Fuzzy Logic Applied to Failure Modes, Effects and Criticality Analysis (FMECA) in Smart Grids

Gonçalo da Rocha Lemos

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Supervisor(s): Prof. Paulo José da Costa Branco

Eng. Andrés Alejandro Zúñiga Rodríguez

Examination Committee

Chairperson: Prof. Célia Maria Santos Cardoso de Jesus

Supervisor: Prof. Paulo José da Costa Branco

Member of the Committee: Prof. Santiago Torres Contreras

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa

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Abstract

Smart grids are here to stay.

The contemporary fast-developing world exponentially relies more on electrical distribution systems, as they are a base for economic and social development. A modern paradigm was proposed to attend to the electrical system's stakeholders' current requirements: the smart grid, a fully autonomous and sustainable grid.

The smart grid concept can usually be divided into two subsystems – a power and a cyber network – that generate interdependencies, increasing the grid system complexity, in addition to the large number of components that composed it. For those reasons, a common reliability assessment as performed in the classical grids may not be enough.

Failure Modes, Effects, and Criticality Analysis (FMECA) can be a suitable methodology for identifying potential failures in smart grids, as already demonstrated for other areas of study. However, there are some drawbacks regarding its ambiguity associated with the RPN conventional rank prioritization procedure and experts' opinions

Therefore, this dissertation proposes the application of a Fuzzy-FMECA methodology to the smart grid context, based on the Fuzzy Inference System Type-I and Type-II, to overcome the referred shortcomings. Two methodologies are also adapted to this work: firstly, an FMECA based on a new risk prioritization model; secondly, a comparison methodology based on an agreement coefficient to compare different FMECA procedures, was applied.

Conclusions show that the application of the Fuzzy-FMECA methodology with an agreement coefficient confers more efficiency and validity to an FMECA procedure.

Keywords: FMECA, Fuzzy Logic, smart grid, Cohen's Kappa, risk analysis, concordance coefficients

Resumo

As redes inteligentes “vieram para ficar”.

O mundo contemporâneo encontra-se em rápido desenvolvimento e depende de sistemas de distribuição elétrica, pois servem como base para o desenvolvimento de paradigmas económico-sociais. Para manter os clientes e os produtores satisfeitos, teve de ser criado um novo sistema para fazer face às exigências atuais: a rede inteligente, uma rede autónoma e sustentável.

O conceito de rede inteligente pode ser dividido em dois subsistemas - rede elétrica e ciber-rede - que geram interdependências, aumentando, assim, a complexidade do sistema de rede, para além do grande número de componentes que o compõem. Por estas razões, uma avaliação comum de fiabilidade, tal como a realizada nas redes clássicas, pode não ser suficiente.

O procedimento FMECA pode ser uma metodologia adequada para a identificação de potenciais falhas nas redes inteligentes, como já demonstrado para outras áreas de estudo. Contudo, existem alguns inconvenientes no que diz respeito à ambiguidade associada ao procedimento de priorização convencional RPN e às opiniões dos peritos

Assim, esta dissertação propõe a aplicação de uma metodologia Fuzzy-FMECA no contexto da rede inteligente, baseada no Sistema de Inferência Fuzzy Tipo-I e Tipo-II, para superar as referidas deficiências. Duas metodologias são também aplicadas a este trabalho: primeiro, um FMECA baseado num novo modelo de priorização de risco; segundo, uma metodologia de comparação baseada num coeficiente de concordância, para comparar diferentes procedimentos FMECA.

As conclusões mostram que a aplicação da metodologia Fuzzy-FMECA com um coeficiente de concordância confere mais eficiência e validez a um procedimento FMECA.

Palavras-chave: FMECA, lógica difusa, redes inteligentes, Kappa de Cohen, análise de risco, coeficientes de concordância

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List of Acronyms

AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
CB	Circuit Breakers
COA	Centroid of Area
DAC	Detection Almost Certain
DAI	Detection Almost Impossible
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DET	Detection
DH	Detection High
DL	Detection Low
DM	Detection Moderate
DMS	Decision Making System
DOE	Department of Energy
EB	Energy Box
EMS	Energy Management System
FIS	Fuzzy Inference System
FM	Failure Mode
FMEA	Failure Modes, Effects and Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
FOU	Footprint of Uncertainty
FRPN	Fuzzy Risk Priority Number
FWGM	Fuzzy Weighted Geometric Mean
HMI	Human Machine Interface
ICT	Information and Communication Technology
IED	Intelligent Electronic Device
ITHWD	Interval Two-Tuple Hybrid Weighted Distance
LAN	Local Area Network
LMF	Lower Membership Function

NASA	National Aeronautics and Space Administration
OCC	Occurrence
OF	Occurrence Frequent
OO	Occurrence Occasional
OP	Occurrence Probable
OR	Occurrence Remote
OVU	Occurrence Very Unlikely
PHEVs	Plug-In Hybrid Electrical Vehicles
PV	Photovoltaic
RE	Risk Extreme
RH	Risk High
RI	Risk Isosurface
RL	Risk Low
RM	Risk Moderate
RMI	Risk Minor
RPI	Risk Priority Index
RPN	Risk Priority Number
SEV	Severity
SH	Severity Hazardous
SL	Severity Low
SM	Severity Moderate
SMI	Severity Minor
SV	Server
SVH	Severity Very High
SW	Ethernet Switch
UMF	Upper Membership Function
US	United States
WAN	Wide Area Network

1. Introduction

1.1. Motivation

In an increasingly developed world, the electrification of things has no turning back point. Pushed by the advancement of technologies, processes, and the ever so much expanding demand associated with the improvement of life conditions, electricity is nowadays a first necessity good not dispensed by a large majority of the world's population.

Consumer requirements have changed in the last twenty years, not only because of the social and economic development in most countries but also with the exponential appearance of new technologies that became part of people day to day. The new prosumers concept was proposed, the development of new renewable energy technologies increased in the last decades, the first electrical vehicles were built, the number of appliances and gadgets in one's home kept increasing, while the number of industries and "not so green" sources had to be maintained or even prospered.

For those reasons, the grids and network systems had to become "smart", combining an array of groundbreaking components with the most classic ones, in an attempt to face the never slowing down new world's demand in addition to the latest trends. However, with the appearance of the so-called smart grids, not only the number of components as well as their interdependences increased, but also the consequent failures, combined with the lack of processes to manage the arising risks.

In that regard, Failure Mode, Effects, and Criticality Analysis, vulgarly known as FMECA, is a qualitative approach method with the primary function of identifying potential system failures, to create necessary maintenance/mitigation plans [1,2]. FMECA was first applied by the U.S military services and rapidly spread across other industries and processes.

Nevertheless, the FMECA methodology carries some shortcomings that will be described throughout this dissertation, which required the introduction of new methodologies with the aim of improving the FMECA procedures. Liu [3] published the first book regarding the improvement of FMEA classical procedures, performing extensive research on uncertainty theories and multi-criteria decision-making methodologies.

By the same token, Bowles and Peláez [4] described a new methodology based on two different Fuzzy inference systems (FIS), applied to a general FMECA case. Results demonstrated that the utilization of Fuzzy Logic has several advantages when compared to the classical numerical method, such as more flexibility to combine risk factors, reduction of ambiguity and imprecision regarding the data, and the introduction of linguistic-based variables.

For these reasons, the Fuzzy Logic methodologies were selected to be applied to the FMECA contexts, in the hope of obtaining a more clear and more efficient failure mode analysis.

1.2. Topic Overview

Concerning this reliability methodology, literature always presents two different procedures, that appear to be the same, but have their differences: FMEA vs FMECA, being the only difference in the word 'Criticality'. In the FMEA case, only two risk factors are utilized for the methodology to characterize a failure mode, while in the FMECA there are three risk factors, plus the computation of the RPN score, that the FMEA does not perform. For those reasons, this work will adopt FMECA, and the topic overview herein mainly contains FMECA-based research.

Fuzzy Logic reasoning has been applied to the FMECA context for several years now. The literature correlating these two concepts is broad and provides positive indicators regarding the utilization of Fuzzy methods in such a framework.

This interrelation of concepts is utilized across an array of industries and systems. For instance, Buffa et al. [5] performed an FMECA on a gas recovery system, located in a nuclear physics studies plant. By using a modified Fuzzy Risk Priority Number, the authors were able to overcome the observed limitations of the classical method and conclude that the Fuzzy approach was not only able to increase the complex's safety but also focus on risk assessments.

Akyuz and Celik [6] implemented the use of Type-II fuzzy sets in the case of a ship's oil spill incident, with the aim of reducing ambiguity and vagueness created by the opinion of five experts. With better handling of the linguistic assessment, the authors calculate a more precise RPN, consequently generating valuable insights regarding safety and risk prevention. Furthermore, other applications to maritime engineering were performed: in [7] the authors executed the FMECA study of a marine boiler using a rule-based Fuzzy method for risk prioritization, modeled based on the opinion of experts and utilizing disparate types of membership functions for the calculations of RPN, where it was concluded that the Fuzzy approach could solve arising problems regarding the classical RPN computation; whereas in [8] the authors' object of study is a supporting system of a ship's main engine, where the FMECA and Fuzzy theory is applied and used to analyze 75 failure modes, showing that the Fuzzy approach has reduced the level of risk demonstrated on the classical FMECA, therefore reducing subjectivity and improving the general perception of risk.

Moreover, applications to the healthcare area have also been analyzed in the literature. Liu et al. [9] implemented an interval 2-tuple hybrid weighted distance (ITHWD) in a blood transfusion problem where FMECA was applied. Results showed that the application of Fuzzy reasoning handled the subjectivity and uncertainty associated with the eleven studied failure modes while coping well with information distortion and incomplete information. In [10], Giardina et al. compare the classical and Fuzzy FMECA approaches in a radiotherapy technique, using the software SAPERO, while attributing relative weights to each of the risk factors. The verified differences in risk prioritization increase the efficiency of procedures to enhance patient and process safety.

Furthermore, in the context of chemical processes, Sanditya et al. [11] applied the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) to an FMECA study regarding an argon purification unit. The application of the Fuzzy-AHP, which attributes a weight to each FMECA factor, was performed with the goal of increasing efficacy and decrease subjectivity regarding the experts' verdict, which is shown by the objectivity of the new RPN weights. In [12], the authors compared the classical FMECA with Fuzzy-FMECA and grey theory, using an atmospheric ammonia storage tank as a study case. The analysis performed between the classical RPN, the fuzzy RPN, and the grey theory RPN, showed that the new approaches provide high flexibility to the system while tackling the limitations of the conventional calculations.

Supply chains are also referred to in literature, as Mzougui et al. [13] utilized two Fuzzy methods as an alternative for the conventional FMECA RPN calculation, in an automotive industry example. Firstly, the Fuzzy-AHP was used to attribute weights to each risk factor, and then the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) to assess the new factors' correlations. With these methods, not only the FMECA vagueness and uncertainty are dealt with, but also the results display the validity of said approaches, generating meaningful output analysis for the automotive industry players. Moreover, regarding transportation networks, the authors in [14] provided a risk assessment on a railway signal system, using both FMECA and Fuzzy-FMECA approaches. The introduction of the Fuzzy approach allows the enhancement of the established safety procedures, as the results provide a more efficient assessment of potential risks and existing failure modes.

Focusing now more specifically on the field of this dissertation, the applications of the Fuzzy reasoning to the FMECA method in the electrical and smart grid contexts are scarce. Additionally, the existing studies focus mainly on the grid's single components or systems, existing almost no literature regarding complete systems and networks, as the case for this work.

Dinmohammadi and Shafiee [15] applied a fuzzy approach to the case of an offshore wind turbine system. Fuzzy linguistic terms were used to represent the experts' opinions, while grey theory analysis was used to define the relative importance of each of the risk factors. Subsequently, a comparison with the classical FMECA was performed, where the authors conclude that the introduction of the Fuzzy reasoning confers more realism and flexibility to the analysis while combining the needed qualitative and quantitative knowledge for this study, in an efficient way. By the same token, Peng et al. [16] use a Fuzzy cost-based FMECA method to understand if the installation of a condition monitoring system on a wind turbine is feasible. The Fuzzy approach also confers effectiveness to the analysis and provides the decision-makers with better information to decide whether the project should advance.

Moreover, Perveen et al. [17] applied the Fuzzy Logic to a solar photovoltaic system, due to the verified disadvantages and limitations regarding the classical FMECA procedure. The ranking of failure modes has been performed based on the Euclidean distance formula and the centroid defuzzification method, which ultimately has the purpose of helping designers and engineers to create more effective systems. Still, within the solar energy components subject, it is possible to find additional relevant literature, with the authors in [18] implementing the Fuzzy reasoning combined with Pareto charts to assess the congruence of an FMECA analysis applied to the manufacturing quality of solar gel batteries. Results have shown the proposed Fuzzy-approach based on the concept of FRPN has efficiently influenced the analysis, being able to better identify the risk's causes and recommend corrective actions. Additionally, still in the solar context, the authors in [19] use the study case of a Solar Array Drive Assembly to apply a Fuzzy Weighted Geometric Mean (FWGM) in order to discover the correspondent FRPNs of eight studied failure modes. Research has shown that the Fuzzy applied approach is highly valuable in dealing with the FMECA experts' opinions and subsequent prioritization of failure modes in a context of ambiguity.

Apart from the wind and solar topics, other existing literature can be found in [20], where the authors analyzed the impact of lightning strike currents on failures in transmission network elements. Some expert systems were applied – one of them FMECA – and combined with a Fuzzy Decision-Making System (DMS) approach. Conclusions have shown that the application Fuzzy DMS allows to accurately determine the location of a lightning strike and consequent failure mode, providing unambiguous information which strengthens the system's security and the elimination of failures.

An analysis regarding a group of components/systems can be found in [21], where it is described the risk evaluation of power system facilities in a smart grid, with the application of Fuzzy reasoning. In this research, the authors analyzed four facilities – gas circuit breaker, transformer, switch, and bus – where the RPN score for each of them was calculated and then compared to the Fuzzy-based approach. Conclusions have shown that the proposed method minimized the distortion of one of the risk factors, meaning that acceptable results can be computed using Fuzzy reasoning. The ultimate goal was to determine an efficient and reliable risk priority order to perform the needed maintenance tasks accordingly.

In sum, the Fuzzy Logic reasoning has been applied successfully to the FMECA and experts' evaluation context, both in an array of industries and in electrical systems' frameworks. However, in the context of electrical grids, more precisely smart grids, a thorough analysis that applies the idea of a Fuzzy-FMECA approach to a complete system is still missing. From the literature review conducted, one can assume that the application of Fuzzy-based approaches leads to more reliable, efficient, and unambiguous results, suggesting a decrease in the potential risks and an increase in the implementation of mitigation measures.

1.3. Objective

As stated in the previous subchapter, the FMECA methodology has been applied extensively to a number of industries and processes, where can be included the electrical systems' context. However, in the particular case of these systems, there is a concept of vagueness and subjectivity affiliated with the FMECA analysis that can lead to imprecise and inadequate conclusions.

For this reason, the main objective of this work is to tackle these vulnerabilities, applying the concepts of a Fuzzy-FMECA approach to the context of the smart grids, to hopefully create a more accurate failure modes risk prioritization. Therefore, a previous work regarding an application of the FMECA method to a smart grid will be used as the basis for this dissertation, and subsequently put against the forthcoming Fuzzy approaches that will be constructed during this work.

Complementary, a second objective can be defined by the introduction of a new methodology based on a coefficient of agreement to compare different FMECA procedures, with the aim of providing a more insightful analysis, that culminate in a better output.

1.4. Thesis Outline

This thesis is divided into nine different chapters. Chapter 1 assumes the role of an introduction to the dissertation's topic, describing the motivations that led to this study and the objectives that one is proposing to achieve and analyze. A topic overview was also performed herein, identifying relevant work performed and providing relevant benchmarks for the context of this study.

Chapter 2 provides a brief description of the concept of a smart grid, characterizing it and describing its general components. A contextualization in today's world will be performed, as this concept serves as the basis for the application of this dissertation's work.

Chapter 3 describes the FMECA method, characterizing some of its applications and explaining some basic terminology, general rules, procedures, and implementations.

Chapter 4 introduces a new risk prioritization model, that will be applied to this dissertation's FMECA context, with the target of obtaining a more robust and efficient study procedure.

Chapter 5 addresses the Fuzzy Logic concept, containing three distinct parts: an introductory part describing the basics and its application to the FMECA context and two parts characterizing the two Fuzzy methods, Type-I and Type-II, that will be implemented in this dissertation.

Chapter 6 describes the use of an agreement coefficient to increase the efficiency of this dissertation's analysis. Additionally, it characterizes the chosen coefficient and presents a practical application concerning the topic of this work.

Chapter 7 presents the study case adopted to achieve the proposed objectives for this work. It also contains a description of some details and assumptions concerning the methodologies put in practice, that need to be taken into consideration to carry the desirable simulations.

Chapter 8 compiles the simulations performed concerning the different approaches presented in this dissertation, combined with the respective analyses and comparisons of the classical methodologies with the Fuzzy-FMECA approaches.

Chapter 9 contains the conclusions and deliberations about the study performed in this dissertation. Furthermore, it also presents some possible guidelines for relevant work to be performed henceforward.

2. Smart Grids

Since the discovery of electricity in the 19th century, electrical grids provide the needed energy supply and can be described as an indispensable element, providing the infrastructure for such a process [22]. However, most of those systems were very ancient, not ready for the rising demand, and operating based on outdated processes that could not accommodate the technological advances in the area, in addition to their increasing unreliability [23].

