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section (SBAA refinery) integrating
FRAM & BN***

Defended on.../.../.....

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ABSTRACT

This dissertation aims to evaluate the resilience of the pre-fractionation section in the Adrar Sbaa refinery by integrating the Functional Resonance Analysis Method (FRAM) and Bayesian Networks (BN). FRAM provides a comprehensive understanding of system functions, variability, and interdependencies, while the BN offers a probabilistic framework for capturing dependencies and making inferences. The research focuses on developing a FRAM model and then converting it to a Bayesian Network model to quantify the resilience of system reliability. The methodology includes data collection, analysis, and synthesis, with a sensitivity analysis to assess the models' robustness. The integrated approach allows for a holistic assessment of the section's adaptive capabilities and recovery potential, facilitating informed decision-making and resilience planning.

Key words: Resilience; Pre-Fractionation; FRAM; Bayesian Network; Variability

RESUME

Cette thèse vise à évaluer la résilience de la section de préfractionnement dans la raffinerie d'Adrar Sbaa en intégrant la méthode d'analyse fonctionnelle de résonance (FRAM) et les réseaux bayésiens (BN). FRAM offre une compréhension complète des fonctions du système, de la variabilité et des interdépendances, tandis que le BN fournit un cadre probabiliste pour capturer les dépendances et effectuer des inférences. La recherche se concentre sur le développement d'un modèle FRAM qui est ensuite converti en un modèle de réseau bayésien pour quantifier la résilience de la fiabilité du système. La méthodologie comprend la collecte, l'analyse et la synthèse des données, ainsi qu'une analyse de sensibilité pour évaluer la robustesse des modèles. Cette approche intégrée permet une évaluation holistique des capacités d'adaptation de la section et du potentiel de récupération, facilitant la prise de décision éclairée et la planification de la résilience.

Mots-clés : Résilience ; Préfractionnement ; FRAM ; Réseau bayésien ; Variabilité.

ملخص

تهدف هذه المذكرة إلى تقييم مرونة النظام ما قبل الفشل في مصفاة أدرار بسبع بدمج طريقة FRAM وشبكة بايزيان (BN). وتوفر FRAM فهماً شاملاً لوظائف النظام وتغيراته وترباطه، في حين توفر الشبكة البايزية إطاراً يمكننا من استخلاص حالات الاعتماد على النظام واستخلاص النتائج. ويركز هذا البحث على تطوير نموذج FRAM ثم تحويله إلى نموذج شبكة بايزيان لتحديد مرونة موثوقية النظام. وتشمل المنهجية جمع البيانات وتحليلها ، مع إجراء تحليل للحساسية من أجل تقييم قوة النماذج. ويتيح النهج المتكامل إجراء تقييم كلي لقدرات القسم على التكيف وإمكانات رجوع إلى الحالة العادية، مما يسهل اتخاذ قرارات والتخطيط لجعل النظام مرناً.

الكلمات المفتاحية : المرونة; التجزئة المسبقة; الشبكة البايزية; FRAM

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TABLE OF CONTENTS

<i>Chapter 01</i>	<i>: Functional Resonance Analysis Method</i>	<i>17</i>
I.1.	Overview	18
I.2.	FRAM key concepts	18
I.2.1	The Equivalence of Failures and Successes	19
I.2.2	Approximative adjustments	19
I.2.3	Emergence	21
I.2.4	Resonance	22
I.3.	Basic concepts in developing a FRAM model	23
I.3.1	Functions and aspects	23
I.3.2	Brief description of the six aspects	25
I.3.3	Relationship between functions	26
I.3.4	Strengths and weaknesses of FRAM	31
I.4.	Development of a FRAM Model	32
I.4.1	How to prepare for data collection	32
I.4.2	How to begin analysis and synthesis of the data	34
I.5.	Application of a FRAM model	35
I.5.1	How to describe the variability	35
I.5.2	Manifestations of variability	36
I.5.3	Potential and actual variability	37
I.5.4	Human Reliability Analysis	38
I.5.5	Dependence between functions	39
I.5.6	Coupling between Output and Preconditions	40
I.5.7	Coupling between Output and Resources	40
I.5.8	Coupling between Output and Control	40
I.5.9	Coupling between Output and Time	41
I.5.10	Coupling between Output and Input	41
<i>Chapter 02</i>	<i>Bayesian Network</i>	<i>42</i>
I.6.	Overview	43
I.7.	Key components of a Bayesian network	43
I.8.	Types of Bayesian Network	44
I.8.1	Static Bayesian Networks	44
I.8.2	Dynamic Bayesian Networks (DBNs)	44
I.8.3	Hidden Markov Models (HMMs)	44
I.8.4	Continuous Bayesian Networks	44
I.8.5	Hybrid Bayesian Networks	45
I.8.6	Dynamic Influence Networks (DINs)	45
I.9.	Modeling with Bayesian Networks	45
I.9.1	Graphical Representation	45

I.9.2. Conditional Probability Distributions	45
I.9.3. Causal Reasoning.....	46
I.9.4. Probabilistic Inference.....	46
I.9.5. Learning from Data	46
I.9.6. Handling Uncertainty	46
I.10. Inference and Reasoning in Bayesian Networks.....	47
I.10.1. Exact Inference.....	47
I.10.2. Approximate Inference.....	47
I.10.3. Approximate Inference.....	47
I.10.4. Handling Large and Complex Networks	48
I.10.5. Sensitivity Analysis.....	48
I.11. Applications of Bayesian Networks.....	48
I.11.1. Risk Assessment and Management.....	48
I.11.2. Fault Diagnosis and Troubleshooting.....	48
I.11.3. Medical Diagnosis and Decision Support.....	49
I.11.4. Natural Language Processing.....	49
I.11.5. Environmental Modeling	49
I.12. Comparative Analysis with Other Models.....	50
I.12.1. Bayesian Networks vs. Decision Trees.....	50
I.12.2. Bayesian Networks vs. Neural Networks.....	50
I.12.3. Bayesian Networks vs. Support Vector Machines (SVM)	50
I.12.4. Bayesian Networks vs. Hidden Markov Models (HMM)	51
I.12.5. Bayesian Networks vs. Gaussian Mixture Models (GMM).....	51
I.13. Strengths and Weaknesses of Bayesian Networks	51
I.13.1. Strengths of Bayesian Networks.....	51
I.13.2. Weaknesses of Bayesian Networks	52
I.14. Conclusion	53
Chapter 03 :	54
I. PRESENTATION OF SONATRACH & RA1D	55
I.1. Introduction	55
I.2. Birth of SONATRACH	55
I.3. Presentation of the SBAA Refinery:.....	57
I.4. Geographical Location of the Refinery.....	58
I.5. The crude oil feedstock and production.....	59
I.5.1. The annual processing capacity	59
I.5.2. Annual production capacity.....	59
I.6. The design of the installation is based on the following principles.....	60
I.7. The 2 main parts of the refinery.....	61
I.7.1. Production units.....	61
I.7.2. Refinery utilities	61
I.8. Safety in the company, what is HSE	61

I.8.1. Organizational chart	62
I.8.2. Tasks of the safety Department.....	62
	I.8.2.1. Prevention 62
I.8.2.2. Intervention.....	63
I.8.2.3. Environment.....	63
I.8.3. Identification of risks related to refining	64
I.15. Conclusion	65
<i>Chapter 04</i>	66
I. APPLICATION OF THE PROPOSED METHODOLOGY	67
I.1. Introduction	67
I.2. Proposed methodology.....	67
I.3. Application of the proposed methodology	69
I.4. Development of FRAM model	70
I.5. Discussion	75
I.5.1. Variabilities between Functions	76
I.5.2. Interaction between functions	77
I.6. Bayesian network model for resilience of system reliability.....	81
I.7. Sensitivity Analysis.....	83
I.7.1. Calculus	84
I.7.2. Results interpretation.....	85
I.8. Conclusion.....	85
<i>BIBLIOGRAPHY</i>	86

List of Figures

FIGURE 1.1: THE PRINCIPLE OF APPROXIMATIVE ADJUSTMENTS	20
FIGURE 1.2: THE RESULTING PROPERTIES OF A SYSTEM.....	21
FIGURE 1.3: TRANSIENT PHENOMENA AND EMERGENCE	22
FIGURE 1.4: THE SIX ASPECTS OF A FUNCTION OR ACTIVITY	26
FIGURE 1.5: COUPLINGS FOR FUNCTION A	27
FIGURE 1.6: COUPLINGS FOR FUNCTION B	28
FIGURE 1.7: COUPLINGS FOR FUNCTION H	29
FIGURE 1.8: COUPLINGS FOR FUNCTION E.....	28
FIGURE 1.9: RELATIONSHIP FOREGROUND AND BACKGROUND FUNCTIONS	30
FIGURE 1.10: FMV DATA INPUT FOR FUNCTIONS AND ASPECTS	35
FIGURE 2.1: SONATRACH ACTIVITIES	57
FIGURE 2.2: A PLAN OF THE RA1D	58
FIGURE 2.3: A PLAN OF THE RA1D REFINERY	59
FIGURE 2.4: ORGANIZATIONAL CHART OF THE HSE DEPARTMENT.....	62
FIGURE 2.5: TREATED WATER DISCHARGE LAKE	63
FIGURE 3.1: OVERVIEW ON THE PROPOSED METHODOLOGY	68
FIGURE 3.2: P&ID OF THE PREFRACTIONATION SECTION.....	70
FIGURE 3.3: FRAM MODEL OF THE PREFRACTIONATION SECTION	74
FIGURE 3.4: HEAT EXCHANGERS AND PREFRACTIONATION COLUMN INTERACTION IN FRAM. 77	
FIGURE 3.5: COOLING SYSTEM AND COLLECTION INTERACTION IN FRAM.....	78
FIGURE 3.6: RECYCLING AND COLUMN PERFORMANCE INTERACTION IN FRAM	78
FIGURE 3.7: HUMAN-DCS INTERACTION IN FRAM	79
FIGURE 3.8: HUMAN-FUNCTION INTERACTION IN FRAM	79
FIGURE 3.9: VALVE-FUNCTION INTERACTION IN FRAM.....	80
FIGURE 3.10: DETECTORS AND HUMAN-DCS INTERACTION IN FRAM.....	81
FIGURE 3.11: ILLUSTRATION OF THE COMPLEX NETWORK BEHIND FRAM MODEL.....	81
FIGURE 3.12: BN MODEL DEVELOPED USING GENIE 4.0	82

List of Tables

TABLE 1.1: FUNCTIONS FOR THE MAINTENANCE OF A TURBOCHARGER AFTER A BREAKDOWN .	24
TABLE 1.2: EXAMPLES OF POSSIBLE QUESTIONS	33
TABLE 2.1: PRESENTATION OF THE CAPACITY OF SBAA (ADRAR).....	60
TABLE 3.1: THE FUNCTIONS AND COUPLING OF VARIABILITY	71
TABLE 3.2: FUNCTIONS CATEGORIZED IN EACH ASPECT	82
TABLE 3.3: FAILURE PROBABILITIES BASED ON OREDA DATABASE.....	83
TABLE 3.4: CALCULUS OF ROV	84

List of Acronyms

BN: Bayesian Networks.....	1, 10
DAG: Directed Acyclic Graph	38
DCS: Distributed Control System.....	73
FMV: FRAM Model Visualizer	30
FRAM: Functional Resonance Analysis Method	1, 10, 14, 32, 48, 65, 85, 87
GMM: Gaussian Mixture Models.....	45
GDP: Gross domestic product	50
HSE: Health, safety and environment.....	52
HES: Heat Exchanging System	79
HMM: Hidden Markov Model	39
HRA: Human Reliability Analysis	33
LPG: Liquefied petroleum gas.....	51
OREDA: Offshore and Onshore Reliability Data.....	65
PPE: Personal Protective Equipment	59
P&ID: Piping and Instrumentation Diagram	67
PSA: Probabilistic Safety Assessment.....	34
RA1D: Adrar Sbaa Refinery.....	50
ROV: Ratio of Variation.....	81
RFCC: Residue Fluid Catalytic Cracking.....	55

RCA: Root Cause Analysis.....	27
UL: Unstable Level.....	79

General Introduction

Evaluating resilience in complex systems plays a vital role in ensuring their ability to adapt and recover from unexpected disruptions. In the context of the Adrar Sbaa refinery, this dissertation focuses on quantifying the resilience of its pre-fractionation section by integrating two powerful methodologies: the Functional Resonance Analysis Method (FRAM) and Bayesian Networks (BN). This comprehensive approach aims to provide valuable insights into the system's resilience and reliability.

First chapter is divided into two parts the first one introduces to FRAM, a method that enables in-depth analysis of system functions, variability, and interdependencies. Key concepts of FRAM, including the equivalence of failures and successes, approximative adjustments, emergence, and resonance, are elucidated. Furthermore, this chapter explores the fundamental concepts in developing a FRAM model, such as functions, aspects, and the intricate relationship between them. It also provides practical guidance on data collection, analysis, and synthesis to construct a robust FRAM model. The application of FRAM model is discussed, emphasizing the description of variability and coupling between different system components.

Second part focuses on the Bayesian network a powerful modeling technique widely used in various domains. It presents an overview of Bayesian networks and their key components, including different types such as static Bayesian networks, dynamic Bayesian networks, hidden Markov models, and more. It provides a graphical and probabilistic framework for capturing dependencies between variables and making inferences based on available evidence. BNs have found applications in various domains, including risk assessment, fault diagnosis, medical diagnosis, natural language processing, and environmental modeling.

Chapter two begins with an overview of Sonatrach and RA1D, offering essential background information on the Adrar Sbaa refinery. Detailed descriptions regarding the refinery's establishment, geographical location, crude oil feedstock, and production capacity are presented. Moreover, the design principles of the installation and the composition of the refinery's main sections are highlighted. This chapter also emphasizes the significance of

refinery utilities in relation to the pre-fractionation section and its role within the broader refinery process to provide a comprehensive understanding.

Chapter 03, the core focus of this dissertation paper, introduces the proposed methodology for assessing the resilience of system reliability. It starts with an introduction to the chapter, followed by the description and application of the proposed methodology. The chapter details FRAM model's development, emphasizing variabilities between functions and the interaction between functions to understand their impact on system reliability. Additionally, it discusses constructing a Bayesian network model to quantify the resilience of system reliability. A sensitivity analysis is conducted to assess the robustness of the models. The insights gained from this chapter contribute to a deeper understanding of system resilience and provide valuable information for enhancing system reliability.

By integrating FRAM and BN methodologies, this dissertation aims to assess the resilience of the pre-fractionation section in the Adrar Sbaa refinery. The developed comprehensive methodology enables a holistic evaluation of the system's adaptive capabilities and recovery potential in the face of disruptions. Through qualitative interpretation using FRAM and quantitative analysis utilizing BN, the resilience of the pre-fractionation section can be effectively quantified. This assessment contributes to informed decision-making and facilitates the improvement of resilience of system reliability planning for the pre-fractionation section.

Chapter 01 :
Functional Resonance
Analysis Method

I.1. Overview

Event trees and fault trees are commonly used for risk assessment in cases of incidents and smaller accidents. These methods provide sufficient explanations for simpler scenarios where factors combine in relatively straightforward ways. However, when it comes to major accidents, their causes often involve complex interactions among multiple factors, some of which may not have apparent relationships beforehand. Event and fault trees are limited in their ability to fully capture and describe these complex accidents due to their static nature. The systemic nature of complex accidents requires a different approach that incorporates dynamic bindings or couplings, such as the functional resonance analysis method. Fixed structures like trees, graphs, or networks are insufficient for representing the dynamic complexities involved in major accidents.

Functional Resonance Analysis Method (FRAM) is a powerful systems-based approach that enables the analysis of complex socio-technical systems. It is widely used in industries where there is a need to manage risks associated with complex systems, such as healthcare, aviation, industries and nuclear power.

The method focuses on understanding how system components interact with each other to achieve the overall system goals, and how the system responds to unexpected events or disruptions. By applying FRAM, system operators and managers can gain a better understanding of the interactions between system components and identify potential sources of variability or risk. This allows them to make informed decisions about system design, process improvements, and risk management strategies. In this chapter, we will provide an overview of FRAM methodology and its applications, discuss its strengths and limitations, and highlight potential areas for further research and development. We will also provide practical examples of how FRAM can be used to analyze and manage risks in complex socio-technical systems.

I.2. FRAM key concepts

FRAM method was developed to analyze everyday activities and recognize successes as well as failures. It is designed to analyze both past and future events and identify potential problems. The method is a model-building tool that aims to explain how things happen rather than interpreting

events in the terms of a model. FRAM was created from scratch, with no preconceived assumptions, and is grounded in the intellectual background of critical. It was developed because there were no comparable Methods for safety assessment, and the underlying principles were formulated to make a virtue out of necessity. The method aims to bridge the gap between accident investigation and risk assessment, recognizing that events happen the same way regardless of whether they are actual past events or possible future events.

I.2.1.The Equivalence of Failures and Successes

The traditional approach to safety is to focus on understanding and preventing what goes wrong, but this overlooks the fact that success and failure are two sides of the same coin. We often assume that things go right because systems are well-designed and well-behaved, but this assumption means we know relatively little about how things go right. When an action is taken, the choice of what to do is based on many factors, including competence, experience, expectations, and available resources. If the expected outcome is achieved, the action is seen as correct, but if the outcome is unexpected, the preceding action is labeled as wrong. However, this labeling is fallacious because the action was chosen based on the expected outcome, not the actual one. Safety practices should also focus on understanding how things go right, rather than just what goes wrong [4].

I.2.2.Approximative adjustments

The performance of individuals in various tasks is susceptible to a multitude of internal and external influences, encompassing aspects such as fatigue, stress, emotional state, cognitive alertness, task complexity, and temporal constraints. Additionally, organizational factors, including communication efficacy and ambiguous guidelines, can further impede workers' endeavors. In intricate work settings, characterized by multifaceted contextual elements, individuals often confront heightened challenges that necessitate autonomous decision-making. Consequently, individuals must adapt their behavior congruent with the system's requirements to achieve desired outcomes, inevitably engaging in a delicate balancing act between operational efficiency and meticulous task execution. Termed as efficiency-thoroughness trade-offs (ETTOs) [4], these adaptive adjustments are both essential and comprehensible. Nevertheless, it is important to acknowledge that any modifications to system behavior may introduce variabilities [5].

Contextual factors such as working conditions, unexpected changes in the environment, and resource limitations can also affect human and organizational performance. In large-scale socio-technical systems, the work situation is often intractable, which means that the conditions of work are underspecified, and resources are limited. As a result, people must constantly adjust their behavior to match the conditions, and these adjustments are often approximate rather than precise. While approximate adjustments are usually good enough to get the job done, they can also be the reason why things sometimes go wrong. Despite this variability, performance variability is not necessarily a liability, and can even be a strength in socio-technical systems. Humans are capable of finding effective ways to overcome problems at work, and this capability is crucial for both safety and productivity. However, since human performance can both enhance and detract from system safety and quality, assessment methods must be able to address this duality. Understanding the factors that affect human and organizational performance is therefore essential for designing and managing effective socio-technical system [7].

