when using qualitative terms (Zadeh, 1973). One must apply natural language to describe the system in question relying on experience (historical data) and the expertise of field experts, which might not always be accessible for the analyst. Since its introduction, significant research projects have been initiated to explore the possible benefits of FRAM and introduce innovative models building on its principles. One of the earliest studies in that direction was Macchi (2009), which aimed at introducing an aggregated representation of performance variability by using ordinal numerical scales (Macchi et al., 2009). Another contribution to the body of research on FRAM was provided by Rosa et al. (2015), who proposed a FRAM framework using the Analytic Hierarchic Process (AHP) to provide a numerical ranking based on the comparison of pairs of criteria (Rosa et al., 2015). The work of Patriarca et al. provided several significant contributions in that regard (Patriarca et al., 2017a & 2017b & 2017c & 2018b). The study proposing a semi-quantitative FRAM model relying on the Monte Carlo Simulation and using discrete probability distributions to better represent functional variability was especially interesting for our project (Patriarca et al., 2017c). Another study applying a probabilistic approach was conducted by Slater (2017), which constructed a FRAM model as a Bayesian network of functions (Lee & Chung, 2018). Lee and Chung (2018) proposed a methodology for accident analysis based on FRAM to quantify the effect of performance variability in human-system interactions (HSI) functions (Lee & Chung, 2018).

Research efforts to address issues related to uncertain information go back to the 20th century, which lead to the introduction of new solutions for dealing with imperfect knowledge such as Fuzzy Set Theory (Zadeh, 1965) and Rough Set Theory (RST) (Pawlak, 1982). The use of fuzzy logic has been especially successful in that aspect since its introduction in 1965 and several frameworks were consequently developed and proposed to push the research work further and provide better and more reliable results. In the previous stage of our project (Slim & Nadeau, 2019), we addressed the lack of quantification and aimed at presenting a possible approach to overcome this limitation by integrating fuzzy logic into the framework of FRAM.

The link between fuzzy logic and FRAM has been identified by Hirose & Sawaragi (2020) (Hirose & Sawaragi, 2020) as well, who proposed an extended FRAM model based on the concept of cellular automation applying a fuzzified CREAM (Cognitive Reliability and Error Analysis Method) (Hollnagel, 1998) to connect the functions and visualize their dynamics (Hirose & Sawaragi, 2020). The fuzzy logic-based approach enabled us to compute with natural language and provide quantifiers for the quality of output through the construction of fuzzy inference systems.

However, despite the many advantages offered by fuzzy logic to provide quantitative outcomes for vague concepts and natural terminology, several limitations were faced in our prototype nonetheless. Firstly, the analyst is forced to develop a quantitative range of values and partition the universe of discourse to determine membership values, which might be relatively subjective. In case the number of input values were high, the issue of "*rules' explosion*" could deem the model unfeasible and difficult to realize. To avoid the rules' explosion problem and constructing a resource-demanding model, the number of variables and associated classes was limited. Additionally, one might not be always able to determine the outcome or the class of the decision relying solely on natural language. The outcome might as well be variable and vague in nature due to the incompleteness of needed information or vague nature of the input variables and outcome itself. In this stage of our project, we aim at further improving our hybrid model by proposing the application of Rough Sets Theory (RST) to handle the input data, generate a more efficient rule base and classify the outcome. RST can be helpful in that case by filtering the available information and identifying patterns to determine the outcome based on data tables (instances, cases, statistics, etc.) (Pawlak, 1998). RST is a data-mining tool capable of deriving decisions from a minimal set of rules generated for input data in the presence of uncertain and vague information. The applications of RST were especially beneficial in the fields of Artificial Intelligence, Knowledge Engineering, Decision Making, etc. The principle of RST employs the notion of approximation space, which states that each object in the universe of discourse can be at least associated with some information (Pawlak, 2004). Objects possess certain shared attributes, which form information about those objects that allow comparing and discerning based on the outcome. Objects, which are characterized by the same information, are indiscernible i.e. they cannot be distinguished in relation to the available information about them. The indiscernibility relation forms the mathematical foundation of rough set theory (Pawlak, 2004). The generated rule base would then be applied in the Fuzzy Inference System (FIS) to generate quantified outcomes for the functions. Finally, the results obtained by this hybrid model are to be compared with the results of the prototyping model for validation and drawing conclusions. In the next section, a brief overview of the features of RST is provided and the proposed approach is afterwards presented.

4.2 Materials and Methods

4.2.1 An overview of Rough Set Theory (RST)

Rough set theory is a mathematical framework proposed by Pawlak in 1982 for handling datasets and computing approximate decisions given a defined set of attributes (Pawlak, 1982). Datasets in RST are organized in two-dimensional matrices (tabular form), which is named an information system (Pawlak, 2004). The columns in an information system represent the condition attributes and the rows the objects in the observed universe of discourse (Pawlak, 2004). For each object, a value can be assigned with respect to the observed attribute. The decision attribute, which is the conclusion of the assigned values for the condition attributes, is provided in the final column of the information system (Table 4.1). The information system is then called a decision system. Mathematically, it can then be represented as: IS= (U, A, V, D), where IS is the decision system; U is a finite set of objects; A is a finite set of attributes; V is the set of assigned values and D is the decision class (Pawlak, 2004).

Table 4.1 An Information System in Rough Sets.

Set of Objects U	**Set of Attributes A**				**Decision D**
	A_1	A_2	.....	A_n	
U_1	V_{11}	V_{12}	.....	V_{1n}	D_1
U_2	V_{21}	V_{22}	.....	V_{2n}	D_2
U_3	V_{31}	V_{32}	.....	V_{3n}	D_3
.....	......	......	.....	......	.....
U_m	V_{m1}	V_{m2}	.....	V_{mn}	D_m

In RST, knowledge depends on the ability to classify objects, which represent real or abstract things, states, concepts, instances or processes (Pawlak, 2012). RST analyzes data tables in terms of equivalence classes by identifying patterns and shared attributes to discern the objects. Equivalence classes are subsets of the original set and represent indiscernible objects, which cannot be distinguished from each other by examining their attributes. The notion of a rough set presents a definition of a set of objects that cannot be defined definitely by these equivalence classes, since it overlaps with at least one of them (Hvidsten, 2010). A rough set, in contrast to a crisp set, consists of a boundary region, in which objects cannot be classified with certainty as either members or non-members of the set (Pawlak, 1998). In other words, the available information on the objects in question is not sufficient to classify the objects as definite elements of the set or not. Therefore, a rough set is defined in terms of a pair of sets: the lower and the upper approximations. The lower approximation is the set of all objects that certainly belong to the original set, and the upper approximation is the set of all objects that possibly belong to the original set.

Following on our definitions above that U be a finite set of objects and A be a finite set of attributes, then $\forall a \in A$, there exists a set of values V_a such that a function f_a: $U_a \longrightarrow V_a$ can be determined. Let B be any subset of A, then a binary relation I(B), called an indiscernibility or equivalence relation, can be defined as follows (Pawlak, 1998):

$$I(B) = \{(x, y) \in U \times U: f_a(x) = f_a(y), \forall a \in \mathrm{B}\} \quad (4.1)$$

An equivalence class containing an element x can then be defined as B(X), and x & y are called B-indiscernible (Pawlak, 1998). The approximations for X can be defined as follows (Pawlak, 1998):

$$B_*(X) = \{x \in U : B(x) \subseteq X\}, \quad (4.2)$$

$$B^*(X) = \{x \in U : B(x) \cap X \neq \emptyset\}, \quad (4.3)$$

$$BN_B(X) = B^*(X) - B_*(X), \quad (4.4)$$

The boundary region $BN_B(X)$ is defined as the difference between the upper approximation $B^*(X)$ and the lower approximation $B_*(X)$. The set B is called rough if the boundary region is not empty. A rough decision class is one that cannot be uniquely represented by the input data for the respective attributes. The usefulness of this method is represented in the ability to approximate X using only the information provided by B through the upper and lower approximations of X. This concept of approximations allows for computing reducts in data tables, which is explained in the following section.

Reducts: Reducts are reduced subsets of the original sets, which contain the same accuracy and essential information as the complete data set (Øhrn, 2000). Only the necessary attributes that provide information to define and discern the decision class are contained in the reduct. Computing reducts is an essential concept in RST and serves the purpose of minimizing the rule base to provide more efficient computation and simplified representation of large data sets. The decision table is examined to identify multiple reducts using a discernibility function (true or false) for each object, which is true for all attributes' combinations that discern the object from the other objects in the data set with different decisions (Hvidsten, 2010). The RST approach allows, through the use of efficient algorithms for evaluating the significance of data and detecting hidden patterns, to determine sufficient minimal data sets (data reduction) and generate a set of decision rules (Hvidsten, 2010). This approach is easy to understand and offers a straightforward interpretation of the obtained results.

Decision Rules: The reducts are then used to generate the decision rules by constructing conditional IF-THEN statements (Øhrn, 2000). The antecedent part (the IF part) is the conditional part derived from the values assigned to the conditional attributes, while the consequent part (the THEN part) is the conclusion or decision class resulting from those values. The generated rules can be evaluated in terms of support, coverage and accuracy (Hvidsten, 2010). The support for a rule represents the number of objects in the decision table that matches the rule (Hvidsten, 2010). The coverage of a rule represents its generality i.e. the number of objects with the same decision class in the decision table matching the IF-part of the rule (Hvidsten, 2010). The accuracy on the other hand represents the number of objects in the coverage group providing also the same decision i.e. matching the THEN-part as well (Hvidsten, 2010). The objective is always to obtain higher accuracy and coverage to provide more validity for the generated rules. The same procedure is repeated for all equivalence classes to construct the rule base. The rules can then be used in a descriptive manner to identify patterns and better understand dependencies and relationships in the dataset. Historical data used to construct the rule base can then be used to predict possible outcomes as well.

Since its introduction, there has been many applications of rough sets, which extended across numerous domains and fields from Artificial Intelligence (A.I.) (Jelonek et al., 1995) over Pattern Recognition (Swiniarski & Skowron, 2003) to Risk Management (Dimitras et al., 1999) and Data & Knowledge Engineering (Parmar et al., 2007) to Hospitality Management (Law & Au, 1998), Health Care (Øhrn, 2000; Komorowski & Øhrn, 1999), Marketing (Kumar et al., 2005) and Human Resource Management (Chien & Chen, 2007) etc. One especially interesting application of rough sets is the deployment as an assisting tool in Decision-Making, where decision rules are derived based on historical information (Alisantoso et al., 2005). These decision rules can then be deployed to classify newly acquired information (Alisantoso et al., 2005). Based on a set of performance conditions i.e., a set of values assigned to the attributes of the information system, a decision or a quality class can be determined. The process for rules' generation relies on the notion of indiscernibility and equivalence relations introduced by the rough set theory. For this purpose, several algorithms can be used to identify equivalence classes and the reducts within the provided information system to extract a minimal but sufficient rule base for classifying input data. Additionally, the relationship between rough sets and fuzzy logic is of special interest in this context. The concepts of rough sets and fuzzy sets are different in so far that they refer to different aspects of vagueness and uncertainty (Pawlak & Skowron, 2007). While fuzzy set theory defines vagueness in terms of a fuzzy membership function, rough sets use the concept of a boundary region to characterize imprecision in the available information (Pawlak, 2004). However, different does not mean unagreeable; rather, the two concepts are closely related and complement each other (Dubois & Prade, 1990). The application of rough sets in conjunction with fuzzy sets is not original since the two methods are related. In the literature, there exists a significant amount of studies that combined the two approaches to utilize the advantages of the two methods (Anderson et al., 2000; Wei & Zhang, 2004). The definition of rough sets as fuzzy sets in fuzzy rough sets or the opposite in rough fuzzy sets are two examples of how close the two methods are (Dubois & Prade, 1990). In this paper, we propose a modified FRAM framework combining the RST approach to analyze data and generate rules and the FIS to apply the generated rule bases and quantify the outcome's quality. It is important here to note first that the objective of this study is not to mainly contribute to the improvement of either fuzzy logic or rough sets. Rather, this study utilized well-established frameworks such as the Mamdani-Assilian Inference System (Mamdani & Assilian, 1975) or the RST model proposed by Aleksander Øhrn and the Rosetta development team (Øhrn, 2000). The main contribution of this study is the proposition of a model combining the two tools within the framework of FRAM. The two methods present advantages in the evaluation of qualitative values expressed in natural language, which can be difficult to achieve with classical statistical methods (Heckerman et al., 1997; Zou et al., 2011). The qualities of those methods are much related to the concept of FRAM and can be helpful to further improve FRAM and present a different approach. The application of rough sets for evaluating complex sociotechnical systems such as aviation generally, and deicing operations specifically, is therefore interesting and could provide insights and a new direction to be addressed by further research efforts in the future. The proposed approach will be explained in the following section.

4.2.2 Proposed Approach

In this section, we present our proposal to modify the framework of FRAM to integrate rough sets and fuzzy logic. It is also important here to note that the objective is not to decompose the system into its components to linearize and simplify the relationships in question. Rather, the goal is to maintain a systemic perspective and propose an additional tool that can complement classical tools. Our objective is to combine the above-mentioned methods, which stem from different fields, to benefit from the advantages that each method presents and consequently overcome some of the limitations faced in our prototyping model. In the prototyping model, we proposed a framework to integrate fuzzy logic into FRAM (Slim & Nadeau, 2019). Therefore, the basics of fuzzy logic and the details on how to construct a fuzzy inference system will not be discussed here in depth again; rather, only the aspects concerning the addition of rough sets and the combination of the two approaches will be explained. For further details on the design and construction of the fuzzy FRAM model, the reader is advised to consult our previous paper (Slim & Nadeau, 2019). The addition of rough sets into the prototyping model is explained in the following five steps.

STEP ZERO: The FRAM framework in its basic form consists of five steps (Hollnagel, 2012a). The first step is concerned with formulating the purpose of the analysis i.e. the main function, process or system to be evaluated (Hollnagel, 2012a). The objective defines as well whether the analysis should be concerned with past events to draw conclusions and learn lessons for the future; or the analysis should be of predictive nature, which builds on historical data to identify possibilities for success and failure.

STEP ONE: The set of functions that constitute the analysis model are to be defined in a task-analysis similar approach. Functions represent a specific objective or task within the selected context of analysis (Hollnagel, 2012a). After formulating the main function and objective in the first step, a list of sub-processes or functions, which constitute the system at hand and taken together form all steps needed to achieve the main function of the system, is selected. The number of functions defines the context and the boundaries of the model, where the background functions serve as the model boundaries and the foreground functions form the focus of the analysis (Hollnagel, 2012a). For each function, there are six aspects: input, preconditions, time, control, resources and output (Hollnagel, 2012a). The first five aspects represent five types of incoming instances linked to the function from upstream functions. The output of the function represent the outcome of the function that will be linked to the downstream functions as one of the earlier-mentioned five aspects. The couplings among the functions define how the functions are linked together within the system. Additionally, for each defined function, a list of relevant Common Performance Conditions (CPC) (Macchi et al., 2009) is selected depending on the type and nature of the function itself to account for the influence of the context on the performance of the function. The characterization of the functions is important for deciding what kind of data will be needed for the analysis. For a predictive assessment, data providing indications on the quality of performance conditions is needed. The data entered into the information system will be utilized to form a discernibility matrix, where the rows represent the objects and the columns the attributes. Each cell in the information system (decision table) contains a value assigned to the object in the same row concerning the attribute in the same column. The $n \times n$ discernibility matrix is then completed to identify indiscernible objects, which have different decision classes for the same attributes' values. In other words, for each row and column in the discernibility matrix, the condition attributes that discern objects with different outcomes or decision classes are identified to determine a minimal but sufficient set of performance conditions.

STEP TWO: The characterization of performance variability for each function in our model takes place over two main steps: The characterization of the internal variability and then the characterization of the external variability. The functions in our previous model were defined in terms of two fuzzy inference systems (FIS). The first FIS was concerned with the Internal Variability Factor (IVF) examining the CPC list to estimate possibilities for variability from within the function. The second FIS was of higher order and was concerned with characterizing the external variability factor (EVF) imposed on the function through the couplings with upstream functions.

The starting point here for inducing variability into the system is from within each function, using the IVF, which can be considered as a seventh aspect for the function. The background functions form the boundary of the analysis context and provide therefore an invariable outcome. The downstream functions, if only the functional couplings were to be considered, would have no way to produce variable outputs, since all incoming aspects would be invariable. Therefore, to provide the means for the analyst to predict or anticipate variable output, the IVF can be utilized. The IVF can be defined as the impact of the working environment and the present performance conditions at the time of execution of the function in question. For our model, we selected the CPC list, which was originally used as a part of the CREAM method (Hollnagel, 1998).

The CPC list is not supposed to represent complex relationships among functions; it merely serves the purpose of representing the impact of the working environment on performance and helps the analyst anticipate possible variability in outcome. The selection of a list of performance conditions or performance shaping factors can be conducted in practice depending on the context, the nature of the system of interest and the functions themselves and is by no means limited to the CPC list. FRAM functions can be classified as one of three types in accordance with the MTO classification concept: huMan, Technological and Organizational functions (Macchi et al., 2009). Depending on the MTO type, a list of relevant CPCs can then be selected. Each CPC will be evaluated as either "*adequate*" or "*inadequate*" for start and the partitions can be of course extended to a three- or five-point scale; however, this would translate into a large number of rules and might create a demanding inference system later.

Whether the CPC list would be needed entirely or partially can be determined using the principle of indiscernibility in RST to identify the set of attributes that is necessary to preserve the same classification information as the original set (Reducts). The two classes will serve firstly as the attribute values in the RST method and secondly, as the membership functions or the two partitions of the universe of discourse in the FIS. Therefore, the qualitative scale with the two values will be used to construct: firstly, the data table to feed to the RST method and then the reduced rule base generated by the RST will be used in the FIS. The data set can be constructed consisting of instantiations of the function in question and by recording historical data for the same operation over time. For example, for the function "*Deicing*", the performance conditions present for the deicing of aircraft 1 are recorded, then aircraft 2 and so on until aircraft n. The more data entry points are accumulated, the higher the accuracy and validity of the generated rules are. The functions in the RST framework represent the objects, while the performance conditions are the condition attributes (Table 4.2).

Table 4.2 An example of an RST data table for characterizing the IVF for a FRAM function

Function	**Common Performance Conditions**				**IVF**
	CPC_1	**CPC_2**	**.....**	**CPC_n**	
Function 1	Adequate	Inadequate	.....	Adequate	Non-Variable
Function 2	Adequate	Adequate	.....	Adequate	Non-Variable
Function 3	Inadequate	Adequate	.....	Inadequate	Variable
.....	......	......	.....	......	.....
Function m	Inadequate	Inadequate	.....	Inadequate	Highly Variable

The decision attribute for the IVF can be then "*non-variable*", "*variable*" or "*highly variable*" (Table 4.2). The data set is usually split randomly into two sets: one training set to identify the reducts and generate the rules and one testing test to check the validity of the rules. The split factor of the dataset is determined first. Then, the suitable algorithm to explore the training set to identify the reducts is selected. The reducts are then determined and the respective rules are generated. For each row in the discernibility matrix, a rule is formulated using logical "*OR*" or "*AND*" operators to formulate the antecedent part (the IF-part). The outcome of the antecedent is determined in the consequent (the THEN-part), where logical "*OR*" and "*AND*" operators can be used if multiple decisions are possible. The generated rules can then be used to classify the testing set to validate the generated rules. The requirements to consider the rules is determined by selecting the acceptable levels of coverage, support and accuracy of the rules. The rules can then be examined by experts to examine the validity and meaningfulness of final set of rules. Afterwards, the rule base can be migrated into the FIS of the function in question to apply as the rule base for classifying and quantifying the outcome. In the FIS, the analyst defines what metrics or assessment scales can be used to evaluate each CPC and assign a value on a scale between zero and ten to each CPC. Figure 4.2 depicts the triangular membership functions for the input values for each CPC, whose universe of discourse is partitioned into the two earlier-mentioned classes: "*inadequate*" or "*adequate*".

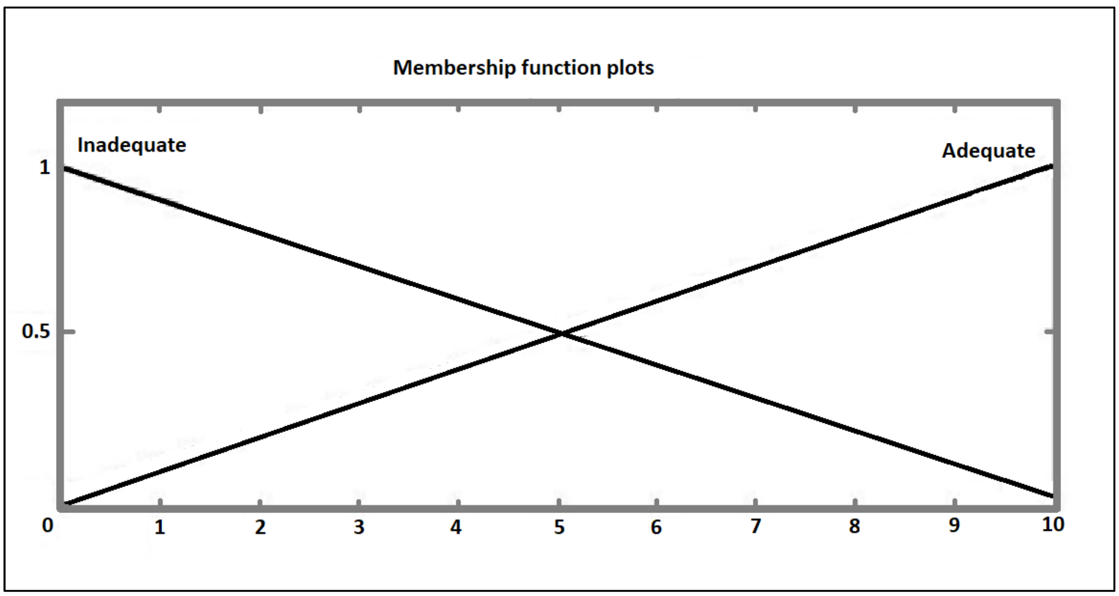

Figure 4.2 Membership functions of the IVF function (Internal Variability).

For the instantiation of the analysis scenario, a score on a ten-point scale is selected for each CPC to run the simulation. The numerical outcome of this first order FIS is then the IVF. The IVF can be calculated using the following formulae:

$$IVF_i(v) = MIN\{v_{1i}, v_{2i}, \ldots, v_{ni}\} \tag{4.5}$$

$$IVF(v) = \sum_{i=1}^{m} IVF_i(v) \quad (4.6)$$

$$IVF_{COG} = \int IVF_i(v).vdv / \int IVF_i(v)dv \quad (4.6)$$

Where v_{ni} here represents the value of the *n-th* CPC for the *i-th* rule, MIN denotes the fuzzy minimum function, $IVF_i(v)$ is the implication value for each rule, $IVF(v)$ is the aggregated value for all $IVF_i(v)$ and IVF_{COG} is the final numerical score calculated applying the centroid method.

The second step in Step Two is to characterize the external variability factor (EVF). The same process can be repeated for the higher order FIS for the external variability factor to reduce the rule base and allow for more efficient processing. The variability of the function's output is normally characterized in terms of timing and precision using a three-point qualitative scale. The EVF is defined in our model as the external variability provided to the function through the couplings with upstream functions. We merged the impact of the timing and precision aspects to provide a simplified variability representation of the output (Figure 4.3). In the proposed model here, this characterization was further simplified and an aggregated representation is proposed for two reasons. First, in a predictive or proactive assessment, it is not always straightforward or obvious what the outcome using qualitative scales should be. There exists a level of vagueness to the different perceptions of the meaning of words between people, the vague nature of the input variables themselves or the lack of quantitative or standardized protocols to determine the result. For some instances, it is sometimes difficult and hardly possible to predict (in a predictive assessment) how the variability is manifested. One might be able to anticipate that in the case of variable resources or preconditions, the output would be variable as well. However, it could be difficult to determine whether the variability would manifest in terms of timing or precision. It would be easier to state that an output would be variable to a certain degree, whether negatively or positively, but more difficult to identify how the variability would translated in practice , for example as a delay, imprecision, earliness, on-time etc. Secondly, the more classes we assign to input variables, the more rules we obtain and the more demanding the construction process of the model would be. Therefore, to design an efficient model, it is advised to keep the number of classes low at this stage, however without trivializing and reducing the meaningfulness of the obtained results. Therefore. The impact of the two phenotypes is combined to produce a three-point scale: “*non-variable*” accounts for positive or neutral impact; “*variable*” represents the outputs with low and medium variability; and “*highly variable*” to represent very critically and negatively variable outputs (Figure 4.3).

⇒ Simplification of Variability Characterization:

Characterization of variability		Time		
		Too early	On time	Too late
Precision	Precise	A: Dampening	B: Highly dampening	C: Low dampening
	Appropriate	D: Low dampening	E: Dampening	F: Slightly variable
	Imprecise	G: Slightly variable	H: Variable	I: Highly variable

Characterization of variability		Time		
		Too early	On time	Too late
Precision	Precise	Non-variable	Non-variable	Variable
	Appropriate	Non-variable	Non-variable	Variable
	Imprecise	Variable	Variable	Highly variable

Figure 4.3 Simplification of the variability impact of the precision and time phenotypes

The EVF is determined in the same manner as the IVF; however, the functional aspects in addition to the IVF are used as attributes in the RST table (Table 4.3) this time with three possible input values or classes as described earlier: “*Non-variable*”, “*Variable*” and “*Highly Variable*” (Figure 4.4). For determining the implication of the fuzzy rules, the “*MIN*” method was used; while for the aggregation, both the “*MAX*” and the “*SUM*” methods were applied depending on the nature of the output. The numerical quality of the output is obtained by defuzzifying the final aggregated fuzzy area and calculating its center of gravity.

Table 4.3 An example of an RST data table for characterizing the output of a FRAM function.