For those reasons, since the beginning of the 21st century, electrical energy systems have been through several developments, innovations, and modifications. Three main factors contribute to those changes [24]:

1) Mass electrification – with the development of living conditions and the rising of the world's population, in addition to the numerous technological advancements, electricity and electrical systems play a crucial increasing role in the day by day of billions of people.
2) Climate changes – a higher electricity demand consequently leads to a higher demand for fossil fuels capable of producing it, in a world where environmental awareness is rapidly rising, and governments are employing laws for limiting nonrenewable sources.
3) Rising energy cost – the fossil fuels' high prices, combined with the skyrocketing demand and high maintenance costs of outdated power plants have been, more than ever, reflecting on the electricity prices to the consumer.

With even more complex electrical energy systems, new advanced methodologies and procedures to optimize operation, are required. Not only is important to create better conditions and improve flexibility for the accommodation of distinct parts of all energy sectors and players but also to optimize the operation of these various structures, aiming for an efficient architecture from the consumer's perspective. In addition, the reliability and cost-efficiency of such systems represent in today's world perhaps two of the primary characteristics that need to be addressed, in the ever so much fluctuating production and demand contexts.

The main purpose of such systems is to provide the best service and infrastructures – both reliable and highly capable – to the producers and consumers while taking into account factors such as efficiency, reliability, safety, costs, and environmental awareness. To rapidly deal with disruptions or fluctuations in energy demand, some technological advancements such as communications systems, energy storage technologies, or automation solutions can be applied to the systems' context and reveal themselves as fundamental to assure a suitable operation.

In consequence of all the previously described reasons, the concept of Smart Grid arose. There are several definitions for this concept, varying across geographies and their corresponding circumstances, either because of specific resources or general demand.

In 2009, the European Technology Platform SmartGrids published the following definition: "A Smart Grid is an electrical network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies.” [25]

In other words, with the support of Figure 2.1 below depicted, the smart grid combines the components of the “past” – the nuclear and thermal plants, while maintaining the same channels of distribution to the consumers –, with the components of the “present and future” – the renewable energies, the communications network, or for instance the addition of microgrid systems for better local performance. Furthermore, it connects all of these systems and components, that compose the power and cyber networks – throughout information and communication technology (ICT), while reducing the dependence on fossil fuels – thus reducing greenhouse gas emissions. More importantly, also provides the grid with better demand management, ever so needed in today’s world, whilst increasing its security and integrity.

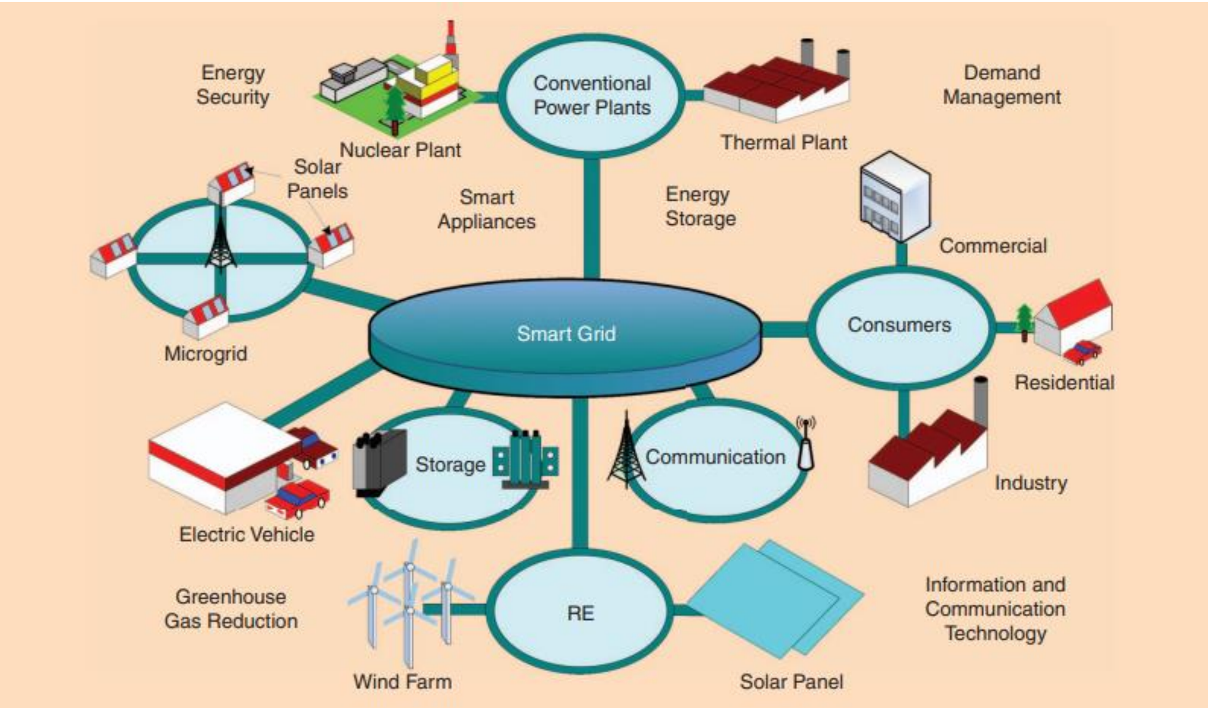

Figure 2.1 – Illustration of a smart grid (extracted from [26])

2.1. Smart Grid Architecture

Various literature concerning the architecture of a smart grid exists, having different proposals according to the context of each author. For instance, the US Department of Energy (DOE) proposed a concept of a smart grid as a system divided into nine areas [27]:

- Transmission automation
- System coordination situation assessment
- System operations

- Distribution automation
- Renewable integration
- Energy efficiency
- Distributed generation and storage
- Demand participation signals and options
- Smart appliances, PHEVs, and storage.

A simpler and more practical structure for smart grids can be found in [28], consisting of four main subsystems:

- Electrical Power System
- Communication and Information system
- Intelligent protection, automation, and distributed control system
- Electricity market system.

2.2. Smart Grid Reliability

As stated previously, smart grids have a larger number of components and subsystems than classical electrical grids. Consequently, there is also a higher probability of these components and systems having interdependences between them, increasing the possibility of, if a failure occurs, more than one component being affected.

The reliability assessments in conventional power network systems are often based on probability models that evaluate each of the power components that compose the grid being the object of study [29,30]. However, with the introduction of smart grids and the appearance of cyber networks aggregated to the power distribution systems, most of the time creating an interdependent cyber-power relation, the usual standard reliability models are ineffective as each of these two networks possesses different operating contexts [31,32]. It is also noteworthy the fact that these reliability models are not prepared to consider the appearance of new potential risks, such as cyber-attacks for instance.

The Failure Mode, Effects, and Criticality Analysis FMECA is a qualitative reliability method that can present itself as a suitable methodology to assess reliability studies in smart grids' context. As one will see in the next chapter, the FMECA methodology has been applied to the reliability assessment for several types of industries and processes, showing great relevance and potential in those studies. As it will be described hereafter, the FMECA is particularly efficient in the design stage of a project, by attempting to mitigate possible risks and improving the general reliability of the project.

3. Failure Mode, Effects and Criticality Analysis – FMECA

Failure Mode, Effects and Criticality Analysis, usually known by its acronyms as FMECA, is a qualitative-based reliability assessment method used to identify potential system failures, analyze their causes and consequences, and classify them using a metric score to ultimately be able to prioritize the potential risks and subsequently create needed maintenance/mitigation plans [1,2].

The FMECA methodology appeared first in the 1940s used by the U.S military services [33]. It was also applied by NASA, in the 1960s, to the Apollo space program, with such relevance that the concept of FMECA is still adopted these days [34]. From there, the aerospace industry started using it as well, but since then it has been applied by a large array of procedures and industries. From the oil and gas industry [35,36], through nuclear power [37,38] and chemical processes [39,40], to the healthcare sector [41,42], among others such as general industrial processes, FMECA is regarded as a dynamic and effective procedure. It is also noteworthy the high relevance of the application of FMECA, with satisfactory results, in extremely dangerous environments and processes, such as the nuclear and chemical contexts.

There are also several applications of the FMECA procedure to electrical power equipment, however, mainly at a component level, not considering a general study of the impacts of a certain failure on a system's performance [43]. For instance, power transformers are the object of several analyses as they can represent a crucial and expensive part of an electrical system. As an example, in [44] the authors apply FMECA to the condition monitoring of oil-immersed power transformers, focusing specifically on three potential failures, while the authors in [45] have analyzed 92 power transformers through FMECA and concentrated the analysis on three components that have the highest probability of failure.

Moreover, wind power and photovoltaic systems are also widely covered. On the one hand, in [46] the authors study the reliability of a 2MW wind turbine, discovering 16 failures modes with the help of reliability software based on FMECA, whereas in [47], the authors analyze the potential risks and failures of both onshore and offshore wind turbines, creating a mathematical methodology that combines economical concepts with FMECA. On the other hand, the authors in [48] present an FMECA application to a PV system, backed by the insights of experts with large working experience in such systems, while the authors in [49] applied FMECA to a specifically designed test system, drawing conclusions about its benefits and limitations.

There are also some applications to energy storage systems, more precisely regarding batteries [50,51], and applications to hydraulic turbines [52], hydropower plants [53], capacitor banks [54], or the transmission efficiency at substations [55].

3.1. Principles of Classical FMECA

The FMECA's main objective relies on improving the design of the project/process being developed, in an attempt to mitigate potential risks that might occur, while simultaneously trying to improve the reliability of said system. Nevertheless, FMECA can be applied to other circumstances at any stage of a project, not only for instance to improve tests, verifications, or process controls, but also to develop preventive maintenance plans, in the quest of minimizing loss of performance and system optimization [1,2,56]

To conduct the FMECA analysis, the first step is to gather a panel of experts that have the responsibility of identifying and characterizing said failures, whilst should also identify the failure detection strategies and recommend actions to safeguard the system's integrity. FMECA does not have a predicting role, as its main aim is to identify and classify possible failures through a procedure based on a risk ranking system [43,57].

This risk ranking system is based on three risk factors [56]:

- Severity (SEV): measures the impact of a failure in the system's operation, based on the worst potential consequences that may happen.
- Occurrence (OCC): frequency of times a failure is likely to occur – can be related to the failure rate concept.
- Detection (DET): represents the likelihood of detecting a failure before it harms the system's operation.

Each of these three risk factors is assigned an integer value by the FMECA methodology, usually between 1 and 10, with each value representing a particular qualitative category describing their risk and level category. Below, Table 3.1 to Table 3.3, describe the methodology and basis used in this dissertation, with each risk factor being divided on a scale of 1 to 10, which were distributed into five categories with their code and label [58].

Table 3.1 – Ratings and categories for Severity used in classical FMECA (adapted from [58])

Ratings	Category	Code	Severity of effect
1	Minor	SMI	Any failure that will cause a minor reduction of energy supply.
2 or 3	Low	SL	Any failure that will cause a low energy supply reduction; corrective maintenance is not required.
4, 5 or 6	Moderate	SM	Any failure that will cause a considerable energy supply reduction but tolerable; corrective maintenance is needed.
7 or 8	Very High	SVH	Any failure that will cause an energy supply reduction beyond tolerable limits, but with acceptable repair time and cost; corrective maintenance is needed.
9 or 10	Hazardous	SHA	Highest severity rating of a failure mode, will occur without warning, the consequences are hazardous for the system, and has extensive repair times and cost expenses; corrective maintenance is crucial.

Table 3.2 – Ratings and categories for Occurrence used in classical FMECA (adapted from [58])

Ratings	Category	Code	Frequency of Occurrence
1	Remote	OR	Any failure with an occurrence around $5x10^{-5}$ per year.
2 or 3	Very Unlikely	OVU	Any failure with an occurrence around $5x10^{-4}$ per year.
4, 5 or 6	Occasional	OO	Any failure with an occurrence around $5x10^{-3}$ per year.
7 or 8	Probable	OP	Any failure with an occurrence around $5x10^{-2}$ per year.
9 or 10	Frequent	OF	Any failure with an occurrence greater than $3.33x10^{-1}$ per year.

Table 3.3 – Ratings and categories for Detection used in classical FMECA (adapted from [58])

Ratings	Category	Code	Likelihood of Detection
1	Almost Certain	DAC	The monitoring system will almost certainly detect the failure.
2 or 3	High	DH	There is a high possibility of failure detection by the monitoring system.
4, 5 or 6	Moderate	DM	There is a moderate possibility of failure detection by the monitoring system.
7 or 8	Low	DL	There is a low possibility of failure detection by the monitoring system.
9 or 10	Almost Impossible	DAI	The monitoring system will not detect the failure.

From these risk factors, one can compute the overall risk of a failure mode, which is defined as Risk Priority Number (RPN), as shown in equation (3.1).

$$RPN = SEV \times OCC \times DET \tag{3.1}$$

In accordance with the RPN score, the failure modes will be ordered from high to low, since the higher the score the higher the risk of hindering the system's operations and reliability. This is the basis for the failure modes' order on an FMECA worksheet, as theoretically, failure modes with higher RPN scores call for more corrective actions in comparison with the ones score lowered, to maintain the system's integrity and performance.

At the end of an FMECA analysis, all components have been analyzed to identify their potential failure modes, the causes that may produce the component's failure, the effects on the system caused by the failure modes have been discussed, plus the actions that must be executed to mitigate the effects of said failure mode, have also been identified. From this analysis, an FMECA worksheet is created, with a similar header as depicted below in Figure 3.1.

Item / Function	Potential Failure Mode	Potential Cause(s) of Failure	**Potential** Consequence(s) /**Mechanism(s)** **Of Failure**	Detection Methods	**Recommended** Actions	Ratings of risk factors			
						SEV	OCC	DET	**RPN**

Figure 3.1 – Example of an FMECA worksheet's header (extracted from [43])

To better understand the FMECA analysis and worksheet, it is important to establish some concepts [3]:

- *Item*: system or component that is being analyzed and carries the probability of failing.
- *Function*: the task each item must execute and is assigned to.
- *Failure mode*: the manner by which a failure is observed, usually describing how the failure started occurring.
- *Failure causes*: events or circumstances that are responsible and cause the appearance of failure modes, ultimately leading to the system or components' failure.
- *Potential consequences/effects*: consequences and impacts that the failures have on the system's operation and performance, with the possibility of being both local, only affecting the component that fails, and global, possibly hindering its neighbors or the entire system.
- *Detection methods*: possible procedures that can be implemented with the hope of increasing the probability of failure detection.
- *Recommended actions*: possible procedures that can be activated in the probable occurrence of a failure, seeking its mitigation or elimination.
- *SEV, OCC, DET, and RPN*: FMECA's risk factors that were described and discussed previously.

Based on the given descriptions, the FMECA procedure can be summarized through the flowchart shown in Figure 3.2 (next page), as it must maintain a certain standardization to provide the necessary robustness to the analysis performed and obtained results.

This systematic procedure starts by defining the scope of the analysis and by assembling the group of experts that will perform the FMECA. It is important to have an interdisciplinary team, in order to cover a vast range of possible problems, always supported by rigorous informed analyses. From there, the team must divide the system into subsystems to understand which components there are, list them and understand what relations may exist between them that can influence the general performance of the system. Moreover, that analysis results in the brainstorming of possible failure modes that might occur in those components or subsystems, to then be further analyzed.

Each of the failure modes resulting from that compilation will be going through several phases, starting by understanding how frequently the failure mode occurs to then consequently attribute an OCC rating, using Table 3.2.

From the occurrence analysis, the causes of the failure mode are determined and subsequently its effect on the system, both locally and globally, so that a SEV rating can be attributed using Table 3.1. By the same token, the control procedures and possible mitigation plans of the failure mode are analyzed to attribute a DET rating based on Table 3.3. Lastly, the RPN score is computed based on equation (3.1) with the previously defined rankings.