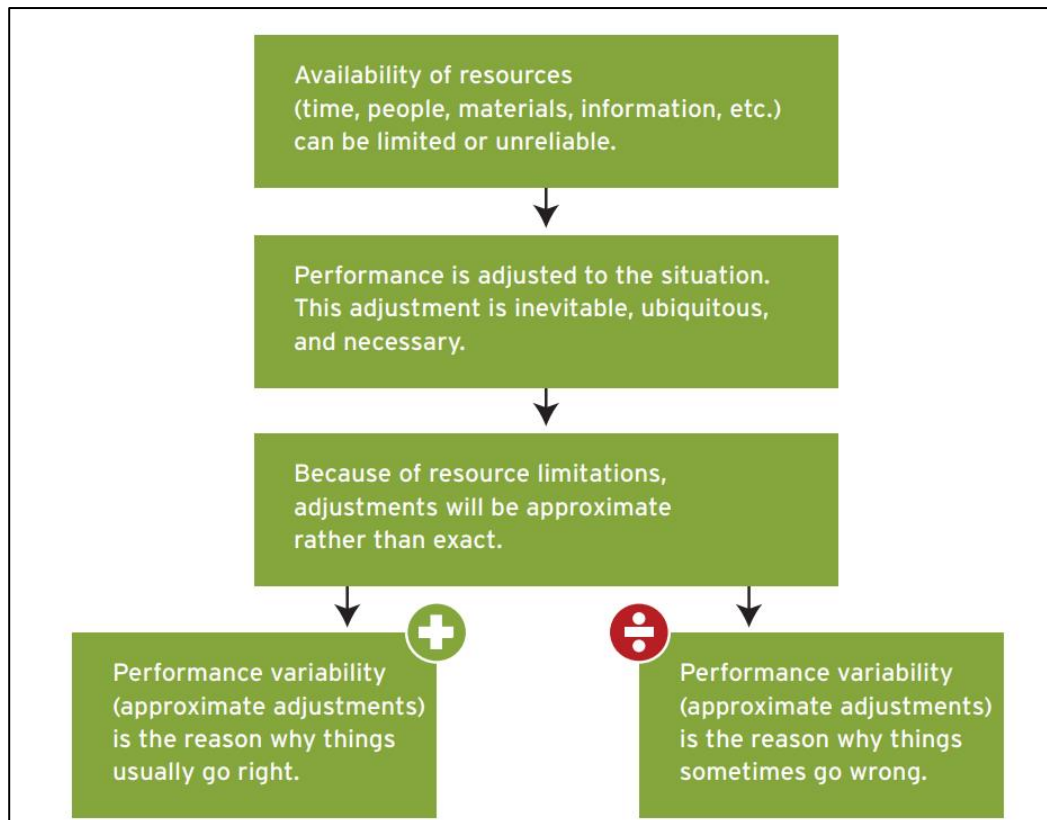


Figure 1.1: The principle of Approximative Adjustments

I.2.3. Emergence

The variability in performance due to daily adjustments is never large enough in itself to serve as the cause of something negative happening. In some situations, it is not possible to find a reason to explain what happened; perhaps nothing is different from what usually exists to justify a failure or deviation. The performance adjustments were those made habitually precisely because they have shown good results in the past. However, the variability of several functions can in a certain sense coincide and influence each other unexpectedly and lead to disproportionate impacts in both negative and positive directions. This way of describing and explaining how consequences can arise is called non-linear. This implies that the results emerge from the variability rather than resulting from it. In simpler terms, a resulting property is either the sum or difference of the component properties of the system. This is not the case for an emergent property; instead of adding measurable propositions to measurable propositions, the system cannot have the property of an element or component of the system in question but still has the property of the system taken as a whole [6]. Additionally, each resulting property can be clearly identified in its components because they are homogeneous and commensurable. This is not the case for emergent properties that cannot be reduced to the sum or difference of the system components.

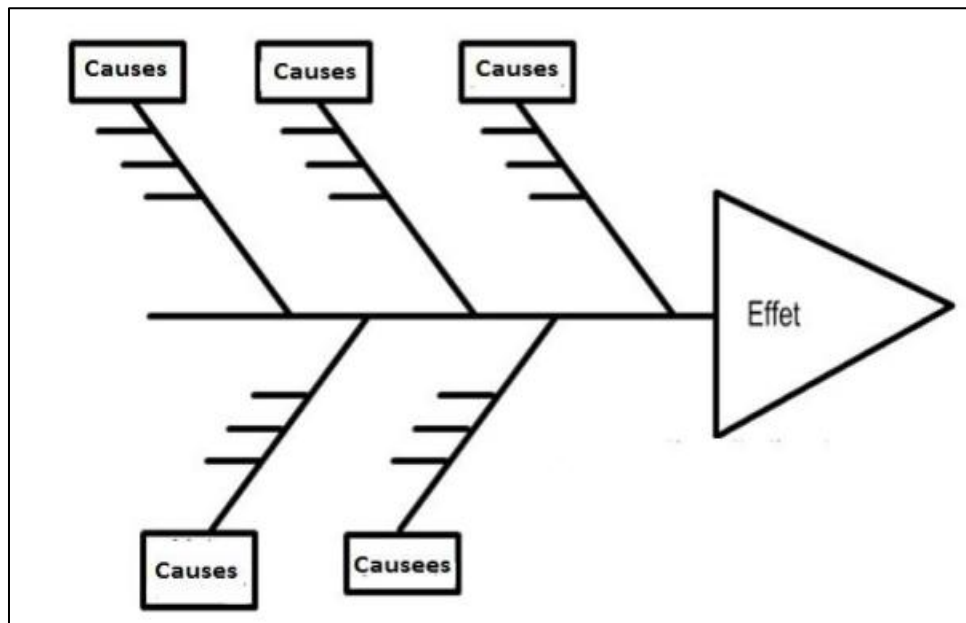


Figure 1.2: The Resulting Properties of a system

Figure 1.2 shows that conclusions based on resultant properties can be determined by one or several identifiable causes. In this case, it relates to components or functions that did not operate correctly or were faulty. By going back, the failures can be identified from the consequences.

On the other hand, Figure 1.3 shows how conclusions/results can arise from combinations of states and events. The consequences cannot be explained by the effects of specific components/functions [8].

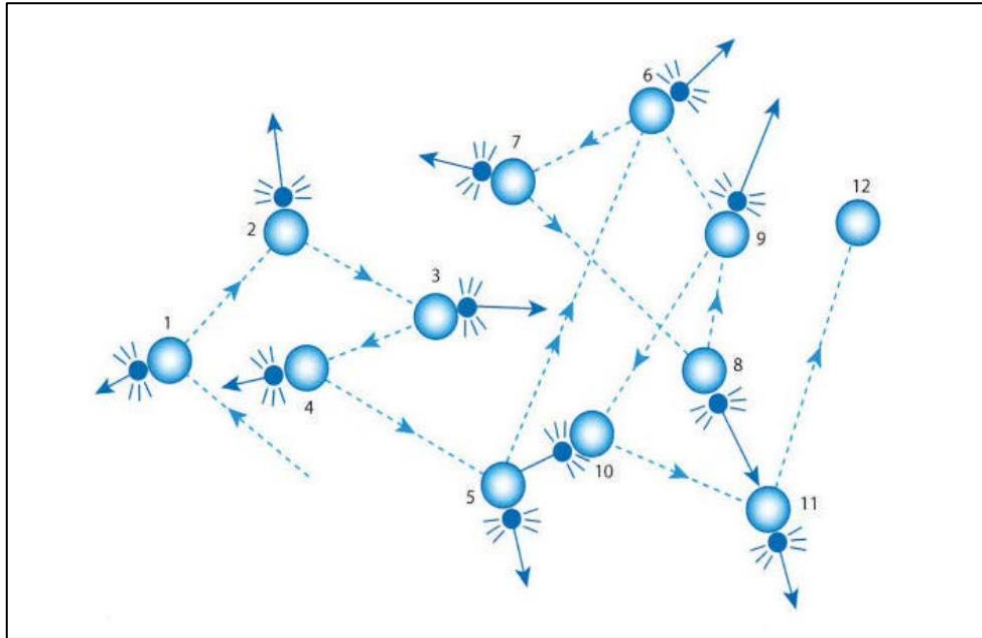


Figure 1.3: Transient Phenomena and Emergence

I.2.4. Resonance

The fourth principle of FRAM highlights the importance of accounting for the evolving couplings or dependencies among the functions in a specific situation. These couplings cannot be precisely predetermined and are not represented by a predefined tree or network structure. The dependencies among functions go beyond simple cause-and-effect relations and can resemble event structures.

The third principle, Emergence, recognizes that there are outcomes and phenomena that cannot be fully understood in terms of causality alone. This necessitates a more powerful principle of explanation. Therefore, the fourth principle introduces functional resonance as a means to explain the dynamics of complex socio-technical systems. Understanding functional resonance requires a brief introduction to classical resonance [20].

I.3. Basic concepts in developing a FRAM model

FRAM is a systematic approach used to construct a representation or description of how a particular activity or sequence of actions is typically performed. This representation is referred to as a FRAM model. The selected event or performance is depicted by identifying the essential functions required to execute the activity, exploring the potential interactions or couplings between these functions, and understanding the inherent variability associated with each function. The primary objective of FRAM is to offer a concise and structured depiction of the "normal" work process as it commonly occurs. In the following sections, the fundamental concepts necessary for constructing a FRAM model to describe the typical execution of work will be presented.

I.3.1.Functions and aspects

I.3.1.1.What is a function

In the context of FRAM, a function represents the necessary means to accomplish a specific goal. It encompasses the actions or activities, whether simple or complex, required to achieve a desired outcome. Functions typically describe what individuals or groups of people need to do to perform a particular task and attain a specific objective. For example, functions can involve activities like triaging a patient or conducting medication reconciliation. Additionally, functions can also pertain to the actions performed by organizations, such as the treatment of incoming patients in the case of an emergency department.

Functions can also apply to the actions performed by technical systems, either independently or in collaboration with one or more individuals (known as interactive or socio-technical functions). For consistency, it is recommended to describe a function using a verb or verb phrase in the infinitive form. For example, "to diagnose a patient" instead of "diagnosing a patient" or "to order medication" instead of "ordering medication" [7].

I.3.1.2.How to find functions

This could be a simplified description of the workflow process. It includes various actions/activities, where each action represents a function and is typically characterized by an

action verb. This differs from the description of states or state changes, which are typically described using nouns. The function description is provided in detail, including the entity responsible for performing them.

Table 1.1: Functions for the maintenance of a turbocharger After a breakdown

Functions	
<ul style="list-style-type: none"> • Isolate equipment • Drain equipment • Inspect equipment to identify nature of breakdown. • Request inspection of equipment • Report breakdown Issue work demands • Prepare work orders • Issue work permits and associated certificates • Schedule activities • Dismantle instruments, piping, probes, etc. • Open equipment • Clean components • Make recommendations 	<ul style="list-style-type: none"> • Grease auxiliary equipment • Replace failed components (pumps, hoses, etc.) Lubricate components • Align equipment • Mount instruments, piping, probes, etc. • Test equipment • Complete and sign-off permits to work and associated certificates • Manage competence • Manage procedures • Manage resources • Inspect opened equipment • Start equipment • Repair identified issues • Lift components

I.3.2. Brief description of the six aspects

Following the function identification, the safety assessment proceeds by characterizing each function in terms of six aspects or parameters namely Input, Output, precondition, resource, Control and Time [21] that are defined in the following terms:

Input: is what is used or transformed by a function to produce output, and can be matter, energy, or information. It can also be the signal or instruction that activates a function. Designated foreground functions in FRAM require defined inputs, while designated background functions do not [6].

Output: The Output of a function refers to the outcome or result of the function's operations, such as the processing of the Input. This Output can manifest in various forms, including material, energy, or information. An example of the latter could be a permission or clearance, or the outcome of a decision. The Output signifies a change in the state of the system or one or more output parameters. In certain cases, the Output may serve as a trigger or signal to initiate another function. When describing the Output, it is recommended to use a noun or a noun phrase to provide a clear and concise representation [6].

Precondition: Functions often require preconditions, which are system states or conditions that must be true before the function can begin. Precondition is not the same as an input, which is what activates a function. It's important to include both in a FRAM analysis, but whether something is labeled as an input or precondition is not critical. A precondition must always be an output from another function and described as a noun or noun phrase [6].

Resource: a resource is something consumed during a function, such as matter, energy, information, or manpower. Time is considered separately. Execution conditions only need to be available during a function, while preconditions are required before a function starts. Resources are different from execution conditions, as resources are consumed while execution conditions only need to be available. The description of a resource or execution condition should be a noun or a noun phrase. Blood plasma during surgery is an example of a proper resource, while competence for an operation is an example of an execution condition [6].

Time: This aspect represents the various ways in which Time can affect how a function is carried out. Time, or rather temporal relations, could be seen as a form of Control, as when Time represents the sequencing conditions. A function may, for instance, have to be carried out (or be completed) before another function, after another function, or overlapping with – parallel to – another function. Time may also relate to a function alone, seen in relation to either clock time or elapsed time

Control: control regulates a function to produce the desired output, and can be in the form of a plan, schedule, procedure, or set of instructions. Social control can also play a role in how work is done, through external or internal expectations. The description of controls should be a noun or a noun phrase [6].

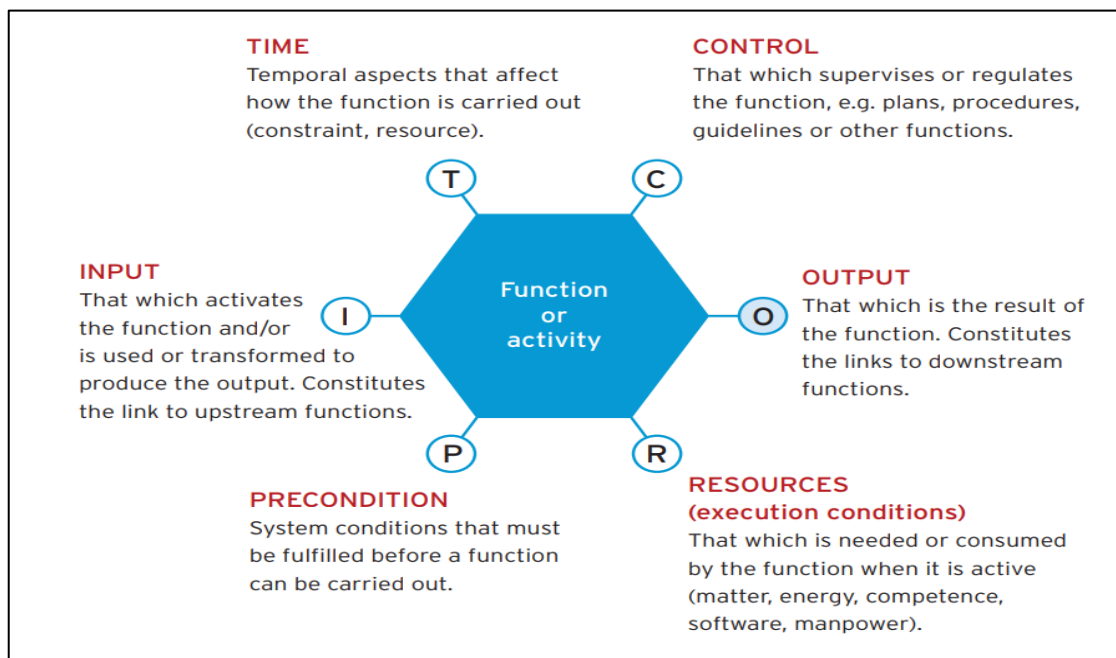


Figure 1.4: The Six Aspects of a Function or Activity

I.3.3. Relationship between functions

All the functions of a FRAM model are characterized by the six aspects. If the same values (names) are assigned to aspects of different functions – for instance the Output of one function and the Precondition of another – then there is a potential dependency or coupling between the functions.

a. Couplings:

The basis for traditional event and risk analyses is a description of relations. It may be the structure of sub-tasks in a hierarchical task analysis, or the order of (sub-)events on a timeline. Relations are often described by means of route or network diagrams (“boxes and arrows”), of which there are many different forms. The starting point for a traditional analysis is the specific relations between elements such as cause and effect, part-whole, goals-means, etc [7].

FRAM starts with describing functions of an activity or process, without focusing on their order or relation. The relations between functions are defined indirectly as coupling through their aspects. Examples of connections are provided in Figure 1.5, Figure 1.7, Figure 1.8Figure 1.6 below. An instantiation of FRAM model represents how a subset of functions can be mutually connected under given conditions at a given time.