Function	Aspects						Output
	IVF	Input	Time	Control	Preconditions	Resources	
Function 1	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable
Function 2	Non-Variable	Non-Variable	Variable	Variable	Variable	Non-Variable	Variable
Function 3	Non-Variable	Non-Variable	Highly Variable	Non-Variable	Non-Variable	Non-Variable	Variable
.....	......	......	.....	.....	.....	......	.....
Function m	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable

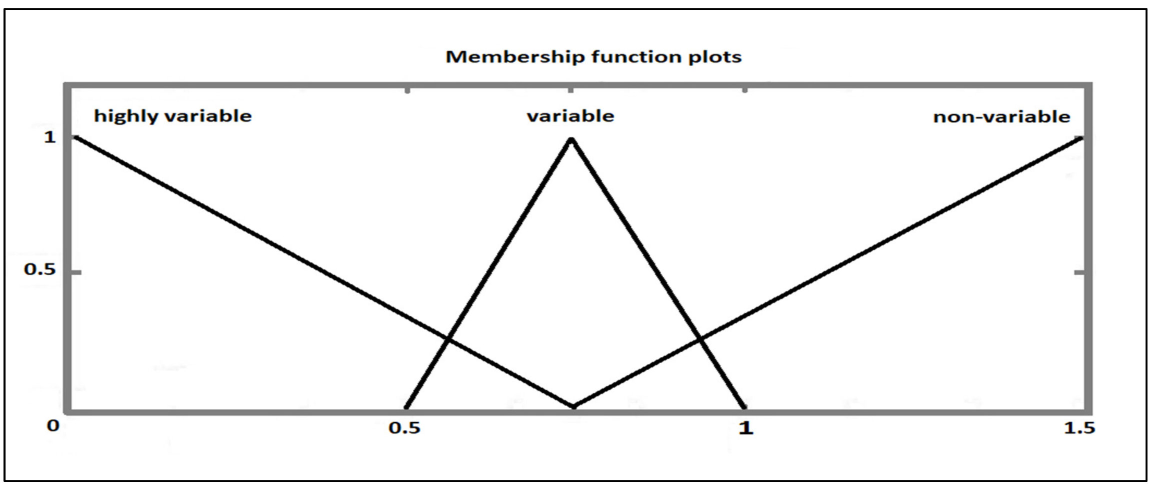

Figure 4.4 Membership functions for the output (External Variability)

STEP THREE: A specific analysis scenario is constructed to apply the developed model. The analysis scenario is different from the FRAM model that it presents specific operational conditions. The FRAM model on the other hand consists of functions that compose the general context that we would like to study without specifying performance conditions and the occurrence of events. Depending on the present conditions, the internal variability for each function can be determined and thereafter the output's variability and its resonance and impact on other functions.

STEP FOUR: The final step would be to evaluate the generated results and examine what countermeasures are necessary to avoid failures and ensure resilience. The numerical outcomes provide in that case an assistive indicator that could point to possible sources of variability (negative or positive) and how high this possibility could be. Figure 4.5 presents an overview of the modified mixed rough sets/fuzzy logic FRAM framework.

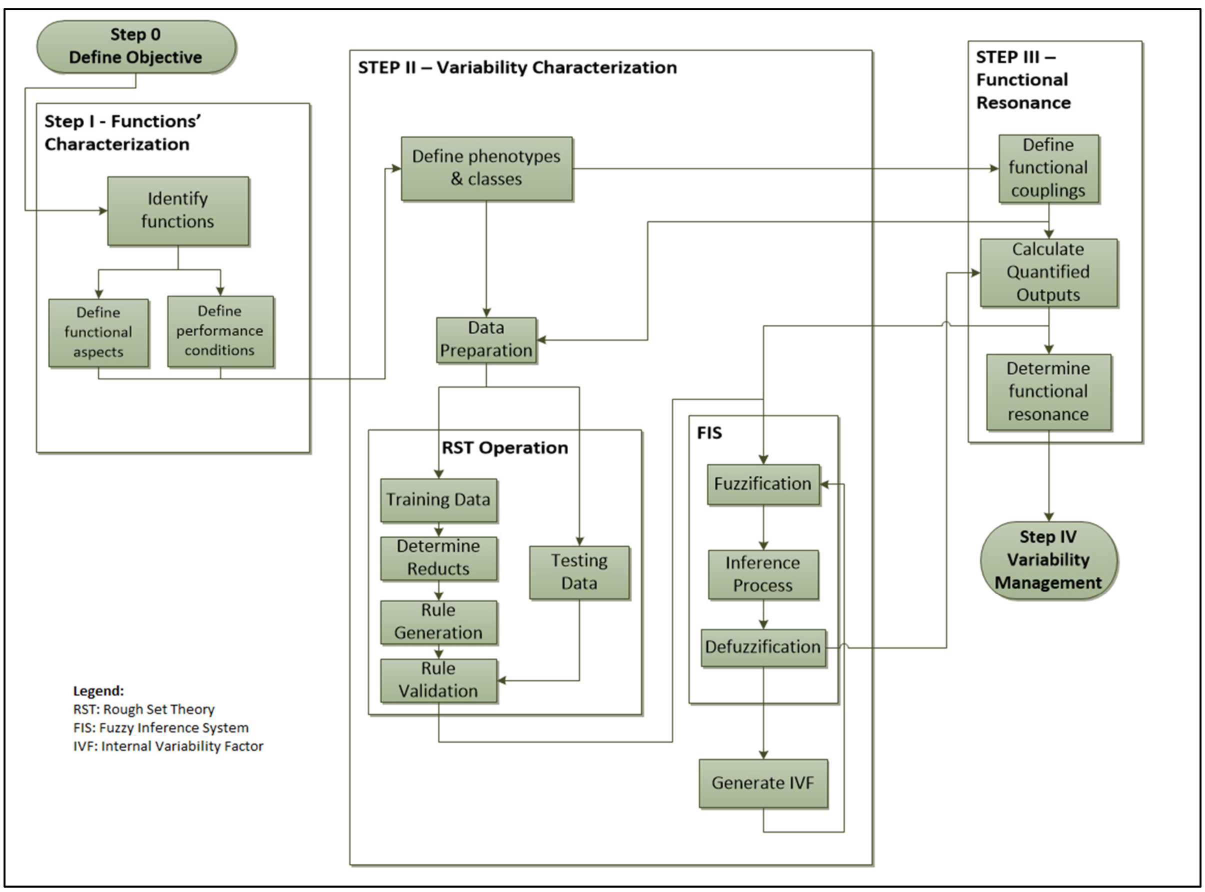

Figure 4.5 A flow diagram presenting an overview of the modified FRAM framework.

4.3 Results: A case study.

4.3.1 Step Zero: Context and objective

The objective of the analysis is still to provide a predictive assessment to provide performance indicators that can be helpful in identifying possible sources of performance variability. The selected context serves the purpose of providing a demonstration for an application scenario and relies to a certain degree on educated assumptions to perform the simulation.

For the application of the developed model, the same application scenario applied in the previous stage (Slim & Nadeau, 2019) is used again here to maintain the same settings and compare the results of the two models: the fuzzy logic-based FRAM model and the mixed fuzzy logic/ rough sets based FRAM model. Airport operations are gaining on complexity year after year with the continuous technological advancements and the increasing traffic volume (Patriarca et al., 2019). The selected analysis context depicts a hypothetical scenario inspired by two accidents related to aircraft deicing operations, namely the Scandinavian Airlines flight 751 crash in 1991 (SHK, 1993) and the Air Maroc accident in Mirabel in 1995 (TSB, 1995) to evaluate aircraft deicing operations. Several events and influential factors that played a significant role in the development of the two above-mentioned accidents were adopted to construct the analysis context for this simulation. The designed scenario presents a setup, in which an international flight is scheduled for departure at a North American airport for a Trans-Atlantic flight. The pilots of the flight were lacking experience with deicing procedures and the instructions and guidelines provided by their airliner did not specify clearly deicing-related communication protocols with the ATC and the deicing tower. Detailed and adequate instructions concerning the required inspection procedures prior to and post deicing operations were also insufficient and underspecified. The aircraft was taxied from the gate to the deicing pad to be deiced by two deicing trucks. The temperature at the time of the operation is around 0°C and snow showers were present. The flight was delayed as a result of high traffic volume and due to the weather conditions and the state of the runways, which affected the movement of the aircraft on the airport grounds. The following performance conditions as a result of the described scenario are not optimal: the provision of adequate training and competence, airliner procedures and instructions, availability of resources and time pressure. The above-described scenario will be used next in Step One to identify the functions that constitute the system in place and which added together characterize the whole process to deice the aircraft before taking-off. The impaired performance conditions will be afterwards used in Step Two to assign the scores to the selected lists of CPC for each function.

4.3.2 Step One: Functions' Definition and Characterization

The definition and characterization of the functions is a very decisive step to determine what kind of data is needed. Each function draws a relationship between the output that we wish to evaluate and the different aspects of the function that affect its quality. The functions are selected based on knowledge gained through an extensive literature review of deicing reports and the research activities of our team. The scope of the analysis is limited mainly to the deicing activities performed at the deicing pad. The functions are characterized in a way that allows for a wide systemic perspective. Totally, there are 4 background functions and 13 foreground functions. The characterization process of functions to define the analysis context is by no means rigid and functions can be well modified or updated in case additional insights or info were to be presented later to achieve better results. Table 4.4 presents a list of the functions and their characteristics.

Table 4.4 A list of the FRAM functions in the deicing model (Slim & Nadeau, 2019)

No.	Function Name	Type	Description
1	**Review meteorological data**	Background	Review of weather conditions for preflight planning and inspections
2	**Aircraft specifications**	Background	Aircraft technical and operational information provided mainly by manufacturer
3	**Regulations and supervision**	Background	Supervision and regulations provided by governmental agencies
4	**ATC supervision**	Background	Clearances provided by the ATC to navigate aircraft on the airport grounds
5	**Resources and equipment**	Organizational	Resources and equipment provided for the inspection and deicing operations
6	**Training**	Organizational	Training provided to the deicing personnel
7	**Airliner instructions & guidelines**	Organizational	Guidelines provided by the airliner for the flight crew and deicing personnel
8	**DSP instructions & guidelines**	Organizational	Guidelines provided by the Deicing Service Provider (DSP) to its personnel
9	**Preflight planning**	Human	Flight planning performed by the pilot and the flight dispatcher
10	**Flight crew supervision**	Human	Supervision provided by the pilot and flight crew to monitor and control operations
11	**Deicing tower control**	Human	Supervision provided by the deicing tower or the bay-lead to monitor and control operations
12	**Pre-deicing inspection**	Human	Inspection of the aircraft to decide if deicing/anti-icing is required
13	**Taxi aircraft to deicing pad**	Human	Taxi aircraft from gate to the deicing pad
14	**Deicing**	Human	The application of deicing fluids and removal of contamination
15	**Post-deicing inspection**	Human	Inspection after deicing to ensure all surfaces are clean
16	**Anti-icing**	Human	The application of anti-icing fluid to keep aircraft clean until take-off
17	**Taxi to runway**	Human	Taxi aircraft from deicing pad to runway for takeoff within the specified holdover time

4.3.3 Step Two: Variability Characterization

The starting point to characterize variability is with the internal variability for each function using the selected CPC lists. The scales to evaluate the CPCs and the form of the membership functions in the FIS can be defined as needed depending on the context of analysis and the nature of the observed instances (numerical or linguistic). In our case, each CPC can be assigned a numerical value on a scale between zero and ten, which will be partitioned in the FIS into two classes: "*adequate*" or "*inadequate*". The chosen form of membership functions for all CPCs is triangular. The training data needed to start was initially provided for the fuzzy inference system by generating the data table using an automatic generator to account for every possible combination of values for the CPCs. In the case of human functions, we have then eight CPCs for each function with two classes, which would translate into a data table with 256 rows or objects (possible combinations of values). In the case of an organizational function, we have three CPCs for each function with two classes, which would translate into a decision table with eight rows. We apply the RST suite using a genetic algorithm to compute the reducts for each function and generate two rule bases: one for the internal variability factor (IVF) and one for the external variability factor (EVF). The decision class (THEN-part) is determined by assigning a numerical score for each class in the antecedent (IF-part).

After generating the rule bases for all functions, the rule bases are migrated into the FIS of the functions and an instantiation of the constructed model is run for testing the RST-generated rule base and to generate numerical results. The RST-generated rule base for the CPC list is used to generate the IVF first for each function (Tables 4.5 & 4.6). For running the instantiation of the model, a numerical score on a scale between zero and ten for each CPC with respect to each function is selected. The numerical scores were selected based on the evaluation of the performance conditions as described above in STEP ZERO. The accuracy of these scores and development of relevant performance indicators in a real-world study would rely heavily on the expertise of the analyst and the context provided as explained earlier. The purpose of these scores here is to serve as input values for our model to run the simulation. The weight for all CPCs is the same and the IVF was considered to have the same weight as the other functional aspects for simplification. This however can be changed depending on the selected functions. The IVF is then used to compute the quality score of the function's output, which is a value between 0.25 and 1.25, where 1 is a non-variable output, any value above one represents positive variability while any value below one represents negative variability.

Table 4.5 The numerical scores of internal variability for organizational functions

No.	Function Name	Conditions of work	Number of goals & conflict resolution	Quality & support of the organization	IVF
1	**Resources and equipment**	**9**	**9**	**9**	**0.969**
2	**Training**	**7**	**9**	**5**	**0.859**
3	**Airliner instructions & guidelines**	**8**	**9**	**4**	**0.845**
4	**DSP instructions & guidelines**	**8**	**8**	**9**	**0.93**

Table 4.6 The numerical scores of internal variability for human functions

No.	Function Name	Availability of resources	Goals & conflict resolution	Quality of communication	Availability of procedures and plans	Training & experience	Available time	Circadian rhythm and stress	Team collaboration	IVF
1	**Preflight planning**	**9**	**10**	**8**	**8**	**8**	**8**	**9**	**10**	**0.985**
2	**Flight crew supervision**	**6**	**10**	**6**	**6**	**6**	**6**	**9**	**10**	**0.815**
3	**Deicing tower control**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**
4	**Pre-deicing inspection**	**8**	**10**	**8**	**8**	**8**	**8**	**9**	**10**	**0.985**
5	**Taxi aircraft to deicing pad**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**
6	**Deicing**	**10**	**10**	**7**	**7**	**7**	**7**	**10**	**10**	**0.891**
7	**Post-deicing inspection**	**10**	**10**	**7**	**7**	**7**	**7**	**10**	**10**	**0.891**
8	**Anti-icing**	**10**	**10**	**8**	**8**	**8**	**7**	**10**	**10**	**0.968**
9	**Taxi to runway**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**1.25**

4.3.4 Step Three: Functional Resonance

The relationships among the functions are defined by linking the outputs of the upstream functions as one of the five incoming aspects of the downstream functions. The output in that case becomes a condition attribute of the downstream function. The IVF and the five incoming aspects are fuzzified to determine the quality of the function's output and so on. The quality of each output is then presented in Table 4.7.

Table 4.7 Numerical scores for the output's quality

No.	Function Name	Output's Score
1	**Review meteorological data**	**1.0**
2	**Aircraft specifications**	**1.0**
3	**Regulations and supervision**	**1.0**
4	**ATC supervision**	**1.0**
5	**Resources and equipment**	**1.08**
6	**Training**	**0.885**
7	**Airliner instructions & guidelines**	**0.867**
8	**DSP instructions & guidelines**	**1.0**
9	**Preflight planning**	**0.916**
10	**Flight crew supervision**	**0.933**
11	**Deicing tower control**	**1.18**
12	**Pre-deicing inspection**	**0.925**
13	**Taxi aircraft to deicing pad**	**1.22**
14	**Deicing**	**0.932**
15	**Post-deicing inspection**	**0.689**
16	**Anti-icing**	**0.849**
17	**Taxi to runway**	**0.866**

The instantiation of the model can next be illustrated in the graphical representation (Figure 4.6), which provides a visualized overview of the relationships among the functions. The graphical representation allows for an easier evaluation and examination of the model to identify possible overlapping and combinations of variability.

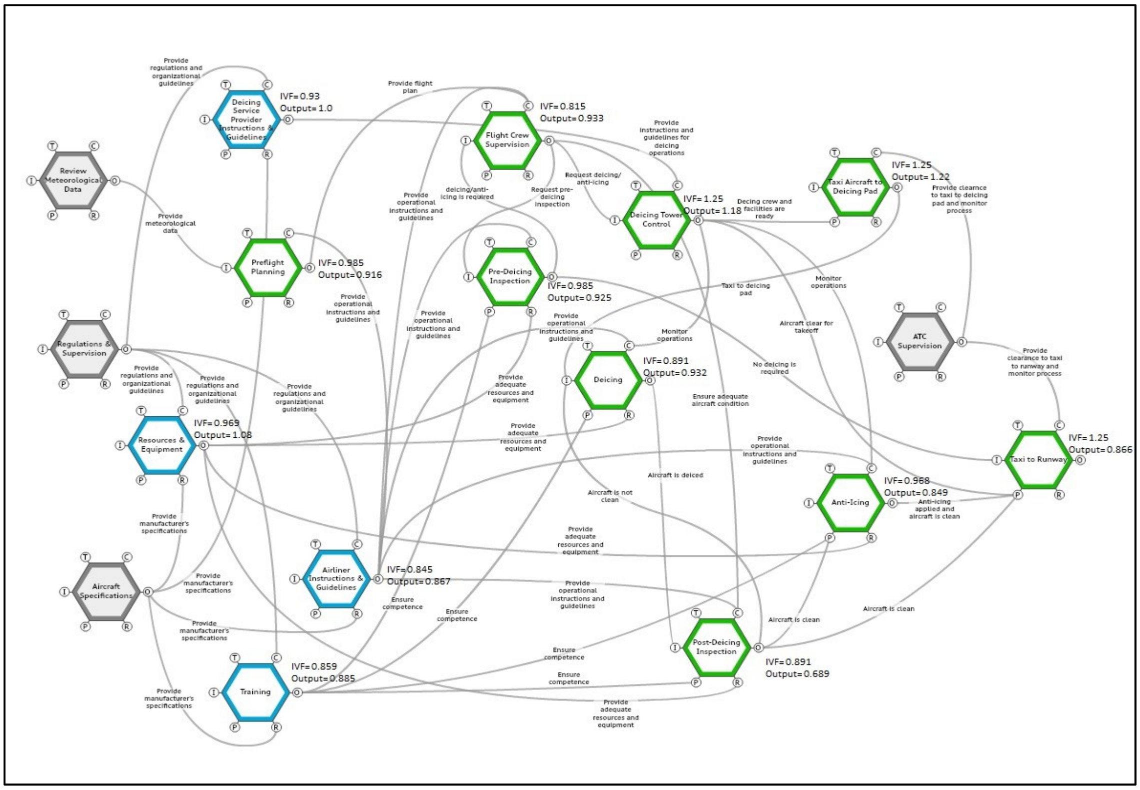

Figure 4.6 A graphical representation of the model with numerical scores.

4.3.5 Step Four: Variability Management

Finally, the provision of numerical outputs as output's variability indicators points at possible variability in the performance of the defined functions. The combination of variability can point as well to weak and strong spots in the studied system. Consequently, this allows us to introduce precautionary and preventive measures to enforce the system and make it more resilient by strengthening the weak components and promoting conditions that ensure desired outcomes. The graphical representation of the functions presents a very helpful tool to illustrate the relationships and dependencies among the functions and how performance variability can affect their outputs.

As mentioned earlier, the analysis scenario was kept the same as in the previous stage implementation. The same settings were kept identical to be able to better compare the results and ensure that any differences in results cannot be attributed to any factors other than the added RST method. The characterization of functions and their relationships in the FMV was kept the same. The scales, the partitioning, the membership functions, and the FIS settings (Fuzzification, Aggregation, Defuzzification, etc.) were kept identical as well. The only element changed was the new rule base generated by the RST method.

Based on the formulated assumptions, the simulation scenario presented a case study, in which airliner training and instructions were inadequate. The flight was delayed as a result of extreme weather conditions and a stressed flight schedule at the airport. The performance conditions for the functions: Training, Airliner Guidelines and Instructions, Planning, Flight Crew Supervision, Pre-deicing Inspection, Deicing, Post-Deicing Inspection, Anti-icing and Taxi to Runway were negatively impacted (negative variability <1). Accordingly, the values in Tables 5 and 6 were chosen to simulate the impact of the defined performance conditions on each function and lead to the generation of internal variability. Functions such as "*Deicing Tower Control*" and "*Taxi Aircraft to Deicing Pad*", whose CPCs were not affected and maintained a maximum score of 10, had a maximum output of 1.25 and impacted the output of the function positively and would dampen any negative variability provided through the couplings. Since we kept the weight equal for all CPCs and aspects, the IVF for the functions "*Deicing*" and "*Post Deicing Inspection*" were also equal after selecting equal input values in Table 6. The four background functions "*Review Meteorological Data*", "*Aircraft Specifications*", "*Regulations & Supervision*" and "*ATC Supervision*" in Table 7 provided invariable outputs as defined and therefore a neutral score of 1. On the other hand, Optimal performance conditions for functions such as "*Resources & Equipment*", "*Taxi Aircraft to Deicing Pad*" and "*Deicing Tower Control*" impacted the output of those functions positively (>1). The obtained numerical scores for the outputs were identical to the results of the first model, which represents an ideal outcome.

4.4 Discussion

In contrast to simple systems, the evaluation of complex systems is not straightforward and offers many complications for the analyst, especially in systems that rely to a great degree on qualitative assessment of the variables in question. Studying qualitative contexts requires imagination and relies mainly on human judgement using natural language to classify objects of interest. The experts in practice make informed decisions based on their years-long experience and in-depth knowledge of the inner workings of the system in question. Whether written records or human expertise, the decision-making relies on experience gained through past events that formed the knowledge in databases or human experts. A limitation with such knowledge is that it is not always straightforward in presenting results or outcomes. It is not always obvious which outcome would be received under certain performance conditions. The observed instances might be vague in nature and therefore difficult to quantify or sometimes even assess using natural language. It would be difficult to quantify such variables as the comfort of a car or the adequacy of instructions (García-Lapresta & Pérez-Román, 2016). This could be as well due to the design of the used scale or due to the different subjective perceptions of humans of qualitative concepts. Incomplete information and the difficulty to make a judgement and assign a specific value to a given variable are therefore common (García-Lapresta & Pérez-Román, 2016). Designing frameworks to handle data to recognize patterns and derive conclusions would be very advantageous to help experts and new decision-makers reach a decision. Mechanisms that facilitate the extraction of knowledge from imprecise, incomplete and vague data will be needed not only to extract the needed knowledge from such data tables but to help classify problems and outcomes as well (Alisantoso et al., 2005).

In the case of reactive or retrospective analyses, the events that transpired are clear and definite and allow in most cases for an exact description of the analysis context (Cacciabue, 2000). Proactive evaluations start with the design phase of a system, during which appropriate design concepts complying with the specified performance requirements are identified (Cacciabue, 2000). The quality assessment should examine whether the proposed concepts comply with the required performance and what challenges might arise in the future following the real-world implementation. To perform this task, the concepts adopted in retroactive or retrospective analysis methods can be utilized as well to anticipate obstacles and challenges. While this task might be easier with simpler systems, it is mostly not possible during the design phase of complex systems to identify all risks and performance-impairing factors since not all parameters can be explicitly known in advance. In proactive or predictive analyses, there exists a certain lack of certainty and results are produced relying mainly on assumptions reached by evaluating historical results. Only, when real world implementation is accomplished and time was given to interact with the real-world operational environment, one might be able to know the implications of the designed system. It is therefore very important to further advance proactive evaluation methods adopting a systemic perspective to comply with the faced challenges. The concepts of Resilience Engineering can prove helpful in this endeavor to design resilient systems capable of adjusting and coping with the complexity of the real world. Relying on traditional statistical methods could be desired in many cases; however, it is not always possible when it comes to uncertain environments. Such methods require large data sets to draw meaningful statistical inferences (Roelen & Klompstra, 2012) and can be affected by other factors such as the independency of variables and the normality of data distribution (Chien & Chen, 2007). Data mining tools as RST and fuzzy logic can be in such cases more suitable to evaluate complex nonlinear contexts, in which qualitative scales are the only possible measurement method. The application of "*IF-THEN*" rules written in natural language is more comprehensible for decision makers and offers more communicative results. These rules can be derived by the RST method without specific limitations and constraints of data distributions or data size (Chien & Chen, 2007). A historical database can be constructed as explained in the methodology section recording events and operations assigning a score to the relevant attributes. The more data points are provided for the RST method, the more accurate and reliable the results are going to be. There will always exist a specific degree of uncertainty with the provided results, but that is just the case with all predictions. The results can be considered as indicators that can point to possible sources of performance variability within the examined context.

The model here presents an evolution of the previously published model (Slim & Nadeau, 2019), which incorporated fuzzy logic as a quantification tool into FRAM. Fuzzy logic has been applied previously in conjunction with CREAM (Konstandinidou et al., 2006) and FRAM (Hirose & Sawaragi, 2020) and proved useful in applications with qualitative scales. However, the model presented here employs solely the CPC list just to account for the impact of the context and provide quantifiers for the internal and external variability of the functions. The addition of RST can help with the rule explosion problem in case of a high number of variables and associated classes and partitions, which results in a large rule base, that can be heavy and resource demanding on the computing machine. Covering all possible combinations of variables and values to provide an output to each specific combination of values would convert into a very unfeasible mission in the presence of thousands of rules. A method for deriving rules from a limited set of data is therefore desirable to provide a more practical approach for analysts. For the construction of our model, the FRAM functions are characterized as fuzzy inference systems to produce a quantified output. The same functions are characterized at the same time as RST decision tables, in which the CPC and the couplings are defined as attributes to derive rules and classify the output. This requires knowledge and expertise in both fuzzy logic and rough sets, which can be somewhat demanding. Additionally, the amount of required data is high and exhaustive, which results in an exhaustive filtration and treatment in the selection process and some extensive efforts in the characterization (attribute selection, partitioning, membership functions, etc.) and the rule evaluation and validation processes. The proposed model here does not necessarily aim at making a significant contribution to fuzzy logic, rough sets or the combined approach. The main contribution lies in the use of these tools within the framework of FRAM to provide quantified outputs and more efficient data classification algorithms. It merely presents a first step and a possible approach to use such techniques in combination with FRAM to present more intersubjective and quantified results using natural language for evaluation.