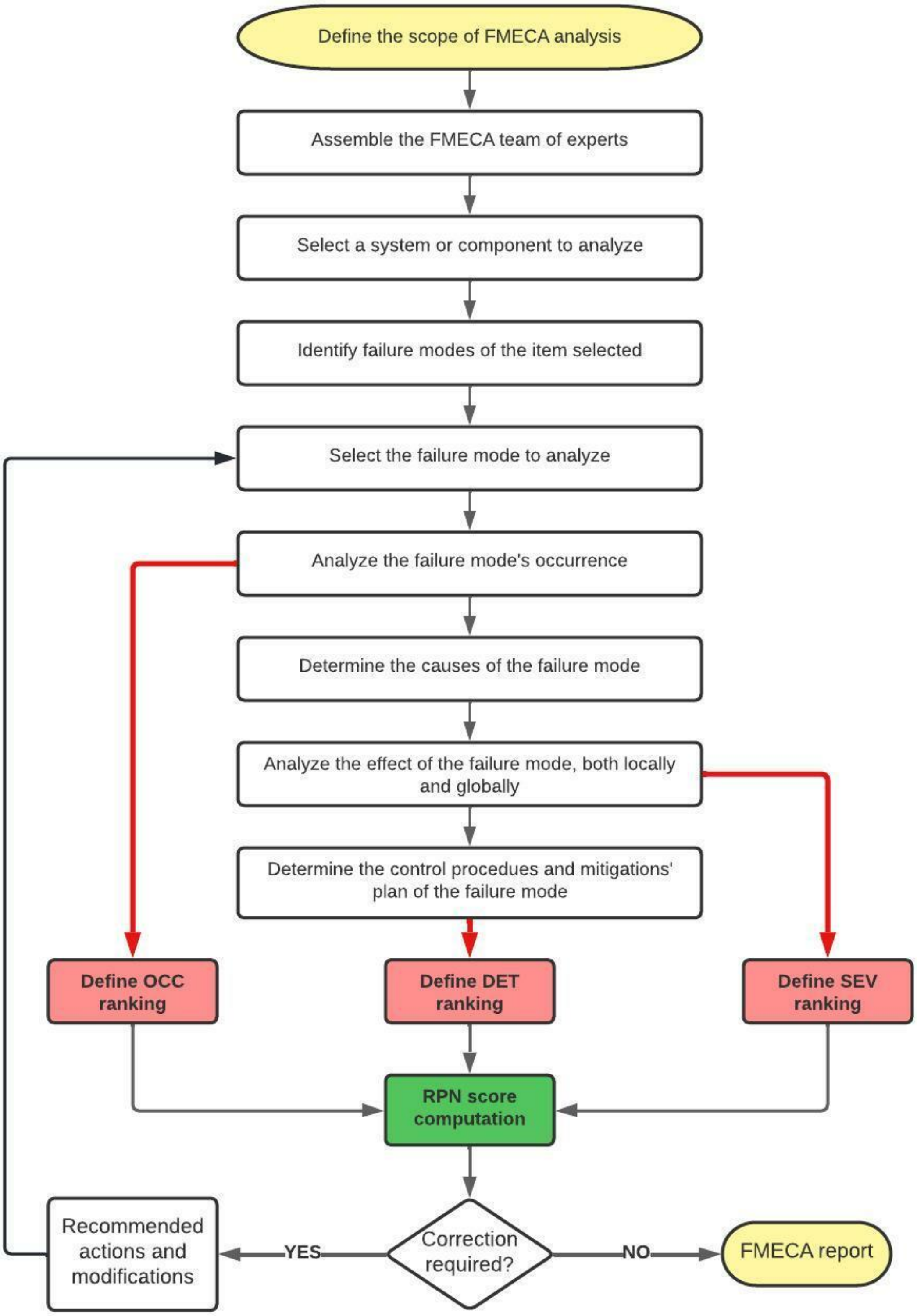

Figure 3.2 – FMECA procedure for a failure mode (adapted from [3,43,56])

As previously described, failure modes are then prioritized in terms of their RPN score, with high-risk failures being ranked higher, and possible recommended actions and modifications to the system are created, to tackle the analyzed risks by eliminating or mitigating them. These corrective actions will theoretically decrease the ratings previously defined for the failure mode, hence why after they are put into practice, the RPN needs to be computed again, hopefully with a lower score after those aforementioned actions. At the end of the process an FMECA report is drafted with all the relevant conclusions and analyses conducted.

3.2. Drawbacks of the Classical FMECA

FMECA analysis is considered a powerful tool for qualitative reliability and risk analysis, however, the RPN score computed by equation (3.1) has no value or meaning in itself, although it is expected that larger RPN values indicate more critical failure modes, this may not be always true.

For instance, Table 3.4 shows a hypothetical example considering three failure modes whose RPNs are equal.

Table 3.4 – Example regarding the RPN subjectivity

Failure Mode	SEV	OCC	DET	RPN
FM1	1	10	10	100
FM2	10	1	10	100
FM3	10	10	1	100

One could say that because the failure mode FM3 has the highest severity ranked as 10 and categorized as ‘Hazardous’, and has the highest occurrence, ranked as 10 and categorized as ‘Frequent’, should be the highest placed of the depicted failure modes; however, the three failure modes in Table 3.4 have the same RPN, meaning that according to the classical FMECA analysis, the three failure modes have the same risk level. This example shows one of the most common classical FMECA weaknesses related to more than one failure mode with the same RPN.

In sum, there are some disadvantages and shortcomings when using the RPN score computation:

- The difficulty in determining the three risk factors, since most of the reasoning is often vague and expressed in a “natural language” using expressions such as “likely,” “around,” or “very high” [3,56]. It is ambitious to represent these risk factors by single integer numbers.
- The computation of the RPN score is based on a simple multiplication between risk factors, which makes it highly sensitive to any variation in the risk factors’ assigned ratings.
- The three risk factors are computed considering the same weight and their relative importance is wrongly disregarded. One could say that probably SEV should have higher importance when compared to OCC and DET, for instance.

- As seen in the example in Table 3.4, different combinations of SEV, OCC, and DET ratings can lead to the same RPN, which as explained can lead to a wrong prioritization of the failure modes.
- The existing relations between the failure modes and their causes are often disregarded and not taken into consideration when performing the classical FMECA.

Although FMECA is still vastly used and considered a reference when analyzing the risk and reliability in critical industries like nuclear, oil&gas or aerospace industries, the basis of this analysis will be always dependent on “normal human language” which can create some drawbacks and uncertainty. For this reason, the implementation of the Fuzzy Logic as intended by this dissertation would be a valid option for the FMECA’s process improvement, due to its ability to translate the human natural language into computer language, to then be able to execute numerical computations as the RPN score case.

The aforementioned drawbacks of the FMECA classical method are well known and have been the object of research since 1995 [4]. For instance, some literature introduces Fuzzy reasoning combined with improved analytical processes for either a better risk prioritization or the attribution of weights to each of the risk factors [60-62]. Additionally, Liu [3] published the first book regarding the improvement of FMEA classical procedures, performing extensive research on uncertainty theories and multi-criteria decision-making methodologies, as well as displaying an array of case studies and possible applications, being used as a reference in many of the studies performed these days.

Another FMECA shortcoming analyzed in this dissertation is the comparison between FMECA’s improved methodologies. Commonly, the efficacy of new FMECA approaches is evaluated qualitatively by comparing the rankings obtained by each method and analyzing individually the three risk factors’ ratings. When the number of failure modes is small this approach can be suitable for application, however, in FMECAs involving a high number of failure modes, this approach becomes unpractical.

To address the abovementioned shortcoming, this dissertation introduces a comparison approach based on the Cohen’s Kappa concordance coefficient, to compare FMECA procedures [85]. The proposed comparison approach requires a reference FMECA ranking, which will then be used as the base ranking to put against the various FMECA-Fuzzy rankings that will be generated.

Because of the FMECA RPN-based rank prioritization drawbacks already mentioned in this chapter, the reference FMECA ranking selected in this work is based on the Risk Priority Index Function (RPI) proposed by Anes et al. in [59]. For that reason, the next chapter describes the fundamentals of the RPI method, also showing a brief application example.

4. Reference Prioritization Model: Risk Priority Index Function

Anes et al. [59] proposed a new failure modes prioritization model based on two functions: the Risk Isosurface Function (RI) and the Risk Priority Index Function (RPI). The RI function prioritizes failure modes following a given order of importance, while the RPI function performs prioritization based on weights given to each FMECA's risk factor. Authors explain that the "injective and surjective nature of these functions (…), makes it suitable for integration in the FMECA context" [59], showing promising results in the prioritization of failure modes, by overcoming the conventional RPN computation shortcomings.

4.1. Risk Isosurface Function – RI

As previously stated, the RI function is applied to the prioritization of risk variables, based on a given order of importance. For that purpose, it relies on the concepts of criticality value and criticality function, where it combines a continuous criticality plane with the concept of risk isosurfaces, to accommodate the three variables that compose the RPN methodology. From these notions and theories, equation (4.1) described below, can be used to compute the RI assuming that the given order of importance between factors A, B, and C is A>B>C [59]:

$$RI(A,B,C)_{A>B>C} = (A-1)\alpha^2 + B\cdot\alpha + C - \alpha \qquad (4.1)$$

Where A, B, C, and $\alpha \in N$, with α representing the scale length of the risk variables. If the order of importance between factors A, B, and C changes to C>A>B, equation (4.1) would be rearranged as described below in equation (4.2) [59]:

$$RI(A,B,C)_{C>A>B} = (C-1)\alpha^2 + A\cdot\alpha + B - \alpha \qquad (4.2)$$

From equation (4.1), one can adapt it to this dissertation's context, as described below in equation (4.3), with the order of importance S>O>D [59]:

$$RI(S,O,D)_{S>O>D} = (S-1)\alpha^2 + O\cdot\alpha + D - \alpha \qquad (4.3)$$

Where α, in this case, represents the number of categories considered for each of the risk factors – 5 categories for the FMECA application as described in Table 3.1 to Table 3.3.

Equation (4.3) can then be manipulated accordingly to the order of importance given to each of the risk factors. For the implementation of this model in this dissertation, six possible combinations of FMECA's risk factors were used, resulting from the different orders of importance given to each of the three risk factors, which can be expressed as S>O>D, S>D>O, O>S>D, O>D>S, D>S>O, and D>O>S.

4.2. Risk Priority Index Function – RPI

As described previously, the RPI attributes weights to each risk factor for the subsequent prioritization of rankings. The idea behind this concept is to apply the RPI weight-based function to the results extracted from the RI function to obtain the best possible rank prioritization. However, one could not apply directly the RPI methodology to the results of equation (4.3), as the risk factors are in different order of importance [59].

For this reason, the results of equation (4.3) are ranked according to each combination of importance, from high to low, and with those rankings one can compute the "delta risk drivers", described in equations (4.4) to (4.6) [59], that represent the average value of the attributed rankings to each risk factor – for instance in Severity, the average between the rankings result of the orders of importance S>O>D and S>D>O.

$$\delta_A = \frac{RI(A,B,C)_{A>B>C\_rating} + RI(A,B,C)_{A>C>B\_rating}}{2} \tag{4.4}$$

$$\delta_B = \frac{RI(A,B,C)_{B>A>C\_rating} + RI(A,B,C)_{B>C>A\_rating}}{2} \tag{4.5}$$

$$\delta_C = \frac{RI(A,B,C)_{C>A>B\_rating} + RI(A,B,C)_{C>B>A\_rating}}{2} \tag{4.6}$$

By conducting these transformations, the delta risk drivers can then be applied to the RPI computations together with the respective weights. Equations (4.7) and (4.8) represent the general RPI formula and the FMECA-based RPI formula, respectively [59].

$$RPI = w_A\delta_A + w_B\delta_B + w_C\delta_C \tag{4.7}$$

$$RPI = w_S\delta_S + w_O\delta_O + w_D\delta_D \tag{4.8}$$

One could select a reasonable value for the three weights to be applied, as long as its summation is equal to 100% (or 1). For this dissertation, the six different scenarios proposed in [59] and denoted by ScX were selected, as described in Table 4.1.

Table 4.1 – Suggested scenarios for weight risk drivers' combinations (adapted from [59])

Scenarios	Ws	Wo	Wd
Sc1	0.5	0.2	0.3
Sc2	0.2	0.5	0.3
Sc3	0.2	0.3	0.5
Sc4	0.3	0.5	0.2
Sc5	0.5	0.3	0.2
Sc6	0.3	0.3	0.4

Nevertheless, the weights scenarios cannot be applied directly to the equations (4.7) and (4.8). Based on the conducted research, the authors in [59] concluded that the addition of a specific correcting factor to the weights is needed to tackle the problem of non-injectivity of the referred equations. Subsequently, those correcting factors were added to the greater weight, with the value of 10^{-3}, and to the intermediate weight, with the value of 10^{-2}, which can be represented respectively by $1/\varepsilon^3$ and $1/\varepsilon^2$, with $\varepsilon = 10$. With that in mind, equation (4.7) can thus be rewritten as described below in equation (4.9) [59]:

$$RPI = \left(\frac{w_A \varepsilon^3 + 1}{\varepsilon^3}\right)\delta_A + \left(\frac{w_A \varepsilon^2 + 1}{\varepsilon^2}\right)\delta_B + w_C \delta_C \tag{4.9}$$

4.3. Practical Example

In this subchapter, a practical example regarding the application of this risk prioritization index function will be shown for better comprehension of the main concepts above illustrated. Consider five hypothetical failure modes in an FMECA analysis, with their corresponding ratings of SEV, OCC, and DET, that were ordered from the highest to the lowest RPN score. The number of categories in each risk factor is 5, thus $\alpha = 5$. Below, Table 4.2 describes the first step, which is the application of the RI function to each failure mode, based on equation (4.3).

Table 4.2 – Application of the RI function to the failure modes

	classical FMECA			*Risk Isosurface function*					
Failure mode	**S**	**O**	**D**	**SOD**	**SDO**	**OSD**	**ODS**	**DSO**	**DOS**
FM1	6	8	10	170	178	210	226	258	266
FM2	9	7	7	237	237	197	189	197	189
FM3	8	8	5	215	203	215	203	143	143
FM4	7	6	5	180	176	160	152	136	132
FM5	6	3	8	143	163	83	91	203	191

Considering the order of importance's possible variations, one can manipulate the equation (4.3) to perform the needed computations, as it is shown below, for the case of the FM1 example:

$$RI(S,O,D)_{S>O>D} = (6-1)5^2 + 8 \cdot 5 + 10 - 5 = \mathbf{170}$$

$$RI(S,D,O)_{S>D>O} = (6-1)5^2 + 10 \cdot 5 + 8 - 5 = \mathbf{178}$$

$$RI(O,S,D)_{O>S>D} = (8-1)5^2 + 6 \cdot 5 + 10 - 5 = \mathbf{210}$$

$$RI(O,D,S)_{O>D>S} = (8-1)5^2 + 10 \cdot 5 + 6 - 5 = \mathbf{226}$$

$$RI(D,S,O)_{D>S>O} = (10-1)5^2 + 6 \cdot 5 + 8 - 5 = \mathbf{258}$$

$$RI(D,O,S)_{D>O>S} = (10-1)5^2 + 8 \cdot 5 + 6 - 5 = \mathbf{266}$$

The functions that give more weight to Detection, have the higher score, as the DET rating is the highest rating regarding the FM1. The next step is to order the results of the RI functions in ranks, for each of the given orders of importance, as shown below in Table 4.3.

Table 4.3 – Failure modes ranking according to RI scores, for different orders of importance

Failure mode	S	O	D	SOD	SDO	OSD	ODS	DSO	DOS
FM1	6	8	10	4	3	2	1	1	1
FM2	9	7	7	1	1	3	3	3	3
FM3	8	8	5	2	2	1	2	4	4
FM4	7	6	5	3	4	4	4	5	5
FM5	6	3	4	5	5	5	5	2	2

From these ranks, equations (4.4), (4.5), and (4.6) can be applied to compute the delta risk drivers, as shown below in Table 4.4.

Table 4.4 – Delta risk driver for each failure mode

Failure mode	S	O	D	δs	δo	δd
FM1	6	8	10	3,5	1,5	1
FM2	9	7	7	1	3	3
FM3	8	8	5	2	1,5	4
FM4	7	6	5	3,5	4	5
FM5	6	3	4	5	5	2

Having computed the delta risk drivers, the next step is to define the weights for each of the risk factors, to calculate the RPI score. From Table 4.1, scenarios 4 and 5 were chosen and the correcting factors define as 10^{-2} and 10^{-3}, $1/\varepsilon^2$ and $1/\varepsilon^3$ which assumes $\varepsilon = 10$, as performed in [59]. Based on equation (4.8), the RPI scores can be computed for scenarios Sc4 and Sc5 – having in mind their weights –, and the failure modes are consequently ranked, as shown in Table 4.5 below. It is important to remember that the lowest RPI corresponds to the highest rank.

Table 4.5 – RPI Scores for each failure mode and respective rankings, for both scenarios

	RPI Scores		*Ranking*	
Failure mode	**Sc4**	**Sc5**	**Sc4**	**Sc5**
FM1	2,0365	2,4185	1	3
FM2	2,413	2,031	3	1
FM3	2,1715	2,267	2	2
FM4	4,089	3,9935	4	4
FM5	4,455	4,455	5	5

As a demonstration, the FM1 RPI scores can be computed as follows, using (4.9):

$$Sc4 \rightarrow RPI = \left(\frac{w_O\varepsilon^3 + 1}{\varepsilon^3}\right)\delta_O + \left(\frac{w_S\varepsilon^2 + 1}{\varepsilon^2}\right)\delta_S + w_D\delta_D = \left(\frac{0.5 \cdot 10^3 + 1}{10^3}\right)1.5 + \left(\frac{0.3 \cdot 10^2 + 1}{10^2}\right)3.5 + 0.2 \cdot 1 = \mathbf{2.0365}$$

$$Sc5 \rightarrow RPI = \left(\frac{w_S\varepsilon^3 + 1}{\varepsilon^3}\right)\delta_S + \left(\frac{w_O\varepsilon^2 + 1}{\varepsilon^2}\right)\delta_O + w_D\delta_D = \left(\frac{0.5 \cdot 10^3 + 1}{10^3}\right)3.5 + \left(\frac{0.3 \cdot 10^2 + 1}{10^2}\right)1.5 + 0.2 \cdot 1 = \mathbf{2.4185}$$

The order of ranking that resulted from the computations, should then be compared with the reference rank to understand what variations occur. As one can see in this example, the three first failure modes change places between them in both scenarios, as they are the failure modes with higher ratings of Severity and Occurrence, the two risk factors with superior weights in the chosen scenarios.