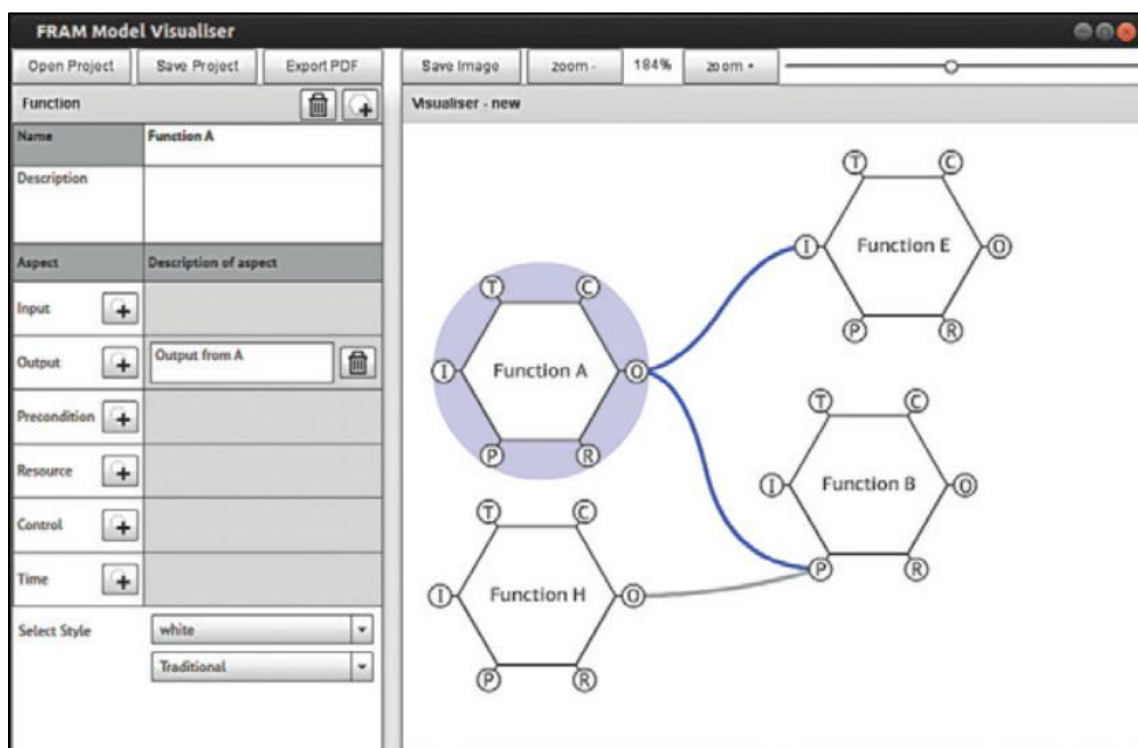


Figure 1.5: Couplings for Function A

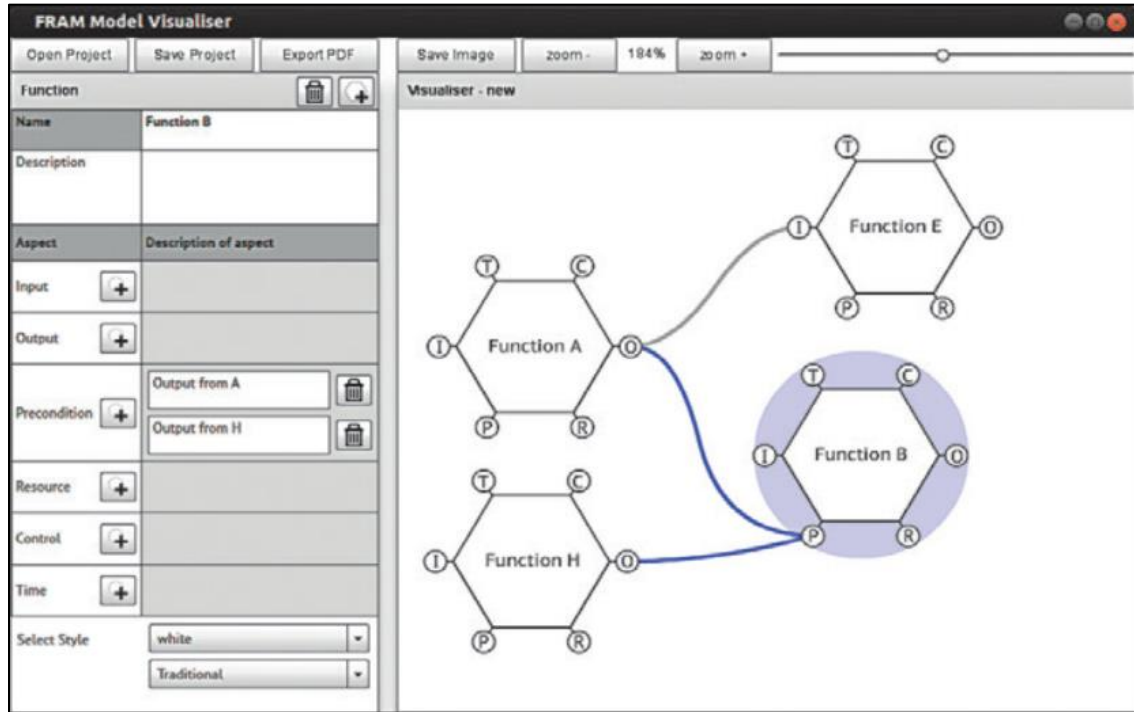


Figure 1.7: Couplings for Function B

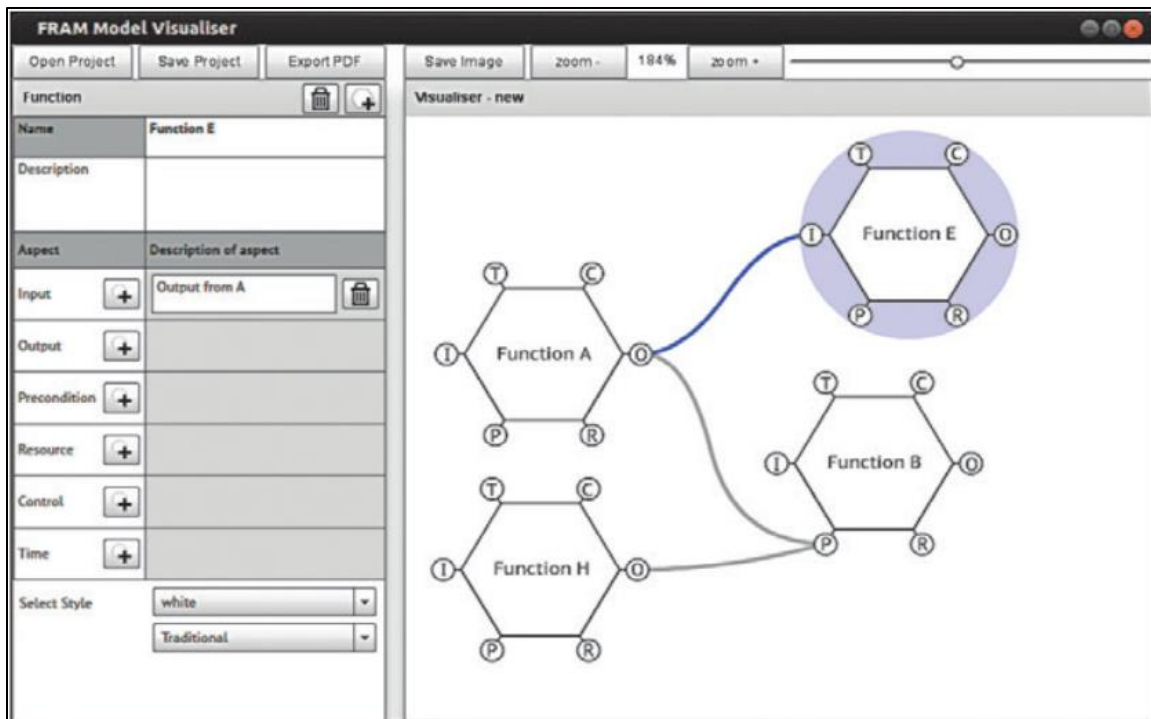


Figure 1.6: Couplings for Function E

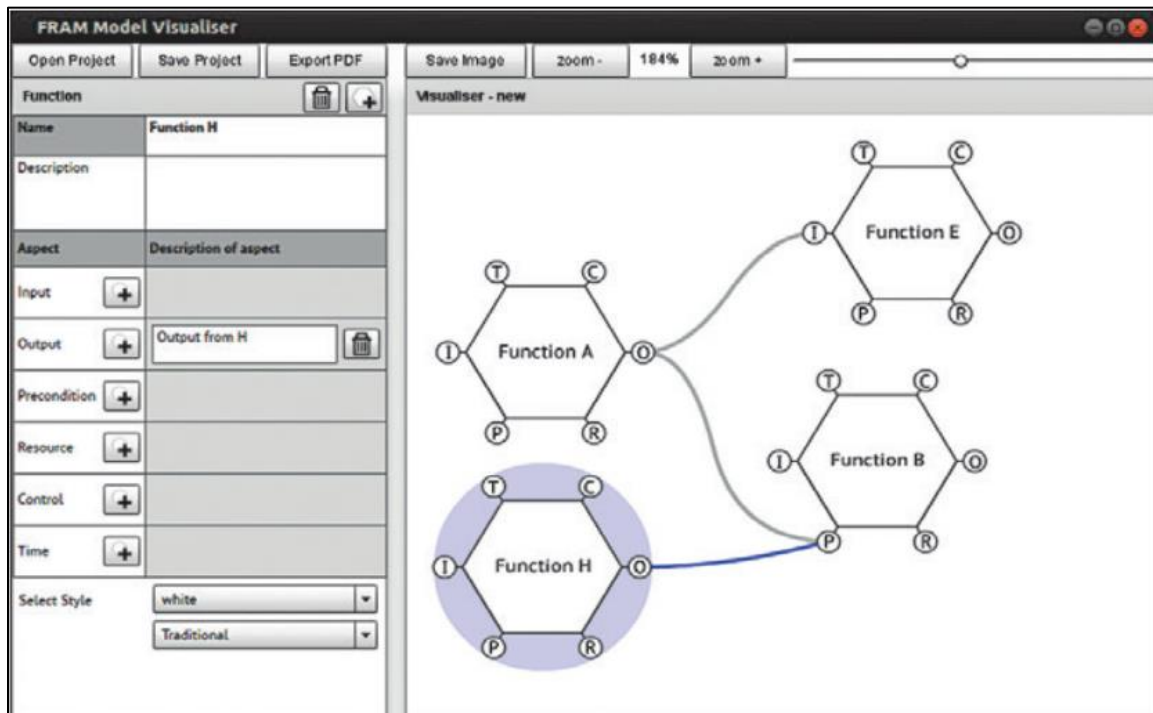


Figure 1.8: Couplings for Function H

b. Foreground and background functions

FRAM models describe the potential couplings between functions based on shared aspect attributes, without referring to any specific situation. Actual couplings occur in a particular scenario.

FRAM functions can be foreground or background. Foreground functions vary and can affect the event or process being studied, while background functions are assumed to remain stable during the incident or process. Foreground and background functions are not types of functions, but rather describe the relative importance of a function in a particular model. Background functions often represent stable resources or instructions. Instructions are generally stable and only change if corrected or modified over a longer time span. The relationship between foreground and background functions can change depending on the study focus.

The terms upstream and downstream in FRAM refer to the temporal relationship between a function in focus and other functions. Upstream functions are those that have already been performed before the function in focus, while downstream functions are those that come after. However, the exact order in which functions are performed can only be determined when the model is instantiated for a specific scenario. In contrast, the labels foreground and background functions refer to the relative importance of a function in the model and remain valid for both FRAM model and its instantiations. Finally, the terms upstream and downstream are relative and not absolute, as a function that is upstream for one instantiation may be downstream for another.

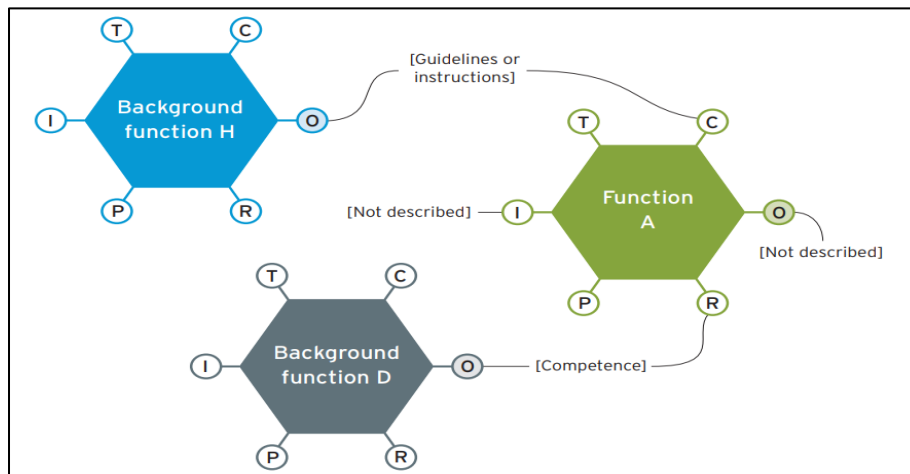


Figure 1.9: Relationship Foreground and Background Functions

c. The Upstream and Downstream Functions

While the background/foreground functions represent the roles of functions in the model, the terms Upstream and Downstream are used to indicate the temporal representation of functions. An Upstream function implies that, for a given instantiation, it is performed before other functions and can therefore affect them.

d. Graphical representation of a FRAM model

In the graphical representation of a FRAM model, hexagons are utilized to depict functions without any explicit lines or connections between them. The orientation or arrangement of the hexagons is not determined by the graphical representation itself. When a FRAM model is instantiated, it

illustrates how a specific subset of functions can be interconnected or interdependent under certain conditions or within a designated timeframe. The couplings depicted in a particular instantiation are assumed to remain stable throughout the scenario being analyzed. In a risk assessment, multiple instantiations are typically included, with each instantiation representing the relationships between upstream and downstream functions at a specific time or under given conditions.

I.3.4.Strengths and weaknesses of FRAM

I.3.4.1.Strengths of FRAM

FRAM possesses a notable advantage in its ability to foster a holistic understanding of the functioning and desired operation of a socio-technical system. Unlike approaches that decompose a system into individual components and their characteristics, FRAM avoids the pitfall of seeking solutions for each isolated cause or factor. Instead, it encourages a more comprehensive perspective.

One of the strengths of FRAM is its capacity to guide the analysis team to ask pertinent questions before seeking answers. Unlike other methods, FRAM does not incorporate a predefined model of a specific system or make assumptions about cause-effect relationships. As a result, it facilitates an exploratory approach that prioritizes inquiry over preconceived answers.

Additionally, the versatility of FRAM enables its application to various forms of performance or activities, including its own utilization in the development of a FRAM model [11].

I.3.4.2.Weaknesses of FRAM

One apparent weakness of FRAM is the potential for it to be time-consuming and challenging to implement. However, this weakness is merely superficial and stems from the fact that FRAM is a relatively new method. Any new method requires significant effort and may initially be difficult to grasp. The perceived difficulty may be magnified if the analysis team is accustomed to a different type of method, particularly one that follows a straightforward cookbook approach, such as Root Cause Analysis (RCA).

As it stands, FRAM is primarily a qualitative method and does not currently support quantification. However, this does not rule out the possibility of incorporating quantification in the future. Any quantification approach employed would need to be distinct, as FRAM focuses on assessing the likelihood of function variability rather than the probability of malfunctioning or failure.

FRAM necessitates a certain level of imagination. Its purpose is to guide and facilitate analysis rather than automating it. Being a method-first approach rather than a model-first approach, FRAM offers guidance and prompts analysts to explore relevant areas but does not provide definitive answers [11].

I.4. Development of a FRAM Model

I.4.1. How to prepare for data collection

***a.* Information needed**

FRAM, serves as a valuable instrument for illustrating and portraying the customary execution of an activity. By employing this approach, the chosen activity is delineated in relation to the essential functions required to accomplish it, the potential interconnections among these functions, and the inherent variability typically observed within the activity [11].

***b.* How to obtain this information**

The individuals actively engaged in the tasks at hand serve as the most reliable sources of information regarding activities of interest. These sources can encompass both individuals present within the specific workplace under examination and those working in similar settings [7]. While interviews constitute the primary means of investigation, additional data can be gathered through field observations and document analysis.

When conducting interviews, it is crucial for researchers to carefully consider the objectives of the study, determining the extent of information required and how it will contribute to the overall understanding. Adequate preparation is key before entering the field, involving a comprehensive review of available resources such as regulations, documents, protocols, job descriptions, and other relevant sources of information. Valuable insights can also be gained from data pertaining to

personnel turnover, equipment, procedures, organizational changes, and significant events [7]. These details will inform the formulation of interview questions, which should primarily focus on daily activities, practices, and their inherent variabilities. Instead of inquiring solely about successes or failures, it is important to delve into routine practices and habits that may be taken for granted or overlooked, including topics that might be suppressed in discussions surrounding adverse events. Additionally, researchers should strive to gather as much information as possible regarding the physical and environmental conditions within the workplace [7]. This may involve examining architectural drawings, photographs, videos, and other relevant materials.

Table 1.2: Examples of Possible Questions

Examples of Possible Questions
• When do you start this activity? What “signals” that you can begin?
• How do you adjust the activity to different conditions? How do you determine how and when to adjust?
• How do you respond if something unexpected happens? For example, an interruption, a pause required by a more urgent task that takes priority, a missing resource, etc.
• How stable is staffing? Is staff allocation permanently assigned or adjusted daily? What happens if staffing is short?
• How stable is the environment? Supplies? Resources? Demands? Etc.

c. Interview

For optimal results, it is advisable to conduct the interview directly at the workplace or the location relevant to the event being studied. This approach allows for a more contextual understanding of the environment. Additionally, providing a guided tour of the workplace can offer the interviewer valuable insights into the physical setting. Before commencing the interview, it is essential to inform the interviewees about the process and obtain their voluntary agreement to participate. To ensure thorough documentation, it is beneficial to have two interviewers present—one actively engaged in the dialogue while the other takes detailed notes. Ideally, one of the interviewers should possess expertise in the relevant work domain, although they should strive to maintain objectivity and avoid any supervisory or managerial roles [7]. With the explicit consent of the interviewees,

recording the interview can be considered as an option to ensure accurate capturing of the information provided.

I.4.2.How to begin analysis and synthesis of the data

To initiate the process, it is important to transcribe the interview notes and combine them with the information gathered during the preparation phase. The team should then proceed to identify the key functions and organize the material in a manner that corresponds to these functions. If possible, distinguishing between foreground and background functions can be done at this stage.

For each foreground function, it is advisable to identify as many of the six aspects as possible: Input, Output, Preconditions, Resources, Control, and Time. At the very least, essential information about the Input and Output aspects should be documented [7]. Special attention should be given to providing a comprehensive description of the Output, taking into account its expected variations in terms of timing and precision. Regarding timing, it is crucial to determine whether the Output demonstrates variations by being delivered too early, too late, on time, or not at all. When it comes to precision, it is necessary to evaluate whether the Output is likely to be imprecise, acceptable, or precise.

a. How to document the Interview

To document an interview, you should identify the function name and provide a description of the function including who performs it. Each function should be characterized by some or all of the six aspects, including Input, Output, Precondition, etc [7]. FRAM Model Visualizer (FMV) can help structure the information and check the completeness of the model

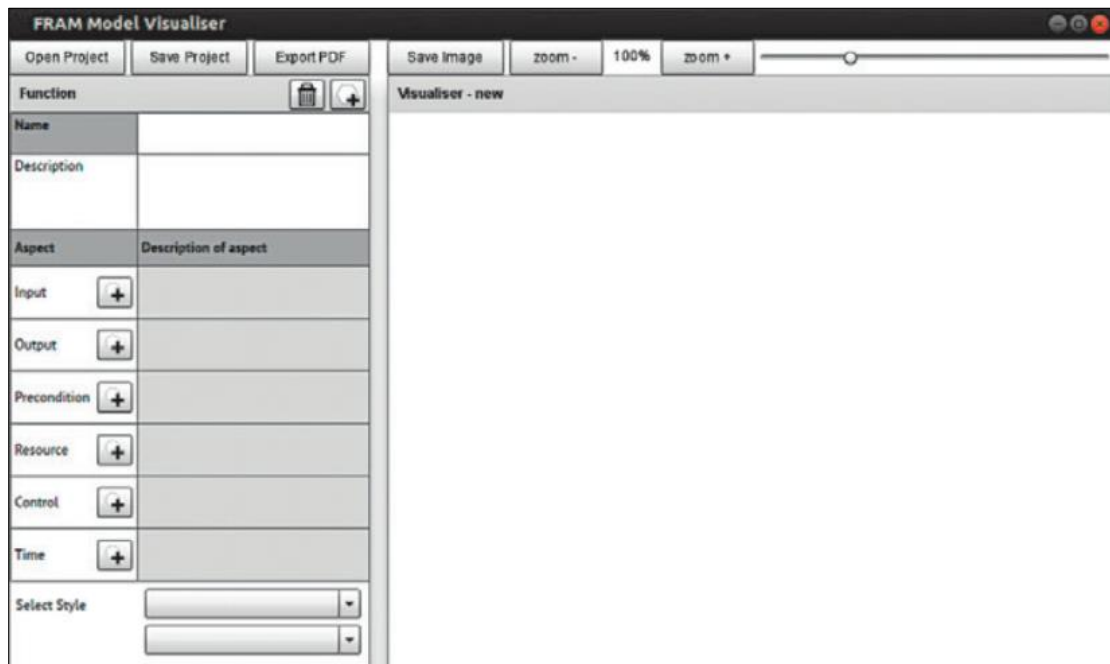


Figure 1.10: FMV Data input for Functions and Aspects

***b.* Finding the first function**

To start building a FRAM model, any function can be chosen as the starting point. However, it may be helpful to begin with a central function of the activity being analyzed. In the example of a Patient with a Spinal Fracture, the function <Respond to test result> is a central function and a possible starting point [7]. This function involves the GP receiving and evaluating information about the patient, which has emerged from tests, surveys, or interviews conducted outside the practice. Based on this assessment, the GP will decide on the next course of action.

I.5. Application of a FRAM model

I.5.1. How to describe the variability

Describing variability in a FRAM model is crucial for comprehending the interconnectivity of functions and potential unexpected outcomes. Rather than focusing on the variability of functions themselves, the analysis emphasizes the variability of function outputs. This is because if a function's performance varies without affecting its output, then the variability is typically not

significant [8]. However, if a function's output varies, then the variability of the function becomes relevant as it impacts the output's characteristics and quality.

There are three primary reasons why a function's output may vary: internal variability, external variability, and upstream-downstream coupling. Internal variability is a result of the function's unique characteristics or nature. External variability arises from variations in the working environment or conditions under which the function is performed. Finally, upstream-downstream coupling occurs when variability in the output of upstream functions influences the input, requirement, resource, control, or time for downstream functions [8]. This coupling forms the basis of functional resonance.

It is also possible for a function's variability to result from a combination of the three conditions: internal variability, external variability, and upstream-downstream couplings.

I.5.2. Manifestations of variability

After identifying the likely sources of internal and external variability, the next step is to explain how this variability will be reflected in the output of the function. This is known as the phenomenology of variability. This step is important because it helps to understand how variability can impact downstream functions and also provides a basis for detecting or observing variability.

The manifestations of variability can be described in two ways - a simple way and a more detailed way. The simple description characterizes the variability of a function's output in terms of time and precision. This approach is efficient but less thorough [8]. On the other hand, the detailed approach is more thorough but less efficient. It is recommended to start with the simple approach and then move on to the more detailed approach if needed.

The simple approach describes the variability of the function's output in terms of time and precision. The output can occur too early, on time, too late, or not at all. The last category can be seen as an extreme version of "too late," and it can result in the output either never occurring or occurring so late that it is useless. If the output is not available on time, it can impact downstream functions in several ways [8].

I.5.3.Potential and actual variability

Potential variability refers to the range of possible outcomes that may occur under different conditions, while actual variability pertains to the expected outcomes under given conditions, taking into account the demands, opportunities, and resources available.

For technological functions, the Functional Resonance Analysis Method (FRAM) assumes that potential variability is unlikely to be realized if the operating conditions are within the nominal range. However, for human and organizational functions, potential variability is assumed to be realized as actual variability, unless the working conditions are perfect.

The level of detail provided in the analysis determines how actual variability will manifest itself. Detailed information about the event being analyzed is necessary for event analysis, while risk analysis requires a high degree of detail regarding the assumptions made for that particular scenario [7].

It is essential to distinguish between potential and actual variability when considering the impact of variability on downstream functions. The analysis of coupling and resonance should be carried out for actual variability, which is always a subset of potential variability. To avoid bias, it is advisable to start by describing potential variability.

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I.5.4.Human Reliability Analysis

it is important to consider the role of human factors and potential human errors in the overall analysis. To address this, the integration of Human Reliability Analysis (HRA) is incorporated. HRA methodology is applied to identify critical tasks within Fram framework, analyze potential human errors, and develop mitigation strategies. By considering human factors and implementing HRA, this dissertation aims to enhance the reliability and validity of Fram analysis, ensuring a more comprehensive understanding of the system dynamics and associated outcomes.

I.5.4.1.Definitions Of “Human Error”

The concept of "error" in the context of human fallibility in the workplace has been a topic of extensive discussion among researchers. Numerous attempts have been made to provide a precise technical definition for this concept [4], but it has proven to be challenging due to the lack of consensus and differing perspectives among experts.