In this paper, the focus was mainly directed to the integration process of rough sets, which should allow for handling a larger number of input variables. However, the settings were kept as defined in the previous stage to provide a better comparison of the results. The numerical results obtained for the outputs in this paper were identical to the last digit to the ones provided in the first model, which presented a combined model of FRAM and fuzzy logic. The findings and derived conclusions of this instantiation align with those of the first one, which enforces the standing of the results and demonstrates the usefulness of rough sets. The same data set was used for both models, which presented an ideal scenario accounting for every possible combination of input values. The advantages, however, for using RST additionally is presented to producing minimal but efficient rule bases (same accuracy in our case). Additionally, the application of rough sets would help in the treatment of data sets obtained from real-world recordings and archived data, which could be incomplete, inconsistent, or limited in size. The RST method using historical data can help in addition to classify outcomes and reach decisions without continuously relying on experts other than for the evaluation at the time of observation. This would result in more efficient and smaller rule bases, which can be generated automatically by the RST method. The use of real-world data shall explore further the merits of such an approach and further insights can be provided once real-world data is used. The size and consistency of the provided data are two significant factors to consider in the process.

At this stage of model development, the framework is a simplification of reality due to the fact that the characterization of functions and data selection process is entirely simulated. As was the case in the first stage, the purpose is still to demonstrate a possible approach to introduce quantification into FRAM without losing its properties and significant advantages in handling complex contexts. This study explores such possibilities utilizing rough sets in this case in addition to fuzzy logic to lay down the theoretical foundation as a first step from a technological readiness perspective. The definition of the analysis scenario relied on assumptions and simplified reality to make things easier. The weights were selected the same for all attributes and the functional aspects as well. This might be different in a real-world application and can be adjusted as deemed appropriate by the analyst depending of course on the significance of each attribute to the execution of the function in question.

The need to adopt a Resilience Engineering perspective in system’s analysis and look at failure and success as complex emergent events has been addressed and advocated in a wide array of studies (Hollnagel, 2014; Patriarca et al., 2018a). Such applications are promising and can provide interesting and helpful results that can complement established methods to better keep up with technological developments and the continuously increasing complexity of sociotechnical systems (Melanson & Nadeau, 2019). However, as is the case with new and innovative methods, the application of such methods from a technology readiness point of view is not without challenges and issues to overcome. The lack of sufficient data and precedence cases at the beginning results in the absence of standardized protocols, which shapes the analyses to rely more on subjective judgement and personal expertise. The rarity of adverse events in high-reliability organizations such as aviation makes the production of sufficiently large databases and meaningful statistics a difficult task. The specificity of case studies makes it difficult to generalize findings to other analysis scenarios. The validation process to ensure the provision of valid and reliable results requires the generation of large databases and a sufficiently high number of case studies to present reproducible results. It would be therefore more helpful to adopt a SAFETY-II approach instead and look at successful outcomes as emergent and complex events as is the case with adverse outcomes. The meaningfulness of the produced results of this model or any other proposed new method depends greatly on the meaningfulness of the provided input data. Therefore, the construction of adequate databases and standardized performance indicators is necessary to utilize innovative methods and adopt new perspectives on safety and system's performance. The application of rough sets as a data-mining tool to filter and classify data in addition to fuzzy logic as a tool for quantification and computing with natural language can prove especially helpful in such endeavors.

The proposed model in this study is still in the design phase and presents the first steps to implement data mining tools as rough sets and fuzzy logic into FRAM. To become application ready and provide more reliable results, further validation and optimization work is still needed. The next step would be to construct a more realistic model using real-world data to examine how the model would perform under realistic circumstances. Going forward, the application of the proposed approach into new contexts can additionally help validate the model and provide more insights on how to further improve and modify the proposed framework. Nonetheless, the obtained results are still promising and present an interesting start point to explore further applications and drive research efforts on that front forward.

4.5 Conclusions

In this paper, we built on the results and methodological propositions achieved in the second stage of this project. To further improve fuzzy-FRAM and ease the modelling process, RST were proposed as a data-mining tool to facilitate the treatment of input data, generate more efficient rule bases, and derive decisions based on recorded historical data. The proposed model was then applied to case study examining performance in aircraft deicing operations maintaining the same settings as in the second stage. The data sets used to generate the reduced rule base were the data sets generated by the fuzzy inference system, which creates an ideal data set accounting for every possible combination of input values. The produced numerical outcomes were identical to the results received in the previous model, which displays the usefulness and accuracy of the RST framework. However, it remains necessary to say at this stage as well that the presented model is still a prototype and requires further validation and optimization in future research work to provide more representative and reliable results.

CHAPTER 5

ARTICLE 3: A PROPOSITION FOR COMBINING ROUGH SETS, FUZZY LOGIC AND FRAM TO ADDRESS METHODOLOGICAL CHALLENGES IN SAFETY MANAGEMENT: A DISCUSSION PAPER

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Abstract

In recent years, the focus in safety management shifted from failure-based analysis to adopt a more systemic perspective redefining successful or failed performance rather as a complex and emergent event than as a conclusion of singular errors or root causes. This paradigm shift necessitated as well the introduction of innovative tools capable of capturing the complex and dynamic nature of modern sociotechnical systems. In our research, we argued at previous stages for adopting a more systemic and human-centric perspective to evaluate the context of aircraft deicing operations. The Functional Resonance Analysis Method (FRAM) was applied in the first stage for this purpose. Consequently, fuzzy logic was combined with FRAM in the second stage to provide a quantified representation of performance variability. Fuzzy logic was used as a quantification tool suitable for computing with natural language. Several limitations were faced in the data collection and rule generation process for the first prototype. In the third phase, the model was further improved by integrating rough sets as a data-mining tool to generate and reduce the size of the rule base and classify outcomes. In this paper, we reflect on the three stages of the project and discuss in a qualitative manner the challenges and limitations faced in the development and application of the models. A summary of the advantages and disadvantages of the three models as experienced in our case are presented at

the end. The objective finally is to present an outlook for future studies to address methodological limitations in the study of complex sociotechnical systems.

5.1 Introduction

Driven by the human need to ensure safety and to be free of harm, significant research efforts have been always directed towards improving the performance of sociotechnical systems. As a consequence of this human drive, the perspective on what constitutes safe and adequate performance went through an evolution over the years since the introduction of the concepts of risk and safety management. Just as everything evolves in this world, an evolution has taken place reshaping the perspectives of practitioners and researchers and redefining how we view safety, risk and performance. In the early ages of reliability assessments, the focus has been mainly directed towards evaluating systems by examining the performance of its parts, adopting a more mechanistic perspective and focusing on the technological aspect of things (Qureshi, 2008). The classical view considered any system decomposable to its parts, well defined, and understood (Qureshi, 2008). Operators performed assigned tasks as required by instructions and procedures and the design phase was expected to account for every possible contingency and implement barriers and protection mechanisms to prevent the occurrence of any adversity. However, since a systemic performance cannot be decoupled from human performance, even the simplest and most closed systems rely largely on human interactions whether it is related to maintenance, examining or repair work and general interactions with the environment. Therefore, it was soon realized that the assessment of systemic performance had to include the human factor, which ushered the age of human error and a shift occurred leading to the introduction of such tools to comply with the newly emerging requirements. Later, the distinction between collective human performance and individual human performance was made and a new understanding of systemic performance led to the inclusion of the organizational factor as well. This resulted in directing research efforts to introduce new concepts identifying the need to innovate and provide modern and adequate tools. During that era, the concept of the MTO classification (Rollenhagen, 1995) was introduced opening the door for the emergence of several methods to provide needed solutions. In recent years, new tools have been introduced building on the years-long progression of systems' assessment to provide a much-needed systemic perspective such as the Systems Theoretic Accident Model and Process (STAMP) (Leveson, 2011), the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2004) and the Resilience Analysis Grid (RAG) (Hollnagel, 2011). Consequently, the discipline of resilience engineering emerged proposing a new outlook and new solutions to address the challenges facing both researchers and practitioners. The topic of resilience engineering has been a popular research item in recent years initiating several and numerous studies addressing the need to innovate, and the topic has been heavily discussed leading to the formation of a significant body of literature and research projects on the topic (Patriarca et al., 2018a & 2020).

This research project started with the objective of evaluating performance of aircraft deicing operations from a systemic and human-centric perspective. Generally, in the aviation sector, deicing operations are carried out by a highly reliable and complex system to ensure the compliance with strict procedures. Despite the high dynamicity and the extreme working conditions, the system in place in most countries, and especially in Canada, performs very well. Deicing-related incidents are a rarity and are rather related to smaller airports and smaller aircraft types than to larger airports and aircraft types (Aventin et al., 2015). Although larger airports have a high traffic volume, the strict procedures and implemented safety nets ensure that the operations are carried out safely and in a very reliable manner. Accordingly, the statistics on deicing incidents might be insufficient for statistical analyses and probabilistic methods given the rarity of such events. Such incidents are unique in their development, which makes generalizations to other contexts difficult. The accidents that may evolve in such systems are therefore very complex by nature and would have to be the result of combinations of highly improbable events and performance conditions. The severity of such accidents is significant and the costs in human lives and material damage could be very high, which is the main reason why these systems undergo such scrutiny to ensure high levels of safety, security and performance. The aircraft deicing industry is faced nonetheless with several challenges in the coming years, which should be addressed in future research projects to ensure that these systems continue to perform as desired. The volume of air traffic prior to the COVID-19 pandemic increased worldwide by 5-6% annually (ICAO, 2020) and is expected to continue its growth after the resolution of the pandemic. Consequently, there is a continuous requirement for larger airports with higher capacities and for more innovation and technological advancements. The gradually increasing utilization of centralized deicing pads to facilitate the deicing of a larger number of airplanes simultaneously requires precise coordination and clear communication between the flight crew, Air Traffic Control (ATC), the deicing team and the deicing tower (Günebak et al., 2016). Significant Research & Development projects are aiming at introducing novel technologies to comply with the rising demand such as the Ground Ice Detection System (GIDS), the application of drones, or the innovation of modern and automated deicing apparatus. With the advent of the fourth industrial revolution and its inevitable expansion to most sectors and domains, it becomes imperative to innovate and develop adequate assessment tools to be well equipped and prepared for the implementations of novel technologies. The very nature of such systems is to evolve and grow in complexity. Such systems become intractable and are difficult to comprehend in their entirety. It is such gaps in knowledge on systemic behavior that could lead to the formation of loopholes in the safety barriers and defense mechanisms, from which adversity could emerge.

In this paper, we aim to reflect on the progress achieved so far in our research and summarize in a qualitative manner the advantages and limitations as experienced in the previous stages of our project. To the best of our knowledge, projects concerned with the evaluation and development of aircraft ground deicing operations from a systemic and humanistic perspective are rare. So far, we argued for the need to adopt a systemic perspective in complex systems' analyses generally, and more specifically in the context of aircraft deicing. Eventually, we proposed a modified model of FRAM combining fuzzy logic at first as a quantification tool and then rough sets as a data classification tool. This paper here aims to look back and discuss the combined model starting with a brief overview of the different disciplines in the next section. The overview serves the purpose of presenting the three axes of the project and defining their relation to provide background for each approach in the following section. The three models are then described briefly in the methods section and discussed to present the main findings that could be generalized to other contexts. This should allow for drawing helpful conclusions and provide an outlook for future studies.

5.2 Background and Motivation

5.2.1 The evolution of systems' analysis: an argument for adopting a systemic perspective

Traditionally, classical safety analysis methods starting with Heinrich's Domino Model of accident causation in 1931 focused on causal and linear relationships (Heinrich, 1931). Heinrich's Domino Model introduced a paradigm shift in safety analyses moving focus from unsafe conditions to human error. Accidents and incidents were described mainly as a chain of discrete events initiated by a root cause and occurring consecutively leading to undesirable outcomes (Qureshi, 2008). Preventive measures therefore focused on breaking the chain of events and avoiding errors and malfunctions that could set the chain in motion. This approach was carried over to other methods later such as the Fault Tree Analysis (FTA) or the Failure modes & Effects Analysis (FMEA), which are still popular tools among analysts and decision makers to this day. These tools have done a great job in securing systems and ensuring their safety and adequate performance. They have become ever since more established and acknowledged in various industrial contexts due to the years-long tradition of applications.

As systems started to gain on complexity in the second half of the 20th century with the introduction of digital technology and the information revolution, new challenges and types of accidents emerged over time. The reliability of technology was not the main challenge facing safety analysts, rather the social component. It was realized that as soon as animate objects become a part of the system, the behavior of the system is no longer easily predictable (Zadeh, 1973). The evaluation of any system decoupled from its human aspects could therefore result in insufficient knowledge about its behavior and the evolution of adverse outcomes. As stated by Adriaensen et al., the majority of, if not all, traditional safety analysis methods require a combination of different types of methods "*to cover all technical and human performance-related hazards and risks*" (Adriaensen et al., 2019). The analysis of such issues in isolation from each other might produce insufficient results about their integration on a higher-order level of human–machine interaction (Adriaensen et al., 2019). Complex nonlinear interactions could be practically invisible for such tools or not immediately comprehensible (Perrow, 1984). Complex Systems are tightly coupled (Perrow, 1984), are more rigid and time-dependent and require more precision. Systemic components cannot be easily substituted and the failure of one component reflects significantly on the rest of the system. Multiple factors could combine in complex ways leading to failures and accidents. Since most accidents can be attributed to the human factor, a purely technological perspective is not sufficient. The human factor adds to the uncertainty and performance variability becomes an inevitability. Work in reality is always underspecified and never carried out as imagined or prescribed (Hollnagel, 2014). This variability in performance is a natural characteristic and is even necessary mostly to ensure successful outcomes. Consequently, there is always a difference between work-as-imagined (WAI) and work-as-done (WAD), between theory and practice (Hollnagel, 2014). While the inclusion of the human factor was recognized from the start, it was simply and mainly viewed in terms of unsafe acts, human errors or cognitive shortcomings.

Epidemiological models emerged in the 1980s as a consequence of the continuous search to improve and redefine the understanding of safety. These models adopted a more complex view on adverse events and explained them as a combination of several influential factors and conditions, which can be active or latent. The human factor was considered herewith more deeply, dividing it into two main sets of conditions: individual human factors, which cause active failures at the sharp end of operations and organizational factors, which reflect the impact of the latent organizational and cultural influences (Reason, 1990; Woods et al, 1994; Qureshi, 2008). Combined with the performance or environmental conditions present at the time of execution, organizational factors can lead to active human failure if no adequate protection layers and barriers were in place (Qureshi, 2008). Reason's perspective on accident causation is best represented in the Swiss cheese Model, which illustrates accidents as emergent events resulting from loopholes in the defense mechanisms and barriers of the system (Reason, 1990). However, the adopted philosophy in epidemiological models was still focused on sequential cause-effect and linear relationships (Hollnagel, 2004). The Swiss cheese Model presented a static snapshot of a mainly complex and dynamic context, which could result in overseeing safety loopholes (Qureshi, 2008).

Rasmussen in the nineties argued that a systems approach based on functional abstraction rather than structural decomposition is needed to model and design safer sociotechnical systems (Rasmussen, 1997). Rasmussen classified six levels of a sociotechnical system: Government, Regulators/Associations, Company, Management, Staff and Work (Rasmussen, 1997). Adequate analyses of dynamic working environments cannot rely on traditional task analysis and should rather assess the issues on several systemic levels in an interdisciplinary manner (Rasmussen, 1997). For providing adaptive systems, it is imperative that all systemic levels are interactive. The implications of implementing change on one level shall be assessed in relation to all remaining levels (Rasmussen, 1997). The hierarchical classification as presented by Rasmussen was analyzed by Leveson, who noted that the model solely focuses on the operational aspects (Leveson, 2011). Influential factors are still modeled at each level as an event chain, which is then linked to the event chain on the lower level and so on. This approach, as stated by Leveson, still assumes the existence of a root cause for accidents and adverse outcomes and describes events in terms of causal relationships. Leveson concludes that causality models are no longer adequate to describe modern sociotechnical systems, which have to be modelled as a whole (Leveson, 2011). Leveson considers safety to be a control problem as well i.e. the emergent properties of a system are to be controlled by imposing constraints on the behavior of that system and the interactions between its components during its design and operation (Leveson, 2011).

The perspective of Rasmussen is shared by Erik Hollnagel as well, who argues as well that systems could not be defined as a collection of separate parts only, but as "*a set of coupled or mutually dependent functions*" (Hollnagel, 2012). Starting with the framework of Cognitive Systems Engineering, Hollnagel and Woods suggested a new paradigm and introduced a gradual shift into the principle of SAFETY-II. Hollnagel considered CREAM to be a short step to FRAM, which provides a functional view of the system and focuses on performance variability and its combinations. The representation of systems in terms of functional couplings forms the basis upon which Hollnagel introduced the Functional Resonance Analysis Method (FRAM), which served as the main framework applied in our project. In FRAM, functions are divided into three categories: technological, organizational, and human in accordance with the MTO classification method (Hollnagel, 2012). FRAM functions are not just hierarchical, rather they are objective or task oriented and accordingly can expand across systemic hierarchical levels. The difference between FRAM and other systemic tools such as STAMP is that, in addition to negative outcomes, FRAM adopts a more resilience-focused perspective considering both negative and positive outcomes (Patriarca et al., 2020).

Thus, SAFETY-II in addition to what goes wrong, looks at what goes right. This is especially helpful to draw conclusions when faced with scarcity of data and statistics since what goes right is the norm and is mostly the outcome. Modern critical systems such as aviation and nuclear power generation are high-reliability systems due to the severe and possibly disastrous consequences of incidents in such systems. It was therefore imperative to direct more attention to securing these systems through research and development and implementing regulations that are supposed to eliminate any possibility for the occurrence of accidents. Consequently, the occurrence of accidents in such domains have become rare to a degree that the task to provide sufficient statistics and databases have become a difficult task. The rarity and uniqueness of such events have made it difficult even to draw meaningful and generalizable conclusions. In high-reliability systems, it would therefore make more sense to adopt a SAFETY-II approach considering both the negative and positive factors. This consequently generates more data for analysis and would help strengthening the system by maintaining the performance conditions that ensure successful outcomes; thus, making the system more resilient. The resilience of any given system can be defined as its intrinsic ability to adapt and adjust its performance to fluctuations and unexpected disturbances to maintain its output within acceptable margins (EUROCONTROL, 2009). Resilience Engineering focuses on the full spectrum of outcomes from extremely positive to extremely negative. Performance variability, whether individual or collective, is a natural and inherent characteristic of any sociotechnical system and can be beneficial to cope with these disturbances (Hollnagel, 2014). The roots of Resilience Engineering lie in Human Factors and Safety Management and the principle of performance variability is strongly linked to the human factor considering the human as the main component of any sociotechnical system. Resilience Engineering can therefore be described with the following four principles (EUROCONTROL, 2009):

- There is always an underspecification of actual performance conditions i.e. the difference between WAI and WAD;
- The principle of performance variability is the main reason why outcomes deviate from the norm or expectations;
- Retrospective Analysis are not sufficient and proactive assessments are needed to anticipate and be well prepared for adversity.
- The strive to maintain highly efficient and productive systems cannot be decoupled from safety, which should be incorporated into the business planning and core processes as a prerequisite for productivity.

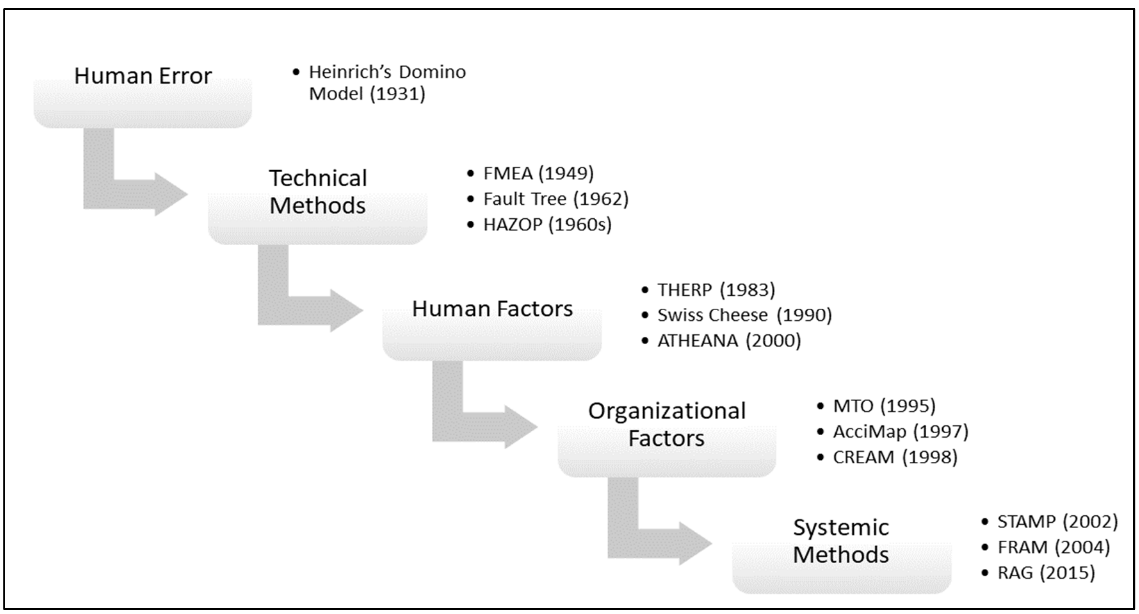

Figure 5.1 An overview of the development of accident & safety assessment methods (EUROCONTROL, 2009).

The continuous drive to make systems function more efficiently and reliably necessitates innovation and thus the integration of smart technologies into the different types of industrial environments. The continuously increasing interconnection of systems and the widening of networks, the backup of data into clouds, the internet of things, the generation of large data sets and the gradually increasing reliance on human-machine interfaces all lead to increased human–machine interaction, complexity and intractability (Nadeau & Landau, 2018). Considering the emergent properties of complex systems, this all could introduce new types of risks and performance impairing factors that are difficult to anticipate in the design phase. The objective of risk and safety assessment models (Figure 5.1) is to evaluate and conceptualize the characteristics of accidents and incidents to provide an explanation for their development. They are therefore useful in all phases from system development to system deployment and operation. Applying classical tools in this case in a retrospective manner and focusing solely on lessons learned from previous events and experiences would eventually result in overseeing loopholes, from which accidents can emerge (Cacciabue, 2000). Retrospective analysis is usually easier to conduct than proactive or predictive ones since they deal with defined conditions and well-known events. The issue with retrospective analysis is the limitation of the scope to what already transpired and therefore draw the definitive pass for the development of an accident and ignore the possibilities for alternative outcomes (Adriaensen et al, 2019). Looking at events in retrospect might give rise to confirmation bias and lead the analyst to believe a one-sided explanation of the event in question (Adriaensen et al, 2019). This would result in possibly overlooking other explanations for the development of the event, since the sequence of events provides only one narrative. In a proactive analysis however, assumptions are to be formulated to anticipate possible sources of risks and adversity (Cacciabue, 2000). Innovative systemic models have therefore become necessary to understand the new structures and better anticipate the behavior of complex sociotechnical systems (Leveson, 2011).

5.2.2 Quantitative and Qualitative methods: Why fuzzy logic?

From a methodological perspective, research activities adopt mainly either qualitative or quantitative methods (Amaratunga et al., 2002). Mathematical analyses and quantification tools offer appropriate methods to measure phenomena more objectively and provide intersubjective results. Experimental methods using quantitative measures aim generally at verifying formulated hypotheses over specific cases to deduce generalizations that can be applicable to different contexts (Amaratunga et al., 2002). The objective hereby is to quantify the observed instances in an objective manner and express them in terms of numbers. This is usually achieved through the reduction of the whole into its parts to simplify the system and define linear relationships that can facilitate the analysis. However, linearizing systemic relationships and relying solely on quantitative measures could result in overseeing certain characteristics of the system of interest such as the significance of the measured values and their meanings for decision makers and analysts. Reducing a system to its parts might be efficient and produce more straightforward results that can be more intersubjective and comprehensible for analysts and stakeholders. However, it can as well prevent the analyst from understanding complex and dynamic relationships, which are rather emergent by nature and only visible in a more holistic approach. Additionally, not all phenomena and contexts are easily quantifiable (Zadeh, 1973). The determination of a precise magnitude for qualitative and uncertain variables is difficult and sometimes even not possible in terms of discrete mathematics. The problem then would be the inability to collect precise data and provide quantifiable analysis results (Zadeh, 1973).

Qualitative assessments can be more suitable for understanding complex relationships considering that even purely quantitative results are meaningless without defining how they relate to their context and what interpretations and conclusions can be drawn (Amaratunga et al., 2002). Using a qualitative approach allows for a more descriptive evaluation over time to clarify dependencies among variables and describe dynamic and more complex relationships. However, here as well, several limitations can be noticed, which might limit the significance of purely qualitative results for some decision makers and practitioners. In comparison, since quantitative approaches define generally simple relationships, the data collection process can be easier and more efficient such as measuring the distance or temperature etc. The same cannot be claimed for qualitative measures, which could be vague by nature and require for interpretation a deeper understanding of systemic functionality. The interpretation of the results depends on the context in question, and different people can perceive the magnitude or meaning of words differently. Linguistic descriptors or scales can only capture the relative but not the precise magnitude of the measured value (Shepard, 2005).

The use of quantitative methods in safety analysis has been sought in a limited fashion so far. This might have several reasons such as the lack of such methods of an internal causation model (Adriaensen et al, 2019). Another limitation is represented in the inability of properly quantifying complex variables in a reliable manner, which lead to focusing on simple systems and the application on a micro-level in ergonomics and safety management (Adriaensen et al, 2019). Another aspect is the lack of sufficient data and statistics in some contexts, which makes the application of probabilistic approaches somewhat difficult and even in some cases not possible. Despite these limitations, several propositions to combine FRAM with quantification mechanisms were presented in recent years (Patriarca et al., 2020), most notably are Patriarca et al. who presented a semi quantitative approach combining Monte Carlo simulation and FRAM (Patriarca et al., 2017). The Monte Carlo simulation has been used to assign probabilities of dependencies within the framework of complexity-thinking models (Patriarca et al., 2017). Bayesian networks on the other hand allow for a better representation of complex relationships than logical operators and are therefore suitable to evaluate tightly coupled systems (Slater, 2017). However, Bayesian networks still rely mainly on causality and tractability (Adriaensen et al, 2019). The degree of uncertainty in the model depends on the quality of the provided data and the degree of knowledgeability on the present performance conditions.