In [59] the authors end their research by stating that the proposed risk prioritization model has a satisfactory potential but should be combined with other relevant prioritization methods for better performance – different from the Fuzzy VIKOR and ITHWD applied in that case. For this reason, one can assume that the applications of Fuzzy-based methodologies are appropriate in this regard, conferring a complete characterization of the FMECA risk prioritization problem. Henceforward, two Fuzzy methodologies will be applied to the context of this dissertation, namely Fuzzy Type-I and Type-II, as described in the next chapter.

5. Fuzzy Logic-based FMECA

The Fuzzy Logic concept was introduced by professor Lotfi Zadeh in the 1960s with the aim, as he wrote, of "modelling the imprecise modes of reasoning that play an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision." [63].

In other words, Fuzzy Logic is a method created to deal with the vagueness and ambiguity of imprecise systems and facts, such as everyday life problems, too tough to model mathematically. On the one hand, the so-called Standard or Boolean logic can only define absolutely true or false events – classifying them with 1 or 0, respectively. On the other hand, the Fuzzy Logic approach allows the possibility of classifying the same events between the values of 0 and 1, with a certain degree of truth, generating a new alternative for indicating belonging. For this reason, Fuzzy Logic is also regarded as an efficient way of translating natural human language into computer language, allowing computers to handle this type of information [64].

For instance, taking the example of height, let 185cm and 180cm be considered hypothetical measures. Based on the Standard or Boolean logic, 185cm can be considered 'tall' and 180cm considered 'short' – two opposite definitions, the 0 and 1 reasoning. However, the Fuzzy Logic would perhaps say that 185cm is 'tall' with a degree of truth of 1 and that 180cm is 'tall' with a degree of truth of 0.7, dealing with the imprecision and subjectivity of the facts. Therefore, it offers an alternative way to the Standard logic's rigid perspective of things.

The Fuzzy Logic reasoning has been applied to the most distinct areas such as defense and military, finance and banking, manufacturing and production, health industry, and general industry sectors [65]. It also serves as a basis for AI and machine learning systems, as for various technologies.

As described in chapter 1, Fuzzy reasoning has been applied extensively to the context of FMECA, showing promising results in the quest to improve this method. In this chapter, it will be explained not only why the Fuzzy reasoning can represent an efficient approach to FMECA, but also some basic concepts and assumptions that need to be made so that one can reach the proposed objectives for this work.

5.1. Application to FMECA

FMECA analysis is largely based and dependent on human criteria and the only way of being characterized is by natural human language, which leads to the association with specific linguistic terms (risk categories), as presented before. For these reasons, the human input can drive this entire process to become imprecise, which the classical FMECA procedure based on the numerical ratings, is not ready to tackle as it does not capture the existing uncertainty. The whole FMECA process culminates in a single score represented by an integer number, which is then assigned to a particular label – a linguistic term – according to ratings related to the three risk factors, as shown in the tables represented in chapter 3.

To further describe this uncertainty created by the classical procedure, based on the scores given, let it suppose that for a hypothetical failure mode, two experts have gathered and assessed it as described in Table 5.1.

Table 5.1 – Ratings for the hypothetical failure modes

	Severity - SEV	Occurrence - OCC	Detection - DET	RPN
Expert 1	Hazardous - 9	Very Unlikely - 3	Moderate - 4	108
Expert 2	Very High - 8	Very Unlikely - 3	High - 3	72

As one can see, the same hypothetical failure mode has a different RPN score, since each expert has classified the SEV, OCC, and DET differently from one another. These differences are explained by the fact of each expert has its own opinions, experiences, or criteria, consequently leading to different scores, and more importantly, leading to different linguistic terms classifications – a marginal difference in the RPN score can lead to a different failure mode risk labeling (Table 5.1). Each of these experts that are usually required to gather in an FMECA analysis, possesses many times different perceptions of the risk level regarding the same failure mode, due to its background and expertise as mentioned, which is the core reason for the existence of uncertainty and vagueness in the classical FMECA procedure.

Based on that, the motivation and objective of this dissertation are to investigate if the use of Fuzzy Logic can improve the FMECA analysis when applied to the context of smart grids. Two Fuzzy Logic approaches were applied to the FMECA analysis: the Type-I Fuzzy Inference System and the Type-II Fuzzy Inference System. Both methods will be described in the next subchapters, but first, some important concepts about Type-I Fuzzy Inference System and the Type-II Fuzzy Inference System will be explained.

5.1.1. Fuzzy Sets and concept of Membership Function

A fuzzy set can be described as an extension of a classical set because it “introduces vagueness by eliminating the sharp boundary that defined when an object belongs to a set (or category) or not” [66].

The main difference between the classical set and fuzzy set is the degree of truth, now defined as pertinence or membership. In classical sets theory, a particular element belongs to its set or not, whereas in Fuzzy Logic terms, most of the time there are elements that belong to its set with a certain degree of membership and can be a member of two or more sets.

For instance, consider the risk category ‘Occurrence Probable’ shown in Table 3.2. This risk category is selected when a particular failure mode’s probability of occurrence is $5x10^{-2}$ occurrences per year. On the one hand, using the classical sets theory, only failure modes with an occurrence’s probability of $5x10^{-2}$ would be considered as ‘Probable’ and no other value of probability would be accepted in this OP category. On the other hand, in Fuzzy Logic terms, this risk category could be a fuzzy set considering that the probability of occurrence can be “around” $5x10^{-2}$ occurrences per year, with the term “around” making the difference here, as the fuzzy set OP would contain not only the failure modes with probability $5x10^{-2}$ but also failure modes whose probability of occurrence is close to $5x10^{-2}$, within a predefined interval.

An example of a fuzzy set OP, whose probability of occurrence is around $5x10^{-2}$, can be defined, for example, by an interval from $3x10^{-2}$ to $3x10^{-1}$, which would mean that all failure modes whose probability of occurrence is within this interval, would belong to the OP fuzzy set, with a certain degree of membership.

The degree of membership in fuzzy sets can be modeled using a pertinence/membership function, defined by $\mu_{OP}(x)$, that assigns a membership grade between 0 and 1, to each element in the interval previously defined. In this sense, in the OP fuzzy set case, the failure modes whose probability of occurrence is exactly $5x10^{-2}$ have a membership grade of 1, the failure modes whose probability of occurrence is exactly $2x10^{-1}$ have a membership grade of 0.4, whereas failure modes whose probability of occurrence is exactly $3x10^{-1}$ have a membership grade of 0, and so forth.

Below, Figure 5.1 shows a membership function that can represent category OP and is defined by the interval stated before – $[3x10^{-2}, 3x10^{-1}]$ – with the membership level varying from 0, representing a non-membership, to 1, in the case of a complete membership.

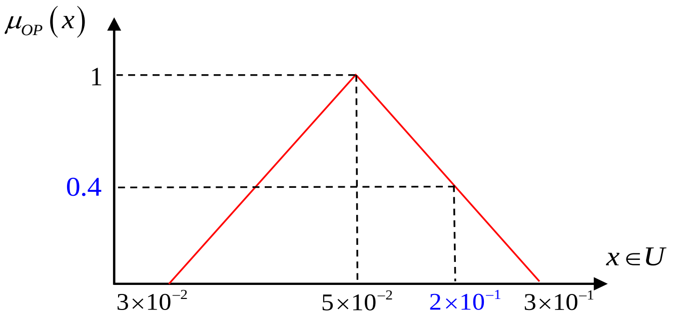

Figure 5.1 – Example of a membership function for the OP category

Formally, a fuzzy set $\tilde{A}$ can be defined as a set of ordered pairs as shown in equation (5.1), where $\mu_{\tilde{A}}(x)$ is the membership function of element (x) in the fuzzy set $\tilde{A}$, meaning the degree that (x) belongs to $\tilde{A}$. In this case, *U*, also shown in Figure 5.1, is described as the “universe of discourse” and represents all possible values for (x) [66].

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in U\} \quad (5.1)$$

The equation (5.1) can also represent so-called ordinary fuzzy sets or Type-I fuzzy sets, which will be analyzed later in this chapter [67,68].

The membership functions can be considered as a subjective way to represent the human language [69] and should be constructed using intuition or inference procedures, or even using neural networks, genetic algorithms, soft partitioning, and other procedures. In general, the main goal and the concept that should not be forgotten is that a membership function represents the experts’ knowledge for a particular application, in the case it is available and is used as a representation of the various risk categories.

5.1.2. Linguistic Variables

The linguistic variable is an important concept in fuzzy logic and approximated reasoning since it represents a variable whose values are words or sentences in natural or artificial language [70].

In this FMECA context, each of the risk factors – SEV, OCC, DET – can be represented in fuzzy terms as a linguistic variable. In other words, one can say that, for instance, the risk factor OCC is a linguistic variable that can be classified with linguistic values, such as 'Remote', 'High' or 'Moderate', instead of the classical numerical values. Fundamentally, these linguistic values are the categories for each risk factor, that can now serve and have a significant value for the Fuzzy sets.

A linguistic variable can be defined by the quintuple $(x, T(x), U, G, M)$. In this quintuple, (x) represents the name of the variable, $T(x)$ is the term-set of (x), meaning the collection of linguistic variables for (x), U is the universe of discourse for (x), G is a "syntactic rule" for generating the terms $T(x)$, and finally, M is a "semantic rule" that associates each linguistic variable with its meaning $M(x)$, where $M(x)$ is a fuzzy set in U [70].

Based on that, the application of fuzzy concepts in FMECA's risk factors carries the following assumptions:

- Linguistic variables are represented by the risk factors Severity (SEV), Occurrence (OCC), Detection (DET), and the Risk Priority Number (RPN).
- FMECA is conducted by human experts, who assign an integer value from 1 to 10 for each of the risk factors. Therefore, the universe of discourse for each factor is as shown in equation (5.2).

$$U = [1, 10] \tag{5.2}$$

Moreover, having in mind what was explained in this subchapter, each of the risk factors should be described as follows:

<u>Severity</u>

- The categories for severity are SMI – 'Severity Moderate', SL – 'Severity Low', SM – 'Severity Moderate', SVH – 'Severity Very High', and SH – 'Severity Hazardous'.
- The term set for Severity is represented by the equation (5.3):

$$T(SEV) = \{SMI, SL, SM, SVH, SH\} \tag{5.3}$$

- The semantic rules M for $T(SEV)$ can be defined as:

- ❖ $M(SMI)$ – fuzzy set "the severity of the failure mode is considered 'Minor', when assessed as the value 1".
- ❖ $M(SML)$ – fuzzy set "the severity of the failure mode is considered 'Low', when assessed between the values of 2 and 3".
- ❖ $M(SM)$ – fuzzy set "the severity of the failure mode is considered 'Moderate', when assessed between the values of 4 and 6".
- ❖ $M(SVH)$ – fuzzy set "the severity of the failure mode is considered 'Very High', when assessed between the values of 7 and 8".
- ❖ $M(SH)$ – fuzzy set "the severity of the failure mode is considered 'Hazardous', when assessed between the values of 9 and 10".

Occurrence

- The categories for occurrence are OR – 'Occurrence Remote', OVU – 'Occurrence Very Unlikely', OO – 'Occurrence Occasional', OP – 'Occurrence Probable', and OF – 'Occurrence Frequent'.

- The term set for Occurrence is represented by the equation (5.4):

$$T(OCC) = \{OR, OVU, OO, OP, OF\} \tag{5.4}$$

- The semantic rules M for $T(OCC)$ can be defined as:

  - ❖ $M(OR)$ – fuzzy set "the occurrence of the failure mode is considered 'Remote', when assessed as the value 1".
  - ❖ $M(OVU)$ – fuzzy set "the occurrence of the failure mode is considered 'Very Unlikely', when assessed between the values of 2 and 3".
  - ❖ $M(OO)$ – fuzzy set "the occurrence of the failure mode is considered 'Occasional', when assessed between the values of 4 and 6".
  - ❖ $M(OP)$ – fuzzy set "the occurrence of the failure mode is considered 'Probable', when assessed between the values of 7 and 8".
  - ❖ $M(OF)$ – fuzzy set "the occurrence of the failure mode is considered 'Frequent', when assessed between the values of 9 and 10".

Detection

- The categories for detection are DAC – 'Detection Almost Certain', DH – 'Detection High', DM – 'Detection Moderate', DL – 'Detection Low', and DAI – 'Detection Almost Impossible'.

- The term set for Detection is represented by the equation (5.5).

$$T(DET) = \{DAC, DH, DM, DL, DAI\} \tag{5.5}$$

- The semantic rules M for $T(DET)$ can be defined as:

  - ❖ $M(DAC)$ – fuzzy set “the detection of the failure mode is considered ‘Almost Certain’, when assessed as the value 1”.
  - ❖ $M(DH)$ – fuzzy set “the detection of the failure mode is considered ‘High’, when assessed between the values of 2 and 3”.
  - ❖ $M(DM)$ – fuzzy set “the detection of the failure mode is considered ‘Moderate’, when assessed between the values of 4 and 6”.
  - ❖ $M(DL)$ – fuzzy set “the detection of the failure mode is considered ‘Low’, when assessed between the values of 7 and 8”.
  - ❖ $M(DAI)$ – fuzzy set “the detection of the failure mode is considered ‘Almost Impossible’, when assessed between the values of 9 and 10”.

In addition to the aforementioned risk factors, there is also the RPN classification, which in the classical FMECA, results from the product between SEV, OCC, and DET, having a range from 1 to 1000. However, in Fuzzy Logic’s context, one can apply the concept of linguistic variables, dividing the RPN into risk categories, simplifying the process, and making it easier to implement the reasoning mechanism. For this reason, the RPN classical range will be disregarded in this thesis, and the universe of discourse is the same as the previous risk factors. With this in mind, the RPN can also be described as follows:

Risk Priority Number

- The categories for the RPN are RMI – ‘Risk Minor’, RL – ‘Risk Low’, RM – ‘Risk Moderate’, RH – ‘Risk High’, and RE – ‘Risk Extreme’.

- The term set for the RPN is represented by the equation (5.6).

$$T(RPN) = \{RMI, RL, RM, RH, RE\} \tag{5.6}$$

- The semantic rules M for $T(RPN)$ can be defined as:

  - ❖ $M(RMI)$ – fuzzy set “the risk of the failure mode is considered ‘Minor’, when assessed as the value 1”.
  - ❖ $M(RL)$ – fuzzy set “the risk of the failure mode is considered ‘Low’, when assessed between the values of 2 and 3”.
  - ❖ $M(RM)$ – fuzzy set “the risk of the failure mode is considered ‘Moderate’, when assessed between the values of 4 and 6”.
  - ❖ $M(RH)$ – fuzzy set “the risk of the failure mode is considered ‘High’, when assessed between the values of 7 and 8”.
  - ❖ $M(RE)$ – fuzzy set “the risk of the failure mode is considered ‘Extreme’, when assessed between the values of 9 and 10”.

5.1.3. Fuzzy IF-THEN Rules

Having defined some important concepts as "fuzzy set" or "linguistic variable", with the definition of each risk factor as a linguistic variable, plus the new organization of the RPN, one can start defining some rules that will be essential for the computation of the new RPN, using the fuzzy reasoning.

In fuzzy logic, approximate reasoning refers to a mode of reasoning in which the input-output relation of a system is expressed as a collection of IF-THEN fuzzy rules where the preconditions and consequents involve fuzzy or linguistic variables [66,69] Fuzzy IF-THEN rules are also known as "fuzzy rules", "fuzzy implications" or "fuzzy conditional statements" [69].

A general structure of IF-THEN rules is:

IF x is A **THEN** y is B

In this structure, "x is A" is named the "antecedent" or "premise", and "y is B" is referred to as the "consequent" or "conclusion" [69]. For a better example, in the case of a specific failure mode, the fuzzy mode IF-THEN rule can be defined as:

IF *(Severity is hazardous)* **AND** (*Occurrence* is *remote*) **AND** (*Detection* is *high*) **THEN** (*RPN* is *moderate*).

The fuzzy rules can be defined in two ways: defined by a group of experts after careful consideration, or, defined by all the possible combinations between the categories of risk factors transformed into linguistic variables. In this present work, the fuzzy rules were considered as all the possible combinations, being the risk factors of SEV, OCC, and DET, the antecedent of the IF-THEN, and the RPN the consequent of that combination. As the new RPN will be computed based on the combination of the three-factor risks, through the fuzzy mechanism, it will be renamed Fuzzy Risk Priority Number – FRPN.

Since each of the three risk factors comprehends five categories each, as demonstrated in Table 3.1 to Table 3.3, and explained in the subchapter of the linguistic variables, there are 125 possible combinations. Each of these combinations, which represent the 125 rules in this Fuzzy system, is associated with its respective FRPN category, accordingly to the new organization given based on the linguistic variables. Considering this description of rules, one could give an example of a proposed fuzzy rule:

- **Rule 79:** If the severity is moderate and the occurrence is remote and the detection is moderate, then the risk is low

Which, subsequently can be transformed into a fuzzy rule, based on the linguistic variables:

- **Fuzzy Rule 79:** If severity is SM and occurrence is OR and detection is DM then FRPN is RL

Having described and elucidated some important concepts, terms, and also the rules that support the fuzzy reasoning, the two Fuzzy-types used in this thesis will be presented next, with the objective of clearly describing how the method works, the reasoning behind it and how can one use it for, hopefully, a more efficient FMECA analysis and consequently more accurate results.

5.2. Type-I Fuzzy Systems

The Fuzzy Type-I is the first of the first approach being analyzed, since is acknowledged as the first step of the Fuzzy Logic reasoning, being the basis for further and more complex approaches. All concepts described in Chapter 5.1 apply to the Fuzzy Type-I, with particular relevance to the equation (5.1), as it refers to ordinary fuzzy sets or Type-I fuzzy sets. From that, one can assimilate the previously mentioned concepts of linguistic variables and fuzzy rules, and advance to the reasoning mechanisms, particularly the inference system.