Scholars such as Embrey, Kirwan, Reason, Senders & Moray, Singleton, and Woods et al. have all acknowledged the difficulty in defining "error" despite its straightforward meaning in everyday life [4]. The lack of agreement stems from different premises and starting points when analyzing the nature and origins of errors.

Engineers, for instance, tend to view human operators as components within a system, treating their successes and failures in a similar manner to equipment. On the other hand, psychologists often emphasize the purposive nature of human behavior and emphasize understanding it in the context of subjective goals and intentions. Sociologists, in their analysis, attribute error modes primarily to socio-technical system features, such as management style and organizational structure, which are seen as mediating variables influencing error rates.

Overall, the complexity and multifaceted nature of error in the work context make it difficult to establish a precise technical definition [4]. Acknowledging the various perspectives and starting points in understanding error is crucial for fostering a more comprehensive and interdisciplinary approach to addressing human fallibility and improving system performance.

I.5.4.2. THE ROLE OF HRA IN PSA

Historically, Human Reliability Analysis (HRA) has been closely associated with Probabilistic Safety Assessment (PSA), with a strong focus on quantification. This approach, combining PSA and HRA, has often discouraged behavioral scientists, including psychologists and ergonomists, from considering HRA as a relevant field. However, such an attitude is unproductive. The practical necessity for HRA has increased as there is a growing requirement to accurately calculate the probability of accidents, guiding resource allocation [4]. Moreover, there is a fundamental need to enhance our understanding of human behavior in system design and develop models and methods to analyze the interaction between individuals and socio-technical systems. These two needs are not contradictory but can coexist effectively.

While the terms "qualitative" and "quantitative" are sometimes used as opposing concepts, the distinction lies primarily in terminology rather than ontology. A quantitative analysis always relies on a preceding qualitative analysis. It is now widely acknowledged that a qualitative analysis can often be sufficient for the purposes of HRA, although there may still be instances where numerical input is required for a PSA [4].

I.5.5. Dependence between functions

Work involves the execution of multiple tasks and sub-tasks, which are referred to as functions. These functions require collaboration among different individuals and coordination of their work. Each function that a person performs must be tailored to the prevailing conditions [10]. However, each function also impacts the conditions of other functions.

Consequently, the adjustments made by an individual at a given time become part of the variability of the environment for downstream functions, whether these functions are performed by the same person or someone else [10]. Downstream functions cannot be certain about the adjustments made

by upstream functions, although it is usually assumed that these adjustments were made in accordance with established practices.

The adjustments to upstream functions, therefore, constitute a source of variability that affects the adjustments made by subsequent (downstream) functions. In a stable working environment with limited organizational variability, the adjustments and variability will eventually match each other, providing the basis for effective everyday performance [8]. However, in an unstable working environment with frequent changes in demands, resources, personnel, etc., unexpected and unwanted situations may easily arise.

I.5.6. Coupling between Output and Preconditions

The Preconditions are a set of conditions that must be satisfied before a particular function can be executed. These Preconditions are derived from the Output of one or more upstream functions. When a function cannot be performed unless certain Preconditions are met, the initial step of the function often involves verifying whether the Preconditions have been established. However, this verification process may vary or be omitted entirely if it is assumed that the situation remains unchanged.

I.5.7. Coupling between Output and Resources

For a function to be carried out, it is necessary to have both Resources and Execution Conditions in place. Resources are utilized during the function's execution and therefore require replenishment or renewal, which is usually provided as Output from an upstream function. This upstream function is typically referred to as a foreground function.

As for Execution Conditions, they are generally assumed to remain stable while the function is being performed. These conditions are usually described as the Output of a background function.

I.5.8. Coupling between Output and Control

Control refers to the factors that direct or influence how a function is executed. If the Output of an upstream function that provides Control of a downstream function varies, it will inevitably result in greater variability of the Output of the downstream function. When Control is standardized, such as in the form of an instruction or a procedure, it can be considered the Output of a background

function. However, if Control is more dynamic and adaptable, it would be more appropriate to describe it as the Output of a foreground function.

I.5.9.Coupling between Output and Time

Time encompasses the various factors that may impact how a function is executed. This may include the amount of time available, the specific time when a function can begin or be completed, and any requirements for synchronization with other functions. The key difference between Time and Control is that Time pertains to when a function is performed, while Control relates to how the function is carried out.

I.5.10.Coupling between Output and Input

The Input is what initiates a function and what is utilized or modified by the function. In the former case, variability in the Output from upstream functions may cause the function to commence either too early or too late, resulting in synchronization and coordination issues. For instance, a function's performance may be "trimmed" to save time. Although such trimming may help to absorb delays, it can also increase the variability of the Output, for example, in terms of precision

Chapter 02

Bayesian Network

I.6. Overview

A Bayesian network, also known as a belief network or graphical model, is a probabilistic graphical model that represents a set of variables and their conditional dependencies [19] through a directed acyclic graph (DAG).

Formally, a Bayesian network is defined as a pair (G, P) , where G is a directed acyclic graph, whose nodes represent variables and directed edges represent direct dependencies between variables [24], and P is a set of conditional probability distributions associated with each variable given its parents in the graph.

The theory and concept of Bayesian networks were introduced by Judea Pearl in the 1980s and have since been extensively studied and applied in various fields, including artificial intelligence, machine learning [19], decision analysis, and expert systems.

I.7. Key components of a Bayesian network

- **Nodes/Variables:** Each node represents a random variable, which can be observed or unobserved. Nodes can represent a wide range of entities, such as symptoms, test results, environmental factors [15], or financial indicators.
- **Edges/Links:** The directed edges connecting the nodes in the graph represent the dependencies and causal relationships between the variables. An edge from node A to node B indicates that A influences B [19].
- **Conditional Probability Tables (CPTs):** Each node has an associated conditional probability table that quantifies the probability distribution of the variable given the values of its parents in the graph [14]. CPTs encode the probabilistic relationships among variables in the network.
- **D-separation and Markov Blanket:** D-separation is a criterion to determine the conditional independence relationships between variables in the graph. The Markov blanket of a node consists of its parents, children, and the other parents of its children [15]. The Markov blanket provides a minimal set of variables needed to infer the node's value.

Bayesian networks enable efficient probabilistic inference through the application of Bayes' theorem and graph theory. They allow for the calculation of posterior probabilities, given observed evidence, by exploiting the graphical structure and conditional independence assumptions [19].

I.8. Types of Bayesian Network

there are different types of Bayesian networks that are used to model specific types of problems or incorporate specific features. Some of the commonly discussed types of Bayesian networks include

I.8.1.Static Bayesian Networks

Static Bayesian networks, also known as fixed structure Bayesian networks, are models that capture relationships between variables assuming a fixed network structure that remains constant throughout the analysis [24].

I.8.2.Dynamic Bayesian Networks (DBNs)

DBNs extend Bayesian networks to model time-dependent systems by incorporating temporal dependencies among variables [13]. They are suitable for modeling processes that evolve over time and enable tasks such as prediction, filtering, and smoothing.

I.8.3.Hidden Markov Models (HMMs)

HMMs are a specific type of dynamic Bayesian network commonly used for modeling sequential data. They consist of hidden states and observable emissions, and are widely applied in speech recognition and natural language processing [13].

I.8.4.Continuous Bayesian Networks

Continuous Bayesian networks allow for the modeling of continuous variables by using probability distributions such as Gaussian or multivariate Gaussian distributions to represent the dependencies between them [14].

I.8.5. Hybrid Bayesian Networks

Hybrid Bayesian networks combine discrete and continuous variables within a single model. They are employed when dealing with systems that involve both discrete and continuous variables interacting with each other [24].

I.8.6. Dynamic Influence Networks (DINs)

DINs extend dynamic Bayesian networks by incorporating external influences on the system [24]. They are useful for modeling the impact of exogenous factors on the dynamics of the variables.

I.9. Modeling with Bayesian Networks

Bayesian networks are powerful models for representing and analyzing complex relationships between variables. They provide a graphical framework that combines probability theory and graph theory to capture dependencies and uncertainties. Here are key aspects of modeling with Bayesian networks:

I.9.1. Graphical Representation

Bayesian networks use directed acyclic graphs (DAGs) to represent the relationships between variables [19]. The nodes in the graph correspond to variables, and the edges represent the probabilistic dependencies between them.

I.9.2. Conditional Probability Distributions

Each node in a Bayesian network is associated with a conditional probability distribution (CPD) that quantifies the probability of the node given its parents [15]. CPDs can be learned from data or specified by domain experts.

I.9.3.Causal Reasoning

Bayesian networks allow for causal reasoning by capturing the cause-effect relationships among variables. The directed edges in the graph indicate the direction of causal influence, enabling the identification of direct and indirect causal pathways [19].

I.9.4.Probabilistic Inference

Bayesian networks enable probabilistic inference by computing the posterior probabilities of variables given evidence. Inference algorithms, such as variable elimination or belief propagation [15], are used to propagate probabilities through the network.

I.9.5.Learning from Data

Bayesian networks can be learned from data using various approaches, such as parameter estimation and structure learning. Parameter estimation involves estimating the CPDs from observed data, while structure learning aims to discover the underlying graph structure from data [2].

I.9.6.Handling Uncertainty

Bayesian networks provide a principled framework for representing and reasoning under uncertainty. They can handle missing data, incorporate prior knowledge [14], and update beliefs based on new evidence using Bayes' theorem.

By effectively capturing complex relationships and uncertainties, Bayesian networks have found applications in various domains, including healthcare, finance, natural language processing, and decision support systems.

I.10. Inference and Reasoning in Bayesian Networks

Inference and reasoning in Bayesian networks involve using the network's structure and probability distributions to make probabilistic inferences and answer queries about the variables of interest. Here are the key aspects of inference and reasoning in Bayesian networks:

I.10.1.Exact Inference

Variable elimination is an exact inference algorithm used to compute the marginal probabilities of variables given evidence. It involves eliminating variables from the network by summing over their possible values while taking into account the conditional probabilities specified in the network's CPTs [14]. The process continues until the desired variables are reached.

I.10.2.Approximate Inference

Markov Chain Monte Carlo (MCMC): MCMC methods, such as Gibbs sampling and Metropolis-Hastings, are used for approximate inference in Bayesian networks. These methods generate samples from the joint probability distribution of variables in the network and approximate the posterior probabilities by analyzing the generated samples [15]. MCMC is particularly useful when exact inference is computationally infeasible or when dealing with large and complex networks.

I.10.3.Approximate Inference

Belief propagation, also known as sum-product algorithm or message-passing algorithm, is an efficient approximate inference algorithm for Bayesian networks with tree-like structures. It computes the marginal probabilities of variables by passing messages along the edges of the graph, incorporating information from neighboring nodes [19]. Belief propagation can be applied to perform inference in networks with cycles by converting them into tree-like structures using techniques like junction tree algorithm.

I.10.4. Handling Large and Complex Networks

Bayesian networks can become computationally challenging when dealing with large and complex networks. Various techniques can be employed to address this issue, including parallelization, approximation methods like MCMC, and exploiting conditional independence properties in the network to reduce computational complexity [15]. Additionally, techniques such as variable grouping, dynamic discretization, and parallel sampling can help improve the efficiency of inference in large networks.

I.10.5. Sensitivity Analysis

Sensitivity analysis is used to assess the impact of changes in evidence or parameters on the network's output. By systematically varying the evidence or parameters, sensitivity analysis helps understand how robust the network's predictions are and how sensitive they are to different inputs [14].

I.11. Applications of Bayesian Networks

Bayesian networks have found application in various fields due to their ability to model and reason under uncertainty. Here are some notable applications of Bayesian networks:

I.11.1. Risk Assessment and Management

Bayesian networks are employed in risk assessment and management across various industries, including finance, insurance, and engineering. They help assess and model risks by considering multiple factors and their interdependencies. Bayesian networks can analyze historical data, expert knowledge, and environmental factors to estimate probabilities of potential risks [16], aiding in decision-making and risk mitigation strategies.

I.11.2. Fault Diagnosis and Troubleshooting

Bayesian networks are used for fault diagnosis and troubleshooting in complex systems, such as manufacturing processes, power grids, and transportation systems. They model the relationships

between system components and symptoms to identify the most likely causes of failures or malfunctions [13]. Bayesian networks enable efficient fault localization and provide insights into the impact of different factors on system performance.

I.11.3. Medical Diagnosis and Decision Support

Bayesian networks have been widely used in medical diagnosis and decision support systems. They can integrate patient symptoms, test results, and medical knowledge to provide probabilistic assessments of diseases and guide treatment decisions. Bayesian networks enable doctors to consider multiple variables and their dependencies when making diagnoses, improving accuracy and efficiency [14].

I.11.4. Natural Language Processing

Bayesian networks have applications in natural language processing tasks, such as text classification, information extraction, and sentiment analysis. They can capture the probabilistic relationships between words and topics, improving the accuracy of language models and enabling more robust language processing algorithms. Bayesian networks are used to model language structures and perform probabilistic reasoning [3] in language-related tasks.

I.11.5. Environmental Modeling

Bayesian networks are employed in environmental modeling and ecological studies. They help assess the impact of environmental factors on ecosystems, species distribution, and climate change. Bayesian networks integrate data from various sources, such as remote sensing, climate models, and biodiversity records, to model complex environmental systems and support decision-making for conservation and sustainable management [1].

I.12. Comparative Analysis with Other Models

When comparing Bayesian networks with other models, it is important to consider their strengths, weaknesses, and suitability for different tasks. Here is a comparative analysis of Bayesian networks with other popular modeling approaches:

I.12.1. Bayesian Networks vs. Decision Trees

Decision trees are intuitive models that represent a sequence of decisions and their associated outcomes. Bayesian networks, on the other hand, capture probabilistic relationships between variables using directed acyclic graphs. Decision trees excel in handling categorical variables and feature interactions, while Bayesian networks are well-suited for modeling uncertain and complex relationships between variables. Bayesian networks provide a probabilistic framework for reasoning under uncertainty and allow for efficient updating of beliefs given new evidence [15]

I.12.2. Bayesian Networks vs. Neural Networks

Neural networks are powerful models for learning complex patterns from data. They excel in tasks like image recognition and natural language processing. Bayesian networks, in contrast, provide a transparent probabilistic framework for modeling uncertain relationships and making probabilistic inferences. Bayesian networks are advantageous when interpretability and reasoning under uncertainty are crucial [2], whereas neural networks are often preferred for their ability to learn intricate patterns and handle large-scale datasets.

I.12.3. Bayesian Networks vs. Support Vector Machines (SVM)

Support Vector Machines are powerful classifiers used for both regression and classification tasks. SVMs find decision boundaries that maximize the margin between different classes. Bayesian networks, on the other hand, model probabilistic relationships between variables and provide insights into the dependencies and conditional probabilities. While SVMs excel in classification tasks, Bayesian networks offer a more comprehensive probabilistic framework for capturing complex relationships and reasoning under uncertainty [18].

I.12.4. Bayesian Networks vs. Hidden Markov Models (HMM)

Hidden Markov Models are widely used for modeling sequential data with hidden states. They are popular in speech recognition, bioinformatics, and natural language processing. HMMs assume a specific temporal structure and are suitable for modeling dynamic processes. Bayesian networks, on the other hand, capture general dependencies between variables and allow for more flexible modeling of complex relationships [18]. Bayesian networks are advantageous when dealing with both temporal and non-temporal data, and when capturing dependencies beyond the sequential structure.

I.12.5. Bayesian Networks vs. Gaussian Mixture Models (GMM)

Gaussian Mixture Models are widely used for modeling data distributions. They assume that the data is generated from a mixture of Gaussian distributions. Bayesian networks, on the other hand, capture dependencies and probabilistic relationships between variables. While GMMs focus on modeling data distributions [18], Bayesian networks provide a more comprehensive framework for modeling complex relationships and reasoning under uncertainty.

It is important to note that the choice of model depends on the specific task, available data, interpretability requirements, and the nature of the relationships being modeled. Each model has its own strengths and weaknesses, and understanding these trade-offs is crucial in selecting the most appropriate model for a given application.

I.13. Strengths and Weaknesses of Bayesian Networks

I.13.1. Strengths of Bayesian Networks

- **Probabilistic Framework:** Bayesian networks provide a probabilistic framework for modeling uncertain relationships between variables. They explicitly capture the conditional dependencies and uncertainties in the data, allowing for principled reasoning under uncertainty [15].

- **Transparent and Interpretable:** Bayesian networks offer transparency and interpretability. The graphical structure of the network represents the causal relationships between variables, making it easier to understand and validate the model [19]. The network can also provide insights into the relative importance and influence of different variables.
- **Efficient Updating of Beliefs:** Bayesian networks enable efficient updating of beliefs based on new evidence. By applying Bayes' theorem, the network can incorporate new data to revise the probabilities of variables [14], providing a principled mechanism for learning and adapting the model.
- **Effective Handling of Missing Data:** Bayesian networks can handle missing data effectively. By leveraging the conditional dependencies between variables, the network can make informed estimates of missing values, allowing for more robust analysis even with incomplete data [15].
- **Incorporation of Prior Knowledge:** Bayesian networks allow the incorporation of prior knowledge and expert opinions through the specification of prior probability distributions. This is particularly useful in situations with limited data [13], as prior knowledge can help guide the modeling process.

I.13.2. Weaknesses of Bayesian Networks

- **Computational Complexity:** Inference and learning in Bayesian networks can be computationally complex, especially for large and complex networks. Exact inference may become intractable, requiring the use of approximation methods such as sampling techniques or belief propagation algorithms [15].
- **Dependency Assumptions:** Bayesian networks rely on the assumption of conditional independence between variables given their parents. While this assumption simplifies the modeling process, it may not always hold in practice [19]. Violation of these assumptions can lead to biased or inaccurate results.
- **Knowledge Engineering and Model Specification:** Constructing a Bayesian network requires domain knowledge and expertise to specify the network structure and conditional

probability distributions. Gathering and encoding this knowledge can be time-consuming and subjective, relying on expert judgment [14].

- **Limited Expressiveness for Complex Relationships:** While Bayesian networks can capture many types of relationships, they may struggle to represent highly complex relationships or non-linear dependencies accurately [13]. Other models, such as neural networks, may be more suitable for capturing intricate patterns in the data.
- **Data Requirements:** Bayesian networks typically require a sufficient amount of data to estimate the parameters accurately. In situations with limited data, model performance and generalization may be compromised [15].

I.14. Conclusion

In summary, this chapter presented a comprehensive examination of two significant modeling frameworks: Functional Resonance Analysis Method (FRAM) and Bayesian Networks (BN). FRAM offers a holistic approach to comprehending complex socio-technical systems by emphasizing the interdependencies among functions and the dynamic nature of these systems. On the other hand, BNs provide a probabilistic graphical model that represents relationships between variables, enabling uncertainty modeling and probabilistic reasoning. By integrating FRAM and BNs, researchers and practitioners can gain valuable insights into complex system behavior, enhance resilience, and make informed decisions in uncertain environments. Further exploration and application of these frameworks across various domains hold promising prospects for advancing our understanding and management of complex socio-technical systems.

Chapter 03 :

I. PRESENTATION OF SONATRACH & RA1D

I.1. Introduction

Sonatrach is an Algerian state-owned company, established in 1963, that specializes in the exploration, production, and marketing of oil and gas. It is considered one of the largest oil and gas companies in Africa and the world, with operations spanning across several countries. The company has played a pivotal role in Algeria's economy, contributing significantly to the country's GDP and providing employment opportunities for thousands of Algerians.

Sonatrach has a diversified portfolio of assets that includes oil and gas fields, refineries, petrochemical plants, and pipelines. Its operations encompass the entire oil and gas value chain, from exploration and production to refining and distribution. The company has established itself as a major player in the global energy market, with its products being exported to several countries around the world.

Despite its success, Sonatrach has faced a number of challenges in recent years, including declining production levels and increasing competition from other global players. However, the company has taken steps to modernize its operations and diversify its portfolio, with a focus on expanding its presence in new markets and investing in new technologies. With its vast resources and strategic positioning, Sonatrach remains a key player in the global energy sector and a crucial component of Algeria's economy.