Applied in a proper manner, the combination of qualitative and quantitative methods is promising and can generate more representative and reliable results. Such applications combining the two methods are already being applied in the aviation sector supporting qualitative methods like the FMEA with quantification tools (Adriaensen et al, 2019). Qualitative analysis methods such as FRAM and STAMP are descriptive by nature and rely mainly on the use of linguistic ordinal scales to assess the system of interest. A solution to combine such approaches with quantitative methods and maintaining most of their advantages could be reached through the integration of fuzzy logic (Zadeh, 1965). The challenge to adopt fuzzy logic into safety analysis and management as a possible way to handle uncertainty remains an understudied topic to be addressed in future research. Fuzzy logic resembles human reasoning and can therefore be suitable to quantify such variables and vague contexts (Zadeh, 1965). In contrast to theoretical idealistic concepts, real life processes are characterized by ambiguity and vagueness. They are never as imagined and are therefore underspecified in the theoretical model. From an operational perspective, even in the most precise applications of procedures and regulations, the operational execution in practice always deviates from the norms and defined standards (WAI & WAD). This deviation is not exceptional or abnormal; rather it is an inherent characteristic of real life applications and is even necessary and beneficial in many cases to ensure the resilience of the system.

In 1965, Lotfi Zadeh presented a formalized definition of many-valued logic and laid the foundations of Fuzzy Set Theory and Fuzzy Logic in his article "*Fuzzy Sets*" (Zadeh, 1965). Since then, the positions on fuzzy set theory in the scientific community have been divided. The theory was faced with harsh criticism and the advantages of fuzzy logic over conventional methods in addressing uncertainty were doubted in the early years (Haack, 1979) (Tribus, 1979). The notion that "*fuzziness*" represented a type of uncertainty distinct from probability was rejected considering that probability theory provides complete and optimal tools to solve problems and manage uncertainty (Laviolette & Seaman, 1994). Early criticism of fuzzy logic as well rejected the new concept for compromising with vagueness and radically and unjustifiably shifting from traditional formalism sacrificing precise, formal rules of inference and consistency of results (Haack, 1979). Furthermore, it was argued that fuzzy logic did not simplify things or avoid the complexities of regimentation; rather, it added more methodological complexity itself (Haack, 1979).

While the adversaries of fuzzy logic believed it to be overrated and questioned its validity, the advocates on the other hand considered the theory to be groundbreaking and a more accurate representation of reality (Pelletier, 2000; Hájek, 1998). Zadeh explained in detail that such views as the ones mentioned above were mainly derived from a misunderstanding of fuzzy logic and from the inability to realize the importance of the concept of linguistic variables

(Zadeh, 2008). In classical set theory, binary logic defines any element as either a member or not a member of any given set; it is either true or false (Sivanandam et al., 2007). Fuzzy Logic as a generalization of classical set theory extends this definition and elements can thus belong to more than one fuzzy set with a certain degree of truth using the concept of the membership function (Shepard, 2005). The rationale for the fuzzy-logic-generalization is based on two main principles: the ability to construct better models of reality and the ability to exploit the tolerance for imprecision and replace numbers with words (Zadeh, 2015). The ability to better represent reality derives from the fact that the information granules are in reality fuzzy, i.e. truth is not black or white, rather grey. The second principle allows for the replacement of numbers with words through the concept of linguistic variables, which are labels of fuzzy sets with specified membership values (Zadeh, 2015). This allows for the design of more cost-efficient and simplified systems relying on comprehensible natural languages (Zadeh, 2015). The concept of fuzzy granulation and use of linguistic variables is a unique feature of fuzzy logic (Zadeh, 2015 & 1997). Methods and approaches that rely on crisp logic to handle uncertainty such as rough set theory or the Dempster-Schafer theory fail "*to reflect the fact that in much, perhaps most, of human reasoning and concept formation the granules are fuzzy (f-granular) rather than crisp*" (Zadeh, 1997).

The application of conventional quantitative methods for system analyses is inappropriate in the case of humanistic systems due to the principle of incompatibility. This means that whenever the complexity of any given system increases, the ability to understand its behavior precisely decreases i.e. it becomes more intractable (Zadeh, 1973). Human reasoning rely rather on linguistic variables than on numbers. Linguistic variables are labels of fuzzy sets, which are classes of objects in which the transition from membership to non-membership occurs gradually rather than abruptly (Zadeh, 1973). Human reasoning does not resemble machine processing and relies on indiscrete logic with continuous functions. It approximates and summarizes information in form of labels, words and sentences. Fuzzy logic therefore works and provides a method to model vague contexts, which is accurate to provide reliable and representative results. It is easy to implement, therefore it became preferable and found application in many fields over the past decades. Fuzzy set theory is consistent and the relationship to probability despite the distinctions is present in the form of possibility theory (Dubois & Prade, 1993). The three concepts of probability theory, rough set theory and fuzzy set theory are non-contradictive and present three different approaches to manage different types of uncertainty (Nurmi, 2009).

5.2.3 Rough Sets: an approach for data classification

For the development of a predictive assessment model, several techniques and methods were applied over the years, mostly probability-based multivariate statistical methods such as logistic regression and discriminant analyses, which can be used to predict the probability of a specific outcome for a given set of input variables. While such methods can be helpful in data analysis given a large set of quantitative data, qualitative judgement of the analyst is still required to understand the influential relationships among variables and interpret the provided results. The provision of an entirely objective approach for data analysis is therefore impossible since subjectivity and biases are still present in the judgement provided through the experts. The objective is therefore to minimize the subjectivity and bias in handling the input data as adequately as possible and work towards providing a more objective and standardized framework. RST provides a mathematical framework adequate for the classification of imperfect and uncertain information by discovering patterns and relationships in archived and historical data (Pawlak, 1982; Øhrn, 2000; Alisantoso, D., et al., 2005). Through the application of several search algorithms to analyze input data provided by experts, RST is capable of automatically and objectively identifying patterns, filtering and classification of data (whether quantitative or qualitative) (Øhrn, 2000). The subjectivity is therefore limited to the input data provided by the experts and to the selection and characterization of the classification method, not to the classification process itself.

RST was proposed by Zdzislaw Pawlak in 1982 and has been ever since applied in several domains and fields, in which it proved very useful to filter and classify large data sets. The main idea in RST is represented in the assumption that with every object in the universe of discourse some information can be associated (Pawlak, 2004). Similar objects characterized by the same information are indiscernible if a decision class cannot be determined based on the values of their considered attributes. In contrast to crisp or classical sets, which are precise and have clear boundaries, a rough set has boundary-line cases, in which objects cannot be classified certainly as members of the set or of its complement given the provided information (Pawlak, 2004). Therefore, the main set in RST is defined by a pair of precise sets, called the lower and the upper approximation (Hvidsten, 2010). The lower approximation consists of all objects, which surely belong to the main set, while the upper approximation contains the objects that possibly belong to the main set. The difference between the upper and the lower approximation is then defined as the boundary region (Pawlak, 1998). A set in RST is called rough if the boundary region is not empty (Pawlak, 1998). The indiscernibility relation and the principle of approximations form the mathematical foundation of rough set theory (Pawlak, 1998). Through the provision of efficient algorithms and the principle of indiscernibility, data sets can be scanned to identify hidden patterns, classified and reduced to eventually generate a minimal but accurate and efficient rule base (Øhrn, 2000). The generated rule base offers easily understandable and straightforward results.

The time, at which RST was introduced in the eighties, witnessed a rising interest in Machine Learning, Artificial Intelligence and Expert Systems (Ziarko, 2000). To produce applicable frameworks within those fields, comprehensive theoretical foundations were needed, which were based upon either classical logic or intuitive algorithms and qualitative methods. From a practical perspective, approaches based on classical logic were rigid and presented difficulty in applications into real-world settings (Ziarko, 2000). On the other hand, the intuition-based approaches lacked a standardized theoretical foundation and a unified representation to produce reliable results (Ziarko, 2000). RST was perceived as a possible solution, which provided a framework with the clarity and algebraic completeness of classical set theory. This initiated research projects at that time aiming at developing algorithms and models based on RST framework to address said limitations. It was noticed thereafter that the RST approach was limited as well in several aspects when it came to real world applications such as inconsistencies in outcome due to inconsistencies in input data (Greco et al., 2001), and the restrictiveness of RST approximations in empirical applications in complex systems involving real world data. This led to several research efforts to overcome these limitations leading to the proposition of several extensions and modifications to the RST framework (Greco et al., 2001). Several algorithms were consequently proposed over the years to help improve the RST data mining process and allow for a better pattern recognition and data classification. Additionally, the combination of RST with fuzzy logic and with probability theory was sought to generate models capable of handling practical applications, in which probabilistic inferences and statistics were provided and could be helpful (Wei & Zhang, 2004). The combination of fuzzy logic and rough sets was especially interesting for our application scenario, since we were facing the problem of collecting sufficiently representative and valid data in our context due to the rarity of significant events in the studied context and the vague nature of collected data. Other limitations such as issues with the discretization and partitioning of the numerical range of values for input data and incomplete information or missing values present challenges as well for the RST method. The discretization process is best provided by domain experts, who rely on their expertise and years-long experience and knowledge to define the partitions for the universe of discourse. Such limitations represent a real challenge to the RST to find more practical implementations and real-world applications. A jump from the theoretical research and academic studies into industrial and real-world implementations is necessary, which would require an expansion in respective research projects with this objective as well. The majority of conducted studies and designed models are of theoretical nature and are limited when it comes to real-world applications (Ziarko, 2000).

The relation between fuzzy logic and rough set theory was discussed in several studies. Many of those studies addressed the mathematical and theoretical issues of both concepts and aimed at either comparing or combining both methods. The scope of this paper is not to conduct an in-depth review of the theoretical foundations of fuzzy logic and rough sets. From a more practical point of view, it is rather more interesting to evaluate the usefulness of both methods and their ability to provide helpful results in addressing some of the limitations faced in traditional approaches. Fuzzy logic and rough sets are two different approaches to address information uncertainty. Fuzzy set theory is older (1965) and developed extensively over more than fifty years to become established and find applications in various fields (Zadeh, 2015).

The theory of rough sets relies on the principle of indiscernibility, which are objects characterized by the same information or attributes (Pawlak, 1991). The principle of approximation is fundamental to rough set theory to handle and process uncertainty in contrast to fuzzy logic, which relies on the membership function and numerical values [0, 1] to define the degree of truth or membership (Greco et al., 1999). However, while fuzzy logic is more suitable for addressing fuzziness and vagueness of data, rough sets are better suited for data classification and addressing inconsistency and incompleteness issues in data (Yao, 1998). This does not however mean that both methods are only applicable in a restricted or specific way. Similar to Boolean logic and classical set theory, fuzzy logic and rough set theory are two mathematical constructs, whose advantages and limitations depend greatly on the direction and form of application. The two methods do not conflict with each other; rather they complement each other and were combined to address both vagueness and incompleteness in the form of rough fuzzy sets and fuzzy rough sets (Dubois & Prade, 1990; Anderson et al., 2000). Mixed frameworks of the two methods were proposed in several studies as well to benefit from the strengths of the two methods in handling the issues at hand (Anderson et al., 2000). It remains for the analyst to decide which methodology is more adequate and in which form it should be applied to handle the issue at hand.

5.3 Methods

In the previous sections, the goal was to present an overview of the development of safety and risk assessment tools and to discuss two possibly promising approaches to overcome their limitations. In this section, a brief overview of the models proposed in each phase is presented. The objective here is not to present a detailed and systematic explanation of each model, but rather to explain the process qualitatively. For a more detailed description on the proposed methodology, the reader might consult the previously published papers (Slim et al., 2018; Slim & Nadeau, 2019; Slim & Nadeau, 2020).

As mentioned earlier, accidents related to deicing operations are rare due to the adequacy of implemented procedures and the high reliability of the system in place. Especially in a country such as Canada, these operations are executed very efficiently and precisely due to the harsh weather conditions and the continuous need for proper deicing technologies. However, despite the rarity of deicing-related accidents nowadays, these can still occur due to the very nature of complex sociotechnical systems as explained above and with severe consequences. The unavoidable need to develop and improve applied technologies and procedures does not diminish. Innovation is inevitable; otherwise, one risks falling behind and at one point becoming obsolete. Looking at the aviation context in general and specifically the deicing context, we are faced with a complex working environment consisting of many technological components (planes, trucks, deicing equipment, communication, control centers, computers, etc.) and human components in the form of operators, engineers, flight crew, deicing personnel, etc. These components interact with each other under the guidance of an organizational structure that specifies policies, procedures and regulations. The work is generally conducted most likely under extreme weather conditions with tight time schedules and a high requirement on adequacy and reliability. All of these aspects shape the deicing working environment to be a very complex and dynamic system in need of continuous assessment and improvement. The expansion of Industry 4.0 into several fields and the introduction of new technologies as the move from gate deicing to centralized deicing, or future innovations such as the new Ground Ice Detection System (GIDS), and possibly the application of drones that uses the internet of things etc. are all challenges that require further research from a safety angle. Such scenarios require an understanding of the performance of deicing operations from a systemic perspective taking into considerations all aspects of the system, whether human, organizational, environmental or technological. Research in deicing from a systemic perspective is rare and to the best of our knowledge, our research team is the only team pursuing such a project. While research and the application of systemic tools in aviation have gained on popularity and significant studies were published, the same cannot be said about deicing operations.

Since the start of this project, we aimed at accomplishing three objectives to eventually realize a basic theoretical framework and provide indicators for future research. The first objective was to analyze the working environment of aircraft deicing operations adopting a complex systemic perspective and to identify influential contextual factors that can possibly affect performance. The Functional Resonance Analysis Method (FRAM), which allows for a functional representation of the studied system, was chosen for this task. The second objective was to conduct a predictive assessment and to provide quantified and more intersubjective results through the integration of fuzzy logic as a quantification tool. The third objective was to address the lack of databases and the issues related to the classification of uncertain and vague information. To this end, Rough Set Theory (RST) was used to classify input data and generate the rule base for our analysis. In the following subsections, a brief overview of the three phases will be presented.

5.3.1 Phase I: Basic FRAM as complex systemic assessment tool

FRAM in its basic form using two phenotypes, namely time and precision, was applied to study the working environment of aircraft deicing operations. For a more detailed explanation of the methodology and the obtained results, the reader might consult Slim et al. (2018). The followed methodology consisted of the following steps:

The objective for the first application was to select an analysis scenario using a well-known deicing-related accident. The crash of Scandinavian Airlines flight SK751 at Gottröra, Sweden, in 1991 (SHK, 1993) was chosen. The accident was investigated and well defined in the official accident report, which allowed for an easier characterization of the functions and their outputs. While the conditions and events leading to the accident were listed in a detailed manner in the report, the objective was to verify whether a FRAM application could add to the findings and present a different perspective. This perspective should be facilitated relying on the distinguishing four principles of FRAM: equivalence of success and failure, approximate adjustments, emergence of outcome and functional resonance (Hollnagel 2012) (Figure 5.2).

The second step then was to characterize the working environment of aircraft deicing operations and create a functional representation of the context by identifying the functions that constitute the system in question. The functional characterization in FRAM describes how the various tasks are related and how the outcome's variability can resonate and affect performance negatively or positively. Consequently, a list of representative functions was identified limiting the scope of the analysis to the functions needed to execute the deicing operations. The chosen analysis scenario would then specifically depict the deicing operation and takeoff process of SK751. Each function could possibly be characterized by six aspects: Input (I), Output (O), Preconditions (P), Resources (R), Time (T), and Control (C) (Hollnagel 2012). However, it is not necessitated that all aspects are provided; rather, it depends on the function in question. The boundaries of the analysis are formed by the background functions, which only provide outputs and are invariable as they are not the focus of the analysis. The functions were described in the form of a table listing all their respective characteristics, which can be derived from the events and data provided in the official accident report published by the Board of Accident Investigation (SHK, 1993). Additionally, three types of functions could be defined: organizational, technological and human functions.

The third step was then to identify sources of performance variability within the designed setup. As mentioned above, variability is characterized in terms of two phenotypes: timing (early, on time, too late and omission) and precision (imprecise, acceptable and precise) (Hollnagel 2012).

Finally, the influential relationships among functions were identified to construct a visual map of the system and illustrate how functional resonance can affect the outputs of the functions. This could explain how performance variability combined and resonated to eventually lead to the crash and what lessons or new findings could this analysis provide.

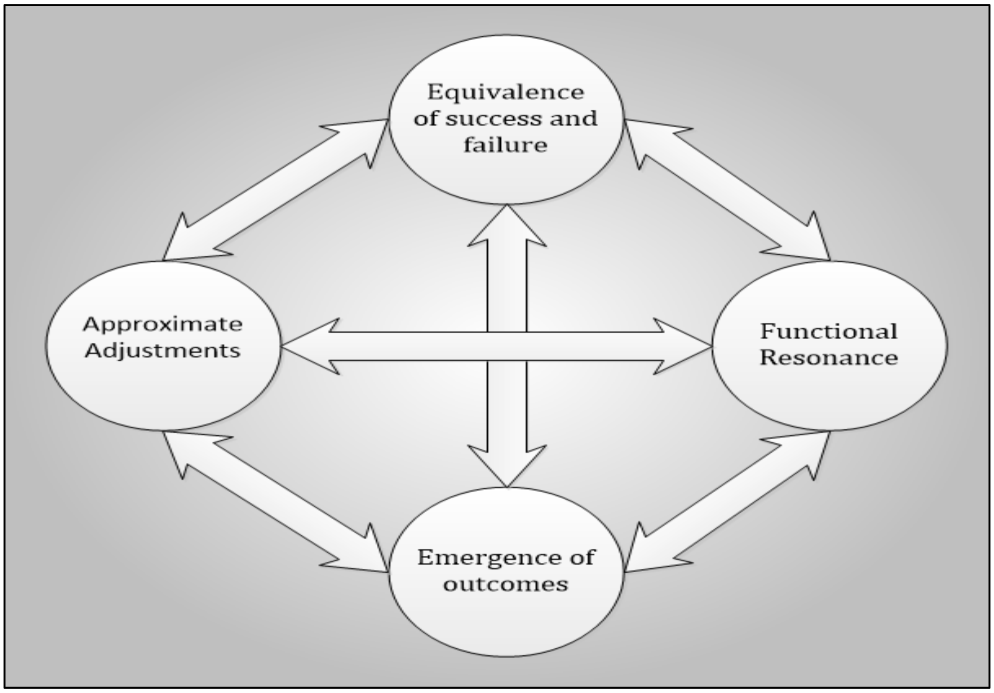

Figure 5.2 The four principles of FRAM (Hollnagel, 2012a).

5.3.2 Phase II: A predictive assessment with quantified results.

The basic FRAM is qualitative and relies on linguistic scales to characterize performance variability. This is advantageous in case of uncertain data and inherently complex factors, which can be hard to measure numerically. The application of FRAM in phase I was straightforward given the well-defined events and conditions in the official accident report. Moving forward to a more generic scenario and attempting to conduct a predictive assessment proved to be more difficult in our case. It was not always possible to identify for each function how a variable input would reflect on the output and to which extent. The classification of inputs and outputs was not always easy and was in some cases not possible, even after understanding the mechanisms of the functions in question. The magnitude and type of variability were not easily deducible in many cases. An additional issue was that people have different perceptions and tend to associate different meanings with words. What one might define as inacceptable for example, another could perceive as adequate and so on. To ensure conformity and provide more intersubjective results, fuzzy logic (Zadeh, 1965) was integrated in phase II into the framework of FRAM as a quantification tool. Fuzzy logic resembles human reasoning and allows for a mathematical representation of natural language. Through the integration of fuzzy logic into FRAM and designing the FRAM functions as rule-based Fuzzy Inference Systems (FIS), the advantages of both methods could be utilized to provide more representative and comprehensible results (Figure 5.3).

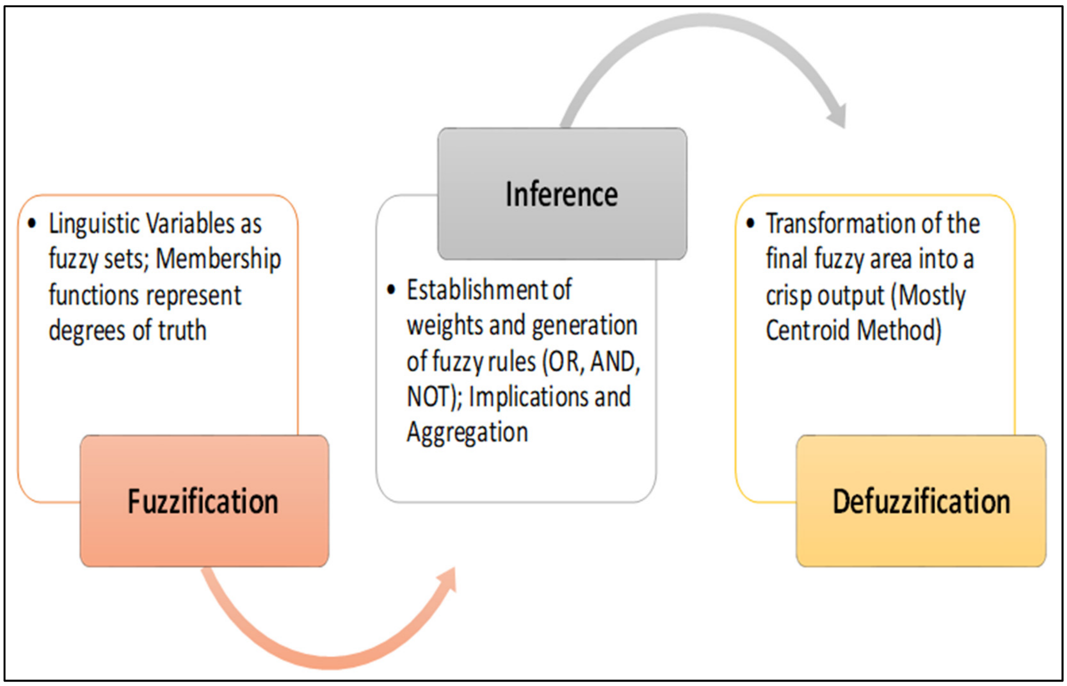

Figure 5.3 The three steps of the Fuzzy Inference System (FIS)

The five steps of FRAM provide a guideline for defining the context of analysis and decomposing the system into functions. We can distinguish between two types of variability: internal from within the function and external through functional couplings. Each function is then defined as a hierarchical fuzzy inference system (Figure 5.4) with an internal FIS to account for the Internal Variability Factor (IVF) and a higher-order FIS to account for the combined variability of both the IVF and the external variability through the couplings with upstream functions. The list of common performance conditions (CPC) was used as evaluation parameters to anticipate the possibility for potential internal variability. The analyst assigns a quality score on a scale between zero and ten to each performance condition. A rule-based fuzzy inference system is then constructed to fuzzify the scores of all respective performance conditions and generate an aggregated quantifier for the potential internal variability of each function. The IVF is then linked to the higher-order fuzzy inference system in addition to the other incoming aspects from upstream functions to generate a numerical output. The impact of the timing and precision phenotypes is combined and simplified into three classes: highly variable, variable and non-variable. The numerical outcome represents an indicator for possible variability, whether negative or positive, in the function's output. On a spectrum between 0 and 1.5, 1 represents a non-variable output. Any value below 1 represents negative variability, while any value above 1 represents positive variability.

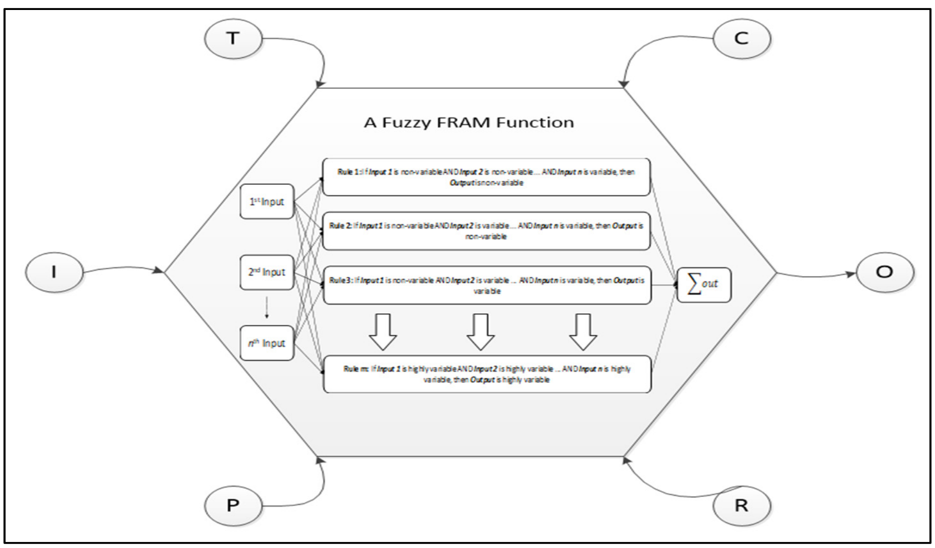

Figure 5.4 A FRAM function represented as an FIS.

An application scenario of aircraft deicing operations was constructed inspired by two deicing-related accidents, namely the Scandinavian Airlines flight 751 crash in 1991 (SHK, 1993) and the Air Maroc accident in Mirabel in 1995 (TSB, 1995). The work environment of centralized deicing was characterized in terms of functions, which describe the set of activities necessary to successfully perform the deicing of airplanes. A total of 17 functions was defined: four background functions (non-variable) and 13 foreground functions (possibly variable). To induce variability into the defined setup, assumptions over prevailing performance conditions such as inadequate airliner guidelines, present extreme weather conditions, inadequate training of flight crew and high temporal stress were formulated.

Based on the formulated assumptions in our simulation, we recorded possible positive variability for functions with an output quality of one or more and possible negative variability for functions with scores below one. This was especially noticeable for the function "*Post Deicing Inspection",* whose score was remarkably low due to the principle of functional resonance and the impact of combined variability from upstream functions. The scores of the IVF and the output were then plotted on the graphical representation generated in the FRAM Model Visualizer (FMV) to provide an illustrative map of the relationships within the studied system. For a more detailed explanation of the methodology and the obtained results, the reader might consult Slim & Nadeau (2019).

5.3.3 Phase III: Rough sets to classify input data

In the third phase of the project, we aimed at addressing several limitations faced in the prototyping model combining fuzzy logic and FRAM. Despite the many advantages provided by the addition of fuzzy logic, the model was still limited in many ways that made the realization of such an analysis somewhat demanding. The number of input variables and associated phenotypes and classes was kept at a minimum to avoid the "*rules explosion*" problem. A higher number of inputs could result in an exhaustive and large rule base, which would make the creation of the fuzzy inference system (FIS) difficult and in many cases unfeasible due to the required effort and resources. Secondly, a decision to determine the class of output was not always easily identifiable in the rule base relying on the provided qualitative scales. The output was in many cases variable and vague in nature due to the vagueness or incompleteness of input information. Additionally, the assignment of a quantitative domain and the partitioning of the universe of discourse were still determined in a subjective manner relying on the expertise of the analyst or the consulted experts. Therefore, to address the above-mentioned limitations, Rough Sets Theory (RST) was integrated into the prototyping model to classify input data and generate a more efficient rule base.