5.2.1. Fuzzy Inference System Type-I

The Fuzzy Inference System, FIS, is a computational framework that entails an input processing stage, where transforms data given, to then based on fuzzy reasoning mechanisms and fuzzy rules producing desired outputs to be analyzed. As described in Figure 5.2, this inference system can be divided into three main phases, according to [58,69].

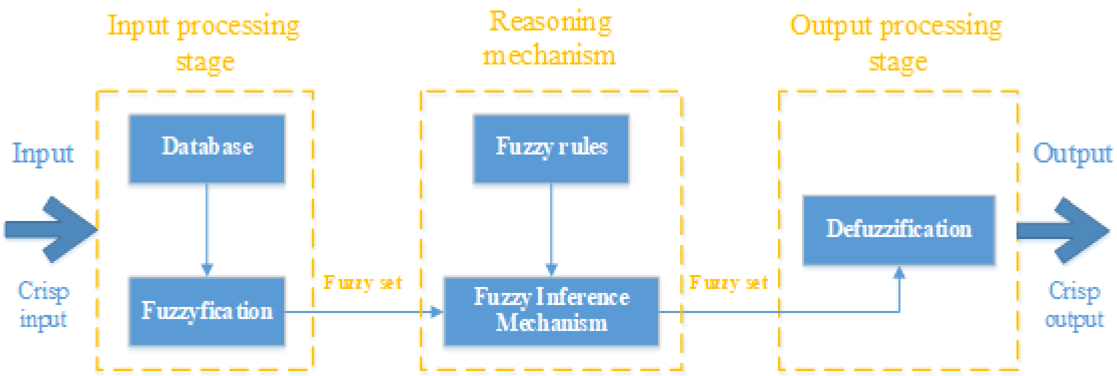

Figure 5.2 – Structure of a FIS Type-I (adapted from [69])

<u>Phase 1</u> – Input Processing Stage:

- The FIS receives a Database, which contains the linguistic variables used as antecedent as well as the membership functions to be used. These inputs can be regular numerical values or fuzzy sets, with the numerical values being called “crisp” [58]
- Then the FIS transforms the input data into fuzzy sets to be used in the next phase, which is a process that may be described as “Fuzzification”.

<u>Phase 2</u> – Reasoning Mechanism:

- Based on the selected fuzzy inference mechanism and the subsequent fuzzy IF-THEN rules created with the Database given, the FIS applies the given inference operation, creating outputs to be processed by the last phase.

Phase 3 – Output Processing Stage:

- In the last phase of the process occurs the possible "Defuzzification", where, if needed, the FIS takes the resulting fuzzy sets from the Reasoning Mechanism and transforms them into a more feasible and representative output, called the "crisp output".

Two of the main fuzzy inference systems are the Mamdani and the Takagi-Sugeno fuzzy inference systems [66,69]. The two procedures present a collection of similarities, being the only relevant difference in the last phase of the FIS process – the consequent of each fuzzy rule. In the Takagi-Sugeno FIS, the output is already a crisp value, while the Mamdani FIS's output is a fuzzy set, which requires defuzzification to obtain the desired crisp output value [58].

Going deeper into the defuzzification concept, five possible procedures to be implemented arise [69]: Centroid of the area (COA) under the fuzzy set output; the bisector of the area under the fuzzy set output; the mean value of the maximum fuzzy set outputs; the largest value of the maximum fuzzy set outputs; and finally, the smallest value of the maximum fuzzy set outputs.

In this dissertation, the Mamdani FIS was the selected fuzzy inference system, for practical reasons, as the MATLAB software used has embedded Mamdani FIS libraries that facilitate the application of the Fuzzy Logic to the FMECA analysis. As the Mamdani FIS was chosen, a defuzzification method is needed, being the centroid of the area method the one applied, as it is the most popular defuzzification method.

With these choices in mind, Figure 5.3 describes how the Mamdani FIS operates in four steps, with the COA as the defuzzification method. For simplification reasons, this example has a different setup from the one used in this work: the two rules showed are based on only a two risk factors analysis – instead of three – and are denoted as x_1 and x_2, but the overall purpose is still maintained.

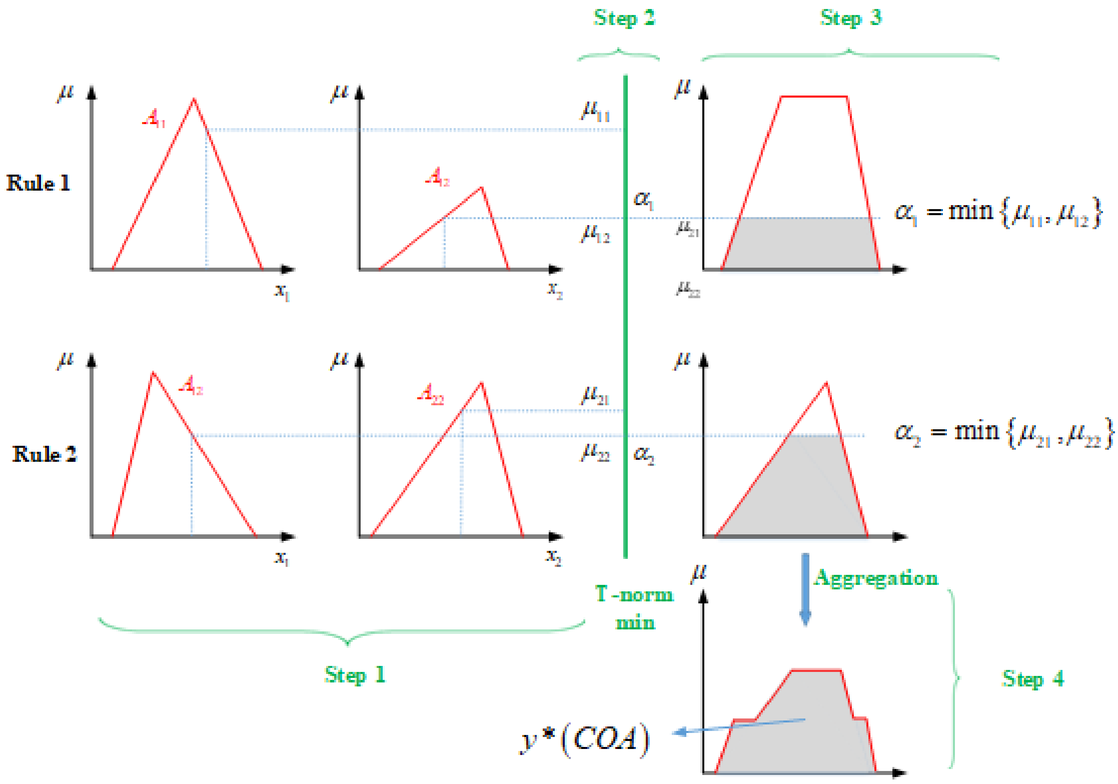

Figure 5.3 – Structure of the Mamdani FIS Type-I (adapted from [69])

Correlating the general FIS explanation with the Mamdani FIS, each step can be described as [58]:

Step 1: The fuzzification takes place. Each input variable of the rules is tested with the chosen membership functions to acquire each linguistic variable's degree of membership.

Step 2: Obtaining the degree of membership values from the precedents to get a weight – named "fire strength" and represented by α – through a fuzzy operator, in this example the T-norm min (•) operator.

Step 3: From the fire strength originated by the precedents – in this case, the minimum α –, the qualified consequents of each fuzzy rule are created to then be aggregated.

Step 4: The aggregation takes place, where all the consequents are gathered on the same set. Afterward, the defuzzification may take place to obtain a crisp value if a fuzzy set is observed, here exemplified by the COA method.

The FIS process was computed in MATLAB, to generate a new FRPN and consequently, possibly, a new FMECA table with new priority risks. To conduct the FRPN computation, the algorithm needs to be given three things: the linguistic variables (and consequent ratings), the membership functions of each risk factor, and the fuzzy rules that will define the FIS. The linguistic variables and fuzzy rules were defined in subchapters 5.1.2 and 5.1.3 respectively, applying to the Mamdani FIS, while the membership functions will be addressed next.

5.2.2. Type-I Membership Functions

As previously mentioned, the membership functions needed for the reasoning mechanism's development, are used to represent each of the risk factors – transformed into linguistic variables in subchapter 5.1.2. In that sense, there will be five membership functions for each of the three risk categories, as demonstrated and simplified in Table 5.2, plus the FRPN.

Table 5.2 – Ratings for each risk category factors

Severity Category	Occurrence Category	Detection Category	Rating
SHA - 'Hazardous'	OF - 'Frequent'	DAI - 'Absolutely Impossible'	9 or 10
SVH - 'Very High'	OP - 'Probable'	DL - 'Low'	7 or 8
SM - 'Moderate'	OO - 'Occasional'	DM - 'Moderate'	4, 5 or 6
SL - 'Low'	OVU - 'Very Unlikely'	DH - 'High'	2 or 3
SMI - 'Minor'	OR - 'Remote'	DAC - 'Almost Certain'	1

Regarding the number of categories in each risk factor, that corresponds to the number of membership functions used for the computations, the authors in [71] use the "seven plus or minus two" criterion described in [72], to establish the number of linguistic terms adequate for decision-making problems. This criterion establishes that the human capacity to process information has an interval limit of "seven plus or minus two" units of information at any given time, meaning that the number of linguistic terms in Fuzzy decision-making problems should be between five and nine. This thesis considers that five linguistic terms is an appropriate number to represent the expert knowledge in the FMECA context.

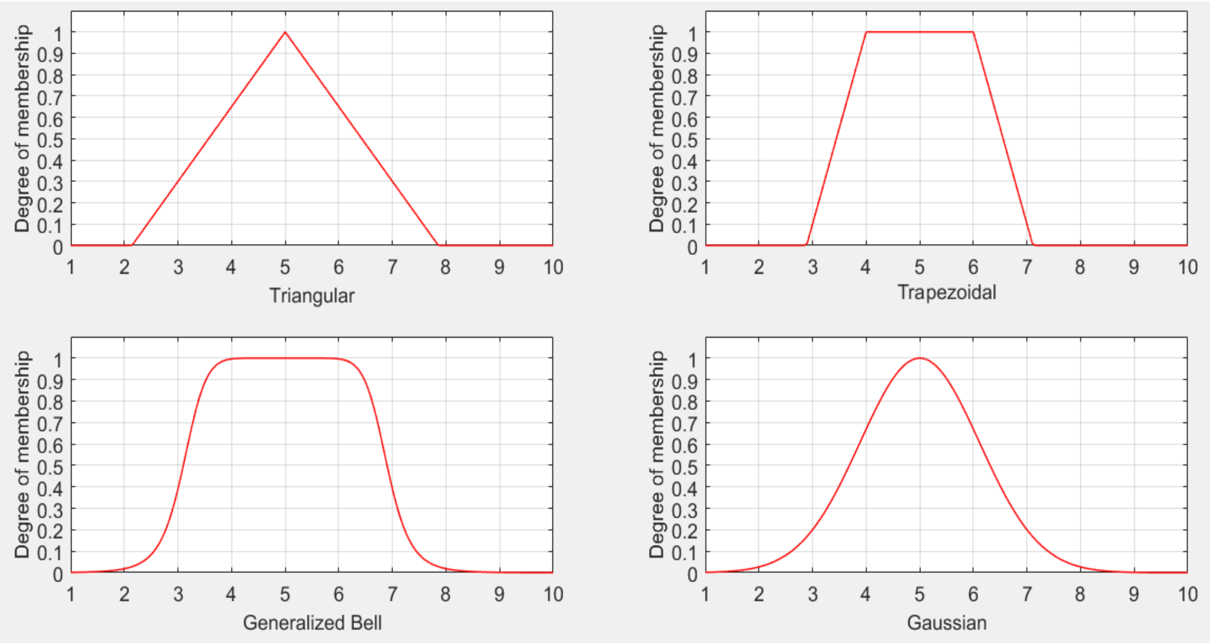

Figure 5.4 – Possible formats for the membership functions

There are four types of membership functions most commonly used that will be presented and were considered in this analysis: a triangular membership function; a trapezoidal membership function; a Gaussian membership function; and also, a generalized bell membership function [66,69]. All four shapes are described above in Figure 5.4.

Each of these four membership functions can be expressed as continuous functions and was computed based on specific parameters that define their shape [69].

The triangular membership function can be defined as equation (5.7), with *'a', 'b'*, and *'c'*, being the three vertexes that compose its shape:

$$triangular(x,a,b,c) = \begin{cases} 0, & x < a \\ (x-a)/(b-a), & a \leq x \leq b \\ (c-x)/(c-b), & b \leq x \leq c \\ 0, & x > c \end{cases} \tag{5.7}$$

The trapezoidal membership is defined as in equation (5.8), with *'a', 'b', 'c'*, and *'d'*, being the four vertexes composing its shape:

$$trapezoidal(x,a,b,c,d) = \begin{cases} (x-a)/(b-a), & a \leq x \leq b \\ 1, & b \leq x \leq c \\ (d-x)/(d-c), & c \leq x \leq d \\ 0, & otherwise \end{cases} \tag{5.8}$$

The Gaussian membership function is defined as in equation (5.9). In this case, 'a' is disregarded as it is always 1 because it represents the function height, which maximum is 1 as it in this study means the highest possible degree of pertinence. Variable *'c'* represents the center of the function, while σ controls the width of the function.

$$gaussian(x,a,c,\sigma) = a.e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{5.9}$$

Finally, the generalized bell membership function is defined as in equation (5.10), with *'c'* being the center of the function, as *'a'* and *'b'* control the width and the slopes' shape of the function.

$$bell(x,a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{5.10}$$

It is important to note that all the described membership functions are inserted in the same universe of discourse defined in equation (5.2), ranging from 0 to 10. Furthermore, these functions have a maximum of 1, which represents the full degree of membership, and a minimum of 0, which represents no degree of membership at all.

5.3. Type-II Fuzzy Systems

Focusing now on the Fuzzy Type-II, most of the concepts defined in subchapter 5.1 are also applied to this Type-II. Not only the linguistic variables but also the IF-THEN rules serve as a base for the computation of the Fuzzy Type-II. The membership functions also adopt the shape of one of the four different types described previously. The main differences, when compared with the Type-I, are in the fuzzy sets and the inference system, both going through adaptations to accommodate the inclusion of the footprint of uncertainty, a term which will be later discussed and analyzed. In general terms, the Fuzzy Type-II systems are an extension of the Type-I systems, that with the addition of this footprint of uncertainty concept, theoretically represent better the uncertainty associated with Fuzzy systems.

5.3.1. Type-II Fuzzy Sets

The concept of a Type-II fuzzy set is an extension of the Type-I fuzzy sets. On the one hand, the Type-I fuzzy sets are used to represent sets whose elements' membership is uncertain while assigning a crisp value in [0,1] to each element. On the other hand, the Type-II fuzzy sets are used to represent fuzzy sets whose elements' membership cannot be determined by a simple crisp number as in Type-I fuzzy sets [68].

According to [73] a Type-II fuzzy set can be defined as equation (5.11) shows:

$$\tilde{A} = \left\{\left((x,u), \mu_{\tilde{A}}(x,u)\right) \mid x \in X, u \in [0,1]\right\} \tag{5.11}$$

Where (x) represents the "primary variable", (u) is the "second variable", and X represents the universe of discourse for the primary variable.

J_x is the "primary membership function" of $\tilde{A}$, regarding (x), and can be defined in the interval $[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)]$ as shown below in equation (5.12)

$$J_x = \{u \in [0,1] \mid \mu_{\tilde{A}}(x,u) > 0\} \tag{5.12}$$

The 3-D membership function of $\tilde{A}$, represented by $\mu_{\tilde{A}}(x,u)$ and called Type-II membership function is defined by the cartesian product $X \times [0,1] \rightarrow [0,1]$.

According to [73] a Type-II fuzzy set can be expressed in terms of J_x and $\mu_{\tilde{A}}(x,u)$, as shown below in equation (5.13).

$$\tilde{A} = \int \int \frac{\mu_{\tilde{A}}(x,u)}{(x,u)}, \quad x \in X, u \in J_x \tag{5.13}$$

Which can be rearranged according to [74] and be written as equation (5.14) shows.

$$\tilde{A} = \int \frac{\int \mu_{\tilde{A}}(x,u)/u}{x} \; x \in X, u \in J_x \tag{5.14}$$

Based on the previous equations, below in Figure 5.5, an image of how a membership function for a Type-II fuzzy set can be represented is depicted, in this particular example as a gauss function.