I.2. Birth of SONATRACH

The National Company of Transport and Marketing of Hydrocarbons "SONATRACH" was created by decree No. 63/491 on December 31, 1963. Its mission was to take charge of the transport and marketing of hydrocarbons in a context marked by the control of foreign companies. In 1985, SONATRACH was restructured and put on new bases that constituted the new activities, which are:

- Exploration and research
- Hydrocarbon system operation

- Gas system operation and transformation
- Pipeline transportation
- Marketing

Through this structural and functional transformation, a new group organization chart was established highlighting the four main activities, namely (Figure 2.1):

- **Pipeline transport:**
 - Storage of liquid hydrocarbons upstream and downstream
 - Pipeline transportation of liquid and gaseous hydrocarbons from primary production locations through the secondary and main network
 - Loading of oil tankers
- **Upstream:**
 - Exploration
 - Research and development
 - Production
 - Drilling
 - Engineering and construction
- **Downstream:**
 - Natural gas liquefaction
 - Separation of LPG
 - Oil refining
 - Petrochemistry (SONATRACH's activity)
 - Studies and development of new technologies
- **Marketing:**
 - Export marketing.
 - Domestic market marketing.
 - Maritime transport of hydrocarbons

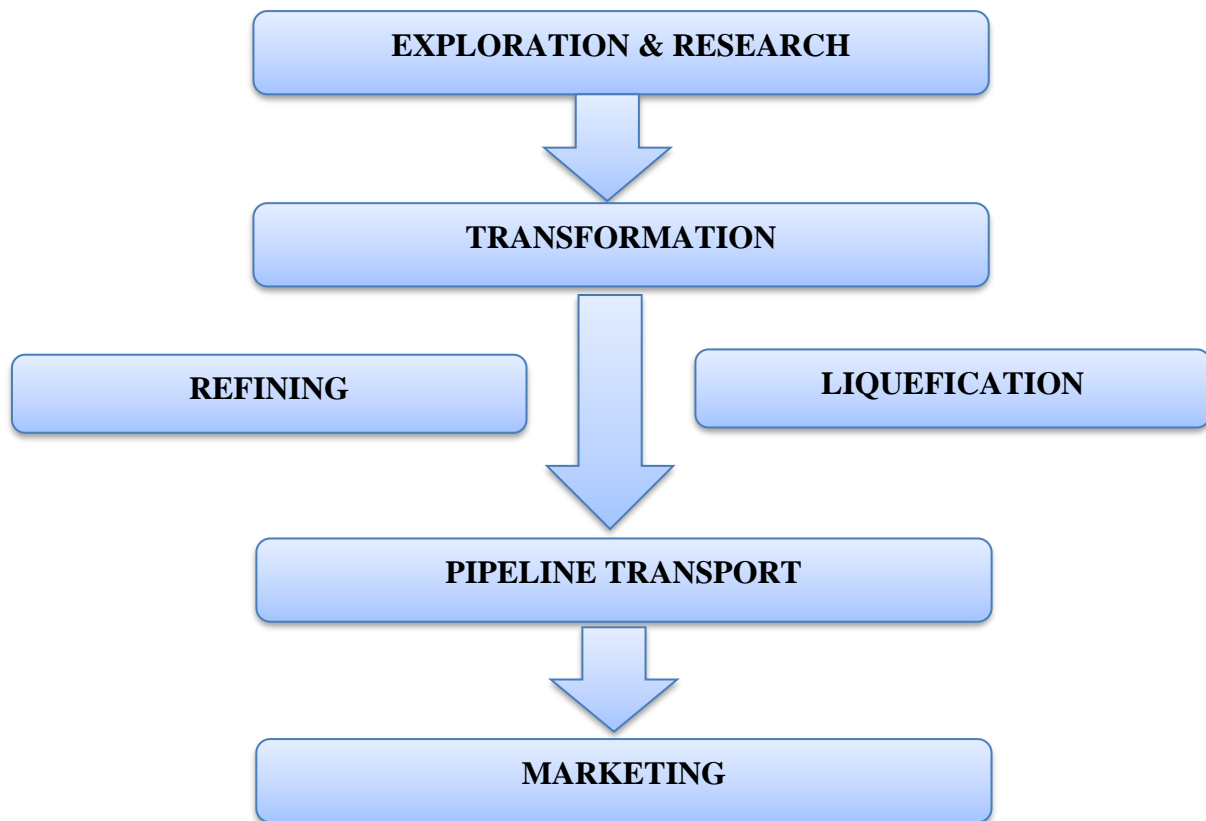


Figure 3.1: SONATRACH Activities

I.3. Presentation of the SBAA Refinery:

The SBAA refinery is built on a site located 2 km east of the SBAA municipality and 44 km north of Adrar. refinery project in Adrar was built in 2006, consists of 7 specialized areas comprising the following facilities:

- Production units;
- Product storage unit;
- Utility unit;
- Administration;
- Analysis laboratory;
- Health, safety, and environment (HSE) department;
- Living quarters.



Figure 3.2: A Plan of the RA1D

I.4. Geographical Location of the Refinery

The refinery is built in the industrial zone of Adrar. The refinery site is located in the eastern part of the city of Sbaa, north of Adrar. The refinery site is approximately 1400 km from Algiers, about 40 kilometers from the city of Adrar, and about 2 kilometers from Sbaa Ville. It is located in the hinterland of the Sahara Desert. However, this area has an abundance of underground water, which is the only source of water available for industry, agriculture, and the daily life of the local inhabitants.



Figure 3.3: A Plan of the RA1D Refinery

I.5. The crude oil feedstock and production

The feeding of crude oil is done from the Touat field basin through an 8-inch pipeline. The refinery is mainly supplied with gas by the various production units (autonomous), in addition to natural gas supply from the SONATRACH station in Sbaa located 6.5 km southeast of the site through a 4-inch pipeline to meet the natural gas needs of the power plant boilers and various unit furnaces.

I.5.1. The annual processing capacity

The annual processing capacity of the Sbaa refinery is approximately 600,000 tons of crude oil over a period of 330 days.

I.5.2. Annual production capacity

The crude oil sucked from the storage tanks, the plant operates and transforms it into various products mentioned in the following table. The following table represents the quantities of products obtained from 411,000 tons of crude oil.

Table 3.1: Presentation of the Capacity of Sbaa (ADRAR)

Quantities Table (Tons/Year)	Products Table
20 500	Propane
32 500	Butane
10 000	Premium gasoline
208 300	Regular gasoline
238 400	Gasoil

I.6. The design of the installation is based on the following principles

- The refinery operates continuously at its annual production capacity
- The valorization of the entire residue from the atmospheric distillation unit into refined products, particularly maximizing the gasoil production
- The refinery operates completely autonomously. All utilities required for the operation of the facilities are produced by the refinery, except for natural gas which comes from the SONATRACH gas field in SBAA
- Raw water for various uses (fire network water, treated water for cooling and steam production, potable water) comes from three wells located approximately 1 km northeast of the refinery
- Cooling water treatment for the facility is prepared by the water treatment unit and operated by the water circulation unit
- Demineralized water treatment for steam production is done by the water treatment unit and pumped to the boilers via two storage tanks with a capacity of 200m³ each
- Steam production to meet the needs of the three electric power and combined units is provided by three boilers, two in service and the other on standby, with support from the RFCC unit
- Electrical energy is produced by three turbo generators, two in service and the other on standby (3x 6000 kw)
- Compressed air (purified and unpurified + nitrogen) for the production of instrument air is provided by three compressors (560Kw), two in service and the other on standby.

I.7. The 2 main parts of the refinery

- Production units;
- Utilities.

I.7.1. Production units

The refinery has three production units:

a) Atmospheric distillation unit 201 (Internal document translation)

The refining process of crude oil begins with distillation or fractionation. This unit is designed to process 600,000 tons of crude oil per year to separate it into different products.

b) Catalytic reforming unit 202

Catalytic reforming processes convert heavy naphtha with low octane rating into aromatic hydrocarbons that can serve as raw materials for the petrochemical industry and constituents for high-octane gasoline, called reformates. The products of this unit are mainly high-octane unleaded fuel commonly known as LPG, reformate, non-condensable gases (fuel for the unit's furnaces), and hydrogen (for process reactions).

c) Catalytic cracking unit 203

Catalytic cracking allows obtaining simpler molecules by breaking down complex hydrocarbons, thus improving the quality and increasing the quantity of lighter and more valuable products while reducing the number of residues. It processes the atmospheric residue, with a capacity of 300,000 tons per year, producing gasoline, light gasoil, LPG, slurry, and non-condensable gases.

I.7.2. Refinery utilities

These installations provide the utilities necessary for the operation of the refinery:

- Water treatment unit;
- Steam production unit;
- Electric power generation unit;
- Compressed air and nitrogen production unit;
- Cooling water and wastewater management unit.

I.8. Safety in the company, what is HSE

- Presentation of various risks associated with the region's activities
- Methods of carrying out work

- How to prevent an accident
- Company HSE policy regarding health, safety, and the environment
- Presentation of the division and its main missions
- Legal obligations and prohibitions
- Instructions related to the work
- Behavior towards the environment
- Actions to take in case of emergency

I.8.1. Organizational chart

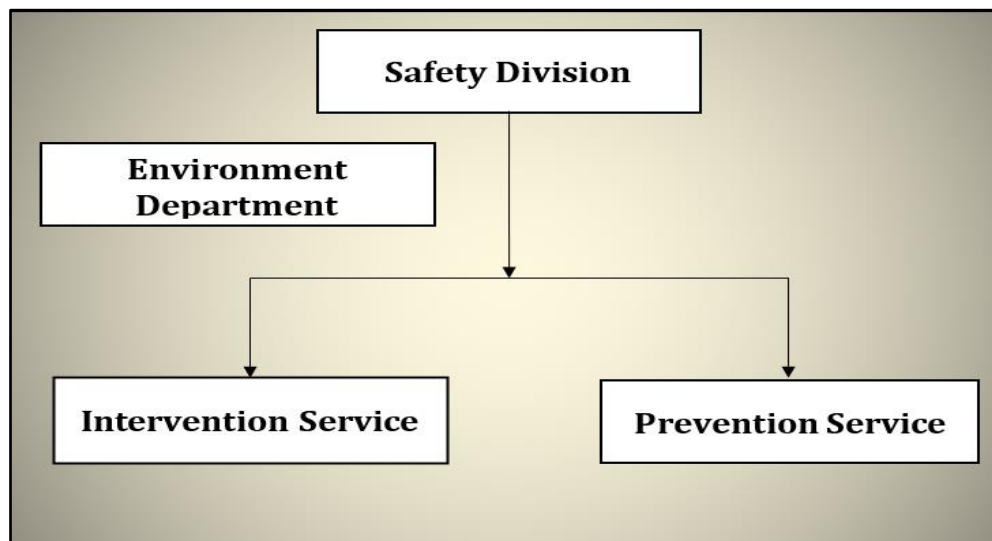


Figure 3.4: Organizational Chart of the HSE Department

I.8.2. Tasks of the safety Department

I.8.2.1. Prevention

- Ensure the monitoring of work under optimal safety conditions.
- Participate in the study and modifications of installations.
- Conduct safety audits of installations.
- Prepare general and specific safety instructions.
- Contribute to the company's overall prevention policy through prevention offices, the health and safety committee, and various prevention campaigns.
- Work in collaboration with occupational physicians.
- Ensure compliance with various regulatory equipment controls and inspections.
- Develop and analyze workplace accident statistics.

- Contribute to risk management and improvement of working conditions.

I.8.2.2. Intervention

- Respond in case of fire or explosion.
- Assist in hazardous work by providing necessary safety coverage.
- Perform preventive maintenance of protection systems, fire-fighting equipment, and materials.
- Train personnel in intervention exercises.
- Establish, update, and implement intervention plans for the Regional Directorate and others.
- Enforce general and specific safety instructions.

I.8.2.3. Environment

- Detection of all sources of pollution generated by the company;
- Provide processes to eliminate or minimize pollution sources;
- Establish a waste management method Compliance with regulatory requirements for environmental protection and contribution to sustainable development;
- Monitoring of the quality of discharges (liquid, solid, and gaseous).



Figure 3.5: Treated Water Discharge Lake

I.8.3. Identification of risks related to refining

1. **Risky Task:** Manual handling
 - Risks involved: Wounds, bruises, cuts, fractures, sprains, dislocation, spinal injuries, back pain, sciatica, herniated disc.
2. **Risky Task:** Mechanized handling (cranes)
 - Risks involved: Tipping, swinging, falling loads, collision with people or installations, people falling.
3. **Risky Task:** Working at heights
 - Risks involved: Falls of materials or people..
4. **Risky Task:** Work inside confined spaces
 - Risks involved: Asphyxiation, burns, fire, explosion, stress.
5. **Risky Task:** Cleaning tanks
 - Risks involved: Asphyxiation, burns, fire.
6. **Risky Task:** Purging capacities
 - Risks involved: Burns (hot products), eye injuries.
7. **Risky Task:** Water cleaning
 - Risks involved: Intoxication, falls.
8. **Risky Task:** Working in a noisy environment
 - Risks involved: Hearing loss, decreased hearing acuity, auditory fatigue.
9. **Risky Task:** Working near electrical installations
 - Risks involved: Electric shock, electrocution, asphyxiation, burns, cardiac syncope.
10. **Risky Task:** Welding in classified zones/molding/dismantling
 - Risks involved: Explosion, fire.
11. **Risky Task:** Working in a chemical storage warehouse
 - Risks involved: Explosion, fire.

12. Risky Task: Mercury recovery from capacities

- Risks involved: Intoxication (irritability, emotional instability, anxiety, insomnia), risk of fire.

13. Risky Task: Forced ventilation

- Risks involved: Electrocution (formation of sparks), asphyxiation.

14. Risky Task: Use of bronze mass

- Risks involved: Projectiles hitting the eyes.

15. Risky Task: Work in non-clean spaces such as passages, ladders, stairs, scaffolding, and work areas that are not cleared of any liquid or other agents.

- Risks involved: Falls, worker slipping, intoxication, fire.

16. Risky Task: Work on screens (computers, etc.)

- Risks involved: Visual fatigue, postural disorders due to furniture characteristics, stress, nervous fatigue.

17. Risky Task: Lifting a load

- Risks involved: Rounded back, load far from the body.

18. Risky Task: Use of pumps

- Risks involved: Risk of explosion in the presence of hydrocarbons, fire.

19. Risky Task: Use of chemical products

- Risks involved: Intoxication, burns, irritation.

I.15. Conclusion

Sonatrach, Algeria's state-owned oil and gas company, holds a prominent position in the industry. With operations covering exploration, production, refining, and marketing, it has a significant domestic and international presence. The company is actively investing in renewable energy, expanding its refining capacity, and engaging in global partnerships. Sonatrach prioritizes corporate social responsibility and environmental protection. Despite challenges, Sonatrach's resilient strategy positions it for sustained growth and contribution to the energy sector while benefiting Algeria's socio-economic development

Chapter 04

I. APPLICATION OF THE PROPOSED METHODOLOGY

I.1. Introduction

Chapter 03 of this dissertation paper focuses on the application of a proposed methodology to assess the resilience of a system's reliability. The methodology combines the Functional Resonance Analysis Method (FRAM) and a Bayesian network model. In this chapter, we explore the development of FRAM model, analyze variabilities between functions, and investigate the interaction between functions to understand their impact on system reliability. Additionally, we discuss the construction of a Bayesian network model to quantify the resilience of system reliability. The chapter concludes with a sensitivity analysis to assess the robustness of the models. The insights gained from this dissertation contribute to a deeper understanding of system resilience and provide valuable information for enhancing system reliability.

I.2. Proposed methodology

In the present study, we propose a methodology that combines the Functional Resonance Analysis Method (FRAM) and a dynamic Bayesian network (BN) to quantitatively measure the resilience of a system in maintaining reliability. Our methodology consists of four main parts, as illustrated in Figure 4.1

Part 1 - FRAM Modeling

Following the principles of FRAM, we identify the functions, variability, and coupling associated with the reliable system. This allows us to model the system's processes and interactions from a functional resonance perspective, capturing the interdependencies and interactions among different functions crucial for maintaining system reliability.

Part 2 - Conceptualization of System Resilience

Building upon the functions identified in FRAM model, we analyze and topologize these functions within the framework of resilience engineering. This step allows us to conceptualize the resilience of the system to stay reliable, even under challenging conditions or disturbances that may occur.

Part 3 - Determination of Essential Parameters

In this step, we determine the essential parameters required for running the Bayesian network. Using the OREDA (Offshore and Onshore Reliability Data) database and expert judgments, we

gather data on component reliability, failure rates, criticality nodes and other relevant parameters. These parameters are then integrated into the Bayesian network framework to capture the probabilistic relationships and dependencies within the system.

Part 4 - Bayesian Network Analysis of System Resilience

The developed Bayesian network model, incorporating FRAM model and the essential parameters derived from the OREDA database and expert judgments, is then simulated to evaluate the resilience of the system in maintaining its reliability. By considering the dynamic dependencies and probabilistic relationships among the identified functions and incorporating the relevant parameters, we gain insights into the system's resilience to stay reliable under various operating conditions and challenges.

In our work, we harmonize these components by applying FRAM methodology to model the functions, variability, and coupling within the reliable system. We integrate this model with a Bayesian network framework, considering essential parameters and data specific to the system under study, including data from the OREDA database and expert judgments. By combining FRAM, Bayesian networks, and leveraging reliable data sources, we aim to provide a comprehensive and quantitative assessment of the system's resilience in maintaining its reliability and effectively addressing potential disruptions or failures.

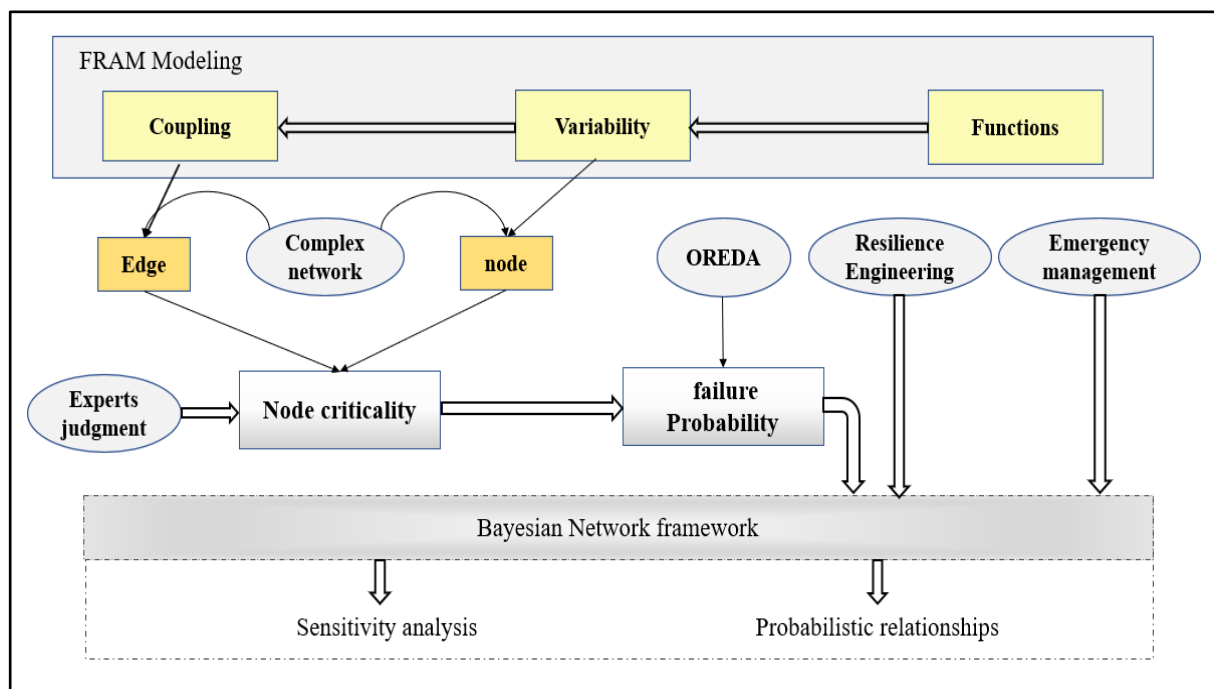


Figure 4.1: Overview on the Proposed Methodology

I.3. Application of the proposed methodology

Description of system

Catalytic Reforming Unit

The catalytic reforming unit is designed to process the naphtha feedstock produced by the atmospheric distillation unit. The products of the unit are mainly high-octane unleaded fuel, commonly referred to as "premium" or "super" unleaded, LPG, light naphtha, refined oil (bottoms from column C-202), non-condensable gases (used as fuel for the unit's furnaces), and hydrogen (used for the process reactions). The catalytic reforming process consists of three main operations:

1. **Charge (untreated NAPHTHA) prefractionation:** This step involves separating the charge into several fractions based on their boiling point using a prefractionation column. This step prepares the charge for the catalytic reforming reaction.
2. **Charge purification:** The prepared charge is then purified to remove impurities that could harm the catalyst used in the catalytic reforming process.
3. **Catalytic reforming:** This step involves reacting the pretreated charge in the presence of a catalyst to produce higher-value products, such as high-octane unleaded fuel. The catalyst used in this step promotes the transformation of light hydrocarbons into higher-value compounds, while minimizing the formation of undesirable compounds such as coke and carbon gases.