The main advantage for using RST is represented in the capability to filter and identify patterns in data tables to classify outcomes and provide a decision relying on historical information. This can be achieved applying the principle of approximation and the indiscernibility relation to classify recorded information in the form of data tables or information systems. The RST approach allows for an automatic generation of a reduced and efficient rule base afterwards, which can be migrated into the FIS instead of manually writing the rule base rule by rule.

Basically, FRAM functions are data tables, which lists the functional aspects as attributes. Thus, the functions can be defined as rough information systems considering each iteration or recorded instance of the function as an object, the functional aspects as attributes and the output as the received decision class. Each recorded instance of the function is an object with respective values for the attributes and a resulting decision class. The data table forms the discernibility matrix, which helps to identify indiscernible objects i.e. rows sharing the same values that have different decision classes. Different types of algorithms can be applied to scan the constructed information system to compute the reducts and generate the rule base. The accuracy of the rule base depends here on the size and accuracy of the provided dataset. The characterization step is important to determine the type of needed data and parameters in the data collection step to perform predictive or proactive assessments.

Table 5.1 An RST information system for determining the Internal Variability Factor (IVF)

Function	**Common Performance Conditions**				**IVF**
	CPC_1	**CPC_2**	**.....**	**CPC_n**	
Function 1	Adequate	Adequate	.....	Adequate	Non-Variable
Function 2	Inadequate	Adequate	.....	Adequate	Non-Variable
Function 3	Inadequate	Inadequate	.....	Adequate	Variable
.....	......	......	.....	......	.....
Function m	Inadequate	Inadequate	.....	Inadequate	Highly Variable

The second aspect to consider is the characterization of performance variability. To determine the internal variability for each function, the CPC's can be defined as attributes and the decision class would then be the IVF. It is important here to mention that the choice of relevant performance conditions can be reevaluated and modified as required by the studied context. The same settings and classes were kept as in the prototyping model i.e. each CPC was classified as either "*adequate*" or "*inadequate*". The decision classes for the IVF were kept the same as well: "*non-variable*", "*variable*" or "*highly variable*" (Table 5.1). The external variability factor (EVF) is determined following the same process as with the IVF, however using a three-class scale for each incoming aspect or attribute. The functional aspects serve this time in addition to the IVF as attributes in the RST table (Table 5.2) with three possible values or classes: "*Non-variable*", "*Variable*" and "*Highly Variable*". The provided dataset for each function is then split randomly into a training set and a testing set. The chosen algorithm scans the training set to identify the reducts, which are then used to generate a reduced rule base. The generated rule base can be validated using the testing set, which helps to determine adequate rules with acceptable levels of coverage, support and accuracy.

Table 5.2 An RST information system for determining the External Variability Factor (EVF) i.e. output's variability

Function	**Aspects**						**Output**
	IVF	**Input**	**Time**	**Control**	**Preconditions**	**Resource**	
Function 1	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable	Non-Variable
Function 2	Non-Variable	Non-Variable	Variable	Variable	Variable	Non-Variable	Variable
Function 3	Non-Variable	Non-Variable	Highly Variable	Non-Variable	Non-Variable	Non-Variable	Variable
.....	......	......	.....	.....	.....	......	.....
Function m	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable	Highly Variable

The final rule base can be then migrated into the FIS and used to run specific instantiations of the model and generate the numerical outcomes for the output (Figure 5.5). The same analysis scenario was kept as in the previous stage to sustain the same settings for a better comparison of the two models. For a more detailed explanation of the methodology and the obtained results, the reader might consult Slim & Nadeau (2020).

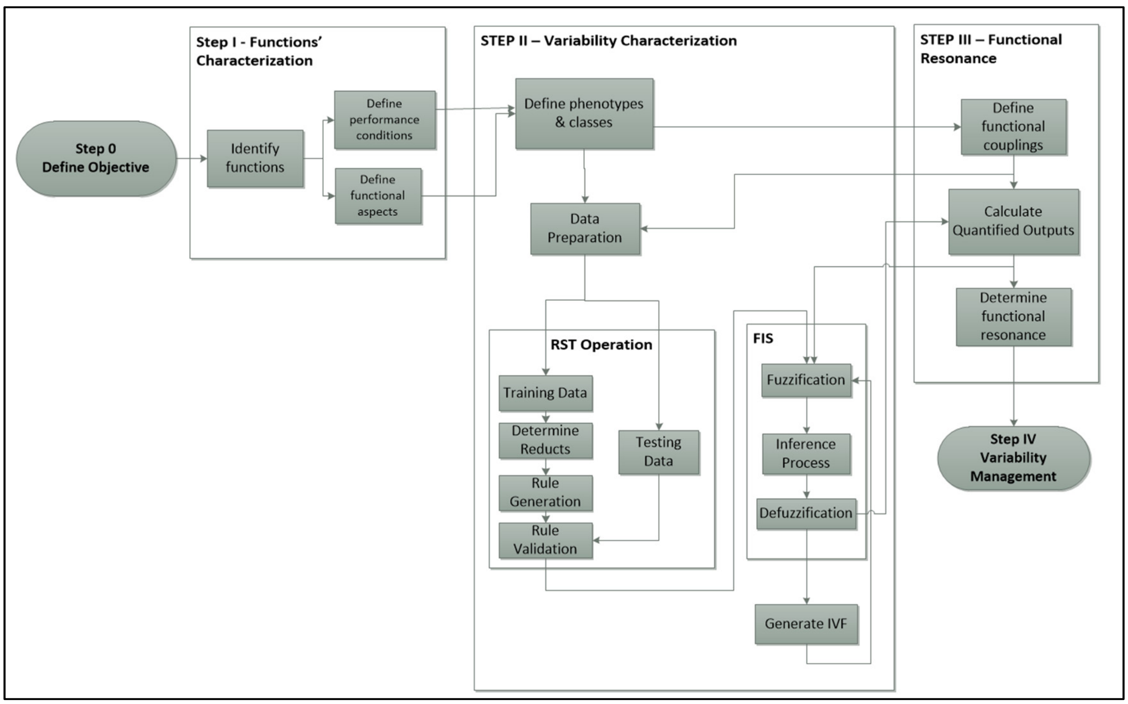

Figure 5.5 An overview of the modified FRAM framework.

5.4 Discussion

Realizing the significance and validity of the principles, on which FRAM was founded, there still existed uncertainty concerning its usefulness in the case of the SK751 crash. The official accident report published by the SHK in 1993 was used as the main source of information to construct the scenario for the simulation. The report provided a detailed list of all causes and circumstances leading to the accident. It is important to note here that the analysis scenario or the instantiation of the model is not the model itself. It can be seen as an iteration of the model with specific performance conditions and parameters. The accident was used as a case study to draw conclusions and identify implications for the context of aircraft deicing operations generally. The model can be reused with different settings and a different set of data inspired by or recorded in real-world environments. The main advantage is still presented in the principles of FRAM, which allow for looking at what went right in addition to what went wrong. The perspective presented by FRAM can provide interesting results, which can be helpful and complementary to traditional assessment tools. FRAM in its basic form relying on simple three-point qualitative scales can capture the dynamic and complex nature of the dominant relationships within the studied system. The FRAM framework provides a functional representation of the system, which enables the analyst to zoom in on processes and tasks of interest without losing the holistic view. The behavior of the system can be evaluated as a function of performance variability and local adjustments that can lead to unforeseen and unexpected deviations in the outcome. Performance variability i.e. the difference between Work-As-Imagined (WAI) and Work-As-Done (WAD) is an inherent characteristic of any given system, which can be utilized and exploited to maintain resilience. Relying solely on the accident report, the focus was entirely directed to what went wrong, which is understandable given that the event is an airplane crash. Nonetheless, the crash could have had a more severe and painful outcome and the actions of the flight crew lead to the survival of all passengers. Applying a SAFETY-II approach such as FRAM can help to better manage variability and predict adversity, which can be difficult to anticipate with classical tools. This is especially true in the case of highly reliable systems such as aviation, in which adverse events are very rare and unique by nature.

Speaking more specifically, the FRAM analysis of the SK751 crash provided a better understanding for the development of the accident over time and the relationships between several variables that lead to that outcome. The official accident report provided a detailed description of the events and aspects of the accident and presented a detailed list of findings describing the development of the accident. However, the data provided by the report was still limited and focused primarily on negative actions and performance conditions. The application of FRAM was helpful to connect the events and draw a map of the system and the dominant relationships that played a significant role in producing the outcome. The characterization of the system as a set of interdependent functions helped to identify the couplings between them and define how performance variability of one function affected the output of the other functions, even the indirectly linked ones. This would allow for pinpointing weak spots, which could be lifted or strengthened through preventative measures to better manage variability in the future. The application was limited and served simply as an example given that the accident report was not sufficient to determine how the influential factors effectively contributed to the accident. It was possible to identify variability in the execution of many functions; however, the extent and magnitude of each influential factor could not be easily determined using a simple three-class scale. Moving forward to a proactive assessment model, it would not be easy to determine how variable inputs would affect the performance of the functions and how variability of the output would manifest. For example, a "*too late*" input could be vague by default and could therefore mean either a "*too late*" output or an "*imprecise*" output.

Therefore, a quantified output would provide a more intersubjective and precise representation of the perceived magnitude of performance variability. Additionally, the provision of a standardized framework to account for variability would facilitate the classification of outputs more precisely. Moreover, it is not always possible in high-reliability systems to quantify certain complex variables without simplifying the systemic relationships and consequently sacrificing the systemic perspective. Furthermore, the lack of sufficient statistics due to the high reliability of those systems and the rarity and uniqueness of adverse events make the use of probabilistic tools difficult. The studied relationships are often vague and uncertain by nature and are therefore better represented with natural language, which can be utilized by fuzzy logic in the form of linguistic variables. The relationships between inputs and outputs can be characterized in a very comprehensible manner using conditional IF-THEN rules enabling the analyst to assign different weights to the inputs or the rules separately. By assigning a numerical scale or range of input values and determining the respective membership functions that better suit the function in question, a numerical output can be obtained providing an aggregated and comprehensible representation of the output's variability. The selection of a numerical scale and the partitioning are conducted in a relatively subjective manner since these domains are defined by the analyst or the consulted experts. However, they still provide a more comprehensible and agreeable representation to most practitioners and decision makers.

The designed fuzzy-FRAM model was applied in the second phase to analyze a case study inspired by two deicing related accidents, namely the SK751 crash in 1991 and the Mirabel accident in 1993. A more generic model of the deicing context was created for this simulation. The number of functions and their respective inputs and outputs was limited in comparison to the original model to ensure an efficient simulation easy on computational resources in this first step. The objective here was to perform a more predictive/proactive type of assessment using the assigned numerical scales and building on the initial characterization of functions, relationships and membership functions. Predictive studies lack certainty in comparison to retrospective studies, in which events are very well known and defined. It might not always be possible to determine the quality of output in a predictive assessment using natural language solely. This can be overcome through the integration of fuzzy logic into the framework of the classical FRAM. The analysis scenario was designed in a subjective manner relying on literature findings, technical reports and the knowledge gained from our years-long project on the deicing working environment. The defined functions described human (individual or organizational) activities that constitute the deicing context and the relationships and couplings that affect the system's performance on a wide scale. The preliminary results of the simulation in MATLAB were promising and the model served primarily as a demonstration for such an application. Given the predefined settings of the model, the calculation process of the numerical outcome was a straightforward task without the need to further hypothesize or assume possible outcomes. The FIS calculates the numerical output providing an indicator of functional variability and the dominant relationships between the different functions within the studied system. The aggregated output does not provide simply a linguistic label pinpointing the output as a member of a definite class; rather, it can be seen as a pointer to sources of positive or negative variability.

Another contribution of the second-phase model was the distinction between the internal and external variability of each function. The basic FRAM model does not present a clear approach to distinguish between the two in the characterization process, which is performed more qualitatively to maintain the complex nature of the described relationships. Considering just the functional couplings would mean in a practical sense the characterization of variability as an external source, even if this was not intended. The internal variability of the function itself was accounted for by the analyst when determining the quality of the output. This is due to the above-explained lack of distinction between the two types of variability, at least in a more practical sense of the word. Therefore, the impact of the inner mechanisms of the function on the output's quality was characterized relying on the Common Performance Conditions (CPC) (Originally proposed for CREAM) (Hollnagel, 1998). The CPC influence represents the influence of the context on the execution of the function, which can be considered an external source as well. However, it serves the purpose of providing indicators, which can point to possible internal variability that cannot be decoupled from external influences. As an example, consider the impact of noise on the hearing capabilities of an operator on the airport grounds. The noise can be characterized as an inadequate performance condition causing the operator to lose concentration or fail to hear instructions over the radio. The variability might be considered in this case an internal factor coming from the state of the operator (psychological or physiological); however, it was amplified by the inadequate conditions. On the other hand, preferable conditions could help avoid such variability or even enhance performance despite a poor physiological state of the operator.

The influence of the CPCs and the incoming aspects for each function on the quality of the output can be represented and weighted in the rule base of the FIS using natural language. However, one important limitation was faced in the design process of the model. The number of input variables and respective classes was kept low (maximum of seven inputs each with three possible classes) to avoid the rule explosion problem. The rule generation process for the Mamdani-type FIS (Mamdani & Assilian, 1975) would be very exhaustive if it were to be performed in a manual fashion, especially if a rule base would consist of thousands of rules. This simplification served the purpose of constructing a more efficient rule base to ensure a timely conclusion of the project and a feasible and less-demanding model. Moreover, the selection of the membership functions and partitioning of the universe of discourse is performed by the analyst in a relatively subjective manner. This would usually necessitate a deep understanding of the system's behavior and would require the knowledge of experts for more reliable and valid results. The same limitation faced with the basic FRAM model in classifying the final output was noticed again in the rule base classification for the consequent part. It was not always clear or sufficiently decisive to identify the class of output relying on qualitative scales. The incompleteness and vagueness of the input values would result in many cases in vagueness in the rule generation and classification. In our case, we used an automatic generator to compute every possible combination for the input values and the selection of the output for each rule was determined by assigning a numerical score or weight for the input classes in the antecedent part of each rule. The weights for the rules and the different functional aspects were kept the same to simplify the process further. Admittedly, this can be seen as a simplification of reality; however, the objective here in the first steps was to lay a theoretical foundation and provide a demonstration with the objective to move on later to an application built on real world settings and recorded data.

These considerations lead to a further modification of our model through the integration of Rough Set Theory (RST) (Pawlak, 1982). RST was integrated into the model as a tool for data mining and filtration, rule generation and output classification. A more efficient rule base was obtained consequently and migrated into the FIS of each function to compute the numerical outputs. The same deicing scenario was used again keeping identical characterizations and settings to better compare the results of both models. The obtained numerical scores using the RST-generated rule base were identical to the numbers of the initial model, which represents maximum accuracy (accuracy of 1.0) and an ideal outcome. Moreover, the generated rule base was significantly reduced in size in comparison to the previous model. This would translate into a less demanding and a more efficient model easier on computing machines for simulation. In addition to rule generation and reduction, RST could be useful in classifying outcomes. In the previous model using fuzzy logic, the classification of the consequent part of each rule was performed manually. In case of a high number of rules, this process would be extremely demanding and time consuming. We managed eventually to use excel formulae to generate the data tables and by assigning numerical scores to each class in the antecedent part, the decision class in the consequent part was determined. The integration of RST would take over this task and consequently allow for an automatic and efficient rule base construction. The decision class in the fuzzy-logic-based model might not be deducible for each rule separately and the rules' generation might be unfeasible in that case. RST can be helpful in this case by providing a method for deriving rules with decisions from a limited set of recorded data.

Admittedly, the use of ideal data sets covering all possible combinations of input values resulted in maximum accuracy. This would not be possible in a real-world application given that the provided input data would be imperfect and would suffer from inconsistencies. Therefore, the use of real-world data would be required to test how useful the RST-based model would be in practice. Nonetheless, in principle, this shows the validity of the RST approach to reduce data and generate minimal rule bases. The accuracy of the rule base in a real-world application would depend greatly on the quality and quantity of collected data. RST as a data-mining tool would allow for deriving decisions from recorded data over time in the presence of uncertain and vague information. The choice of uniform scores or weights for classes and input variables has to be reconsidered in real world applications. Depending on the nature of the function and the respective variables, the magnitude of each input value might differ and be unique to each variable. Furthermore, the implementation of RST would require additional effort and knowledge from the analyst. The model requires additional software, data acquisition tools and eventually a more complicated design process.

Traditional statistical methods are desirable in most cases; however, as mentioned in this paper several times, it can be difficult to generate adequate databases in complex and highly reliable systems. Such tools require large datasets to provide helpful results, which can be difficult to achieve given the scarcity and uniqueness of events in such systems. Tools as RST and fuzzy logic can be more helpful in such contexts through the provision of qualitative scales and the possibility to compute with natural language. The use of conditional rules is comprehensible and allows for a straightforward representation of the relationships between inputs and outputs.

RST is especially helpful in the data treatment process by allowing for deducing meaningful relationships even when faced with a limited set of data. A specific inaccuracy is still present in the provided results when using RST; however, that is just the case in predictive assessments generally and the results are still useful and more reliable than using plain heuristics for example.

Table 5.3 provides a qualitative comparison between the three models. The list is not limited to the mentioned points and summarizes the main factors that we found to be most relevant to our application scenarios.

Table 5.3 A short comparison and presentation of the advantages and disadvantages of each model.

Model	**Basic FRAM**	**Fuzzy FRAM**	**Rough-Fuzzy FRAM**
Advantages	• Four principles of FRAM • Allow to characterize complex relationships qualitatively • Use of simplified qualitative ordinal scales • Less demanding in comparison to modified approaches • Requires no additional software other than the FMV • Easier for conducting expert elicitation	• More intersubjective results • Quantified results • A more precise representation of the magnitude of variability • Allows for an easier predictive assessment • Provision of a more standardized approach to characterize internal and external variability	• Allows for a larger number of input variables and classes • Provision of reduced and more efficient rule bases • Data filtration and classification based on historical and archived data • Limited need to experts' input • Automatic generation of rules

Table 5.3 A short comparison and presentation of the advantages and disadvantages of each model (continued).

Model	Basic FRAM	Fuzzy FRAM	Rough-Fuzzy FRAM
Limitations	• More subjective results • Lack of a standardized framework for characterizing internal and external variability • Results can be vague (magnitude) or interpreted differently • Inability to determine output's class sometimes relying on simplified scales	• Limitation on the number of input variables and respective classes • Resource demanding: computing, additional software, data acquisition, time etc. • Requires additional knowledge and effort from the analyst • Subjective characterization of the universe of discourse, partitions, scales and weights.	• Requires additional effort from analyst and knowledge in three disciplines • Resource demanding: computing, additional software, data acquisition, time etc. • Less accuracy using real data (dependent on the quality of provided data) • Subjective partitioning and scale assignment

5.5 Conclusions

The objective in this paper was to provide a qualitative summary and a discussion of the main findings and challenges faced within our research project. The three frameworks of FRAM, fuzzy logic and rough sets were briefly discussed to provide context and clarify the advantages offered by these methods in resolving some of the issues facing safety management tools and to address some of the limitations yet to overcome. Technological advancements such as the imminent implementation of Industry 4.0 into the majority of industrial contexts will inevitably add to the complexity of systems. Classical models originating from the era before digital technology have not been updated or kept pace with technological innovations over time. The adoption of a more complex and systemic perspective has become a requirement to be well equipped for the continuous changing and dynamic nature of modern systems. The human component in this context is a major contributor to success or failure. Technological systems have been evolving and advancing in recent years at a faster pace than regulations and guidelines, which makes the proposition of adequate solutions even more vital. FRAM as a systemic analysis tool allows for capturing complex relationships to construct a functional map of the system and identify the routes for negative and positive propagation of performance variability. Fuzzy logic combined with FRAM facilitates the quantification of natural language and provides a more systematic approach to account for variability. Finally, rough sets offer efficient algorithms to classify input data and generate reduced rule bases. These tools should by no means simply replace traditional and well-established tools. However, they can serve the purpose of complementing the classical tools to provide a more comprehensive and complete picture of the modern systems of today (Melanson & Nadeau, 2016).

The initial results within this project are very promising and provide a good start to initiate further research work investigating further possibilities and improvements. The model at this stage is still a simulation and a simplification of reality and from a technology-readiness perspective is still in the theoretical development phase (TRL 4 – Technology development and validation in simulated environments). The purpose so far in this project was still to present an alternative approach for integrating a quantification method into FRAM without losing its properties and significant advantages in handling complex systems. The provision of sufficient real-world data and representative performance indicators to facilitate analyses of the deicing system is still lacking and can be possibly helped by rough sets. Future studies would be required to provide validation and optimization through the deployment of the model in a real-world setting using real data. Additionally, the application of the model into new contexts and analysis scenarios could provide more insights to further improve the proposed framework.

CONCLUSION

Modern sociotechnical systems are complex structures, in which the human aspect is the main contributor and driver of success. This realization in risk and safety management requires a reconsideration of the followed analysis methods to provide better representative results of the behavior of such systems. In this aspect, the working environment of aircraft deicing operations is no different. The majority of tasks in deicing operations relies mainly on the human factor from start until takeoff, whether in the inspection phase at the gate, or during the deicing operation itself or in the post-operation inspections. However, the majority of published studies and reports, which were reviewed within this project, were found to focus on the technical and operational aspects of the system in place. With the exception of our research team, studies focusing on the human factor and adopting a systemic perspective were very rare and mostly non-existent to the best of our knowledge. As explained within this thesis, the working environment of aircraft deicing is a very complex and dynamic one. While it is true that the procedures are carried out reliably and operational research in recent years lead to the implementation of strict safety measures, it is still required to evaluate and advance along with the changing surrounding context, whether within the aviation field or beyond. Modern sociotechnical inevitably evolve and gain on complexity. The continuous introduction of novel technologies, expansion of the systems and rise of human-machine interconnectivity necessitate that even highly reliable systems are adjusted and further improved. As a consequence of the high levels of security, safety and reliability in such systems, the incidents that could slip through safety barriers and emerge would have to be complex necessarily with severe outcomes, since the established tools accounted for the largest proportion of simple errors and events that could possibly happen making these systems as reliable as they are. Therefore, novel techniques are required to enable looking at the system in place from different angles of view to uncover loopholes, from which adversity might arise. Technological and economic growth should be accompanied by an advancement in safety management as well as an imperative aspect of productivity.

To achieve this, the classical and well-established tools that adopt mainly a simple-system approach, while necessary, are not sufficient. Due to the complex nature of the newly emerged systems, novel and more innovative approaches become necessary to compliment the traditional methods and cover the full spectrum of adversity as much as possible. The recently emerging field of Resilience Engineering offers new insights and presents a new way of looking at what constitutes safety and adequate performance. Creating resilient and adaptive systems that are capable of maintaining outcomes within tolerable margins when faced with disturbances and performance fluctuations can add to the levels of safety and ensure that such systems continue to perform as designed and expected. FRAM as the main tool in the arsenal of Resilience Engineering provides a powerful and useful framework to compliment traditional methods. By considering various complex factors and providing a functional representation of the system at hand, it allows for analyzing complex and dynamic relationships and dependencies among the different sections or parts of the system. In contrast to the traditional view of SAFETY-I, FRAM adopts a SAFETY-II approach focusing on what goes right in addition to what could go wrong. The probability for adverse and failed outcomes is by far less than successful ones, especially in highly reliable systems such as aviation. The uniqueness of accidents in such systems leads to a scarcity of data and statistics and makes generalizations to other contexts more difficult. By focusing on what goes right, the performance conditions that ensure successful outcomes can be maintained to create resilient systems.

The working environment was modelled, and FRAM was used initially in a retrospective manner as an accident analysis tool using the crash of SK751 as a case study. In its basic form, it was possible to draw conclusions and link the events to provide a better understanding for the dominant relationships and the evolution of the accident. However, moving forward to a more generic and proactive model was found to be more demanding. FRAM provides a basic conceptual framework for achieving the above-described objectives. It lacks a standardized and systematic methodology to precisely account for variability, distinguish between the different types of variability and weight the different aspects and influential conditions. By relying on qualitative linguistic scales, the characterization of complex relationships becomes possible in contract to quantitative measures. However, there exists accordingly a difference in perception for the produced values as well, which can be resolved through quantification to provide more intersubjective results. It would be difficult to quantify such variables given their complex nature without sacrificing the advantages offered by FRAM. Fuzzy logic as a capable tool of computing with natural language was used to resolve this issue and provide quantified outputs. The deicing context was remodeled creating a more generic scenario than the previous one. Fuzzy logic enabled the construction of rule bases to define the relationships between inputs and outputs for each function. The rule base using natural language facilitated the assignment of different weights to the functional aspects and performance conditions. In our model, for simplicity reasons, we maintained same weights for performance conditions and functional aspects, since the main objective was to provide a theoretical foundation and a demonstration for modelling and running such a simulation. The rule base written in natural language resembles human reasoning and judgement and would therefore present more comprehensive results.

The model combining fuzzy logic and FRAM was still limited in several aspects. The integration of fuzzy logic into FRAM did not go smoothly and the proposed model was faced with several limitations. The design of an FIS model of FRAM relied mainly on the subjective judgement of the analyst. The selection of a range of values, the partitioning of the universe of discourse and the selection of the membership functions were all done subjectively, which is not unusual. Secondly, it was not always possible to determine the outcome for each rule using natural language solely. The used approach for the assignment of values to the antecedent part was a simplified representation. The outcome of the function can be often vague by default and it would not be possible to determine how the variability of the output would be manifested in reality in a predictive analysis. The variables serving as inputs were in many cases vague by nature, which made reaching a decision for the respective rules difficult. Additionally, the number of input variables was kept low to construct a more feasible model. The generation process of a rule base accounting for all possible combinations of input values resulted in some cases in large rule bases consisting of thousands of rules. The expert elicitation process was found consequently unfeasible and would not have been possible within the timeframe of this project. In the presence of a high number of input variables and their respective classes, the rules explosion problem forced us to limit the number of input variables to seven inputs. A higher number was of course possible; however, this would have resulted in an exhaustive and inefficient rule generation process. Additionally, the required computing resources would have been significant for the simulation. While going higher with the number of inputs would be possible, the required effort and resources in that case would make the model demanding and possibly not useful for practical applications, if efficiency was the main concern. The number of the produced rules would be immense. Moreover, faced with a scarcity of data and statistics, the construction of such rule bases could become more difficult. Therefore, the possibility to implement an additional tool to provide a possible solution to these limitations was explored in the third phase of this project. The RST method equipped the designed model with the means to classify large datasets, which could be possibly gained through field observations and historical data. The human input would be limited here to the data collection process and the characterization of the analysis model. The rule generation and classification processes will happen automatically. The RST method facilitated the construction of reduced and more efficient rule bases as well. The modified model was applied to the same case study as in the previous phase maintaining the same settings and characterizations to allow for a better comparison. The generated numerical outputs were identical to the ones received in the fuzzy FRAM model. The generated rules were reduced significantly in size maintaining the same accuracy and requiring much fewer computing resources and human effort.