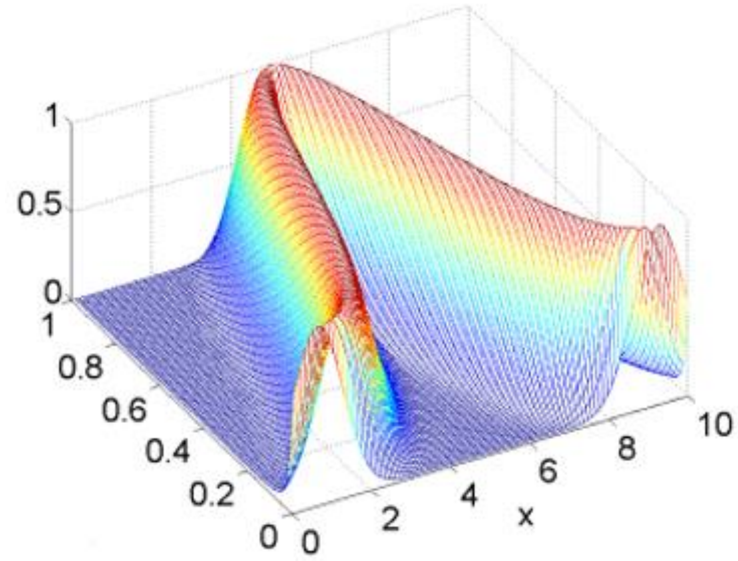

Figure 5.5 – 3-D representation of a membership function for Type-II fuzzy set (extracted from [75])

Moving forward, the secondary membership function of $\tilde{A}$, represented by $\mu_{\tilde{A}}(x)$, is the restriction of function $\mu_{\tilde{A}}(x,u)$, and can be called a “vertical slice” of $\mu_{\tilde{A}}(x,u)$. An embedded Type-I fuzzy set, represented by A_e is a function with a range within the subset of $[0,1]$, depending on $\mu_{\tilde{A}}(x)$, and defined as shown in equation (5.15).

$$A_e = \{(x,u) \mid x \in X, u \in J_x\} \tag{5.15}$$

More practically, to be more plausible the use of the Fuzzy Type-II, 2-D support is used, based on the “vertical slice” mentioned in the previous paragraph, which creates the so-called footprint of uncertainty. The footprint of uncertainty is represented by $FOU(\tilde{A})$ and can be defined as equation (5.16).

$$FOU(\tilde{A}) = \{(x,u) \in X \times [0,1] \mid \mu_{\tilde{A}}(x,u) > 0\} \tag{5.16}$$

The FOU is represented by the area between the upper membership function of $\tilde{A}$, denoted by $\overline{\mu}_{\tilde{A}}(x)$ or $UMF(\tilde{A})$, and the lower membership function of $\tilde{A}$, denoted by $\underline{\mu}_{\tilde{A}}(x)$ or $LMF(\tilde{A})$, hence why the membership of an element (x) is in the interval of $[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)]$.

Furthermore, the $FOU(\tilde{A})$ can be represented considering all the embedded Type-I fuzzy sets using the “Wavy Slice Representation Theorem” [73], shown in equation (5.17).

$$FOU(\tilde{A}) = \bigcup_{\forall j} A_e^j \tag{5.17}$$

Based on these concepts and equations, the footprint of uncertainty can be represented as depicted below in Figure 5.6. The FOU is obtained through the parametrization of the UMF and LMF, which is done consonant with what type of membership function is chosen and what are the parameters of said function.

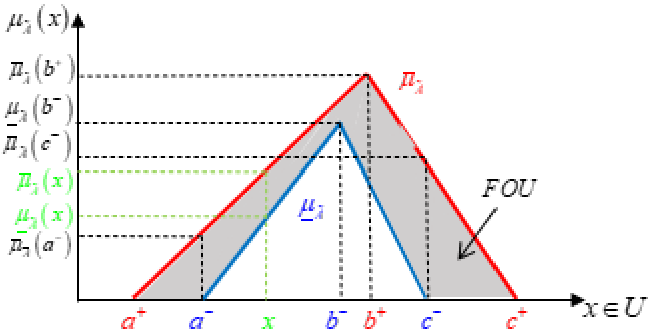

Figure 5.6 – Example of a representation of the FOU in Fuzzy Type-II

Additionally, the Type-II fuzzy set $\tilde{A}$ can now be expressed as shown in equation (5.18), in accordance with [74]:

$$\tilde{A} = \left(\left(a^+, b^+, c^+; \overline{\mu}_{\tilde{A}}(b^+)\right), \left(a^-, b^-, c^-; \underline{\mu}_{\tilde{A}}(b^-)\right)\right) \tag{5.18}$$

In this thesis, the Type-II fuzzy sets will be expressed in terms of UMF and LMF's parametrization, as shown in Figure 5.6. In subchapter 5.3.3, one can see how the UMF and LMF can be defined and what assumptions need to be made to create these functions. In this way, one can have control over the parameters, being also easier to demonstrate said functions, consequently having a better perception of the computations being made and using it as a basis for a better understanding of any results that will originate from the Type-II reasoning mechanism.

5.3.2. Fuzzy Inference System Type-II

The general structure of the FIS Type-II is very similar to FIS Type-I, as shown below in Figure 5.7. From the three-phase description made in subchapter 5.2.1, the main difference relies on the output processing stage.

On the Type-II an extra operation called "type-reduction" is conducted, that transforms the resulting Type-II fuzzy set from the reasoning mechanism, into a Type-I fuzzy set. This allows, as explained previously, that one can represent in 2-D the membership functions, having a better grasp of the results and what originates from the reasoning mechanism. At the end of the process, as in the FIS Type-I, this Type-II fuzzy set is "defuzzified" to obtain a crisp output [76].

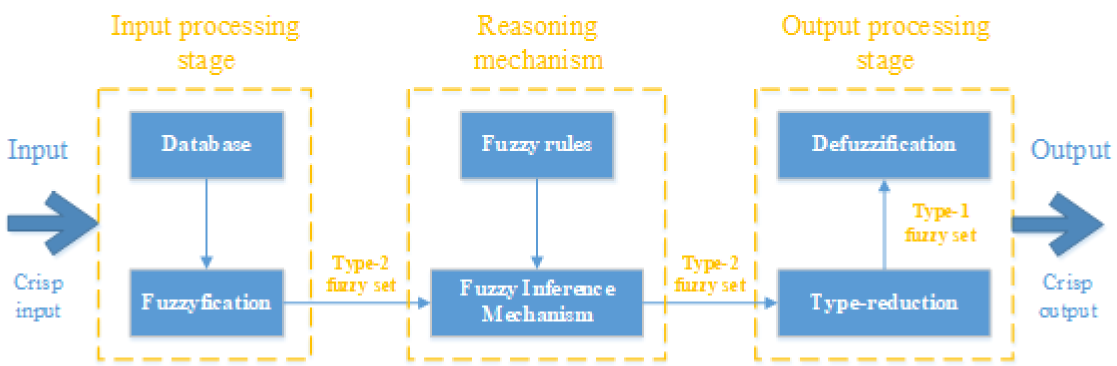

Figure 5.7 – Structure of a FIS Type-II (adapted from [73])

Furthermore, the FIS Type-II also uses the two inference systems reported in the FIS Type-I – the Takagi-Sugeno system and the Mamdani system – being the latter also used in the FIS Type-II context [73]. As for the type-reduction process needed in the Mamdani case, one of the most used methods in the FIS Type-II context is the Karnik-Mendel algorithm [73]. This algorithm will be applied to this study for simplification reasons and is based on the representation theorem for Type-II fuzzy sets, as it establishes that the centroid for a fuzzy set is the union of the embedded Type-I fuzzy sets centroids [77].

Based on these considerations, Figure 5.8 below, depicts the procedures of a Mamdani FIS Type-II in five steps, also using the COA defuzzification method, in addition to the Karnik-Mendel algorithm for the type reduction procedure. Each step presented, follows the same reasoning as the Mamdani FIS Type-I, applying the two risk factors example, and can be described as follows:

Step 1: The fuzzification takes place, where both the upper and lower limits are tested with the membership functions, to obtain the respective degrees of membership.

Step 2: The antecedents are combined, once more using the T-norm min (•) fuzzy operator, to get the respective weight – the fire strength.

Step 3: From the fire strengths, the qualified consequents of each fuzzy rule are created, having in mind both upper and lower limits.

Step 4: All of the consequents are gathered on the same set, limited by the upper and lower limits.

Step 5: The type-reduction occurs, where the generated Type-II fuzzy set output is transformed into a Type-I fuzzy set, for the defuzzification to take place and obtain a resulting crisp value.

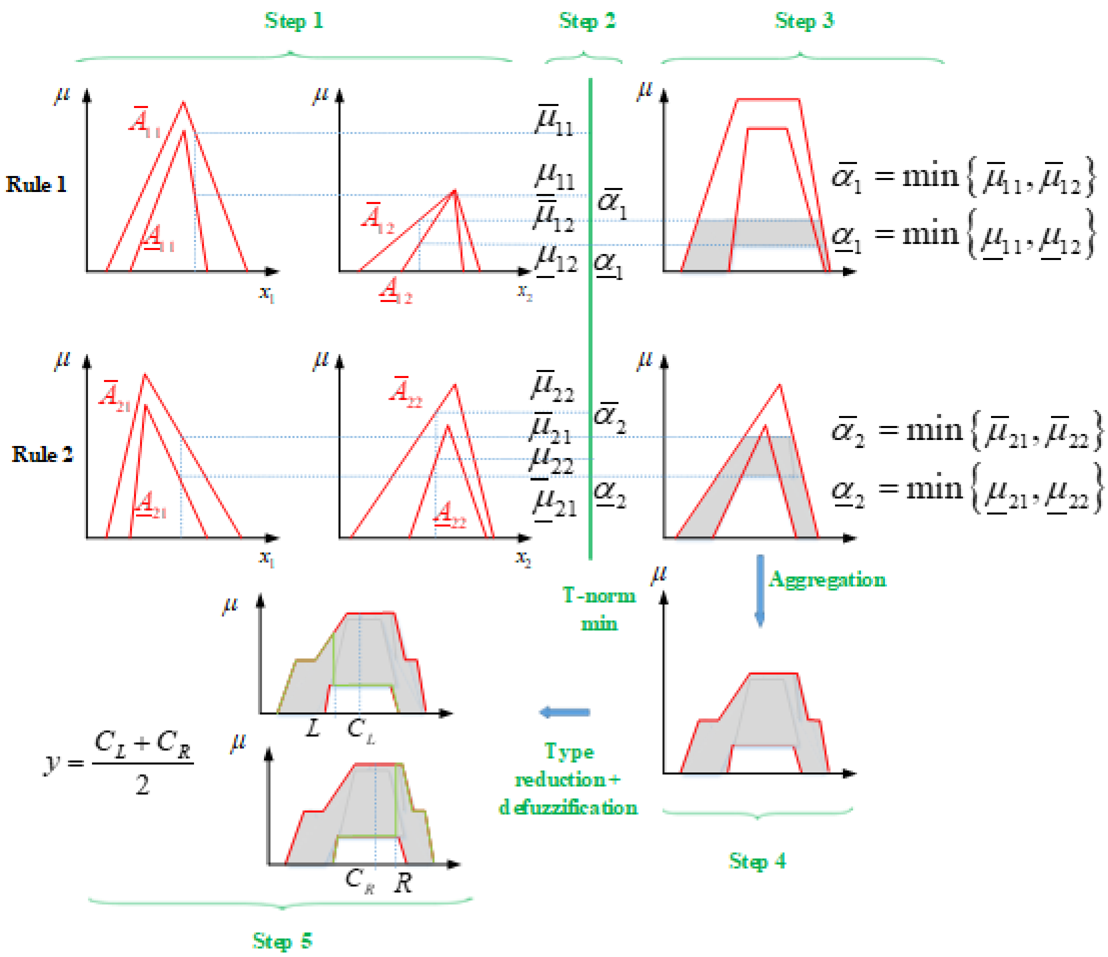

Figure 5.8 – Structure of the Mamdani FIS Type-II (adapted from [76])

By the same token as the FIS Type-I, the FIS Type-II was also computed in MATLAB, to obtain the new FRPN and analyze the new shape of the FMECA table. As explained before, the algorithm needs the linguistic variables, the fuzzy rules that will define the FIS – fuzzy rules described in subchapter 5.1.3 are applicable as described –, and the membership functions that will be described next.

5.3.3. Type-II Membership Functions

Based on the same reasoning presented on the FIS Type-I, one must define the membership functions that will be used by the reasoning mechanism. In this regard, there will be no differences: the membership functions to be applied can assume the shape of each of the four different function types described in subchapter 5.2.2., and consequently they will represent each of the categories shown in Table 5.2, as they did before.

However, as explained in the previous subchapter, Type-II membership functions are only possible to demonstrate in 2-D based on the footage of uncertainty concept, meaning that they will possess a more complex design, in addition to the existence of more variables to be dealt with. Below, in Figure 5.9, the four possible membership functions are shown with their updated design to support the FOU concept.

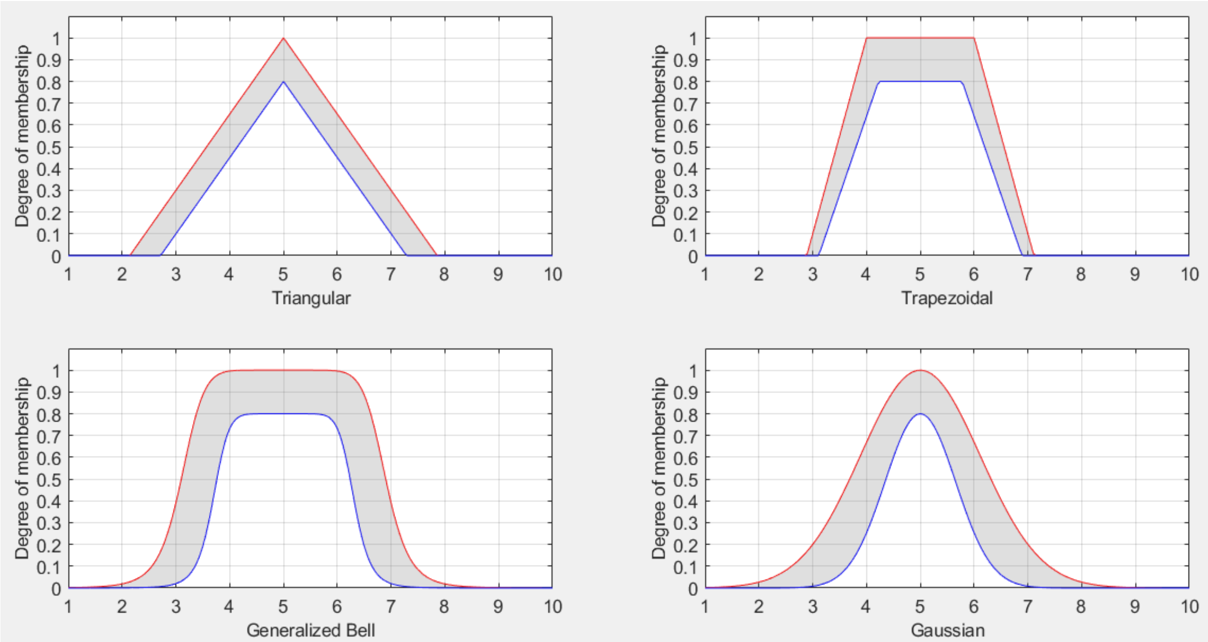

Figure 5.9 – Possible shapes of Type-II membership functions, showing the FOU.

These four possible membership functions can also be defined as continuous functions, based on the equations from (5.7) to (5.10). The FIS Type-I universe of discourse is also applicable – 1 to 10 –, as well as the maximum and minimum values a function can assume – 1 in full membership and 0 with no membership at all. Nevertheless, there are some assumptions to be made when creating the Type-II membership functions:

- The UMF is inserted in the algorithm as one of the four possible membership functions presented, as in the case of the FIS Type-I.
- The LMF is automatically computed by the algorithm, theoretically having not only the same shape but also the same slope as the UMF. However, the user can influence the FOU's size by having control of two variables described in Figure 5.6:
    - ❖ a^{-} can be defined as "lower lag" and can be a value between 0.1 and 0.9 that defines how late the LMF starts to be created in relation to the UMF.
    - ❖ b^{-} can be defined as "lower scale", can also be a value between 0.1 and 0.9, and defines the value of the LMF maximum membership.

Having established the general lines for the Fuzzy implementation to the FMECA context, the next chapter will introduce the statistical-based comparison approach to compare the agreement between FMECA improved methodologies, in order to tackle some of the drawbacks related to the classical RPN-based FMECA, already mentioned at the end of chapter 3.

6. Comparison Method for FMECA methods: Agreement Coefficient

As discussed previously, one of the main objectives of this dissertation is to conduct a comparison between the FMECA classical analysis and the Fuzzy Logic approach to the FMECA case. Usually, when more than one FMECA analysis is performed, the efficiency of those FMECA procedures is accessed solely on a qualitative basis, comparing each of the ranks of the different approaches performed, one by one. The FMECA output is ultimately represented by rank numbers of failure modes, which is a valid concept to be used as a benchmark to perform the qualitative comparison between FMECA methods.

With the notion of comparison arise the concepts of “concordance” or “agreement”. An agreement can be expressed as “the degree of concordance between two or more sets of measurements” [78]. To further understand better such comparisons, the assessment of agreement can strike as extremely useful since it employs statistical-based metrics that allow a quantitative evaluation of concordance across different methodologies, models, or experts.

These agreement coefficient metrics have been applied in some analyses and research that make use of the FMECA method, for instance in the context of a manufacturing process [79], medical risk analysis [80], or automotive components issues [81]. However, these analyses merely describe evaluations between the comparison of FMECA results with the opinion of experts – the method versus the human opinion.

Nonetheless, this dissertation will assume that these coefficients can still be applied to the idea of comparing two FMECA ranking methods – Classical vs Fuzzy – creating a subsequent quantitative evaluation and ranking concordance, with the purpose of improving the prioritization of failure modes.