Prefractionation

The feedstock is drawn from the storage tank by P-30205/1.2 and then pumped through the heat exchangers E-202 101/1.2.3 for heating. Upon leaving the heat exchangers, the feedstock reaches a temperature of 159°C and enters the prefractionation column C-202 101 at trays 20 and 24. After separation, the lighter fractions are cooled by air coolers A-202 101 and the condenser E-202 107, and then collected in the reflux drum D-202 102. The non-condensable gases are vented to the fuel gas system, while the liquid phase is recycled to the top of the column as reflux by P-202 102/1.2 and by P-202 103/1.2 to the inlet E-202 203/1-3 (heat exchangers for the stabilizer C-202 201) and to storage as light naphtha. as shown in the P&ID Figure 3.2

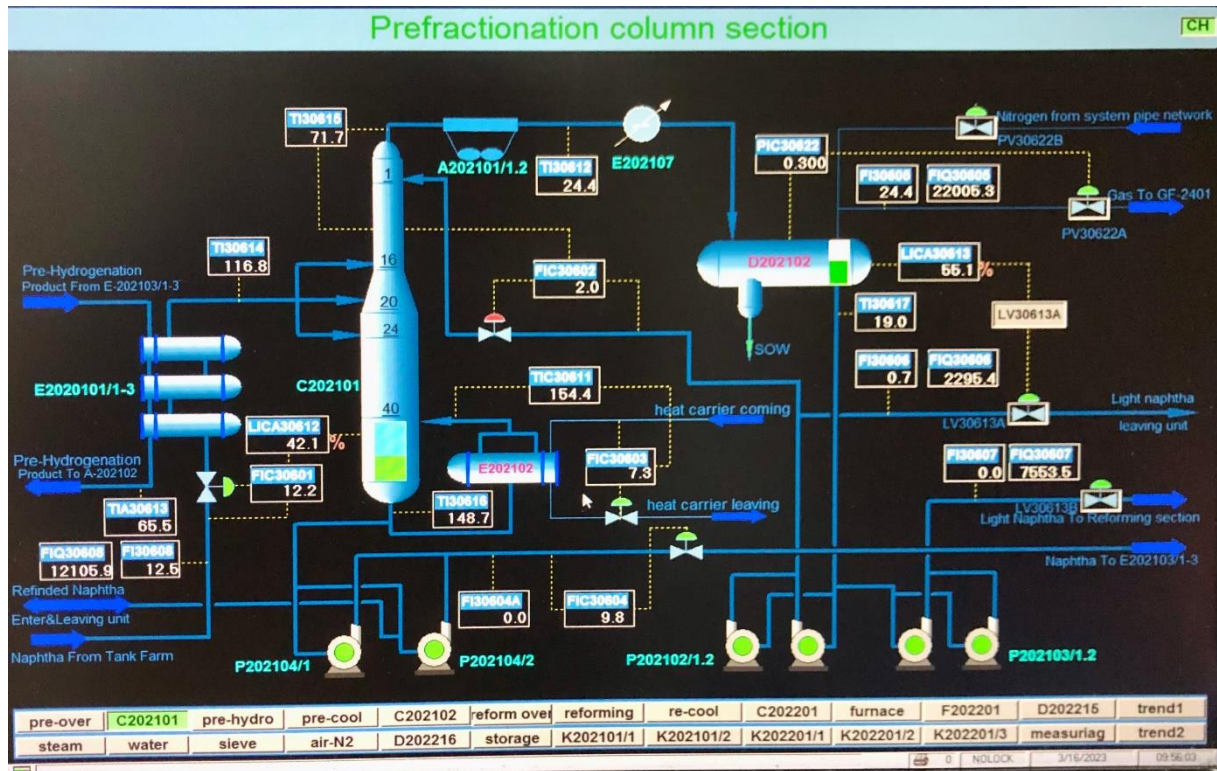


Figure 4.2: P&ID of the Prefractionation Section

I.4. Development of FRAM model

Using the methods and principals of FRAM analysis mentioned in the first chapter helped us to examine and analyze the resilience of the system to stay reliable and construct our FRAM model for our system (prefractionation section).

First, it focuses on determining the functions related to the system studied with the help of multiple experts at SONATRACH facility to come up with 38 functions. then find direct links and undirect links between each function as shown in the Table 4.1 in order to give a better understanding and reasoning to build FRAM model, then it's integrated in FRAM model visualizer, which can be found at <https://functionalresonance.com>, to illustrate it as shown below Figure 3.3

Table 4.1: The functions and coupling of variability

Function Coding	Description	The coupling of variability
F1 (To Separate)	Untreated Naphtha Enters the Prefractionation Column C-202 101 At Trays 20 And 24. To Separate Light Naphtha Heavy Naphtha	$F1(O) \Rightarrow F2(I), F9(I), F9(O), F21(O), F13(O), F18(O), F5(O)$
F2(To Heat)	Heating The Naphtha In the Exchanger E-202 101/1.2.3 Until It Reaches 159c°	$F2(O) \Rightarrow F3(I), F4(R), F1(O)$
F3 (To Supply Naphtha)	Naphtha From Tank Farm P-30205/1.2	$F3(O) \Rightarrow F11(I), F2(O)$
F4(To Supply Treated Naphtha)	Supply Treated Naphtha from E202103 With High Temperature	$F4(O) \Rightarrow F2(R)$
F5(To Cool)	Lighter Fractions Are Cooled by Air Coolers A-202 101	$F(5) \Rightarrow F1(I), F6(O)$
F6(To Condense)	The Condenser E-202 107	$F6(O) \Rightarrow F5(I), F6(O)$
F7(To Separate)	Separate Light Naphtha from Water In D-202 102	$F7(O) \Rightarrow F6(I), F26(O), F25(O), F8(O), F17(O), F37(O), F27(O), F34(C)$
F8(To Discharge)	Leaving Unit to RFCC For Dysulfiration	$F8(O) \Rightarrow F7(I)$
F9(To Heat)	E202102 Reboiler	$F9(O) \Rightarrow F1(I), F1(O), F20(O)$
F10(To Supply Gasoline)	Heat Carrier	$F10(O) \Rightarrow F19(O)$

F11(To Regulate)	Regulation Valve 30601	F11(O) \Rightarrow F3(O), F12(C)
F12(DCS)	Distributed Control System	F12(O) \Rightarrow F15(I), F33(I), F23(I), F20(I), F27(I), F37(I), F13(I), F36(I), F31(I), F32(I), F28(O), F29(O), F14(O), F30(O), F22(O), F11(O), F19(O), F26(O), F16(O), F34(O)
F13(To Detect Level)	Lica30612	F13(O) \Rightarrow F1(I), F12(O)
F14(To Alert Flow)	To Alert the Operator	F14(O) \Rightarrow F12(I), F15(O)
F15(To Operate Flow)	Operate On Valve 30601	F15(O) \Rightarrow F14(I), F12(O)
F16(To Regulate 30602)	To Regulate Feedback Light Naphtha Flow	F16(O) \Rightarrow F17(I), F1(O), F12(C)
F17(To Pump)	To Pump Feedback Light Naphtha P202102	F17(O) \Rightarrow F7(I), F16(O), F36(O)
F18(To Detect T°1)	Ti30616	F18(O) \Rightarrow F1(I), F12(O)
F19(To Regulate)	To Regulate 30603 Gasoline Flow That Heats E202102	F19(O) \Rightarrow F10(I), F9(O), F12(C)
F20(To Detect T° 2)	Temperature Sensor	F20(O) \Rightarrow F9(I), F12(O)
F21(To Pump P202104)	Pumping Heavy Naphtha to E202103	F21(O) \Rightarrow F1(I), F22(O), F23(O), F24(O)
F22(To Regulate)	Valve 30604	F22(O) \Rightarrow F21(I), F24(O), F12(C)
F23(To Detect F)	Flow Sensor	F23(O) \Rightarrow F21(I), F12(O)
F24(To Discharge Naphtha)	Naphtha To E202103	F24(O) \Rightarrow F21(I), F22(C)
F25(To Discharge Sow)	To Discharge Sow	F25(O) \Rightarrow F7(I)
F26(To Regulate 30622a)	Valve 30622a	F26(O) \Rightarrow F7(I), F35(O), F12(C)
F27(To Detect Pressure 30622)	Pressure Sensor	F27(O) \Rightarrow F7(I), F12(O)
F28(To Alert Level)	Alarm	F28(O) \Rightarrow F12(I), F32(O)
F29(To Alert T 1)	Alarm	F29(O) \Rightarrow F12(I), F33(O)
F30(To Alert T2)	Alarm	F30(O) \Rightarrow F12(I), F31(O)

F31(To Operate T2)	Operate to regulate temperature	F31(O) \Rightarrow F30(I), F12(O)
F32(To Operate L)	Operate to regulate level	F32(O) \Rightarrow F28(I), F12(O)
F33(To Operate T1)	Operate to regulate T	F33(O) \Rightarrow F29(I), F12(O)
F34(To Regulate 30622b)	Valve 30622b	F34(O) \Rightarrow F35(I), F7(O), F12(C)
F35(To Store Nitrogen)	Nitrogen	F35(O) \Rightarrow F26(I), F34(O)
F36(To Regulate 30613a)	Valve 30613a	F36(O) \Rightarrow F17(I), F38(O), F12(C)
F37(To Detect Level 30613)	Level Sensor	F37(O) \Rightarrow F7(I), F12(O)
F38(To Discharge To RFCC)	Discharge to RFCC unit	F38(O) \Rightarrow F36(I)

I.5. Discussion

The application of FRAM (Functional Resonance Analysis Method) to analyze the described system, with a specific focus on the prefractionation process, provides valuable insights into its complexity, variability, and interdependencies. The system comprises a series of functions, including the drawing of feedstock from the storage tank, pumping it through heat exchangers for heating, prefractionation in a column, separation of lighter fractions, cooling using air coolers and a condenser, collection in a reflux drum, recycling or storage of the liquid phase, human operation on DCS (distributed control system) and more as mentioned in Error! Reference source not found.

FRAM analysis highlights the various factors that introduce variability into the system, such as variations in feedstock composition and temperature, heat exchanger efficiency, column operation, and tray conditions. Understanding these sources of variability allows for a comprehensive assessment of the system's behavior and potential risks. Additionally, the analysis reveals the performance conditions under which the system functions, such as the feedstock entering the column at specific trays and the cooling of lighter fractions to a certain temperature.

Interactions between the functions within the system play a crucial role in overall performance. Variability or changes in one function can propagate and influence other functions, emphasizing the non-linear dynamics of the system. Furthermore, the integration of human operators within a distributed control system (DCS) is a vital aspect of the analysis. The operators are responsible for monitoring, controlling, and making decisions within the system, leveraging their expertise and interacting with the DCS interface to ensure safe and efficient operations.

By recognizing the role of human operators, FRAM analysis captures the socio-technical nature of the system. Human factors, such as workload, decision-making, and interaction with equipment, are considered alongside the technical functions and variability factors. This comprehensive understanding enables the identification of challenges related to human-system interaction, and decision support tools.

In addition to that, Valves play a crucial role in the system by regulating fluid flow and serving as control points for operators. They enable adjustments to flow rates, pressures, and directions of the feedstock and process streams. Positioned strategically at critical points, such as heat exchangers, the prefractionation column, and the reflux drum, valves have a significant impact on system performance. Variations in valve positions, opening/closing rates, or malfunctions directly influence flow rates, temperatures, and pressures, introducing variability and potential risks. Operators must monitor and adjust valve positions to maintain desired process conditions and mitigate the associated challenges.

FRAM analysis provides a foundation for proactive risk assessment and system improvement. By identifying potential risks, vulnerabilities, and areas for enhancement, informed decisions can be made to optimize safety, efficiency, and overall performance. The analysis supports the development of strategies to enhance system resilience, operator performance, and control strategies within the distributed control system.

I.5.1. Variabilities between Functions

- 1. Feedstock Temperature:** Changes in the temperature of the feedstock entering the system can affect the heating requirements, reflux rate, and subsequent separation in the column.
- 2. Equipment Performance:** Variations in the efficiency and reliability of equipment, such as heat exchangers, and condensers, can influence the heating, cooling, and separation processes.
- 3. Human Operator Decision-Making:** Variations in the decision-making process and strategies employed by human operators within the DCS can introduce variability into the system. Factors such as experience, and cognitive factors can influence the choices made by operators, thereby impacting the overall system behavior.
- 4. DCS Performance:** Variations in the performance and reliability of the DCS, including software, interfaces, and communication systems, can affect the ability of human operators to monitor and control the system effectively.
- 5. Valve Performance:** Variations in the performance of valves, such as their response time, accuracy, and reliability, can introduce variability into the system. Valve malfunctions,

leakage, or suboptimal operation can impact the control of flow rates, temperatures, and pressure levels.

6. Detector Sensitivity: Variations in the sensitivity of detectors can influence their ability to accurately measure and monitor specific parameters, such as temperature, pressure, or composition. Changes in detector sensitivity can impact the information fed into the DCS and subsequent control actions taken by human operators.

7. Detector Calibration: Variations in detector calibration can introduce discrepancies in the measurements, leading to potential inaccuracies in the monitoring of system parameters. Inconsistent calibration can impact the reliability of information provided to human operators and affect their decision-making processes.

8. Control Signal Variability: Variations in the control signals sent to valves, either manually by human operators or automatically through the DCS, can affect the precise control of the system parameters. Inaccurate or inconsistent control signals can lead to fluctuations or deviations in the desired process conditions.

I.5.2. Interaction between functions

- 1. Heat Exchangers and Prefractionation Column:** The performance of heat exchangers directly affects the temperature of the feedstock entering the prefractionation column, which, in turn, impacts the separation efficiency and the composition of collected fractions.

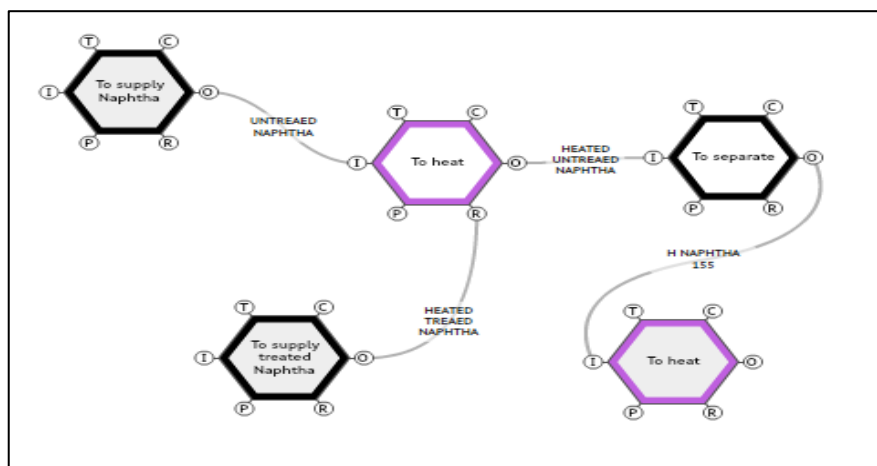


Figure 4.4: Heat Exchangers and Prefractionation Column interaction in FRAM

2. **Cooling System and Collection:** The cooling process using air coolers and a condenser directly affects the temperature and condensation of the lighter fractions, impacting their collection and subsequent storage.

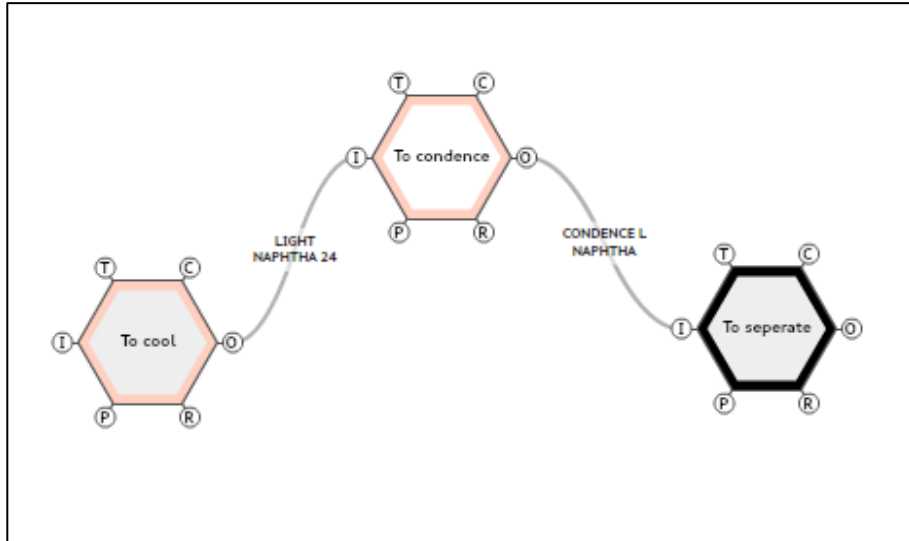


Figure 4.5: Cooling System and Collection interaction in FRAM

3. **Recycling and Column Performance:** The recycling of the liquid phase as reflux influences the stability and efficiency of the prefractionation column, affecting the separation of desired fractions and the overall system performance.

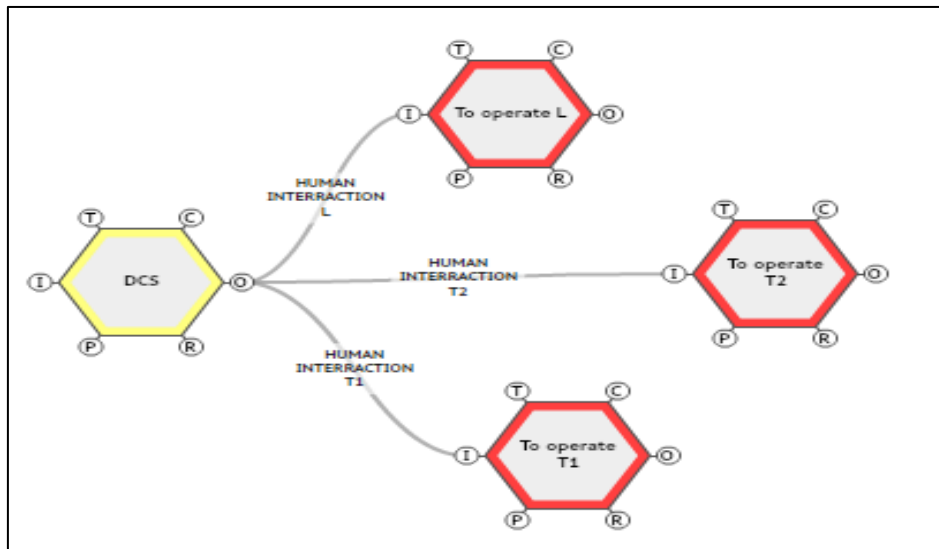


Figure 4.6: Recycling and Column Performance interaction in FRAM

4. **Human-DCS Interaction:** The interactions between human operators and the DCS are critical for monitoring and controlling the system. Variations in how operators interpret

information from the DCS interface, respond to alarms, adjust control settings, and execute control actions can influence the behavior of the functions within the system.