The proposed models are admittedly simplified in many aspects, as is the case with theoretical studies. From a technology-readiness perspective, this model still requires further optimization and several applications into real-world settings using real data. The main objective here was to lay the foundation for such an approach and illustrate an application scenario. Specifically, the usefulness and requirement to adopt a new systemic perspective was rationalized and demonstrated. Through the combination of FRAM with fuzzy logic and rough sets, a new perspective on the subject of complex system analysis can be presented and new complementary methods added to the set of classical analysis tools. The applications of fuzzy logic and RST are promising and should be further investigated in future studies in the field of safety and risk management. These tools offer many advantages when it comes to quantification of natural language and data classification. Research conducted for the analysis of deicing/anti-icing operations is generally rare, especially from a human factors and systemic perspective. Therefore, we hope that this project revealed new results and provided some insights, which might reflect positively on the economic, technological, and organizational aspects of the deicing industry and beyond. The improved method should assist in enhancing performance, safety measures and minimizing risks to provide better aircraft ground deicing/anti-icing operations and better protection for humans and machines. Finally, it is hoped that the findings of this study may contribute to the field of safety and risk management in the years to come and open the door for further projects and studies in the future.

RECOMMENDATIONS

The results of this study revealed several new findings that could offer many benefits and advantages to both the industrial and research communities. The new findings could be addressed in future studies to provide more optimized and reliable models adopting the used techniques within this project. Additionally, several limitations that were identified for each application could be addressed to offer better or alternative solutions. The following recommendations summarize the main areas that we think should be addressed in future research projects:

- At first, the applications presented within this project were simulations. A step forward would be achieved through an application of the proposed approach in the real world. A real-world application should verify the usefulness and efficacy of the proposed model. Additionally, applications into other environments and system-types other than deicing could help generalize and validate the findings of this study.
- The characterization of the functions for the deicing model was performed relying mainly on literature findings and technical reports. This could be done in a more realistic manner through field observations and expert elicitation to construct and characterize more reality-representative functions. Field observations could focus on defining the boundaries of the functions and their characteristics and inner mechanisms to gain a better understanding for how they function. To this end, surveys and questionnaires can be used to elicit knowledge from experts, managers and operators.
- The list of the CPC was chosen as a representation of the contextual influence on the execution of the FRAM functions. The CPC is a more generic list presenting a generalized view on performance shaping factors. To provide more representative results, the identification of a more detailed list of performance conditions specific to the evaluated context could be addressed. Literature on human reliability assessment and performance shaping factors should be reviewed to compile a more representative list for the defined objective of the analysis. Expert and experienced operators' input is

valuable as well and should help to identify which factors are most influential for the set of functions.

- Generally, the provided data for constructing the analysis model was limited, which made the whole process more challenging. The provision of more data to help identify influential factors and characterize the system more appropriately would allow for a better representation of the system and consequently better results. This would require recording data over time and gaining access to enterprises, organizations, and locations to compile a significant data set.
- The application of fuzzy logic within FRAM was accompanied with several challenges that made the realization of the model more demanding. Many limitations were addressed with RST in the third phase of the project. Alternative solutions could be explored through the combination of FRAM and fuzzy logic with other techniques as well that could lift the identified limitations here. Such techniques can stem from probabilistic approaches such as the Monte Carlo Simulation, and Bayesian networks or other tools such as neural networks and so on.
- Furthermore, the applications here simplified several aspects of the characterization process for running a smooth simulation and save time. While this might have been required for a first step to run this prototype, it would be advisable to address these simplifications in future studies and projects. These simplifications concern the assignment of weights to the different aspects of functions and performance conditions in relation to each function, the selection of the membership functions and partitions of the universe of discourse, the exploration of alternative fuzzy operations for implication, aggregation and defuzzification etc.
- The RST approach utilized the same ideal data sets generated for the second phase by an automatic generator covering all possible combinations of input values. An application using gathered real world data could be aspired here to verify the usefulness of the RST approach for the purposes used in this study. A real-world data set would consist of incomplete data, inconsistent entries, and missing values, which would present a bigger challenge for the model. A real-world data could therefore produce

less accurate results, if the quality of obtained field data was insufficient or of low quality.

- Additionally, the use of other optimized search algorithms can be explored to compute the reducts and generate the reduced rule bases. This could lead to the improvement of the reliability of the model and allow for a more representative and accurate classification with RST.
- To the best of our knowledge, the applications of fuzzy logic and rough sets in the field of safety management have been limited so far. These tools offer many advantages that could help analysts overcome many of the above-discussed limitations. The leap from theoretical studies into more practical projects is needed to provide more reliable techniques and tools. Additionally, FRAM and the discipline of Resilience Engineering generally offer interesting insights and alternative ways to achieve required levels of safety and productivity. To the best of our knowledge, the discipline has not been extensively utilized in North America so far. This could be addressed more extensively as well in future studies to explore possible benefits and advantages provided by this newly emerging discipline.

ANNEX I

FRAM: A COMPLEX SYSTEM'S APPROACH FOR THE EVALUATION OF AIRCRAFT ON-GROUND DEICING OPERATIONS

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Abstract. Proper aircraft on-ground deicing operations are critical for the safety of aviation. The complex work environment of deicing operations requires continuous performance adjustments to cope with the dynamic work conditions. This study aims at presenting a new approach by examining the applicability of the Functional Resonance Analysis Method (FRAM) to evaluate performance in aircraft on-ground deicing operations and related issues that might endanger flight safety. To achieve this purpose, the deicing socio-technical system was modeled to analyze the SAS flight 751 crash at Gottröra in 1991 and show how safety issues can arise through the combination and overlapping of functional variability. The results demonstrate the usefulness of FRAM as an additional tool that can be applied in a complementary way with the existing methods.

Keywords: risk, safety, deicing, assessment, aviation, functional resonance analysis

1. Introduction:

The "*Clean Aircraft Concept*" requires the removal of any ice, frost or snow contaminants from the aircraft surfaces prior to takeoff (Transport Canada 2004). The execution of aircraft deicing operations occurs in a complex working environment under very dynamic conditions.

The sociotechnical system of deicing operations is characterized, among other factors, by tight time schedules, extreme weather conditions, work overload and stress, etc. (Transport Canada 2004). Such factors affect the capabilities of deicing workers and might degrade their performance significantly. Accordingly, performance adjustments are continuously necessary to provide adequate operations as required by procedures and regulations. Despite the significance of deicing operations to aviation safety, research has been rarely conducted to analyze performance-degrading factors from a human factors perspective. Traditional safety assessment methods and investigation tools focus primarily on identifying errors, singular events or failures of systemic components (Leveson 2009). Classical approaches are not sufficient to provide a complete and comprehensive analysis of modern sociotechnical systems (Leveson 2009). Many issues in the applications of aircraft deicing procedures arise due to the complexity of the deicing operations and the context, in which they are performed. The main objective of this study is to examine the applicability of a new approach, namely the Functional Resonance Analysis Method (FRAM) (Hollnagel 2012), to evaluate performance in deicing operations and possibly resulting safety issues. Therefore, the context of deicing operations was modeled to analyze a case study, which should demonstrate the applicability and advantages of FRAM. As a scenario for analysis, the crash of the SAS flight 751 at Gottröra, Sweden, in 1991 was selected. The interesting aspect about this accident is that it happened despite the efforts of the flight crew and deicing technicians to clean the aircraft. It presents a suitable case to demonstrate how accidents can result from routine performance adjustments and the combination of variability in the execution of required tasks. The FRAM analysis considering the contextual conditions shall explain the gradual development of the accident through the overlapping of functional variability within the deicing sociotechnical system. The analysis thus will provide a new perspective to understand how accidents come to happen rather than simply providing a list or sequence of mistakes and failures as causes.

2. Scandinavian Airlines Flight 751:

On December 27, 1991, an aircraft of Scandinavian Airlines (SAS) of type DC-9-81 took off at 08:47 hrs. at Stockholm/Arlanda and crashed four minutes and seven seconds later in a field in Gottröra. The aircraft had arrived the night before at 22:09 hrs. coming from Zurich and was scheduled to fly to Copenhagen in the morning. It cruised for approx. one hour and forty minutes at altitudes with outside temperatures between -53°C and -62°C and landed with 2550 kg of cold fuel remaining in each wing tank, which represents 60% of the tank's capacity. The aircraft was parked outdoors at gate 2 at the international terminal during the night. The weather conditions during the night and in the morning before take-off were ideal for clear ice formation (Temperature between -0°C and +1°C) (SHK 1993).

A flight technician inspected the aircraft during the night and noted that clear ice has formed on the wings. In the morning, the mechanic noted the formation of frost on the wings' undersides. The formation of rime on the lower surfaces was a clear indicator that clear ice might have formed on the upper surfaces. The mechanic climbed the ladder, put his knee on the wings' leading edge and checked the upper side of the left wing near the fuselage. The mechanic concluded wrongly that there was no clear ice formation. The Pilot In Command (PIC) was fully responsible for ensuring that deicing has been performed adequately and that the "*Clean Aircraft Concept*" was maintained. The technical division was responsible for the deicing application and inspecting that it was done adequately. The technical division issued during the year bulletins and provided training to prepare personnel for the winter season. Each mechanic was provided with a checklist, which required that a tactile inspection must be performed to check the wings' upper surfaces for clear ice. The provided instructions did not specify how the inspection was to be performed exactly, how to remove clear ice and how to report to the PIC. The means provided to the mechanic did not allow him to reach the area, where the clear ice really formed. The mechanic should have climbed onto the wing completely to check all spots carefully and thoroughly. The wing's slippery condition did not allow such a practice to take place. The mechanic consulted with the PIC and requested deicing for both upper and lower sides of the wings. The aircraft was filled with additional 1400 kg of fuel and was ready at 08:30 hrs. for deicing. A total of 850 liter of heated deicing fluid type I at 85°C was applied for deicing. The upper wings' sides were deiced again after a first spraying to ensure a full removal of slush and snow. The mechanic did not check again after deicing for clear ice, since he assumed there was no clear ice present and the instructions did not require doing so. The deicing technician operating the spray nozzle reported "*he saw that one of the* *four indication tufts fixed on the upper side of each wing moved during spraying*". A passenger sitting at the window during the deicing operation contradicted that story and reported that the tufts did not move. The mechanic informed the PIC that deicing was finished and the aircraft was clean and "*perfect*". The aircraft was taxied afterwards to runway 08 for takeoff (SHK 1993).

The risk of clear ice formation and ingestion by the engines was common to this aircraft type due to the aircraft design and configuration of the wing tanks. This issue was known to SAS and it was covered in internal information and bulletins. However, the training of the MD-80 pilots did not deal with the issue of clear ice and there were no special instructions for the pilots on how to act in case of clear ice risk. The technical staff was familiar with the issue of clear ice through training and the Line Maintenance Handbook (LMH) required inspecting the wings' upper surfaces tactually in case of doubt of clear ice formation. However, the LMH lacked detailed instructions on how to perform the clear ice inspection and report observations of clear ice. The technical staff lacked as well special tools and means to reach the clear ice area on the upper side of the wing without endangering their personal safety (SHK 1993).

3. Methodology:

The Functional Resonance Analysis Method (FRAM) will be applied to analyze the deicing operation and departure procedure for flight SK751. The distinction about FRAM is its ability to describe adverse outcomes as a result of the combinations of functional variability (Hollnagel 2012). FRAM relies on four principles: equivalence of success and failure, approximate adjustments, emergence of failures and functional resonance (Hollnagel 2012). The first step is to identify and characterize the functions to construct a FRAM model for the deicing operation and takeoff process of SK751. FRAM functions are characterized by six aspects: Input (I), Output (O), Preconditions (P), Resources (R), Time (T), and Control (C) (Hollnagel 2012). Each function is described in the form of a table listing all its characteristics. The data to construct the model was obtained mainly from the official accident report published by the Board of Accident Investigation (SHK) in 1993. The analysis will be limited to the deicing and departure procedures until takeoff. Past takeoff, events are beyond the scope of this study. There are three types of functions: organizational, technological and human functions. Secondly, the sources of variability within the constructed model are to be determined and characterized. Variability is characterized in terms of timing (early, on time, too late and omission) and precision (imprecise, acceptable and precise) (Hollnagel 2012). Finally, the third step is to determine how that variability combined and resonated to eventually lead to the crash (For further information on FRAM, please consult the website: http://www.functionalresonance.com).

4. Results:

The governmental agency STK did not follow up on their supervision duties after assigning a new technical representative at Arlanda and "*assumed*" that the clear ice problem "*was being well taken care of through SAS' own checks*" (SHK 1993). The control aspect provided by the function "*Regulations & Supervision*" was "*imprecise*" and influenced the performance of the SAS functions "*Provide Instructions & Guidelines*", "*Provide Training*" and "*Provide Resources & Equipment*". The instructions and guidelines provided by SAS were found "*inadequate to ensure that clear ice was removed*" (SHK 1993).

Table 1. The list of the FRAM functions with respective outputs and variability

Function	***Output***	***Variability***
Landing in Stockholm/Arlanda	Park aircraft at gate 2	
Overnight Inspection	Report results of inspection	
	Ensure aircraft adequate condition	Imprecise
Review Meteorological Data	Provide meteorological data	
Provide Training	Provide training & competence	Imprecise
Pre-Flight Planning	Provide planning	
	Provide Time	
	Provide flight release document	
Provide Instructions & Guidelines	Provide operational instructions & guidelines	Imprecise
Provide Resources & Equipment	Provide appropriate resources & Equipment	Imprecise

Table 1. The list of the FRAM functions with respective outputs and variability (continued).

Function	***Output***	***Variability***
Regulations & Supervision	Provide supervision & organizational guidelines	Imprecise
Civil Aviation Authority Control	Provide supervisory bodies to control SAS operations	
Provide Aircraft Information	Provide technical & operational information	
Facilities & Maintenance	Provide adequate facilities	Imprecise & too late
Prepare Aircraft for Departure	Aircraft ready for departure	Imprecise
ATC Clearances	Provide clearance for deicing	
	Provide taxi clearance	Imprecise
	Provide taxi time	Too late
	Provide takeoff clearance	
	Provide takeoff time	
Pre-Deicing Inspection	One-step procedure	Imprecise
	Two-step procedure	
	No deicing required	
Deicing	Perform deicing	Imprecise
Post Deicing Inspection	Aircraft is clean	Imprecise
	Aircraft is not clean	
Anti-Icing	Perform anti-icing	
Taxi Briefing/Checklist	Provide taxi briefing & checklist	
Taxi to Runway	Ready for takeoff	
Pre-Takeoff Inspection/Checklist	Provide pre-takeoff inspections & checklist	Imprecise
	Takeoff if within HOT & aircraft is clean	
	Return to gate if HOT is exceeded or aircraft is not clean	
Takeoff		Imprecise & too late

The clear ice issue was not mentioned in the training documents for the MD-80 pilots. The equipment for aircraft inspection was inadequate and did not facilitate the on-wing tactile inspection. The function "*Overnight Inspection*" received an imprecise control aspect provided by the function "*Provide Instructions & Guidelines*". The instructions did not require the flight technician to report his detection of clear ice during the overnight inspection to the mechanic responsible for deicing. The function "*Pre-Deicing Inspection*" received an imprecise control aspect provided by the function "*Provide Instructions & Guidelines*", an imprecise precondition by the function "*Training*" and an imprecise resources aspect by the function "*Provide Resources & Equipment*". The PIC did not ask about clear ice during the conversation with the mechanic. The mechanic performed an inadequate inspection by climbing the ladder and only checking the forward part of the left wing with his hand and the air inlet of the left engine. The function "*Deicing*" received imprecise control aspects provided by the functions "*Provide Instructions & Guidelines*" and "*Post Deicing Inspection*", an imprecise precondition by the function "*Training*" and imprecise inputs by the functions "*Pre-Deicing Inspection*". The deicing application failed to remove the clear ice at the roots of the wings. The deicing technician saw one indication tuft moving out of four and did not report further his observation. The function "*Post Deicing Inspection*" received an imprecise control aspect provided by the function "*Provide Instructions & Guidelines*", an imprecise precondition by the function "*Training*", an imprecise resources aspect by the function "*Provide Resources & Equipment*" and an imprecise input by the function "*Deicing*". The mechanic did not inspect the wings again after deicing for clear ice since he assumed none existed. The function "*Prepare Aircraft for Departure*" received an imprecise control aspect provided by the function "*Provide Instructions & Guidelines*" and an imprecise input by the function "*Overnight Inspection*". The air intakes of the aircraft engines were not covered during the night as required. The function "*ATC Clearances*" received an imprecise and late input by the function "*Facilities & Maintenance*". The aircraft departure was delayed and the aircraft crossed a strip of slush while taxiing out. The function "*Taxi to Runway*" received an imprecise and late resources aspect by the function "*Facilities & Maintenance*" and imprecise preconditions by the functions "*Post Deicing Inspection*" and "*Prepare Aircraft for Departure*". The aircraft taxied eventually with clear ice on the wings without adequate inspection of the aircraft surfaces or protecting the engine inlets from slush. The function "*Pre-Takeoff Inspection/Checklist*" received an imprecise control aspect provided by the function "*Provide Instructions & Guidelines*". The aircraft was assumed clean and a rolling takeoff was performed. No further inspection of the wings was performed. The function "*Take-Off*" received an imprecise and late input by the function "*Taxi to Runway*" and imprecise precondition by the function "*Pre-Takeoff Inspection/Checklist*". The result was an inadequate takeoff with contaminated surfaces.

5. Discussion & Conclusions:

The official accident report published by the SHK in 1993 stated that "*the accident was caused by SAS' instructions and routines being inadequate to ensure that clear ice was removed from the wings of the aircraft prior to takeoff*" (SHK 1993). The aircraft was inspected and deiced prior to takeoff and the inspection failed to detect the existence of clear ice. Clear ice can form on chilled wings under conditions of high humidity or precipitation. The primary concern about clear ice is the difficulty to detect it on the aircraft surfaces. Tests under realistic environmental conditions have shown that humans were not able by visual inspection to detect ice sheets less than 0.8 mm and complete ice films less than 1mm on white surfaces (Sierra et al. 2006). The visual inspection in case of clear ice would not be sufficient and a thorough tactile inspection is far more effective and becomes necessary (Sierra et al. 2006). Performed usually by deicing technicians, the tactile inspection is accomplished by sweeping the palm of the hand on the aircraft surfaces and using the tips of their fingers for a more in-depth checking (Eyre 2002). The environmental and work conditions present at the times of the pre-deicing and post-deicing inspections can affect the performance of the workers adversely. The degree of effectiveness and aspects of aircraft tactile and visual inspections for ice, snow and frost should be addressed in more in-depth studies to provide more effective inspection procedures.

The results of the FRAM analysis in this study provided a better understanding for the development of the accident as a result of the combinations of functional variability. The scope of this paper does not allow going further into all details of the analysis. Additionally, the data provided for this analysis was limited, since this study is conducted many years after the accident and it only depended on the information provided by the SHK accident report. The accident report provided a thorough investigation listing all findings and conclusions about the reasons that lead to the accident. The application of the FRAM analysis is beneficial through the provision of a new perspective on the conditions and circumstances before and at the time of the accident. To clarify, in addition to the inadequate SAS instructions, the analysis linked other events as well through the functional couplings to the accident such as the overnight inspection (leaving the engines' inlets uncovered) and the airport facilities (slush strip crossing during taxi). Relying exclusively on the accident report, it is not possible to determine how effectively those factors contributed to the accident. Nonetheless, to learn lessons for better performance and outcomes, those sources of potential variability were addressed, which would consequently enable a better variability management.

6. References

Eyre F.W (2002) Tactile inspection for detection of ice on aircraft surfaces – notes on current practice. Transports Canada, Report No. TP 13858E, 2002. Accessed November 1, 2017. http://bibvir2.uqac.ca/archivage/17100950.pdf.

Hollnagel E (2012) FRAM, the functional resonance analysis method: modelling complex socio-technical systems. Ashgate Publishing, Ltd.

Leveson N (2011) Engineering a safer world: Systems thinking applied to safety. MIT Press.

SHK, Swedish Board of Accident Investigation (1993) Report C 1993:57 Air Traffic Accident on 27 December 1991 at Gottröra, AB county Case L-124/91. Stockholm, Sweden. Accessed November 1, 2017. http://www.havkom.se/assets/reports/English/C1993_57e_Gottrora.pdf.

Sierra E. A. Jr., Bender K., Marcil I., D'Avirro J., Pugacz E. et Eyre F. (2006) Human Visual and Tactile Ice Detection Capabilities under Aircraft Post Deicing Conditions, DOT/FAA/TC-06/21. Accessed November 1, 2017. http://www.tc.faa.gov/its/worldpac/techrpt/tc06-21.pdf.

Transport Canada. (2004). TP 10643E - When in Doubt... Small and Large Aircraft- Aircraft Critical Surface Training for Aircrew and Ground crew. 7th Edition. 138 pages. Accessed November 1, 2017. http://www.tc.gc.ca/Publications/en/tp10643/pdf/hr/tp10643e.pdf

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ANNEX II

THE APPLICATION OF ROUGH SETS THEORY AS A DATA-MINING TOOL TO CLASSIFY COMPLEX FUNCTIONS IN SAFETY MANAGEMENT

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Abstract. In recent years, considerable research efforts in safety management were directed at proposing innovative methodological frameworks to address the complexity of modern sociotechnical systems. The significance of results in such endeavors, whether quantitative or qualitative, relies largely on the quality of input data and the validity of the implemented methods to model such systems. To provide more objective and valid results, new protocols and tools for data processing are needed as well. An interesting data-mining tool for computing with incomplete and uncertain information is Rough Set Theory (RST). In this study, we propose the application of RST to generate comprehensible IF-THEN rule bases for classifying outcomes within the framework of the Functional Resonance Analysis Method (FRAM). The steps for the integration process of both frameworks are introduced in this paper and an illustrative example is consequently provided to demonstrate a possible approach for realizing the combination. Such an approach could allow for an efficient rule generation and data classification process, which could aid in addressing classification challenges and input data limitations in safety management. The model however still requires further optimization and validation using expert's input data in future applications.

Keywords: FRAM, rough sets, safety management, sociotechnical system, functional resonance, decision making

1. Introduction:

Technology in recent years has been making huge leaps and several game-changing applications were introduced lately reshaping how systems function and behave. This evolution can pose challenges for system analysis and safety management in the years to come. The field of safety management in recent years has been witnessing significant research efforts as well emphasizing the need to adopt additional perspectives. Consequently, innovative tools such as the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2004) were introduced to address the objectives of safety analysis from a new systemic perspective. FRAM, as a resilience engineering tool, adopts new concepts for redefining safety such as SAFETY-II and the distinction between work as imagined (WAI) and work as done (WAD). Performance variability in FRAM is a natural characteristic of any sociotechnical system and is even considered necessary and beneficial. The principles of FRAM allow for characterizing complex and dynamic relationships using qualitative scales expressed in natural language. However, several limitations can be observed in such analyses such as lack of data, uncertain information, and classification problems. Therefore, the adoption and standardization of such innovative tools is faced with many challenges, which require further research to provide more representative and reliable results.

In our project, we directed our efforts at exploring new approaches to address safety and performance challenges in the field of aircraft deicing. To this end, we applied the Functional Resonance Analysis Method (FRAM) at a previous stage in conjunction with fuzzy logic. The objective thereby was to introduce a systematic methodology to account for internal variability considering present performance conditions and generate a quantified and more precise representation of the output's variability. The prototyping model was however still faced with several limitations. The application with a high number of variables, associated phenotypes and classes translated into a significant number of rules. To avoid the rules' explosion problem and construct an efficient model, the number of variables and associated classes was limited, and the impact of the phenotypes was simplified. Additionally, the consequent part or the decision class was not always easily identifiable using qualitative scales. The vagueness of the provided input information could affect the decision-making process and make the assignment of a decision class a difficult task to achieve in many cases. In a predictive assessment, it would not be always possible using a qualitative scale to determine whether the output would be variable and to which extent. Differences between expert judgements to conclude a definitive decision can often be faced in such assessments. Therefore, we aimed in the next step at proposing a possible solution to address these limitations. In the third phase of this project, we proposed the application of Rough Sets Theory (RST) as a data-mining tool to generate a more efficient rule base and classify outcome relying on historical and recorded data. The integration process shall be presented in a simplified way in this paper.

2. Rough Set Theory (RST):

The concept of Rough Sets was introduced by Zdzislaw Pawlak in 1982 (Pawlak, 1982). RST provides mathematical tools for processing imperfect information, classify data sets, and generate comprehensible conditional rules in the presence of uncertainty, inconsistency and incompleteness of information. The RST approach has proven to be helpful so far in solving problems of data mining and classification in several fields such as machine learning, decision analysis, expert systems, and pattern recognition. It can therefore offer promising solutions in the field of safety management generally and specifically to recently emerging concepts and tools such as FRAM and the discipline of Resilience Engineering. Complex analysis tools as FRAM rely mainly on natural language to characterize variables in question, for which RST could be helpful. The generated rules are easily understandable and offer a straightforward interpretation of the obtained outcomes.

An information system (IS) in RST is a two-dimensional matrix or data table consisting of a pair of sets (U, A), namely a finite non-empty set of objects (U) and a finite non-empty set of attributes (A) so that: $a: U \rightarrow V_a$ for every $a \in A$, where V_a is the value set of ***a*** with respect to each object (U). A decision system (DS) consists accordingly of the IS adding a decision set D ($d \notin A$) such that $DS = (U, A \cup (D))$.