There are several coefficients of agreement that can perform this task, such as the Scott’s Pi, the Gewt AC2, the Cronbach Alpha, or the Kendall’s Tau [82]. The coefficient chosen to be applied in this dissertation was the Cohen’s Kappa not only as it is the most commonly used one, but also as it is the most intuitive to be applied and assimilated, suiting the purpose of comparing a Classical approach with a Fuzzy approach.

Furthermore, there have been some applications of the Cohen’s Kappa to the comparison of algorithms/methods efficiencies used for classification, moving forward from the concordance metrics between only humans. References [83] and [84] are examples of agreement assessments between machine learning algorithms – some with Fuzzy-type approaches – in various applications, using the Cohen’s Kappa, thus validating the use of this statistical coefficient to measure computational algorithms’ agreements in the FMECA context. It is also noteworthy the considerable relevance that the FMECA analysis had on these new applications, providing valuable benchmarks for their developments and critical analysis.

6.1. Cohen’s Kappa

Cohen’s Kappa, usually denoted by κ, is a statistical mechanism used for inter-rater or intra-rater reliability measures, which compares the proportion of objects on which raters have agreed with the proportion of objects where they are projected to disagree [85,86] Considering Table 6.1 and to better explain the Cohen’s Kappa reasoning, one can apply the concepts from the FMECA context and say that N failures ($n = 1, 2, \ldots, N$) are classified by two experts (m experts) into k rankings – to represent the original Cohen’s concepts of N objects, m raters, and k categories.

Table 6.1 – Example of N failures ranked by 2 experts (based on [87])

Failure	Expert A	Expert B
Failure 1	Ranking 4	Ranking 2
Failure 2	Ranking 3	Ranking k
$\vdots$	$\vdots$	$\vdots$
Failure n	Ranking k	Ranking 5
$\vdots$	$\vdots$	$\vdots$
Failure N	Ranking k	Ranking k

Following that, below, Table 6.2 represents the proportions of categorized failures for each ranking. Let p_{ij} be the proportion of failures categorized as ranking i, with $i = 1, 2, \ldots, k$, by expert A, and categorized as ranking j, with $j = 1, 2, \ldots, k$, by expert B.

Table 6.2 – Proportions of categorized failures for each ranking (based on [87])

		Expert B						
	Rankings	1	2	…	j	…	k	Total
Expert A	1	p_{11}	p_{21}	…	p_{1j}	…	p_{1k}	p_{1+}
	2	p_{21}	p_{22}	…	p_{2j}	…	p_{2k}	p_{2+}
	$\vdots$	$\vdots$	$\vdots$	…	$\vdots$	…	$\vdots$	$\vdots$
	i	p_{i1}	p_{11}	…	p_{ij}	…	p_{ik}	p_{i+}
	$\vdots$	$\vdots$	$\vdots$	…	$\vdots$	…	$\vdots$	$\vdots$
	k	p_{k1}	p_{k2}	…	p_{kj}	…	p_{kk}	p_{k+}
	Total	p_{+1}	p_{+2}	…	p_{+j}	…	p_{+k}	1

The proportions p_{i+} and p_{+j} represent the probability of a certain failure being categorized with a ranking i or ranking j, by experts A and B respectively [88,89]. These proportions can be determined as equations (6.1) and (6.2) demonstrate:

$$p_{i+} = \sum_{j=1}^{k} p_{ij} \tag{6.1}$$

$$p_{+j} = \sum_{i=1}^{k} p_{ij} \tag{6.2}$$

Where $\sum_{i=1}^{k} p_{i+}$ and $\sum_{j=1}^{k} p_{+j}$ are both equal to 1, as are the summations of all the proportions.

Let p_o be the "observed" proportion of agreement between experts, meaning they prioritize the failure identically. This proportion does not take into consideration the "agreement obtained by chance" [90]. For that reason, the proportion of agreement result of chance, designated by p_e, must be taken into account and represents the probability of both experts categorizing a failure with the same ranking by pure chance. Both p_o and p_e can be expressed as shown by equations (6.3) and (6.4) [88,89].

$$p_0 = \sum_{i=1}^{k} p_{ii} \tag{6.3}$$

$$p_e = \sum_{i=1}^{k} (p_{i+} \cdot p_{+i}) \tag{6.4}$$

From those two concepts, one can define the Cohen's Kappa coefficient as described in equation (6.5) [85,88,89].

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{6.5}$$

Cohen's Kappa can range from -1 to 1, nevertheless in most cases lies between 0 and 1. This occurs because if the κ is lower than 0, it would represent that the expected agreement by chance is higher than the observed agreement, which consequently would represent an inefficient and not representative test [90]. In the same way, a positive κ represents that the observed agreement is higher than the expected agreement by chance. A perfect agreement is represented by κ equal to 1 and happens when $p_{i+} = p_{+j}$ [85], whereas a κ equal to zero represents that the expected agreement by chance is identical to the observed agreement. Ultimately, Table 6.3 shows some interpretations of the value of κ, that were used in this dissertation to classify the strength of agreement examined [91].

Table 6.3 – Strength of agreement according to the obtained κ coefficient (from [91])

Range of κ	Strength of agreement
$\kappa < 0.00$	Poor agreement
$0.00 < \kappa \leq 0.20$	Slight agreement
$0.20 < \kappa \leq 0.40$	Fair agreement
$0.40 < \kappa \leq 0.60$	Moderate agreement
$0.60 < \kappa \leq 0.80$	Substantial agreement
$0.80 < \kappa \leq 1.00$	Almost perfect agreement

6.1.1. Kappa weighted version

However, the original Cohen's Kappa can generate unexpected results and so-called "kappa paradoxes", regarding the observed proportion p_o and the agreement expected by chance p_e [88]. For that reason, to reduce these paradoxes and avoid disagreements on results, Cohen's weighted Kappa, defined by κ_w, was created. With the introduction of the weights, this coefficient can now be represented as shown in equation (6.6) [92].

$$\kappa_w = \frac{p_o^w - p_e^w}{1 - p_e^w} \tag{6.6}$$

Where the weighted observed proportion of agreement, defined by p_o^w, can be represented as shown in equation (6.7), and where the weighted expected proportion of agreement by chance, defined by p_e^w, can be represented as shown in equation (6.8) [92].

$$p_0^w = \sum_{i=1}^{k} \sum_{j=1}^{k} w_{ij} p_{ij} \tag{6.7}$$

$$p_e^w = \sum_{i=1}^{k} \sum_{j=1}^{k} w_{ij} p_{i+} p_{+j} \tag{6.8}$$

The weights represented on the last two equations, defined by w_{ij}, can be determined by a panel of experts, in accordance with the system in scrutiny, or be based on any given theory [93]. However, the most commonly used formulas are the linear and quadratic weights [89,90,93] and can be represented by equations (6.9) and (6.10), respectively [93].

$$w_{ij}^{(2)} = 1 - \frac{|i - j|}{n - 1} \tag{6.9}$$

$$w_{ij}^{(2)} = 1 - \left(\frac{i - j}{n - 1}\right)^2 \tag{6.10}$$

Where both equations use the difference between the rankings i and j, previously described.

In this dissertation, the weighted version of the Cohen's Kappa is the one applied, based on the theoretical improvement experienced by the results' agreements. As for the weights needed for this method, both the linear and quadratic weight formulas were tested, with the second showing a higher level of agreement, thus chosen as the one to apply.

6.1.2. Test of significance

As the Cohen's Kappa characterizes itself as a statistical procedure, a test of significance must be performed for every case, while considering H_0 as the null hypothesis, represented as "the observed agreement is not greater than the expected agreement by chance" and that κ_w probability distribution can be represented as normal distributed [94].

Consequently, the estimated variance when the null hypothesis H_0 is verified can be computed as shown in equation (6.11) [95].

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{k}\sum_{j=1}^{k}\left(p_{i+}\,p_{+j}\left[w_{ij}\left(\overline{w}_{i+}+\overline{w}_{+j}\right)^2\right]-p_e^2\right)}{n(1-p_e)^2} \tag{6.11}$$

With $\overline{w}_{i+} = \sum_{j=1}^{k} w_{ij}p_{+j}$ and $\overline{w}_{+j} = \sum_{i=1}^{k} w_{ij}p_{i+}$, representing the weighted average of the weights in the i^{th} and j^{th} row, respectively [95].

This ultimately means that, by following the assumption of a normal distribution, the hypothesis test presented previously can be tested by the formula represented in equation (6.12) below, having as basis the standard normal distribution [92].

$$z = \frac{k_w}{\hat{\sigma}} \tag{6.12}$$

If $|z| \geq z_\alpha$ the null hypothesis H_0 is rejected, with α representing the chosen level of significance. For this dissertation, the objective was that the null hypothesis H_0 was rejected for every test, which meant that the observed proportion of agreement was always greater than the expected proportion of agreement by chance. Every Cohen's Kappa coefficient of agreement detailed in this dissertation has the null hypothesis H_0 rejected, with an associated level of significance of 0.05 – chosen because of efficiency and simplification reasons –, meaning that for rejection of H_0, $|z| \geq z_{0,05} \rightarrow |z| \geq 1.645$ [96].

6.1.3. Practical Example on FMECA

Regarding the pertinence of Cohen's Kappa application to the FMECA context, one can say that this coefficient is capable of comparing two different FMECA approaches applied to the same problem, using one as a reference. In this dissertation, the RPI-based FMECA method will be regarded as the reference as previously mentioned, with the computed Fuzzy FMECA approaches being compared against the said reference.

To demonstrate how the Cohen's Kappa coefficient of accordance can be applied, a short example will be conducted. As shown by Table 6.4, two different FMECA approaches are considerable, identically to this dissertation, a classical – the reference – and a certain Fuzzy approach.

Table 6.4 – Example of possible rankings for a classical and a fuzzy method, ready for comparison

Failure mode	Classical	Fuzzy
FM1	1	1
FM2	2	4
FM3	3	2
FM4	4	5
FM5	5	3

Five failure modes, $N = 5$, were categorized in five different rankings, $k = 5$, and were characterized by two experts, i.e., two FMECA methods. Furthermore, the proportions p_{i+} and p_{+j} were computed based on equations (6.1) and (6.2), as one can see below in Table 6.5, as well as the correspondent quadratic weights to be applied, using equation (6.10) and shown in Table 6.6.

Table 6.5 – Proportions of failure modes for the two exemplificative methods

		Fuzzy Method					
	Rankings	1	2	3	4	5	p_{i+}
Classical Method	1	0.2	0	0	0	0	0.2
	2	0	0	0	0.2	0	0.2
	3	0	0.2	0	0	0	0.2
	4	0	0	0	0	0.2	0.2
	5	0	0	0.2	0	0	0.2
	p_{+j}	0.2	0.2	0.2	0.2	0.2	1

Table 6.6 – Quadratic weights to be applied, concerning the two exemplificative methods

		Fuzzy Method				
	Rankings	1	2	3	4	5
Classical Method	1	1	0,9375	0,75	0,4375	0
	2	0,9375	1	0,9375	0,75	0,4375
	3	0,75	0,9375	1	0,9375	0,75
	4	0,4375	0,75	0,9375	1	0,9375
	5	0	0,4375	0,75	0,9375	1

For Table 6.5 the proportion is correspondent to one-fifth – since there are five failure modes – and is assigned to the correspondent rankings i and j, retrieved from Table 6.4 results. As in the case of Table 6.6, the weights for each combination of rankings were computed, as stated, using equation (6.10), which can be shown as follows:

$$Combination\ of\ rankings\ (3;2) \rightarrow \boldsymbol{w}_{\boldsymbol{32}}^{(\boldsymbol{2})} = 1 - \left(\frac{3-2}{5-1}\right)^2 = 0.9375$$

Having performed these preparatory computations, one can now compute the observed proportion of agreement p_o^w, and the expected proportion of agreement by chance p_e^w, using equations (6.7) and (6.8) respectively.

$$\boldsymbol{p_o^w} = w_{11}p_{11} + w_{32}p_{32} + w_{53}p_{53} + w_{24}p_{24} + w_{45}p_{45}$$
$$= 1 \times 0.2 + 0.9375 \times 0.2 + 0.75 \times 0.2 + 0.75 \times 0.2 + 0.9375 \times 0.2 = \mathbf{0.875}$$

$$\boldsymbol{p_e^w} = w_{11}p_{1+}p_{+1} + w_{12}p_{1+}p_{+2} + w_{13}p_{1+}p_{+3} + \cdots + w_{54}p_{5+}p_{+4} + w_{55}p_{5+}p_{+5} = \mathbf{0.75}$$

With both these computations, the Cohen's weighted Kappa can finally be computed, as equation (6.6) demonstrates:

$$\boldsymbol{\kappa_w} = \frac{0.875 - 0.75}{1 - 0.75} = \mathbf{0.5}$$

This agreement of 0.5 between the hypothetical classical and fuzzy methods, can be classified as 'Moderate', as shown in Table 6.3.

Having defined the concepts of FMECA and Fuzzy Logic, in addition to the applied comparison method described in this chapter, one can now choose and start evaluating a specific study case to serve as the basis for this dissertation's analysis.

7. Study Case

An FMECA analysis applied to the electrical network introduced in [97] is used to test the proposed Fuzzy-based FMECA methodologies and the comparison approach for the FMECA methods; in [97] the author conducts a classical FMECA analysis to identify and prioritize the failure modes in a specific smart grid test system.

Later in this chapter, the results of the classical FMECA analysis performed by the author at [97] will be presented, in addition to the Fuzzy Logic parameters chosen to perform the needed computations, with both serving as a base for the future discussion between the classical and Fuzzy FMECA analysis.

7.1. Smart Grid Test Case

Figure 7.1 (next page) shows the basic architecture of the smart grid test system analyzed in [97]. This grid can be divided into two subsystems: the power network and the cyber network.

7.1.1. Power Network System

The power network test system – represented by the black contours in Figure 7.1 – is a 30kV simplified power distribution network that includes four 30kv substations, each delimited by the four existing busbars, from B1 to B4, being connected in a ring configuration and conferring redundancy to the grid.

Each of the busbars is associated to the following generation stations:

- At busbar B1, a 110MW conventional generation station is connected, denoted by CG.
- At busbar B2, a distributed renewable generation station is connected, more precisely a 130MW wind power plant – represented by WE.
- At busbar B3, a 50MW energy storage system is connected, denoted by ES.
- At busbar B4, a distributed renewable generation is also connected, in this case, a 100MW photovoltaic power plant, represented by PV.

In addition, the power network also contains a total of four power transformers and fifteen circuit breakers, represented by TRx and CBx respectively. There are also three load points named LPBx, connected to busbars B2, B3, and B4, which represent the hypothetical users/consumers of this grid. LPB2 represents a 20MW residential area, LPB3 represents an 85MW industrial area, and LPB4 represents a 40MW commercial area.

For this dissertation, based on the assumptions conducted by the author of [97], only the busbars, the power cables – aerial lines –, the circuit breakers, and the power transformers are taken into account for the FMECA analysis, as they represent the biggest threats for the grid's operation. The energy generation and storage systems, being connected to each busbar and conveyed as "receiving" systems, in the sense they are dependent on the grid's operation to work and do not represent a substantial threat to the system, are not considered for the FMECA studies.

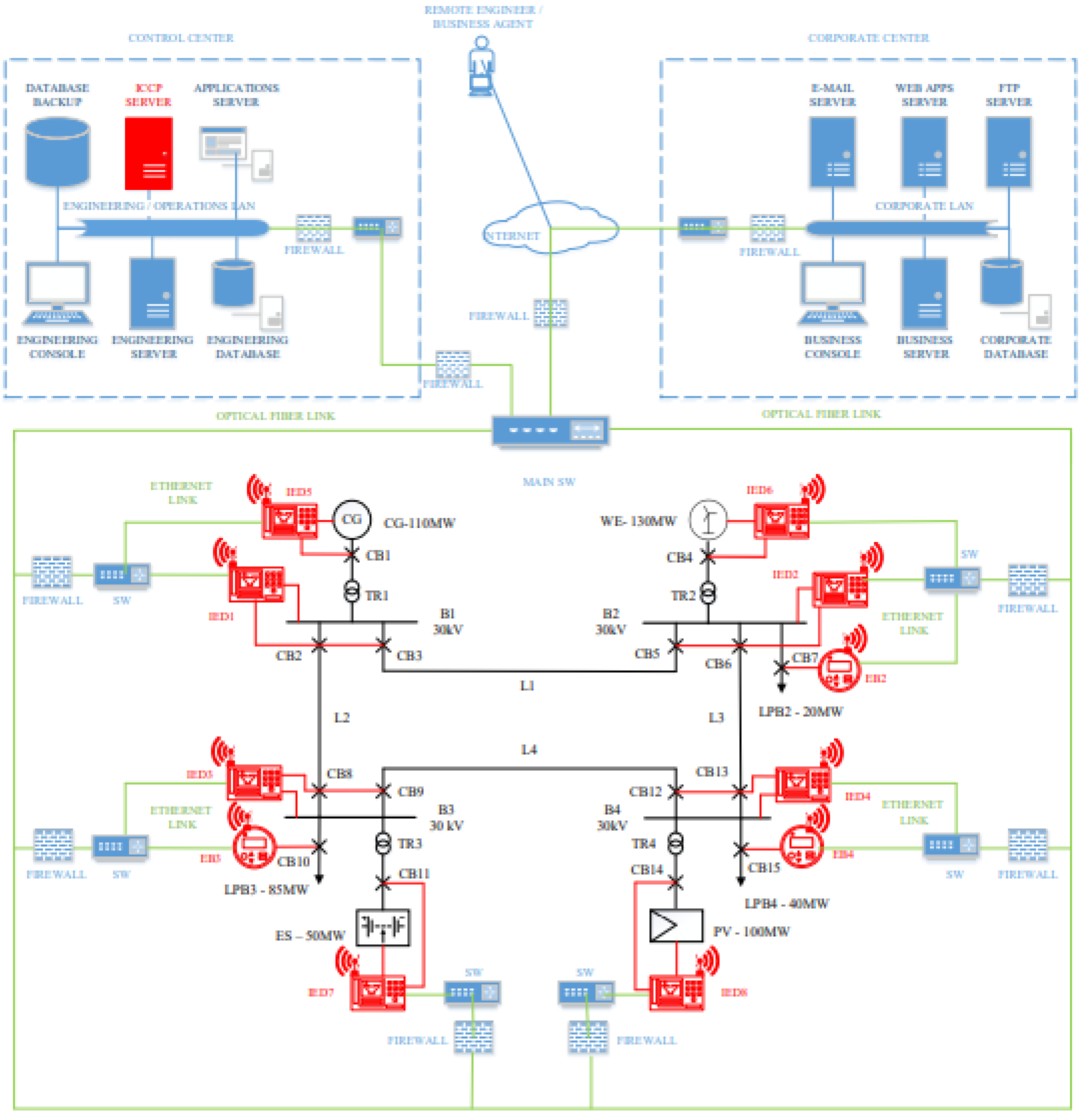

Figure 7.1 – Smart grid's cyber-power network (extracted from [97])

7.1.2. Cyber Network System

The primary function of a cyber network is to safeguard and regulate the power system previously described and is depicted in Figure 7.1 by red, blue, green, and orange components.