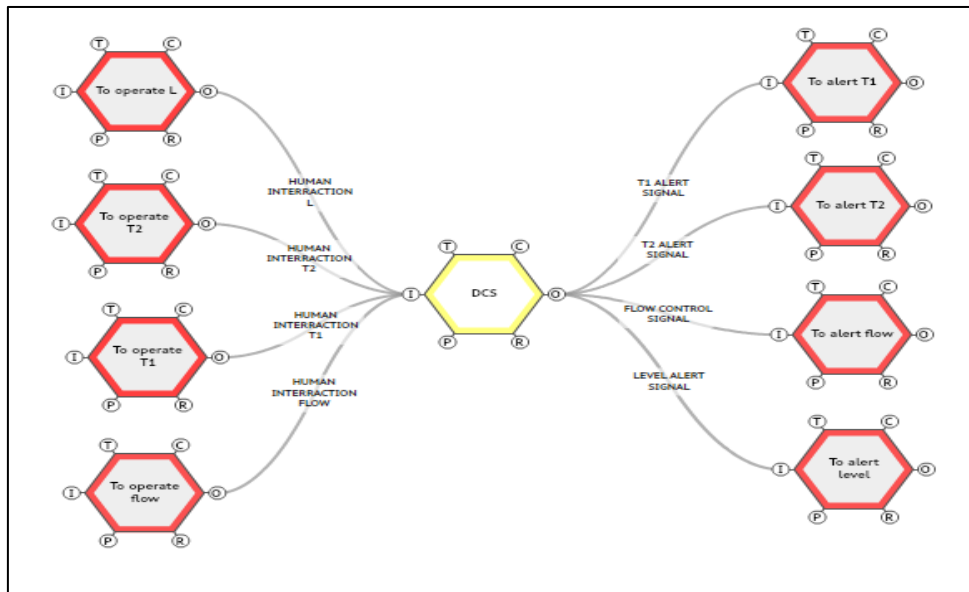


Figure 4.7: Human-DCS Interaction in FRAM

5. Human-Function Interaction: Human operators directly interact with various functions within the system. For example, operators may adjust the settings of heat exchangers, control the reflux rate, or manage the collection and recycling processes. Variations in human-operator actions can impact the performance and outcomes of these functions.

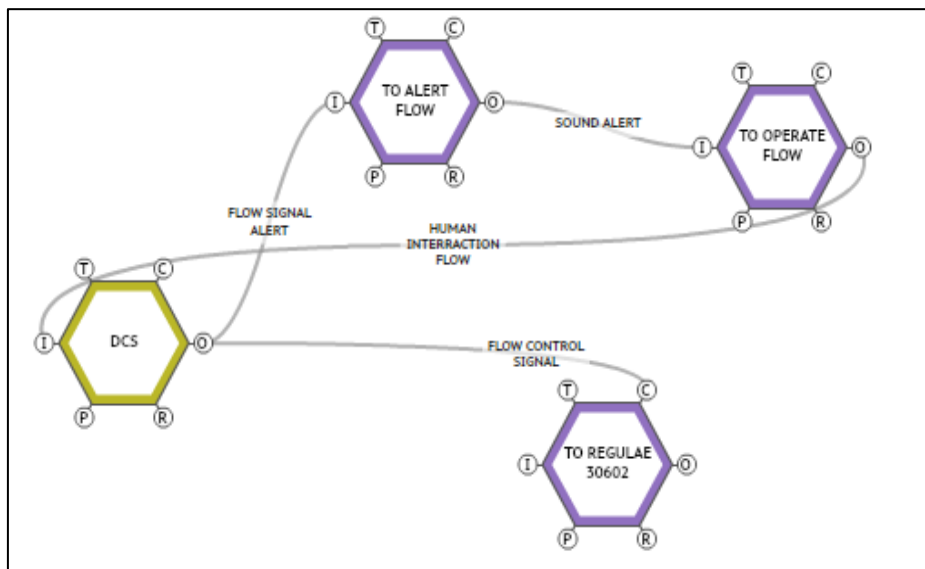


Figure 4.8: Human-Function Interaction in FRAM

- 6. Valve-Function Interaction:** Valves are directly involved in controlling the flow of fluids, such as feedstock, coolant, or reflux, to different functions within the system. Variations in valve positions, openings, or closures influence the rates of flow, which, in turn, impact heating, separation, cooling, or recycling processes.

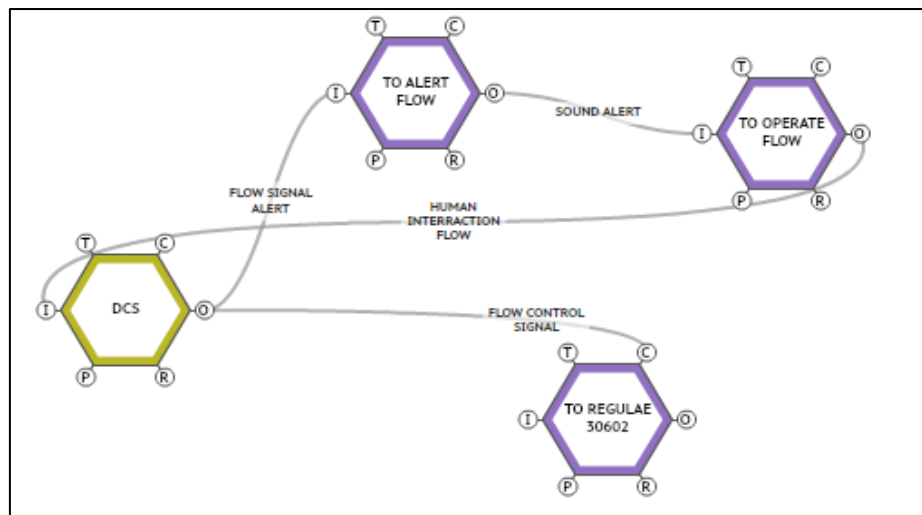


Figure 4.9: Valve-Function Interaction in FRAM

- 7. Valve-Human-DCS Interaction:** Human operators, through the DCS interface, interact with valves to adjust control settings, change flow rates, or respond to alarms. Variabilities in operator actions, such as the speed and accuracy of valve adjustments, can introduce variations in the system's control and performance.
- 8. Detectors and Human-DCS Interaction:** Detectors play a crucial role in providing real-time information to human operators through the DCS interface. Variations in detector readings can impact the operators' perception of the system's status, potentially influencing their decision-making process and control actions.

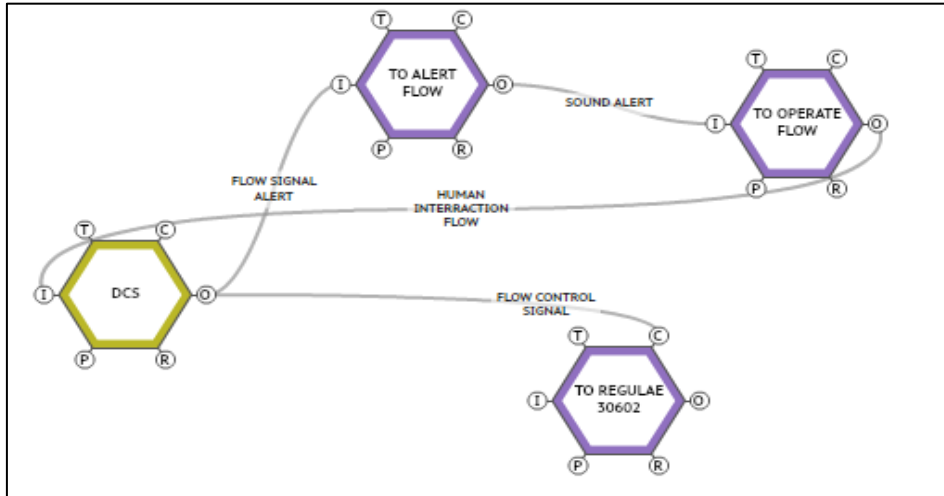


Figure 4.10: Detectors and Human-DCS Interaction in FRAM

I.6. Bayesian network model for resilience of system reliability

the resilience of system to stay reliable can be evaluated from four aspects, namely, Product separation system (HES 1\UL), Dehydration system (HES 2\UP), Monitoring, response.

To provide a more comprehensive and visually informative representation, we have constructed a graph that illustrates the functions categorized under their aspects. This graph serves as a visual aid to enhance and understanding Figure 3.11.

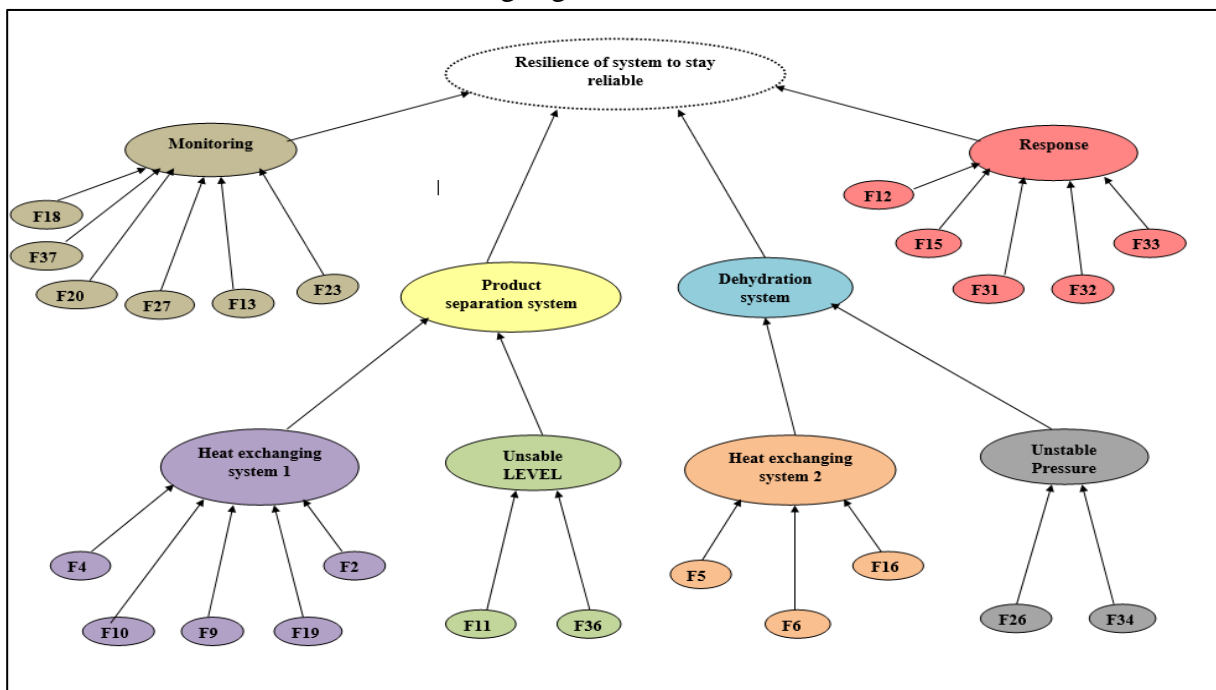


Figure 4.11: Illustration of the Complex Network Behind FRAM Model

The functions identified in Table 4.1 are categorized into the abovementioned aspects as shown in Table 4.2, the results can be found in Figure 3.12 and appendix which was developed using GENIE 4.0 Academic software.

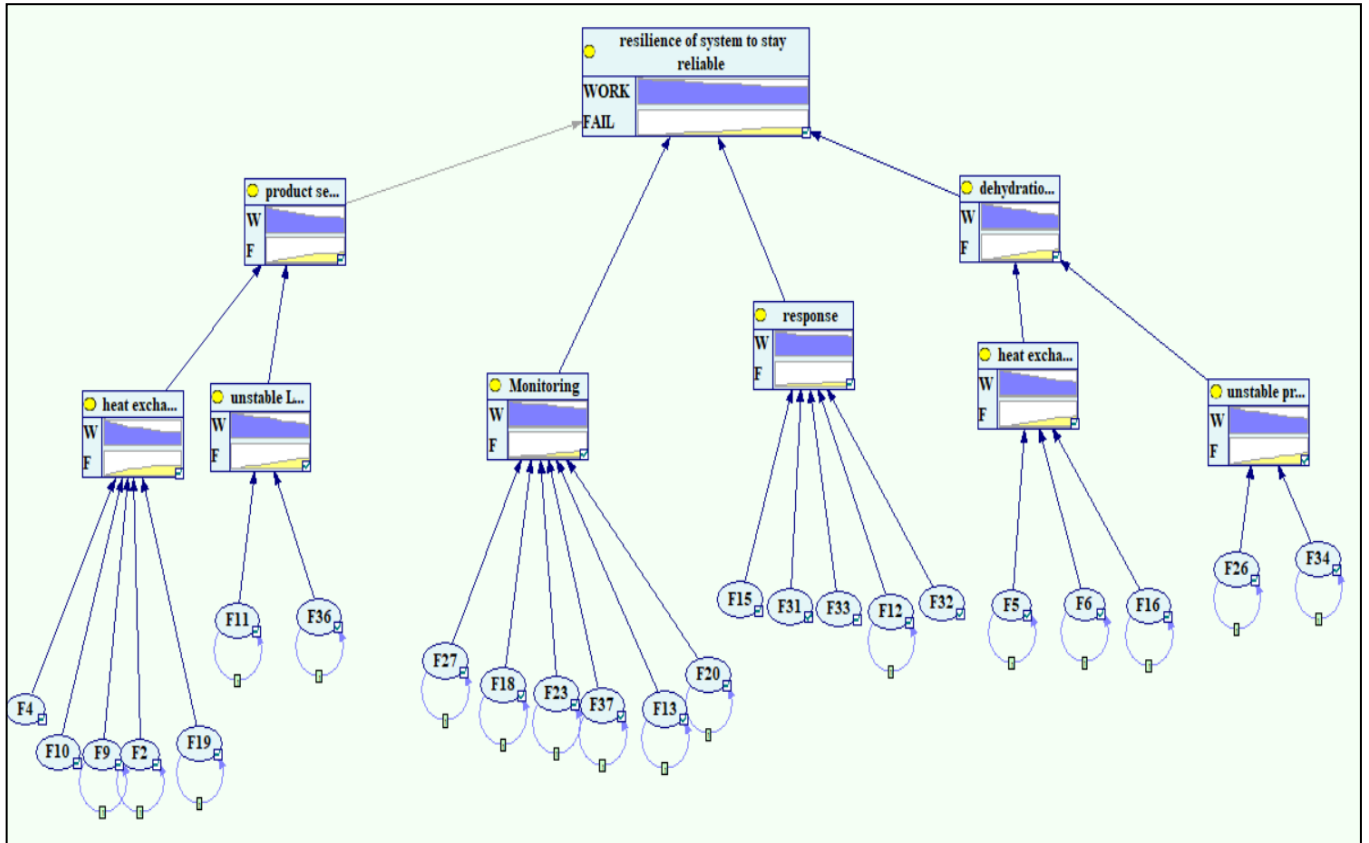


Figure 4.12: BN Model Developed Using GENIE 4.0

Table 4.2: Functions categorized in each aspect

Resilience aspects	Functions
Product separation system (HES 1)	F4, F10, F9, F19, F2
Product separation system (UL)	F11, F36
Dehydration system (HES 2)	F5, F6, F16
Dehydration system (UP)	F26, F34
Monitoring	F18, F37, F20, F27, F13, F23,
response	F15, F31, F32, F33, F12

Table 4.3: Failure probabilities based on OREDA database

FUNCTIONS	FAILURE RATE (FPY)	FAILURE PROBABILITY
F6/F23	0.0311788	0.0306977
F13/F37	0.078036	0.0768689
F20/F18	0.0136896	0.0135778
F27	0.0481344	0.0475561
F5	0.0910368	0.0897449
F12	0.1524072	0.1448735
F9	0.5010768	0.3771629
F11/F36/F16/F26/F34/F19	0.0604876	0.0595795
F2	0.25005024	0.0584353
F32/F33/F31/F15	/	0.1

I.7. Sensitivity Analysis

The most efficient characteristics of the BN are focused on event likelihood updating (posterior) of each event given the occurrence of the initiating event. They show the accident features better than prior probabilities and thus are less uncertain. The ratio of variation (ROV) in **Equation 1** can involve a dependable proportion of significance in any system failure and sensitivity analysis [25].

$$Rov = \frac{\pi(Xi) - \theta(Xi)}{\theta(Xi)}$$

Equation 1: The Ratio of Variation

Where $\pi(Xi)$ and $\theta(Xi)$ denote, respectively, the posterior and prior probabilities of Xi

I.7.1. Calculus

Table 4.4: Calculus of ROV

FUNCTIONS	θ (XI)	π (XI)	ROV
F4	0	0	0
F10	0	0	0
F9	0.90627135	0.90627135	0
F2	0.71306965	0.71306965	0
F19	0.25996767	0.25996767	0
F11	0.26445298	0.26445298	0
F36	0.26445298	0.26445298	0
F27	0.21621486	0.33113169	0.531493673
F18	0.066070296	0.10741006	0.62569364
F23	0.14434988	0.2268101	0.571252432
F37	0.32962639	0.47839031	0.45131071
F13	0.32962639	0.47630083	0.444971775
F20	0.066070296	0.10949954	0.657318744
F15	0.1	0.1144564	0.144564
F31	0.1	0.11388273	0.1388273
F33	0.1	0.1144564	0.144564
F12	0.54275199	0.58088002	0.070249452
F32	0.1	0.11388273	0.1388273
F5	0.37509269	0.39439684	0.051465013
F6	0.17082204	0.18248714	0.068288027
F16	0.26445298	0.28581264	0.080769217
F26	0.26445298	0.29115255	0.100961502
F34	0.26445298	0.29115255	0.100961502

I.7.2. Results interpretation

According to the findings depicted in Figure 3.13, the probabilities F31, F37, F13, and F23 exhibit the highest increases in the Measure of Risk of Value (RoV). These probabilities correspond to the operation of valve 30603, level sensor 30613, level sensor 30612, and flow sensor 30608, respectively. Consequently, they represent the most crucial functions that contribute significantly to the disruption of system reliability. The results have been effectively synthesized and presented in a bar graph using the MATLAB software, as illustrated in Error! Reference source not found..

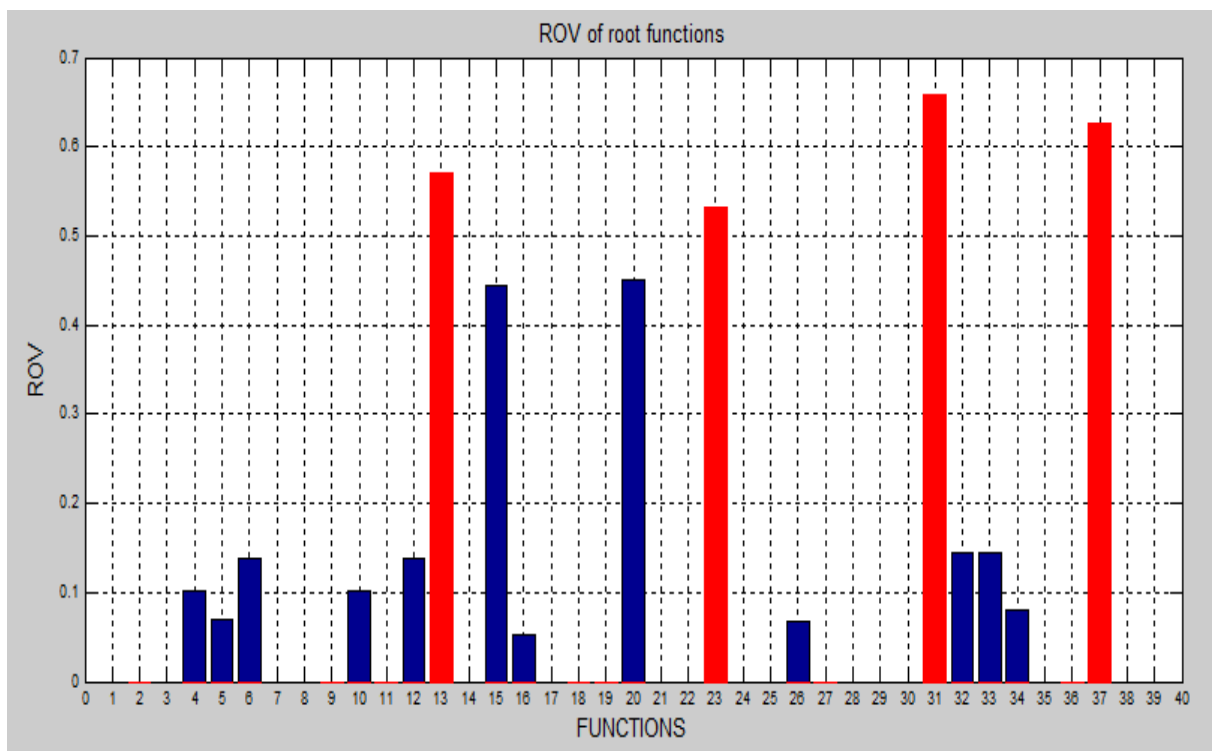


Figure 4.13: Presentation of Functions and their RoV on Bar Graph by MATLAB

I.8. Conclusion

the integration of FRAM (Functional Resonance Analysis Method) and a dynamic Bayesian network offers a comprehensive and quantitative methodology for evaluating the resilience of a dependable system. Our dissertation findings highlight the criticality of specific functions, namely F31, F37, F13, and F23, in ensuring and preserving system reliability. This study significantly contributes to enhancing our comprehension of system vulnerabilities from diverse resilience perspectives, with a particular emphasis on the monitoring aspect. Notably, three of

the crucial functions identified (valve 30603, level sensor 30613, and level sensor 30612) fall under the monitoring category. Thus, the improvement of monitoring aspects becomes imperative for enhancing safety and resilience within the system.