Table 1. A decision system in RST

Set of Objects U	Set of Attributes A				Decision D
	A_1	A_2	.....	A_n	
U_1	V_{11}	V_{12}	.....	V_{1n}	D_1
U_2	V_{21}	V_{22}	.....	V_{2n}	D_2
U_3	V_{31}	V_{32}	.....	V_{3n}	D_3
.....	......	......	.....	......	.....
U_m	V_{m1}	V_{m2}	.....	V_{mn}	D_m

A rough set has a boundary region, which contains objects that cannot be classified with certainty as members of the set or of its complement. This means that the available information is not sufficient to definitively classify these elements. In RST, any set of objects is replaced by a pair of precise sets, called the lower and the upper approximations. The lower approximation consists of all objects that are certain members of the original set, and the upper approximation contains all objects that could possibly belong to the original set (Pawlak, 1982). The difference between the upper and the lower approximation constitutes the boundary region. Approximations are two basic operations in rough set theory. The principle of indiscernibility forms the basis, which is utilized to identify equivalence classes. The indiscernibility relation is a binary relation, which represents the sets of objects for which a decision cannot be discerned given a specific array of values of the attributes. The set of indiscernible objects form an equivalence class. A discernibility matrix is then constructed for the equivalence classes to determine the respective discernibility functions and reducts. To this end, efficient algorithms can be utilized for identifying hidden patterns in data tables to produce minimal sets of data (data reduction), evaluating the significance of data, and generating representative sets of decision rules.

3. Proposed Approach: Rough FRAM

To integrate RST with FRAM, the FRAM function would be redefined as an RST decision system in the form of a table consisting of objects, which represent the many iterations of the function recorded over time, and the set of respective attributes, which would then represent the functional aspects as defined in FRAM. The values assigned to the objects with regard to each attribute would therefore consist of the classes that each functional aspect can assume: {dampening, variable or unpredictable}. Accordingly, the five steps of FRAM would be structured as follows:

Step Zero: The start is with defining the objective of analysis and what is to be achieved. This step is unchanged and would define the context and type of application needed to achieve the defined objective.

Step One: Next, the set of functions that constitute the system is defined and characterized specifying the aspects for each function and accordingly the relationship to other functions since the output of upstream functions serves as an input or an incoming aspect for downstream ones. For each function, there are six aspects: input, preconditions, time, control, resources, and output (Hollnagel, 2012). The characterization of the functions is decisive to determine the type of data needed for constructing the data tables. The recorded data can be generated relying on expert input and thereafter entered into the RST information system. Using the principles of approximation and indiscernibility, the set of equivalence classes can be identified, and a discernibility matrix is then built. The discernibility matrix is then completed to identify the set of reducts and accordingly generate a reduced set of rules, which could maintain the same accuracy of the original set of attributes.

Step Two: Performance variability is classified usually in basic FRAM using two phenotypes, each with a qualitative three-point scale, namely precision and time. In our prototyping model, we simplified the scale further to one phenotype to minimize the number of generated rules and since it made more sense in a predictive assessment. Each aspect is classified accordingly as: {dampening (or non-variable), variable and unpredictable (or highly variable)}. The data table is then fed to the RST software to compute reducts using a genetic algorithm and consequently generate the reduced set of conditional If-then rules.

Step Three: A specific analysis scenario is selected for running instantiations of the developed model with specified performance conditions. A list of performance conditions can be used to anticipate the potential of each function to produce a variable output due to the internal variability coming from within. Depending on the present conditions, the internal variability for each function can be determined and thereafter, the output's variability and its resonance and impact on other functions can be tracked within the system using the graphical representation as a map of the dominant relationships within the studied system.

Step Four: For variability management, the results of the FRAM analysis can be used as indicators to point to possibilities of variable outputs and accordingly measures can be implemented to ensure preferable performance conditions that promote a resilient systemic behavior. For further details on the developed model, the reader is advised to consult Slim & Nadeau (2020).

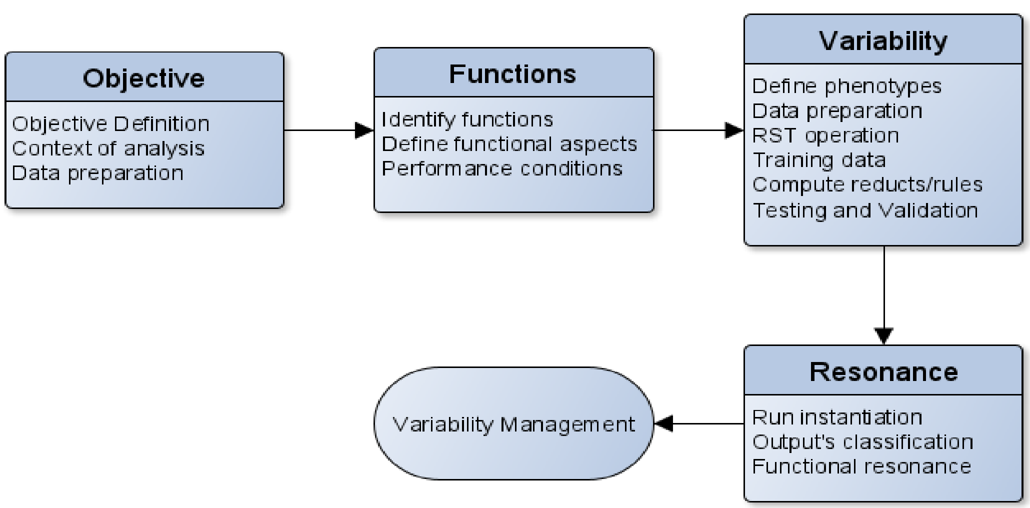

Figure 1. A graphical illustration of the steps of Rough FRAM.

4. An illustrative example: A FRAM function as an RST decision system

In this section, an illustrative example is presented to demonstrate how a FRAM function can be constituted as an RST decision system. To this end, we assume that we have a FRAM function with four connected incoming aspects: {Input 1, Input 2, Resource and Control} and one {Output}. The four ingoing aspects are accordingly defined as attributes {A1, A2, A3, A4} and the output as the decision class {D} of the function, which can possess one of three possible qualities: {dampening, variable and unpredictable}. Twenty-six random instances of the function are recorded, each of which represents an object in the decision system. We can accordingly construct our FRAM decision system as shown in Table 2.

Table 2. A data table showing the example described in this section

Function	**Input (A1)**	**Input (A2)**	**Resource (A3)**	**Control (A4)**	**Output (D)**
1	unpredictable	unpredictable	unpredictable	variable	unpredictable
2	variable	variable	variable	variable	unpredictable
3	variable	unpredictable	dampening	unpredictable	unpredictable
4	variable	variable	variable	unpredictable	unpredictable
5	unpredictable	unpredictable	dampening	unpredictable	unpredictable
6	unpredictable	dampening	variable	unpredictable	unpredictable
7	dampening	dampening	variable	dampening	dampening
8	unpredictable	variable	dampening	variable	unpredictable
9	unpredictable	variable	dampening	dampening	variable
10	dampening	dampening	unpredictable	unpredictable	unpredictable
11	dampening	dampening	unpredictable	variable	variable
12	dampening	dampening	unpredictable	dampening	variable
13	variable	variable	variable	variable	variable
14	variable	unpredictable	dampening	dampening	variable
15	variable	variable	unpredictable	unpredictable	unpredictable
16	variable	variable	unpredictable	variable	unpredictable
17	variable	dampening	dampening	variable	variable
18	variable	dampening	dampening	dampening	dampening
19	unpredictable	unpredictable	unpredictable	dampening	unpredictable
20	dampening	variable	variable	dampening	variable
21	dampening	variable	dampening	unpredictable	variable
22	dampening	variable	dampening	variable	variable
23	dampening	variable	dampening	dampening	dampening
24	dampening	dampening	variable	unpredictable	variable
25	dampening	dampening	variable	variable	variable
26	dampening	variable	dampening	dampening	variable

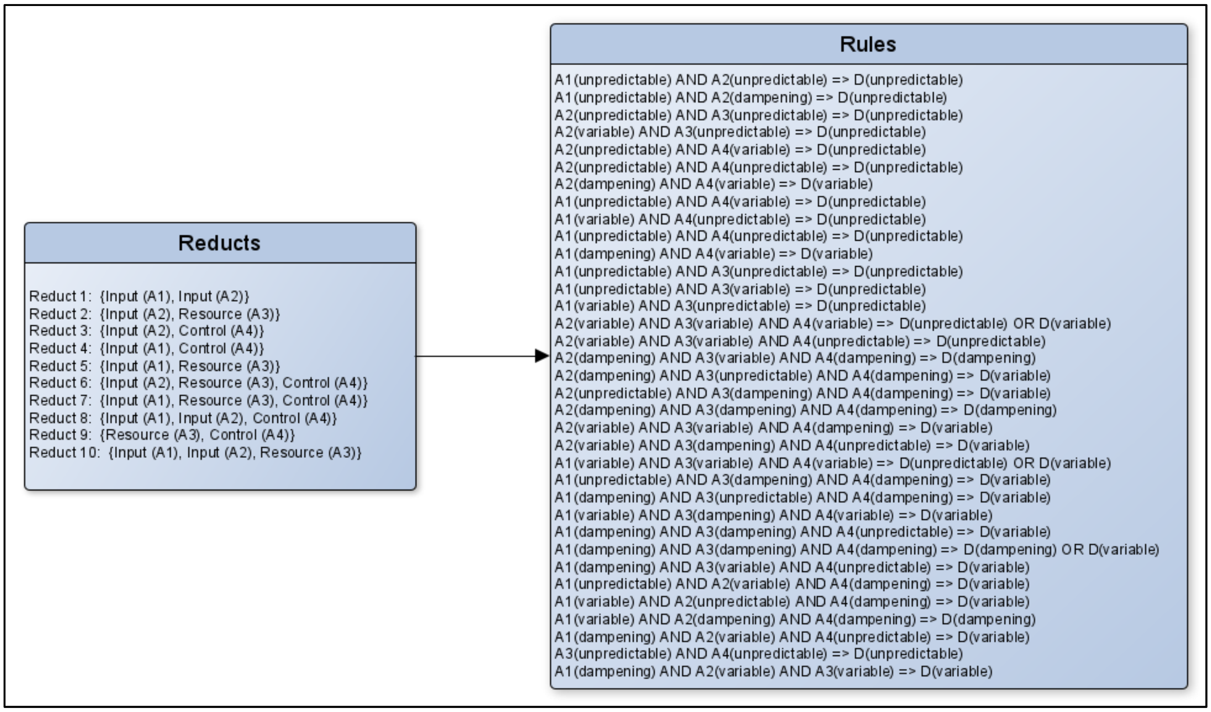

Figure 2. The computed set of reducts and the consequent reduced set of conditional rules

The data table can be constructed in a real—world setting using historical data or data collected from field observations. The table above is used as the training set, which is processed using a searching algorithm to identify patterns and determine equivalence classes, and consequently construct the discernibility matrix. The set of reducts and the rule base are determined by simplifying the discernibility function. The rules can be tested running many instantiations of the FRAM model. The reduced set of rules generated considering the set of reducts in exchange for the original set allows for a more efficient rule base. The accuracy depends significantly on the quality of provided data concerning size, consistency and completeness. A threshold of accuracy can be defined to consider only reliable rules and discard of insufficiently accurate ones (Figure 2).

5. Conclusions:

Innovative solutions are needed in safety management to address challenges associated with modern sociotechnical systems. Tools as RST can be helpful in this regard offering tools to address uncertain information. Systemic methods as FRAM combined with such approaches can offer promising and practical solutions. This paper shows how the basic FRAM model can be combined with the RST method by providing a simplified example of a FRAM function redefined as an RST decision system. The combined approach can be helpful to address limitations concerning limited input data, inconsistencies, incompleteness, and output classification. The RST approach allows as well to produce reduced and efficient rule bases, which can be used in conjunction with fuzzy logic to provide a more intersubjective representation of performance variability. The conditional IF-THEN rules are more comprehensible and can be automatically deduced from the provided data table recorded from field observations or retrieved from archived data. The FRAM framework with its principles rooted in Resilience Engineering allows for characterizing complex relationships and interdependencies within the system in question. The phenotypes were simplified here to facilitate the integration with RST and allow for an easier predictive assessment at this stage. Going forward, the model would require further optimization and validation providing a full-fledged model and building on a real-world case study. The approaches discussed in this paper are solely for illustrative purposes and provide a mere skeleton of the model, which should be further developed and improved in future projects.

6. References

Hollnagel E (2004) Barriers and Accident Prevention. Aldershot, UK: Ashgate Publishing.

Hollnagel E (2012) FRAM, the functional resonance analysis method: modelling complex socio-technical systems. Ashgate Publishing, Ltd.

Pawlak Z (1982) Rough sets. International Journal of Computer & Information Sciences, 11(5), 341-356.

Slim H, Nadeau S (2020) A mixed rough sets/fuzzy logic approach for modelling systemic performance variability with FRAM. Sustainability, 12(5), 1918.

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ANNEX III

THE NEED FOR A SYSTEMIC PERSPECTIVE IN AIRCRAFT DEICING: A PROPOSAL OF A RISK AND SAFETY ANALYSIS METHOD COMBINING FRAM AND FUZZY LOGIC

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Abstract. Safety is a top priority. This is especially true when it comes to highly controlled systems as aviation. Aircraft on-ground deicing operations are a significant contributor to the safety of aviation and perform a critical and essential task. The context of application for deicing operations is a complex one characterized by dynamic interactions of social and technological components. Operations are to be executed in a strict manner in accordance with guidelines and regulations to ensure high reliability and desired safety levels. Operations are conducted under temporal constraints and in extreme weather conditions. In recent years, advances in aircraft deicing as the centralization of operations and the improvement of applied technology increased the efficiency and effectiveness of applied deicing procedures. Despite the high levels of reliability and safety in deicing operations, the growing complexity of such a system and the continuous technological advancements require continuous research and improvements to maintain adequate performance and tackle any arising challenges. With the exception of a few studies, research projects conducted in the field of aircraft deicing focus on the technical and operational aspects. However, limiting the scope of analysis without

considering the emergent and complex properties of a sociotechnical system does not provide a complete picture of the system status. To provide a more complete and comprehensive picture, safety and performance analyses should additionally adopt a more holistic and systemic perspective considering contextual, organizational and human factors as well. Considering above-mentioned aspects, the objective of our research project is to present a possible systemic approach through the combination of the Functional Resonance Analysis Method (FRAM) and fuzzy logic.

FRAM is a systemic analysis method, proposed by Erik Hollnagel in 2004, which describes successful and failed outcomes as a result of performance variability and functional resonance. FRAM is especially suitable for studying non-linear relationships and complex contexts, which can be difficult to represent in quantitative terms. Fuzzy logic, on the other hand, is much older and was introduced by Lotfi Zadeh in 1965. Fuzzy logic resembles human reasoning and allows for a mathematical representation of linguistic scales, on which FRAM relies to evaluate variability. Through the integration of fuzzy logic into FRAM and designing the FRAM functions as rule-based fuzzy inference systems, the advantages of both methods can be utilized to provide more representative and comprehensive results. Relying on literature and research work conducted by our team over recent years, the deicing context was simulated and characterized in terms of functions, which describe the set of activities necessary to successfully perform the deicing of airplanes. The functional characterization describes how the various tasks are related and how the outcomes' variability can resonate and affect performance negatively or positively. A list of contextual performance conditions was used as an evaluation parameter to assign a quality score on a ten-point scale for each selected factor. A rule-based fuzzy inference system was constructed to fuzzify the scores of all respective performance conditions and generate an aggregated quantifier for the potential internal variability of each function. The internal variability factor was then linked to a higher-order fuzzy inference system in addition to the other incoming aspects from upstream functions to generate a numerical output for the function in question. The numerical outcome represents an indicator for possible variability, whether negative or positive, in the function's output. On a spectrum between 0 and 1.5, 1 represents a non-variable output. Any value below 1 represents negative variability, while any value above 1 represents positive variability.

The preliminary results of the simulation in MATLAB are promising and present a comprehensible example on how to construct such a model. The defined functions described human (individual or organizational) activities that constitute the deicing context and the relationships and couplings that affect the system's performance on a wide scale. A realistic analysis scenario inspired by actual accidents and events was constructed and a few assumptions concerning the performance conditions were formulated to induce variability such as inadequate airliner guidelines, present extreme weather conditions, inadequate training of flight crew and high temporal stress. The assumptions made translated into creating a context that impacted the performance of several functions. The addition of fuzzy logic to FRAM allowed for the calculation of numerical quantifiers for the quality of the outputs to represent the potential for variability based on the defined scenario. The proposed framework presented a complex system analysis of the deicing context, which modelled human activities as functions and characterized the resulting variability due to performance adjustments. The principle of functional resonance provided a better understanding for the dynamic relationships among functions and the emergence of successful or undesired outcomes. The simulation was a simplification of reality and was constructed based on a hypothetical scenario. The process of characterizing the functions and generating the fuzzy inference systems can be time- and effort-exhaustive and the simulation requires high computing resources as well. To avoid the problem of creating unfeasible rule bases, the characterization of the functions and the selection of influential factors and variables have to be simplified and limited in number. The analyst performing the analysis should therefore be knowledgeable in the system he/she intends to analyze. Further experiments and optimization work are still needed to validate the proposed model and ensure its reliability. Nonetheless, the improved method promises to provide a supportive tool, which can be complementary to the established classical methods and present a different needed perspective.

ANNEX IV

A REVIEW OF APPLIED METHODS FOR AIRCRAFT ON-GROUND DEICING

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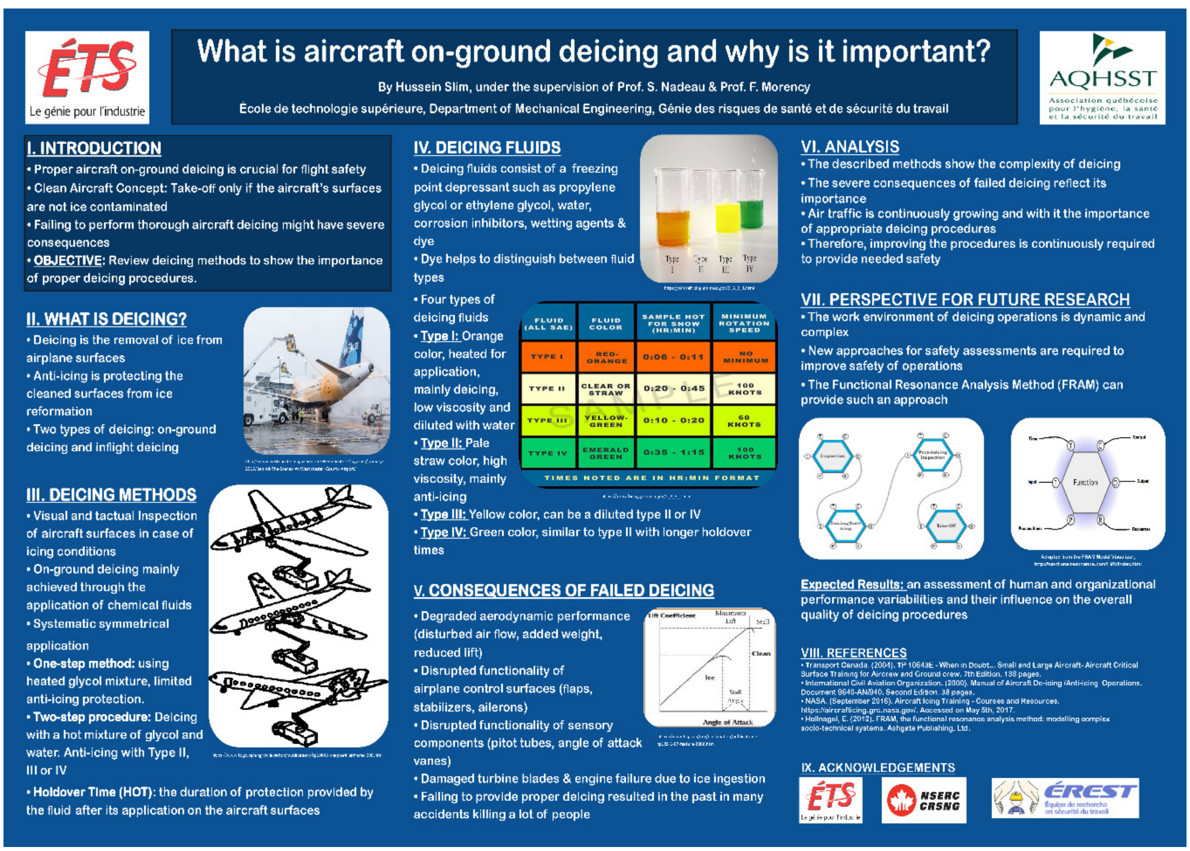

APPENDIX A

LIST OF PUBLICATIONS

Published Journal Articles

- Slim, H., Nadeau, S. (2020). A Proposition for Combining Rough Sets, Fuzzy Logic and FRAM to Address Methodological Challenges in Safety Management: A Discussion Paper. Safety 2020, 6(4), 50.
- Slim, H., Nadeau, S. (2020). A Mixed Rough Sets/Fuzzy Logic Approach for Modelling Systemic Performance Variability with FRAM. Sustainability 2020, 12(5), 1918.
- Slim, H., Nadeau, S. (2019). A proposal for a predictive performance assessment model in complex sociotechnical systems combining fuzzy logic and the Functional Resonance Analysis Method (FRAM). American Journal of Industrial and Business Management, Volume 9, Number 6.

Conference Publications

- Slim, H., Nadeau, S. (2019). The need for a systemic perspective in aircraft deicing: a proposal of a risk and safety analysis method combining FRAM and fuzzy logic. In CASI-AERO 2019 (Laval, QC, Canada, 14-16 mai 2019)
- Slim, H., Nadeau, S., Morency, F. (2018). FRAM: A Complex System's Approach for the Evaluation of Aircraft On-ground Deicing Operations. Kongress der Gesellschaft für Arbeitswissenschaft, vol. 64. GFA Press.The 64th GfA-Frühjahrskongress der Gesellschaft für Arbeitswissenschaft (GfA) Title: Arbeit(s).Wissen.Schaf(f)t Grundlage für Management & Kompetenzentwicklung, Frankfurt, Germany (6).

Conference papers (accepted for review)

- Slim, H., Nadeau, S. (2021). The application of Rough Sets Theory as a data-mining tool to classify complex functions in safety management. Kongress der Gesellschaft für Arbeitswissenschaft, vol. 67. GFA Press. The 67th GfA-Frühjahrskongress der Gesellschaft für Arbeitswissenschaft (GfA) Title: HumAIne - Human-centered AI job design (67th Spring Congress), Bochum, Germany.

Vulgarizations

- Slim, Hussein Nadeau, Sylvie Morency, François. (2017). A Review of Applied Methods for Aircraft On-ground Deicing.Congrès annuel AQHSST. Congrès annuel AQHSST, Victoriaville, Canada (1).

LIST OF BIBLIOGRAPHICAL REFERENCES

Adriaensen, A., Decré, W., & Pintelon, L. (2019). Can Complexity-Thinking Methods Contribute to Improving Occupational Safety in Industry 4.0? A Review of Safety Analysis Methods and Their Concepts. Safety, 5(4), 65.

Albery, S., Borys, D., & Tepe, S. (2016). Advantages for risk assessment: Evaluating learnings from question sets inspired by the FRAM and the risk matrix in a manufacturing environment . Safety Science, 89(Complete), 180-189. doi:10.1016/j.ssci.2016.06.005

Alisantoso, D., Khoo, L. P., Lee, B. I., & Fok, S. C. (2005). A rough set approach to design concept analysis in a design chain. The International Journal of Advanced Manufacturing Technology, 26(5-6), 427-435.

Amaratunga, D., Baldry, D., Sarshar, M., & Newton, R. (2002). Quantitative and qualitative research in the built environment: application of "mixed" research approach. Work study.

Anderson, G. T., Zheng, J., Wyeth, R., Johnson, A., Bissett, J., & GROUP, T. P. (2000). A rough set/fuzzy logic based decision making system for medical applications. INTERNATIONAL JOURNAL OF GENERAL SYSTEM, 29(6), 879-896.

Aventin, A., Morency, F., & Nadeau, S. (2015). Statistical study of aircraft accidents and incidents related to de/anti-icing process in Canada between 2009 and 2014 . In 62nd CASI Aeronautics Conference and AGM 3rd GARDN Conference. Abstract book (Montreal, QC, Canada, May 19-21, 2015), pp. 201-209

Bar-Yam, Y. (2002). General features of complex systems . Encyclopedia of Life Support Systems (EOLSS), UNESCO, EOLSS Publishers, Oxford, UK.

Baxter, G., & Sommerville, I. (2010). Socio-technical systems: From design methods to systems engineering . Interacting with computers, 23(1), 4-17.

Boivin, D. B., & Boudreau, P. (2014). Impacts of shift work on sleep and circadian rhythms . Pathologie Biologie, 62(5), 292-301.

Bodenschatz, E. (2009). Complex systems. Max Planck Gesellschaft, 3-6.

BEA. (2012). Final Report On the accident on 1st June 2009 to the Airbus A330-203 registered F-GZCP operated by Air France flight AF 447 Rio de Janeiro - Paris . Retrieved on August 15th 2020 from https://www.bea.aero/fileadmin/documents/docspa/2009/f-cp090601.en/pdf/f-cp090601.en.pdf

Belmonte, F., Schön, W., Heurley, L., & Capel, R. (2011). Interdisciplinary safety analysis of complex socio-technological systems based on the Functional Resonance Accident Model: An application to railway traffic supervision. Reliability Engineering and System Safety, 96, 237-249. doi: 10.1016/j.ress.2010.09.006.

Cacciabue, P. C. (2000). Human factors impact on risk analysis of complex systems. Journal of Hazardous materials, 71(1-3), 101-116.

Carayon, P., Hancock, P., Leveson, N., Noy, I., Sznelwar, L., & Van Hootegem, G. (2015). Advancing a sociotechnical systems approach to workplace safety–developing the conceptual framework. Ergonomics, 58(4), 548-564.

Chien, C. F., & Chen, L. F. (2007). Using rough set theory to recruit and retain high-potential talents for semiconductor manufacturing. IEEE Transactions on Semiconductor Manufacturing, 20(4), 528-541.