Conclusion

Integrating the Functional Resonance Analysis Method (FRAM) and a dynamic Bayesian network presents a powerful approach for assessing the resilience of a dependable system. Through our dissertation research, we have identified specific functions, such as F31, F37, F13, and F23, that are critical in maintaining system reliability. These findings shed light on the system's vulnerabilities and emphasize the importance of focusing on the monitoring aspect.

The functions associated with valve 30603, level sensor 30613 and level sensor 30612, are of particular significance which fall under the monitoring domain. The enhancement of monitoring aspects emerges as a key factor in improving safety and bolstering resilience. By effectively monitoring these critical functions, potential failures can be promptly detected and mitigated, thereby reinforcing the system's overall reliability.

Beyond the findings mentioned above, applying the application of the Functional Resonance Analysis Method (FRAM) within this study has yielded paramount importance in evaluating system resilience. FRAM offers a unique perspective by considering the interactions and dependencies among various functions within the system. This holistic approach enables a comprehensive examination of system vulnerabilities and the identification of critical functions that significantly influence on system reliability.

In conclusion, integrating FRAM with a dynamic Bayesian network offers a quantitative and scholarly methodology to comprehensively assessing system resilience. The identification of critical functions underscores the pivotal role of robust monitoring practices. By addressing these vulnerabilities, system operators can effectively enhance the safety and reliability of the system, thereby contributing to a more resilient operational environment.

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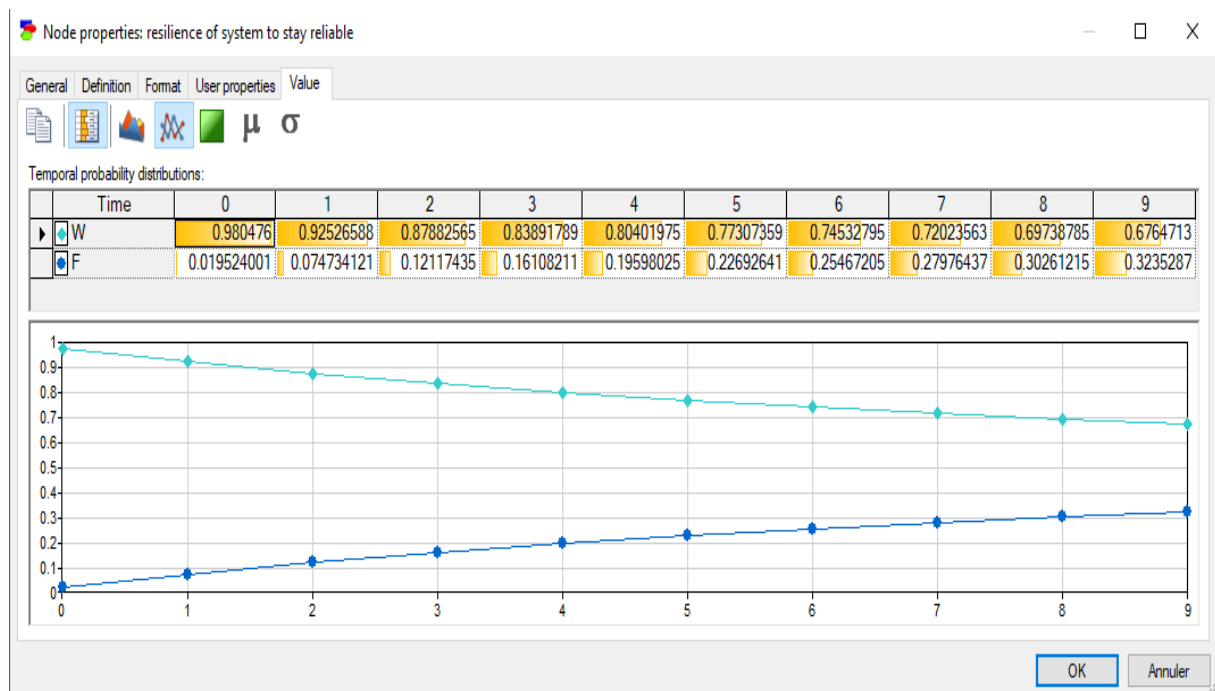
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Appendix

Genie software:

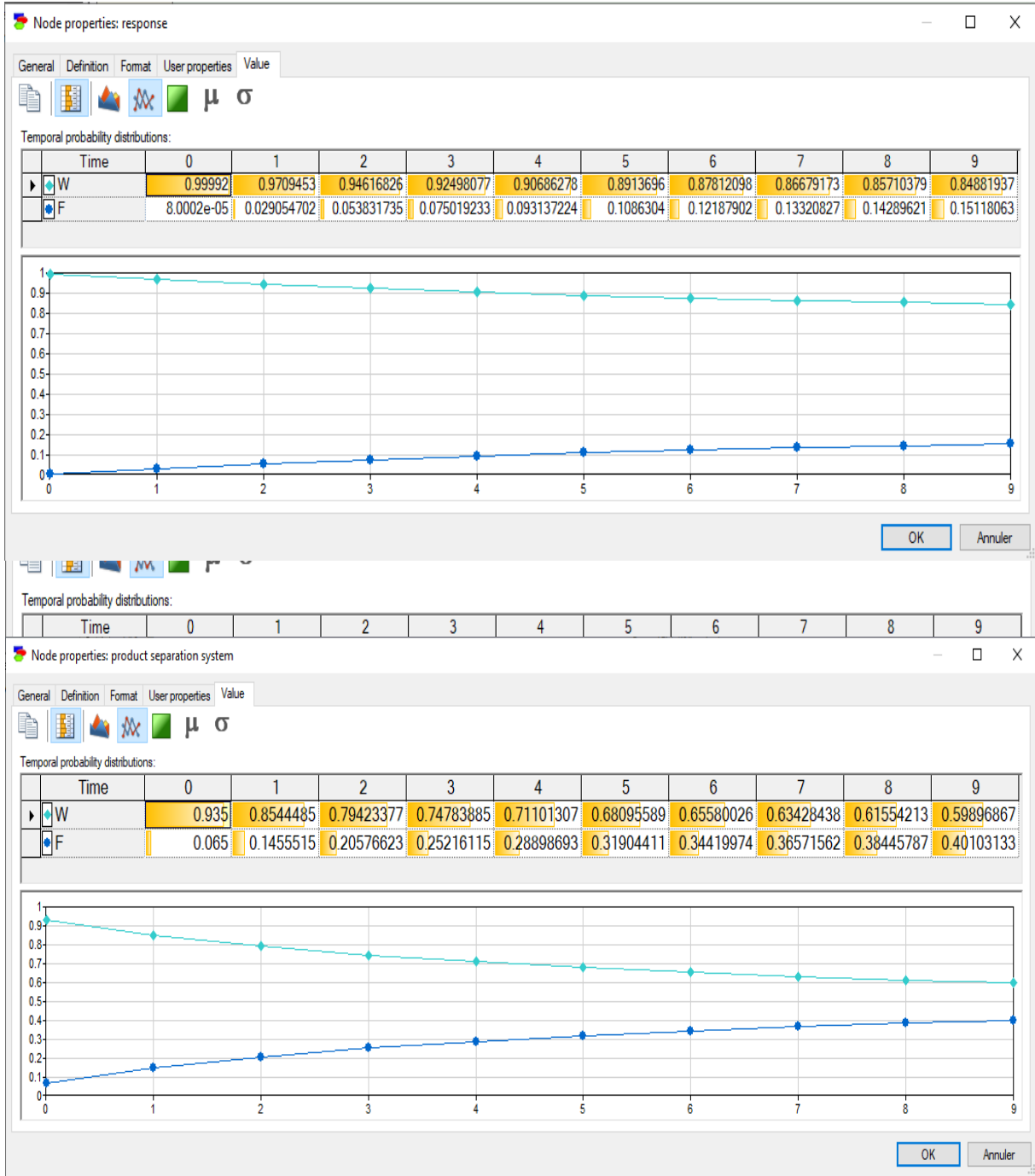
"Genie" is an open-source software tool developed by the Decision Systems Laboratory at the University of Pittsburgh, designed for learning the structure of Bayesian networks from data. With its diverse functionalities, Genie provides users with the ability to automatically discover the dependencies and causal relationships between variables through structure learning. The software enables the estimation of parameters (conditional probabilities) for each node in the Bayesian network based on observed data, a process known as parameter learning. Users can perform probabilistic inference in the learned Bayesian network, computing probabilities of various variables given evidence on others. Genie also facilitates model evaluation, allowing users to assess the quality and performance of the learned Bayesian network model. With a possible graphical user interface (GUI), Genie offers a user-friendly experience, enabling interaction with the software and visualization of the learned Bayesian network

Values and charts of resilience of system to stay reliable taken by Genie 4.0



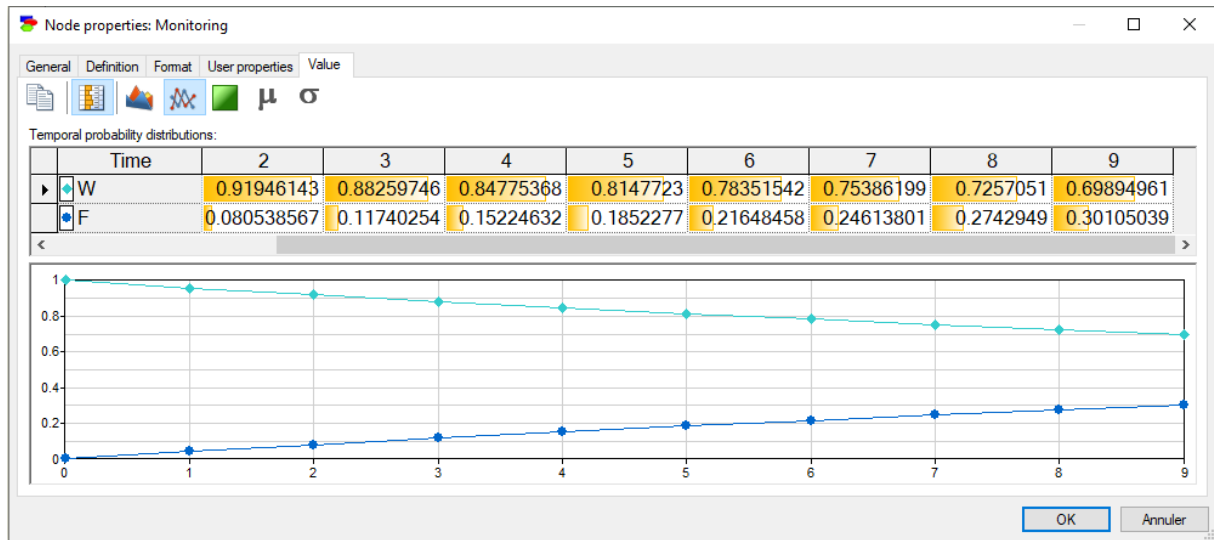
Resilience of system to stay reliable

Dehydration system Chart



Response Chart

Product Separation System Chart



Monitoring Chart

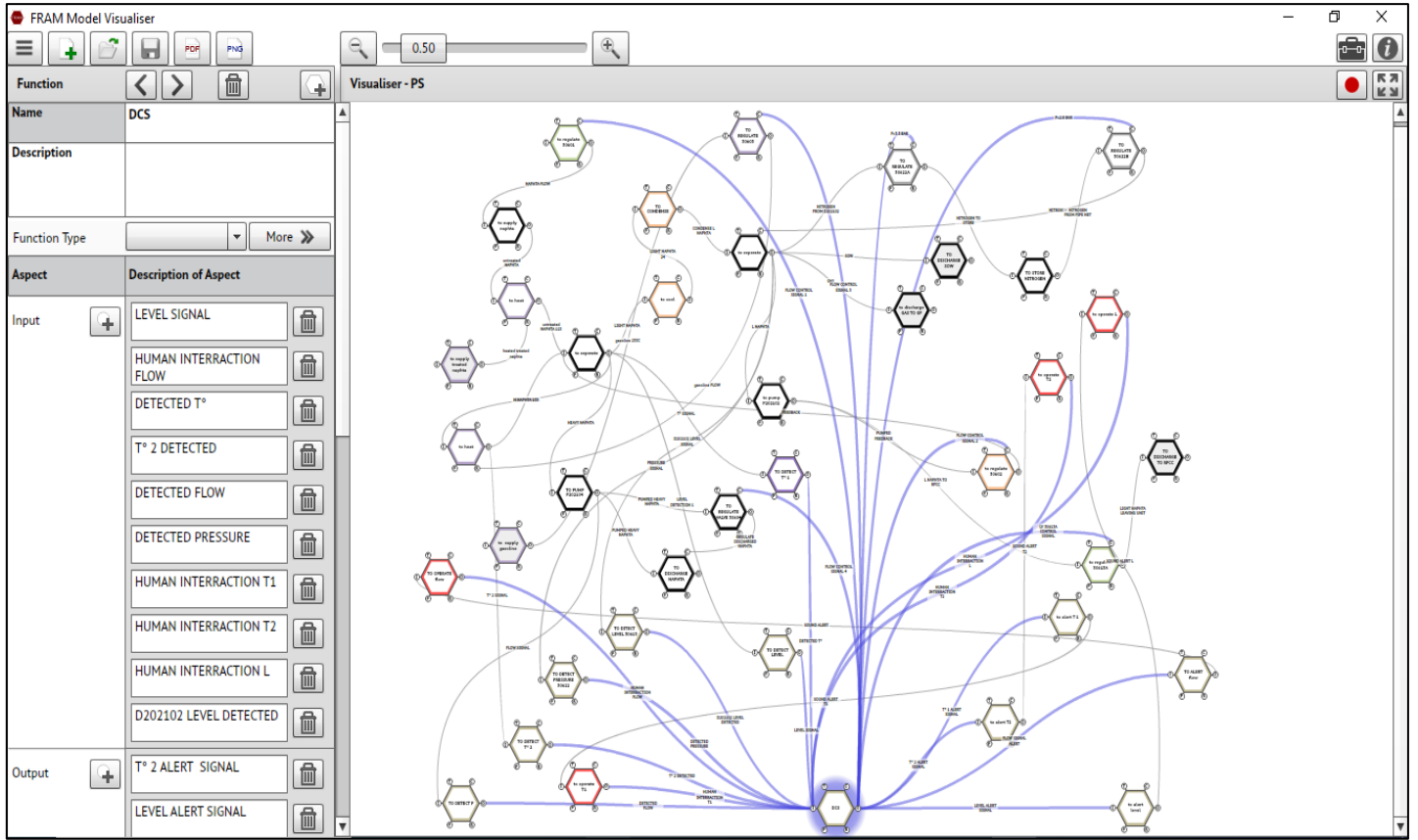
FRAM Model Visualizer:

The FMV - FRAM Model Visualizer likely provides a dedicated platform for creating, visualizing, and analyzing FRAM models. As FRAM is used for understanding the functioning and safety of systems, this tool likely enables users to represent the functions, variability, and interdependencies within the socio-technical system being studied.

With the FMV - FRAM Model Visualizer, users can potentially create graphical representations of the FRAM model, using boxes, arrows, and other visual elements to illustrate the different functions and their interactions. This visualization capability can aid in comprehending the dynamic behavior and complexity of the system under analysis.

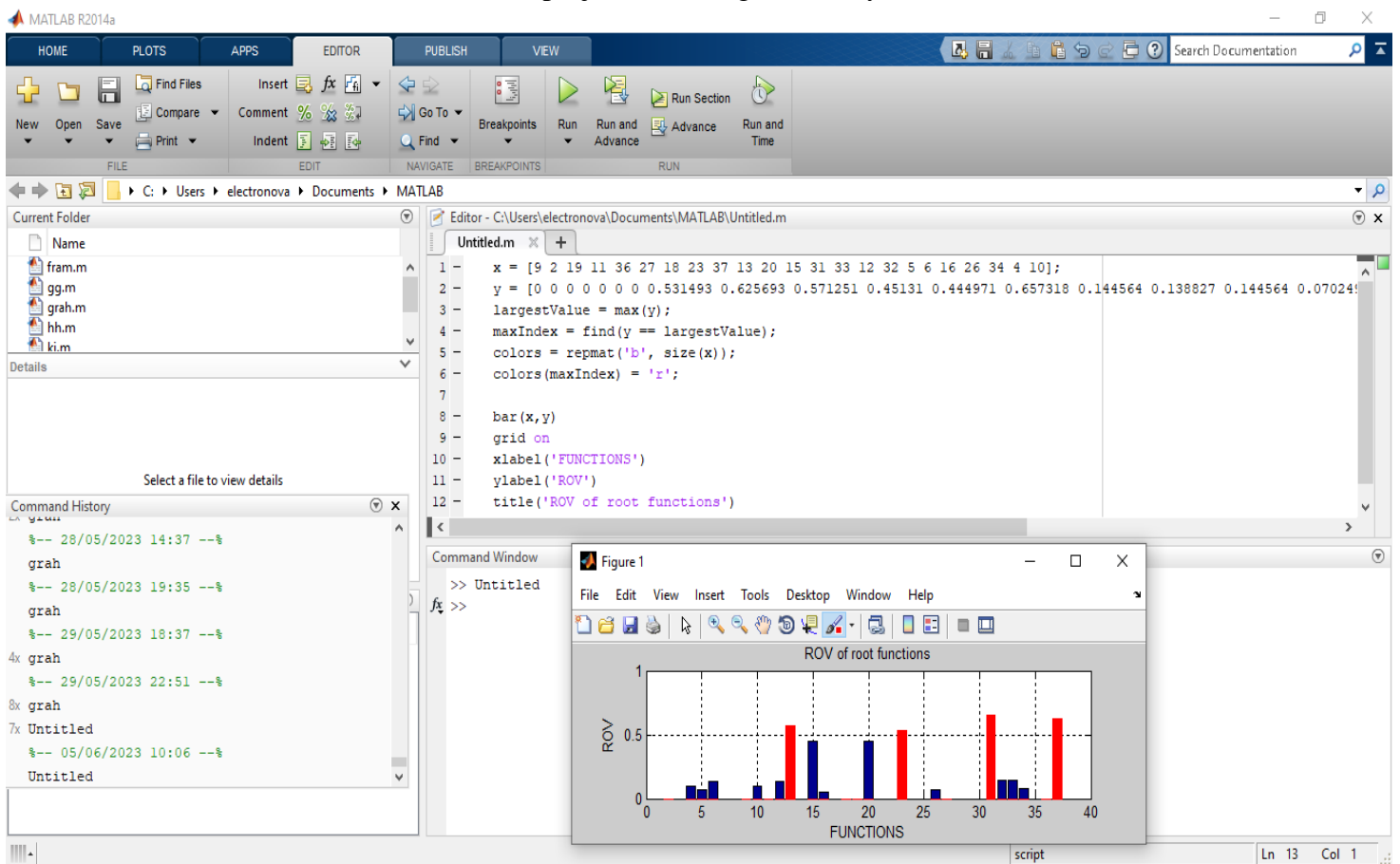
As with any specialized tool, it's essential to refer to the official documentation or website of the FMV - FRAM Model Visualizer for detailed information on its features, capabilities, and how it supports the application of the Functional Resonance Analysis Method in modeling complex socio-technical systems

FRAM Model realized by FRAM Model Visualize



MATLAB:

Matlab (MATrix LABoratory) is a powerful high-level programming language and interactive environment extensively utilized for numerical computing, data analysis, and visualization. Developed by MathWorks, Matlab finds widespread application in diverse fields such as engineering, science, finance, and more. Its array of capabilities includes conducting complex mathematical calculations and manipulations with matrices, arrays, and vectors, facilitating data processing, statistical analysis, and data visualization. Matlab is equipped with specialized functions and toolboxes for signal and image processing, making it ideal for various scientific and engineering applications. Additionally, it serves as a valuable platform for simulating and modeling dynamic systems, implementing machine learning and deep learning algorithms, and developing interactive graphical user interfaces (GUIs). With built-in optimization functions and tools for control system design and analysis, Matlab has become a go-to solution for academic, research, and industrial projects, offering versatility and ease of use to its users.



Bar Chart realized by MATLAB