Cox, E. (1994). The Fuzzy Systems Handbook: a practitioner's guide to building, using, and maintaining fuzzy systems. Academic Press, Inc.

De Carvalho, P. V. R. (2011). The use of Functional Resonance Analysis Method (FRAM) in a mid-air collision to understand some characteristics of the air traffic management system resilience. Reliability Engineering & System Safety, 96(11), 1482-1498.

Dernoncourt, F., & Métais, E. (2011). Fuzzy logic: introducing human reasoning within decision-making systems. Conservatoire National des Arts et Métiers. Paris.

Dimitras, A. I., Slowinski, R., Susmaga, R., & Zopounidis, C. (1999). Business failure prediction using rough sets. European Journal of operational research, 114(2), 263-280.

DOW. (2004). UCAR PG Aircraft Deicing Fluids Concentrate"55/45" Aircraft Deicing Fluids for Safe Winter Operations . Retrieved on August 15th 2020 from http://msdssearch.dow.com/PublishedLiteratureDOWCOM/dh_0953/0901b803809531a3.pdf?filepath=/aircraft/pdfs/noreg/183-00024.pdf&fromPage=GetDoc

Dubois, D., & Prade, H. (1990). Rough fuzzy sets and fuzzy rough sets . International Journal of General System, 17(2-3), 191-209.

Dubois, D., & Prade, H. (1993). Fuzzy sets and probability: misunderstandings, bridges and gaps . In Fuzzy Systems, 1993., Second IEEE International Conference on (pp. 1059-1068). IEEE.

Environmental Protection Agency (EPA). (2000). Preliminary Data Summary Airport Deicing Operations (Revised) . Washington, DC, USA. Retrieved on August 15th 2020 from https://www.epa.gov/sites/production/files/2015-06/documents/airport-deicing-pds-2000.pdf

Érdi, P. (2008). Complexity explained . Springer. doi: 10.1007/978-3-540-35778-0

EUROCONTROL. (2009). A White Paper on Resilience Engineering for ATM. Report of the Project Resilience Engineering for ATM.

Eyre, F.W. (2002). Tactile inspection for detection of ice on aircraft surfaces – notes on current practice . Transports Canada, Report No. TP 13858E, 2002. Accessed August 15th 2020. http://bibvir2.uqac.ca/archivage/17100950.pdf

García-Lapresta, J. L., & Pérez-Román, D. (2016). Consensus-based clustering under hesitant qualitative assessments. Fuzzy Sets and Systems, 292, 261-273.

Garrido, A. (2012). A Brief History of Fuzzy Logic . BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 3(1), 71-77.

González Dan, J. R., Arnaldos, J., & Darbra, R. M. (2017). Introduction of the human factor in the estimation of accident frequencies through fuzzy logic . Safety Science, 97 (Supplement C), 134-143. doi: https://doi.org/10.1016/j.ssci.2015.08.012.

Greco, S., Matarazzo, B., & Slowinski, R. (1999). The use of rough sets and fuzzy sets in MCDM. In Multicriteria decision making (pp. 397-455). Springer, Boston, MA.

Greco, S., Matarazzo, B., & Slowinski, R. (2001). Rough sets theory for multicriteria decision analysis. European journal of operational research, 129(1), 1-47.

Günebak, S., Nadeau, S., Morency, F., & Sträter, O. (2015). Towards a safer and more efficient communication process for aircraft ground deicing: review of human factors and team communication literature . AERO 2015: 62nd CASI Aeronautics Conference and 3rd GARDN Conference, At Montréal, Canada

Günebak, S., Nadeau, S., Morency, F., & Sträeter, O. (2016). Aircraft ground deicing as a complex sociotechnical system: towards a safer and more efficient communication process for aircraft ground deicing . In 62nd CASI Aeronautics Conference and AGM 3rd GARDN Conference. Abstract book (Montreal, QC, Canada, May 19-21, 2015), pp. 189-199.

Haack, S. (1979). Do we need fuzzy logic?. International Journal of Man–Machine Studies, 11: 437–45.

Hájek, P. (1998). Metamathematics of fuzzy logic (Vol. 4). Springer Science & Business Media.

Heckerman, D.; Mannila, H.; Pregibon, D.; Uthurusamy, R. (1997). In Proceedings of 3rd international conference on knowledge discovery and data mining; AAAI Press: Menlo Park, CA.

Heinrich, H. W. (1931). Industrial Accident Prevention. A Scientific Approach; McGraw-Hill: New York, NY, USA, 1931.

Hettinger, L. J., Kirlik, A., Goh, Y. M., & Buckle, P. (2015). Modelling and simulation of complex sociotechnical systems: Envisioning and analysing work environments. Ergonomics, 58(4), 600-614.

Hirose, T., & Sawaragi, T. (2020). Extended FRAM model based on cellular automaton to clarify complexity of socio-technical systems and improve their safety. Safety science, 123, 104556.

Hirose, T., Sawaragi, T., Horiguchi, Y., & Nakanishi, H. (2017). Safety analysis for resilient complex socio-technical systems with an extended functional resonance analysis method. Int J Astronaut Aeronautical Eng, 2, 012.

Hollnagel, E. (1998). Cognitive reliability and error analysis method (CREAM). Elsevier.

Hollnagel, E. (2004). Barriers and Accident Prevention. Aldershot, UK: Ashgate Publishing.

Hollnagel, E. (2011). Epilogue: RAG. The resilience analysis grid. In E. Hollnagel, J. Paries, D. Woods, & J. Wreathall (Eds.), Resilience engineering in practice (pp. 275–296). Farnham, UK: Ashgate.

Hollnagel, E. (2012a). FRAM, the functional resonance analysis method: modeling complex socio-technical systems. Ashgate Publishing, Ltd.

Hollnagel, E. (2012b). Research 2013:09 An Application of the Functional Resonance Analysis Method (FRAM) to Risk Assessment of Organisational Change. Sophia Antipolis Cedex - France: MINES ParisTech Crisis and Risk Research Centre (CRC). Retrieved on August 15th 2020 from http://www.stralsakerhetsmyndigheten.se/Publikationer/Rapport/Sakerhat-vid-karnkraftverken/2013/201309/

Hollnagel, E. (2014). Safety-I and Safety–II: The Past and Future of Safety Management. Ashgate Publishing, Ltd.

Hollnagel, E., & Speziali, J. (2008). Study on Developments in Accident Investigation Methods: A Survey of the" State-of-the-art. SKI Report 2008:50. Sophia Antipolis, France, Ecole des Mines de Paris.

Hollnagel, E., Wears, R. L., & Braithwaite, J. (2015). From Safety-I to Safety-II: a white paper. The resilient health care net: published simultaneously by the University of Southern Denmark, University of Florida, USA, and Macquarie University, Australia.

Hollnagel, E. (2020). A FRAM Glossary. http://functionalresonance.com/a-fram-glossary.html Accessed on August 15th 2020.

Hollnagel, E., Pruchnicki, S., Woltjer, R., & Etcher, S. (2008). Analysis of Comair flight 5191 with the functional resonance accident model. In 8th International symposium of the Australian aviation psychology association (pp. 8-pages).

Hvidsten, T. R. (2010). A tutorial-based guide to the ROSETTA system: A Rough Set Toolkit for Analysis of Data. Journal of Computer and Communications.

International Civil Aviation Organization. (2000). Manual of Aircraft De-icing /Anti-icing Operations . Document 9640-AN/940. Second Edition. 38 pages.

International Civil Aviation Organization. (2020). Forecasts of Scheduled Passenger and Freight Traffic. http://www.icao.int/sustainability/pages/eap_fp_forecastmed.aspx. Accessed on August 15th 2020.

Ishizaka, A. (2014). Comparison of fuzzy logic, AHP, FAHP and hybrid fuzzy AHP for new supplier selection and its performance analysis. International Journal of Integrated Supply Management, 9(1-2), 1-22.

Jelonek, J., Krawiec, K., & Slowiński, R. (1995). Rough set reduction of attributes and their domains for neural networks. Computational intelligence, 11(2), 339-347.

Klir, G. J. (1987). Where do we stand on measures of uncertainty, ambiguity, fuzziness, and the like?. Fuzzy sets and systems, 24(2), 141-160.

Konstandinidou, M., Nivolianitou, Z., Kiranoudis, C., & Markatos, N. (2006). A fuzzy modeling application of CREAM methodology for human reliability analysis. Reliability Engineering & System Safety, 91(6), 706-716.

Komorowski, J., & Øhrn, A. (1999). Modelling prognostic power of cardiac tests using rough sets. Artificial intelligence in medicine, 15(2), 167-191.

Kumar, A., Agrawal, D. P., & Joshi, S. D. (2005). Advertising data analysis using rough sets model. International Journal of Information Technology & Decision Making, 4(02), 263-276.

Landau, K., Nadeau, S., Le Floch, T., Morency, F. (2017). Ergonomic Time and Motion Studies of Aircraft De-icing Work. Journal of Ergonomics 7: 204. doi: 10.4182/2165-7556.1000204

Landau, K., Nadeau, S., Le Floch, T., Morency, F. (2018). Arbeitsprozesse und Wertschöpfungsbeiträge bei der Flugzeug-Enteisung . In Gesellschaft für Arbeitswissenschaft (Frankfurt, Germany, Feb. 21-23, 2018) Coll. « Kongress der Gesellschaft für Arbeitswissenschaft », vol. 64. GFA Press.

Law, R., & Au, N. (1998). A rough set approach to hotel expenditure decision rules induction. Journal of Hospitality & Tourism Research, 22(4), 359-375.

Laviolette, M., & Seaman, J. W. (1994). The efficacy of fuzzy representations of uncertainty . IEEE Transactions on Fuzzy Systems, 2(1), 4-15.

Le Floch, T., Nadeau, S., Landau, K. & Morency, F. (2018). Aircraft deicing in open baskets: Study of the effects of activities on heart rate variability. In Gesellschaft für Arbeitswissenschaft (Frankfurt, Germany, Feb. 21-23, 2018) Coll. « Kongress der Gesellschaft für Arbeitswissenschaft », vol. 64. GFA Press.

Lee, J., & Chung, H. (2018). A new methodology for accident analysis with human and system interaction based on FRAM: Case studies in maritime domain. Safety science, 109, 57-66.

Leveson, N. (2011). Engineering a safer world: Systems thinking applied to safety. MIT Press.

Lim, R. W., Wogalter, M. S. (2002). Human factors design considerations of alarm clocks . In Proceedings of the Human Factors and Ergonomics Society 46th Annual Meeting (pp. 705–709). Santa Monica, CA: SAGE Publications.

Macchi, L., Hollnagel, E., & Leonhard, J. (2009). Resilience Engineering approach to safety assessment: an application of FRAM for the MSAW system . Dans EUROCONTROL Safety R&D Seminar (pp. 12 pages). EUROCONTROL. Retrieved on August 15th 2020 from https://hal-mines-paristech.archives-ouvertes.fr/hal-00572933

Macchi, L. (2010). A Resilience Engineering approach for the evaluation of performance variability: development and application of the Functional Resonance Analysis Method for air traffic management safety assessment (École Nationale Supérieure des Mines de Paris). English. <NNT : 2010ENMP0037>. <pastel-00589633> Retrieved on August 15th 2020 from https://pastel.archives-ouvertes.fr/pastel-00589633

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. International journal of man-machine studies, 7(1), 1-13. https://doi.org/10.1016/S0020-7373(75)80002-2.

Melanson, A., & Nadeau, S. (2016). Managing OHS in complex and unpredictable manufacturing systems: can FRAM bring agility?. In Advances in Ergonomics of Manufacturing: Managing the Enterprise of the Future (pp. 341-348). Springer, Cham.

Melanson, A., & Nadeau, S. (2019). Resilience engineering for sustainable prevention in the manufacturing sector: A comparative study of two methods of risk analysis. American Journal of Industrial and Business Management, 9(01), 267.

Moshansky, V. (1992). Commission of Inquiry into the Air Ontario accident at Dryden, Ontario (Final Report, Vol. I, Parts 1-4). Ottawa, ON: Ministry of Supply and Services, Canada. Retrieved on August 15th 2020 from http://publications.gc.ca/collections/collection_2014/bcp-pco/CP32-55-1-1992-1-eng.pdf

Mumford, E. (2006). The story of socio-technical design: Reflections on its successes, failures and potential . Information Systems Journal, 16 (4), 317-342.

Nadeau, S. (2003). Co-operation in Health and safety: A game theory analysis . Pierce L. Rev., 1, 219.

Nadeau, S., & Landau, K. (2018). Utility, advantages and challenges of digital technologies in the manufacturing sector. Ergonomics International Journal, 2018, 2(12).

Nadeau, S., & Morency, F. (2017). De-icing of aircraft: incorporating business risks and occupational health and safety . International Journal of Safety and Security Engineering, Vol. 7, No. 2 (2017) 247–266

National Transportation Safety Board. (1996). Aircraft Accident Report In-Flight Icing Encounter and Loss of Control Simmons Airlines, d.b.a. American Eagle Flight 4184 Avions de Transport Regional (ATR) Model 72-212, N401AM Roselawn, Indiana October 31, 1994 . Retrieved on August 15th 2020 from http://www.ntsb.gov/investigations/AccidentReports/Reports/AAR9601.pdf

Negnevitsky, M. (2005). Artificial intelligence a guide to intelligent systems . Addison Wesley. Pearson Education Lt. Second Edition.

Njå, O., Solberg, Ø., & Braut, G. S. (2017). Uncertainty—Its ontological status and relation to safety. In The illusion of risk control (pp. 5-21). Springer, Cham.

Nolan, D. P. (2011). Fire fighting pumping systems at industrial facilities . William Andrew.

Nouvel, D., Travadel, S., & Hollnagel, E. (2007). Introduction of the Concept of Functional Resonance in the Analysis of a Near-Accident in Aviation. In 33rd ESReDA Seminar: Future challenges of accident investigation (pp. 9-pages).

Nurmi, H. (2009). Probability and Fuzziness–Echoes from 30 Years Back . In Views on Fuzzy Sets and Systems from Different Perspectives (pp. 161-174). Springer, Berlin, Heidelberg.

Øhrn, A. (2000). Discernibility and Rough Sets in Medicine: Tools and Applications. Department of Computer and Information Science. Trondheim, Norway, Norwegian University of Science and Technology: 239.

Parmar, D., Wu, T., & Blackhurst, J. (2007). MMR: an algorithm for clustering categorical data using rough set theory. Data & Knowledge Engineering, 63(3), 879-893.

Patriarca, R. (2018). New trends for risk and safety management in the aviation domain: A resilience engineering perspective. New Trends in Civil Aviation; CRC Press: Boca Raton, FL, USA, 283-288.

Patriarca, R., Adriaensen, A., Peters, M., Putnam, J., Costantino, F., & Di Gravio, G. (2019). Receipt and dispatch of an aircraft: a functional risk analysis. In REA Symposium on Resilience Engineering Embracing Resilience.

Patriarca, R., & Bergström, J. (2017a). Modelling complexity in everyday operations: functional resonance in maritime mooring at quay. Cognition, Technology & Work, 19(4), 711-729.

Patriarca, R., Bergström, J., & Di Gravio, G. (2017b). Defining the functional resonance analysis space: Combining Abstraction Hierarchy and FRAM. Reliability Engineering & System Safety, 165, 34-46.

Patriarca, R., Bergström, J., Di Gravio, G., & Costantino, F. (2018a). Resilience engineering: Current status of the research and future challenges. Safety Science, 102, 79-100.

Patriarca, R., Di Gravio, G., & Costantino, F. (2017c). A Monte Carlo evolution of the Functional Resonance Analysis Method (FRAM) to assess performance variability in complex systems. Safety science, 91, 49-60.

Patriarca, R., Del Pinto, G., Di Gravio, G., Costantino, F., (2018b). FRAM for Systemic Accident Analysis: A Matrix Representation of Functional Resonance. International Journal of Reliability, Quality and Safety Engineering, vol. 25 (1), doi: 10.1142 / S0218539318500018.

Patriarca, R., Falegnami, A., Costantino, F., & Bilotta, F. (2018c). Resilience engineering for socio-technical risk analysis: Application in neuro-surgery. Reliability Engineering & System Safety, 180, 321-335.

Patriarca, R., Gravio, G. D., Costantino, F., Tronci, M., Severoni, A., Vernile, A., & Bilotta, F. (2017d). A paradigm shift to enhance patient safety in healthcare, a resilience engineering approach: scoping review of available evidence. International Journal of Healthcare Technology and Management, 16(3-4), 319-343.

Patriarca, R., Di Gravio, G., Woltjer, R., Costantino, F., Praetorius, G., Ferreira, P., Hollnagel, E. (2020). Framing the FRAM: A literature review on the functional resonance analysis method. Safety Science, 129, 104827, doi:10.1016/j.ssci.2020.104827.

Pavard, B., & Dugdale, J. (2006). The contribution of complexity theory to the study of socio-technical cooperative systems . Unifying themes in complex systems, 39-48.

Pawlak, Z. (1982). Rough sets . International journal of computer & information sciences, 11(5), 341-356.

Pawlak, Z. (1991). Imprecise categories, approximations and rough sets. In Rough sets (pp. 9-32). Springer, Dordrecht.

Pawlak, Z. (1998). Rough set theory and its applications to data analysis. Cybernetics & Systems, 29(7), 661-688.

Pawlak, Z. (2004). Some issues on rough sets. In Transactions on Rough Sets I (pp. 1-58). Springer, Berlin, Heidelberg.

Pawlak, Z. (2012). Rough sets: Theoretical aspects of reasoning about data (Vol. 9). Springer Science & Business Media.

Pawlak, Z., & Skowron, A. (2007). Rudiments of rough sets. Information sciences, 177(1), 3-27.

Pelletier, F. J. (2000). Metamathematics of fuzzy logic . The Bulletin of Symbolic Logic, 6(3), 342-346.

Perrow, C. (1984). Normal Accidents: Living with High Risk Technologies, 2nd ed.; Princeton University Press: Princeton, NJ, USA.

Pickup, L., Atkinson, S., Hollnagel, E., Bowie, P., Gray, S., Rawlinson, S., & Forrester, K. (2016). Blood sampling - Two sides to the story . Applied Ergonomics , 59, Part A , 234-242. doi: http://dx.doi.org/10.1016/j.apergo.2016.08.027.

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences. Acta psychologica, 104(1), 1-15. http://dx.doi.org/10.1016/S0001-6918(99)00050-5

Qureshi, Z. H. (2008). A review of accident modelling approaches for complex critical sociotechnical systems. DEFENCE SCIENCE AND TECHNOLOGY ORGANISATION EDINBURGH (AUSTRALIA) COMMAND CONTROL COMMUNICATIONS AND INTELLIGENCE DIV.

Rasmussen, J. (1997). Risk Management in a Dynamic Society: A Modelling Problem, Safety Science, 27, 2, 183-213

Reason, J. (1990). Human Error. Cambridge: Cambridge University Press.

Roelen, A. L. C., & Klompstra, M. B. (2012). The challenges in defining aviation safety performance indicators. Helsinki, Finland. PSAM, 11.

Rollenhagen, C. (1995). MTO: en introduktion: sambandet människa, teknik och organisation. Studentlitteratur.

Rosa, L. V., Haddad, A. N., & Carvalho, P. V. (2015). Assessing risk in sustainable construction using the Functional Resonance Analysis Method (FRAM). Cogn. Technol. Work, 17 (4), 559-573. doi: 10.1007/s10111-015-0337-z

Sawaragi, T., Horiguchi, Y., & Hina, A. (2006). Safety analysis of systemic accidents triggered by performance deviation. In 2006 SICE-ICASE International Joint Conference (pp. 1778-1781). IEEE.

Shafaei Bajestani, N., Vahidian Kamyad, A., Nasli Esfahani, E., & Zare, A. (2017). Prediction of retinopathy in diabetic patients using type-2 fuzzy regression model. European Journal of Operational Research, 264(3), 859-869. doi: https://doi.org/10.1016/j.ejor.2017.07.046.

Shepard, R. B. (2005). Quantifying environmental impact assessments using fuzzy logic. Springer Science & Business Media.

SHK Board of Accident Investigation. (1993). Report C 1993:57 Air Traffic Accident on 27 December 1991 at Gottröra, AB county Case L-124/91 . Stockholm, Sweden. Retrieved on August 15th 2020 from http://www.havkom.se/assets/reports/English/C1993_57e_Gottrora.pdf

Sivanandam, S. N., Sumathi, S., & Deepa, S. N. (2007). Introduction to fuzzy logic using MATLAB (Vol. 1). Berlin: Springer.

Slater, D. (2017). Modelling, Monitoring, Manipulating and Managing? Modelling Process Flow in Complex Systems. CAMBRENSIS 2017.

Slim, H., Nadeau, S. (2019). A Proposal for a Predictive Performance Assessment Model in Complex Sociotechnical Systems Combining Fuzzy Logic and the Functional Resonance Analysis Method (FRAM). American Journal of Industrial and Business Management, 9 (6), 1345–1375.

Slim, H., & Nadeau, S. (2020). A mixed rough sets/fuzzy logic approach for modelling systemic performance variability with FRAM. Sustainability, 12(5), 1918. https://doi.org/10.3390/su12051918

Slim, H., Nadeau, S., & Morency, F. (2018a). FRAM: A Complex System's Approach for the Evaluation of Aircraft On-ground Deicing Operations. Kongress der Gesellschaft für Arbeitswissenschaft, vol. 64. GFA Press.The 64th GfA-Frühjahrskongress der Gesellschaft für Arbeitswissenschaft (GfA) Title: Arbeit(s).Wissen.Schaf(f)t Grundlage für Management & Kompetenzentwicklung, Frankfurt, Germany (6).

Slim, H., Nadeau, S., & Morency, F. (2018b). The application of the Functional Resonance Analysis Method (FRAM) to evaluate factors affecting times-to-completion and graduation in graduate studies.

Sugeno, M. (1985). Industrial applications of fuzzy control. Elsevier Science Inc..

Swatton, P. J. (2000). Aircraft Performance Theory for Pilots . Oxford, UK: John Wiley & Sons.

Swiniarski, R. W., & Skowron, A. (2003). Rough set methods in feature selection and recognition. Pattern recognition letters, 24(6), 833-849.

Torres, Y., Morency, F., Nadeau, S. (2013). Factors influencing performance of aircraft ground deicing operations: perspectives in ergonomics and occupational safety . AIHCE conference, American Industrial Hygiene Association, Montréal, Canada.

Torres, Y., Nadeau, S., Morency, F. (2016). Study of fatigue and workload among aircraft de-icing technicians . Occupational Ergonomics, 13(2), 79-90.

Transport Canada. (2004). TP 10643E - When in Doubt... Small and Large Aircraft- Aircraft Critical Surface Training for Aircrew and Ground crew . 7th Edition. 138 pages. Retrieved on August 15th 2020 from http://www.tc.gc.ca/Publications/en/tp10643/pdf/hr/tp10643e.pdf

Transport Canada. (2005). TP 14052E - Guidelines for Aircraft Ground Icing Operations. Second Edition. 148 pages. Retrieved on August 15th 2020 from http://www.tc.gc.ca/Publications/en/tp14052/pdf/hr/tp14052e.pdf

Transport Safety Board of Canada. (1995). Aviation Occurrence report: Collision Royal Air Maroc Boeing 747-400, CN-RGA, Montreal (Mirabel) International Airport, Québec 21 January 1995 . Report Number A95Q0015, TSB Canada. Retrieved on August 15th 2020 from http://www.tsb.gc.ca/eng/rapports-reports/aviation/1995/a95q0015/a95q0015.pdf

Tribus, M. (1979). Comments on" Fuzzy sets, fuzzy algebra, and fuzzy statistics". Proceedings of the IEEE, 67(8), 1168-1169.

Trist, E. (1981). The evolution of socio-technical systems . Occasional paper, 2, 1981.

Underwood, P., & Waterson, P. (2012). A critical review of the STAMP, FRAM and Accimap systemic accident analysis models. In Advances in human aspects of road and rail transportation (pp. 385-394). CRC Press, Boca Raton.

Vaishnavi, V. K., & Kuechler, W. (2015). Design science research methods and patterns: innovating information and communication technology. Crc Press.

Vasilyeva, A. (2009). Aircraft Deicing Operations Final Project 1.231/16.781/ESD.224 Airport Systems Planning & Design.

Weaver, W. (1948). Science and complexity . In Facets of Systems Science (pp. 449-456). Springer US.

Wei, L. L., & Zhang, W. X. (2004). Probabilistic rough sets characterized by fuzzy sets. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 12(01), 47-60.

Woods, D. D., Johasnnesen, L. J. & Sarter, N. B. (1994). Behind Human Error: Cognitive Systems, Computers and Hindsight. SOAR Report 94-01, Wright-Patterson Air Force Base, Ohio: CSERIAC.

Yang, Z. L., Bonsall, S., Wall, A., Wang, J., & Usman, M. (2013). A modified CREAM to human reliability quantification in marine engineering . Ocean Engineering, 58, 293-303.

Yao, Y. Y. (1998). A comparative study of fuzzy sets and rough sets . Information sciences, 109(1-4), 227-242.

Zadeh, L. A. (1965). Fuzzy Sets . Information and control, 8(3), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X.

Zadeh, L. A. (1973). Outline of a new approach to the analysis of complex systems and decision processes . IEEE Transactions on Systems, Man and Cybernetics, 1100, 38-45.

Zadeh, L. A. (1978). Fuzzy sets as a basis for a theory of possibility. Fuzzy sets and systems, 1(1), 3-28.

Zadeh, L. A. (1996). Fuzzy logic= computing with words . IEEE transactions on fuzzy systems, 4(2), 103-111

Zadeh, L. A. (1997). Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic . Fuzzy sets and systems, 90(2), 111-127. https://doi.org/10.1016/S0165-0114(97)00077-8

Zadeh, L. A. (2008). Is there a need for fuzzy logic?. Information sciences, 178(13), 2751-2779.

Zadeh, L. A. (2015). Fuzzy logic—a personal perspective. Fuzzy sets and systems, 281, 4-20. https://doi.org/10.1016/j.fss.2015.05.009

Ziarko, W. (2000). Rough sets: Trends, challenges, and prospects. In International Conference on Rough Sets and Current Trends in Computing (pp. 1-7). Springer, Berlin, Heidelberg.

Zou, Z., Tseng, T. L. B., Sohn, H., Song, G., & Gutierrez, R. (2011). A rough set based approach to distributor selection in supply chain management. Expert Systems with Applications, 38(1), 106-115.