This cyber-control network is considered "a bus topology LAN-Ethernet and WAN-optical fiber network consisting of human-machine interfaces (HMIs), Ethernet switches (SWs), servers (SVs), energy boxes (EBs) (…), intelligent electronic devices (IEDs), and Ethernet and optical fiber links", as described by the author in [97]. The network assumes a cyber-ring topology because of its redundancy for the exchange of information and its adequate level of stability.

As shown in Figure 7.1, there are two types of control and monitoring components, the EBs and IEDs, that can be described as follows:

- Energy Boxes: can be designated as smart meters since their primary function is to gather data about energy consumption. Because of that, there are three EBs represented (EB2, EB3, and EB4) that are connected to each of the three existing load points, which in turn represent the consumers of the grid.
- Intelligent Electronic Devices: serve as an interface between the power and cyber communication networks. Accountable for managing and optimizing the energy usage between generation and load, along with executing the HMIs transmitted commands. Eight IEDs controllers are connected to the CG, WE, ES, and PV systems, as well as each of the existing busbars and circuit breakers.

These two components are connected to a corresponding Ethernet switch, represented in blue, through a LAN-Ethernet link. Each of the Ethernet switches is then connected to each other through a WAN-optical fiber link, represented by the green lines and based on the described ring topology, with the primary objective of connecting each of them to the main SW. This main SW collects the information transmitted via ethernet and fiber links, from each of the SW spread across the grid, to then send it to the control and corporate centers, depicted above the grid in blue.

The control center is composed of several HMIs that allow the control, analysis, and decision-making regarding the data resulting from the power grid's components and later transmitted by the communications infrastructures. This control center can also store big amounts of data and allow real-time data manipulation and monitoring, which provides the backup to be able to schedule power generation and solve any grid problems that may arise. On the other hand, the corporate center gathers all the information regarding the energy market and stakeholders to provide the best price-quality ratio.

7.2. Classical FMECA Analysis

Based on the smart grid used as the study case, the author in [97] performs an extensive analysis of the potential failure modes that can put the grid's operation at risk. The identified failure modes that were divided into two classes: the failure modes in power equipment – buses, cables, circuit breakers, and transformers – and the failure modes in cyber network equipment – IEDs, SVs, HMIs, SWs, EBs, optical fiber links, and ethernet links. Once identified the potential failure modes, the author conducts the criticality analysis.

Below, Table 7.1 shows an excerpt of the classical FMECA analysis performed in [97]. The forty-three failure modes with the RPN score above 90 were selected and ordered from the highest to lowest.

Table 7.1 – Classical FMECA results for the study case (based on [97])

Rank	Equipment	Failure Modes	SEV	OCC	DET	RPN
1	SV	Hardware crash	8	6	10	480
2	Transformer	Transformer explosion	9	5	10	450
3	HMI	Operational failure	5	8	10	400
4	IED	Control failure	8	7	7	392
5	Bus bar	Loss of structural integrity	7	6	9	378
6	Cable	Electrical operation failure	6	6	10	360
7	SW	Operational failure (SW blackout)	6	6	10	360
8	Bus bar	Loss of electrical continuity	8	4	10	320
9	Bus bar	Electrical disturbances	8	4	10	320
10	Transformer	Distortion, loosening or displacement of the winding	7	5	9	315
11	CB	Bushing breakdown	6	5	10	300
12	SV	Data errors	6	5	10	300
13	Transformer	Winding overheating	7	6	7	294
14	Cable	Cable integrity defect	8	7	5	280
15	CB	CB contacts degradation	6	5	9	270
16	SW	Performance decrease	6	7	6	252
17	IED	Communication failure	6	5	8	240
18	Transformer	Winding isolation degradation or breakdown	6	4	10	240
19	Transformer	Bushing breakdown	6	4	10	240
20	Transformer	Tank rupture	8	3	9	216
21	IED	Power outage	7	3	10	210
22	SV	Power outage	7	3	10	210
23	CB	Insulation failure	6	5	7	210
24	SV	Security failure	10	2	10	200
25	CB	Bushing terminal hot spot	6	4	8	192
26	IED	Security failure	9	3	7	189
27	IED	Monitoring failure	6	5	6	180
28	HMI	Security failure	9	2	10	180
29	SW	Power outage	6	3	10	180
30	SW	Network/Cyber storm	6	4	7	168
31	Transformer	Cooling system failure	8	3	7	168
32	CB	Wrong operation (Spurious opening and closure)	7	6	4	168
33	Transformer	Magnetic-Core delamination	6	4	7	168
34	Transformer	Bushing terminal hot spot	6	4	7	168
35	Transformer	Tap changer contacts degradation	6	3	9	162
36	EB	Power consumption misreading	4	5	8	160
37	HMI	Power outage	5	3	10	150
38	EB	Operation failure	4	4	8	128
39	Optical fiber link	Fracture	4	3	10	120
40	Optical fiber link	Humidity induced	4	3	10	120
41	EB	'Catastrophic' failure (burning, melting or explosion)	8	3	4	96
42	Transformer	Loss of dielectric strength in bushings	6	4	4	96
43	CB	CB mechanical failure in operating mechanism	6	5	3	90

Nevertheless, this work is focused solely on the application of Fuzzy approaches to improve the computation of the RPN, and not focused on the FMECA procedure itself. For that reason, the detailed FMECA process described in [97] will not be described, being used only as a guide for the discussions to be done, relating to the Fuzzy-FMECA reasoning efficiency. Next sections show the application of Fuzzy Logic to the FMECA analysis of the smart grid test system.

7.3. Fuzzy Parameters for Fuzzy-FMECA Analysis

In section 5.1 were defined the linguistic variables and Table 5.2 shows the risk categories considered for this work and their respective ranking. For this application, five risk categories were considered for the risk factors, and 125 fuzzy rules consisting of all the possible combinations between the risk factors were defined, as mentioned previously.

Table 7.2 shows three sets of membership functions selected for the applications. Both Type-I and Type-II fuzzy systems will use the same set of membership functions to help maintain coherency in the results.

Table 7.2 – Three selected sets of membership functions, applied to the Fuzzy Logic method

	Severity	***Occurrence***	***Detection***	***RPN***
Set 1	triangular	triangular	triangular	triangular
Set 2	triangular	gaussian	trapezoidal	trapezoidal
Set 3	trapezoidal	gaussian	trapezoidal	gaussian

In the first set, the triangular membership function is selected for all the linguistic variables. According to [98] and [99], the triangular membership function is the most frequent membership function found in the literature, regarding Fuzzy applications, due to its simplicity. One can say that its rigid approach can confer more reliable results when analyzing given linguistic variables.

For the second set, the trapezoidal and Gaussian membership functions are introduced. The triangular membership function still represents Severity, whereas, for Detection and FRPN, trapezoidal membership functions were used due to the existing lack of information and vagueness, which can be tackled by the membership function having a broad upper limit – a wide range of values with the maximum degree of membership. Triangular and trapezoidal membership functions are predominant because one is dealing with discrete values and not continuous ones, which may require another type of approach. Nevertheless, for the Occurrence case, Gaussian membership functions are applied, assuming that this probability-related variable can assume a normal distribution, as represented similarly by a gauss function. Gaussian functions are also regarded as popular in literature because of their smoothness and nonzero at all points [98,99].

In the third set, Severity is represented now by a trapezoidal membership function, while the FRPN is represented by a Gaussian function. By making these two changes concerning group 2, the intention was to understand if the modification of two types of functions, that encompass different spans of membership values, would affect the output results and subsequent analyses.

With the description of the three sets of membership functions that will be applied in this dissertation, two different methods of parameterizing the membership functions were defined. These two methods are the result of two distinct parameterizations that will be proposed in this dissertation: a reasoning based on Witold Pedrycz's perspective, and an author's personal view denoted as Standard.

Standard parametrizing

- This parameterization is based on the formulation of symmetrical membership functions.
- Membership functions must have their maximum degree of membership at the mid-point of the function (triangular and Gaussian) or for the entire length of the category (trapezoidal and bell). For instance, considering categories of Severity SL (ratings 2 and 3) and SM (ratings 4, 5, and 6), on a universe of discourse between 1 and 10 as applied in this dissertation:
  - ❖ On the one hand, triangular and Gaussian functions should have their maximum degree of membership at the value of 2.5 at SL and the value of 5 at SM, as they represent the intermediate points of their categories.
  - ❖ On the other hand, trapezoidal and bell functions cannot have a single maximum point due to their shapes, hence why they should have their maximum degree of membership from 2 to 3 at SL, and from 4 to 6 at SM, which represents the categories' entire span.
- The membership functions of each category must have a certain degree of membership of the rating immediately prior to and immediately posterior to said category. For instance, taking the example of category SL that comprises ratings 2 and 3, both ratings 1 and 4 – prior and posterior respectively – should belong to this category by, as an example 30%, meaning that the membership function used to represent this category, with a maximum membership at 2.5, would cross the ratings 1 and 4 at the degree of membership value of 0.3.
  - ❖ For the Severity linguistic variable, surroundings with a degree of 30%
  - ❖ For the Occurrence linguistic variable, surroundings with a degree of 10%
  - ❖ For the Detection linguistic variable, surroundings with a degree of 40%
  - ❖ For the FRPN linguistic variable, surroundings with a degree of 20%
- The previously attributed percentages were defined after analyzing each linguistic variable ambiguity. For instance, Occurrence, as it is mainly characterized by Gaussian functions does not need a high membership value from the surrounding categories, whereas Detection can beneficiate from a high attributed percentage due to the lack of data regarding this risk factor category. The main idea was also limiting these percentages to under 50% due to the next set of parameterization rules, while spreading the available values through the four linguistic terms.

Pedrycz's "50% Overlap" parametrizing

- This parameterization is based on [100], where Pedrycz demonstrates that the use of triangular membership functions with an overlap between them of 0.5, i.e. 50%, is satisfactory for applications in Fuzzy-based systems, especially in problems that required optimization. In this dissertation, not only the 0.5 overlap will be applied to the triangular membership functions, but also to the remaining membership functions, for further analysis.

- The idea of symmetrical functions is still applied in this case, with the assumption of having the maximum degree of membership, either in the middle of the category or represented by the entire category's span, depending on the function type, being also put into practice.
- Nevertheless, the idea of each category having a certain degree of membership from the surrounding ratings is dropped. The focus now is that each of the 5 membership functions, when coinciding with its neighbors, has an overlapping point that occurs at a membership degree value of exactly 0.5, i.e., 50%.

Following the theoretical explanation and the assumptions covered, the next step is to detail the membership functions' parameters in conformity with what was previously described. Firstly, Table 7.3 to Table 7.5 below, represent the applied parameters for both the Type-I and Type-II membership functions, in the case of the "Standard" parametrization, for each of the three sets.

Table 7.3 – Set 1 parameters for the "Standard" membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	triangular(x;1;1;2.429)	triangular(x;1;1;2.111)	triangular(x;1;1;2.667)	triangular(x;1;1;2.25)
2 or 3	triangular(x;0.357;2.5;4.642)	triangular(x;0.833;2.5;4.167)	triangular(x;0;2.5;5)	triangular(x;0.625;2.5;4.375)
4, 5 or 6	triangular(x;2.143;5;7.857)	triangular(x;2.778;5;7.222)	triangular(x;1.667;5;8.333)	triangular(x;2.5;5;7.5)
7 or 8	triangular(x;5.357;7.5;9.643)	triangular(x;5.833;7.5;9.167)	triangular(x;5;7.5;10)	triangular(x;5.625;7.5;9.375)
9 or 10	triangular(x;7.357;9.5;11.643)	triangular(x;7.833;9.5;11.167)	triangular(x;7;9.5;12)	triangular(x;7.625;9.5;11.375)

Table 7.4 – Set 2 parameters for the "Standard" membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	triangular(x;1;1;2.429)	gaussian(x;1;0.47;1)	trapezoidal(0;1;1.25;2.5)	trapezoidal(0;1;1.25;2.188)
2 or 3	triangular(x;0.357;2.5;4.642)	gaussian(x;1;0.7;2.5)	trapezoidal(0.333;2;3;4.667)	trapezoidal(0.75;2;3;4.25)
4, 5 or 6	triangular(x;2.143;5;7.857)	gaussian(x;1;0.935;5)	trapezoidal(2.333;4;6;7.667)	trapezoidal(2.75;4;6;7.25)
7 or 8	triangular(x;5.357;7.5;9.643)	gaussian(x;1;0.7;7.5)	trapezoidal(5.333;7;8;9.667)	trapezoidal(5.75;7;8;9.25)
9 or 10	triangular(x;7.357;9.5;11.643)	gaussian(x;1;0.7;9.5)	trapezoidal(7.333;9;10;11.667)	trapezoidal(7.75;9;10;11.25)

Table 7.5 – Set 3 parameters for the "Standard" membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	trapezoidal(0;1;1.25;2.321)	gaussian(x;1;0.47;1)	trapezoidal(0;1;1.25;2.5)	gaussian(x;1;0.56;1)
2 or 3	trapezoidal(0.571;2;3;4.429)	gaussian(x;1;0.7;2.5)	trapezoidal(0.333;2;3;4.667)	gaussian(x;1;0.837;2.5)
4, 5 or 6	trapezoidal(2.571;4;6;7.429)	gaussian(x;1;0.935;5)	trapezoidal(2.333;4;6;7.667)	gaussian(x;1;1.115;5)
7 or 8	trapezoidal(5.571;7;8;9.429)	gaussian(x;1;0.7;7.5)	trapezoidal(5.333;7;8;9.667)	gaussian(x;1;0.837;7.5)
9 or 10	trapezoidal(7.571;9;10;11.429)	gaussian(x;1;0.7;9.5)	trapezoidal(7.333;9;10;11.667)	gaussian(x;1;0.837;9.5)

Secondly, Table 7.6 to Table 7.8 represent the applied parameters for both the Type-I and Type-II membership functions, considering the “50% overlap” parametrization, for each of the three sets.

Table 7.6 – Set 1 parameters for the “Overlap 50%” membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	triangular(x;1;1;2)	triangular(x;1;1;2)	triangular(x;1;1;2)	triangular(x;1;1;2)
2 or 3	triangular(x;0.5;2.5;4.5)	triangular(x;0.5;2.5;4.5)	triangular(x;0.5;2.5;4.5)	triangular(x;0.5;2.5;4.5)
4, 5 or 6	triangular(x;2;5;8)	triangular(x;2;5;8)	triangular(x;2;5;8)	triangular(x;2;5;8)
7 or 8	triangular(x;5.5;7.5;9.5)	triangular(x;5.5;7.5;9.5)	triangular(x;5.5;7.5;9.5)	triangular(x;5.5;7.5;9.5)
9 or 10	triangular(x;7.5;9.5;11.5)	triangular(x;7.5;9.5;11.5)	triangular(x;7.5;9.5;11.5)	triangular(x;7.5;9.5;11.5)

Table 7.7 – Set 2 parameters for the “Overlap 50%” membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	triangular(x;1;1;2)	gaussian(x;1;0.425;1)	trapezoidal(0;1;1.25;1.75)	trapezoidal(0;1;1.25;1.75)
2 or 3	triangular(x;0.5;2.5;4.5)	gaussian(x;1;0.85;2.5)	trapezoidal(1;2;3;4)	trapezoidal(1;2;3;4)
4, 5 or 6	triangular(x;2;5;8)	gaussian(x;1;1.275;5)	trapezoidal(3;4;6;7)	trapezoidal(3;4;6;7)
7 or 8	triangular(x;5.5;7.5;9.5)	gaussian(x;1;0.85;7.5)	trapezoidal(6;7;8;9)	trapezoidal(6;7;8;9)
9 or 10	triangular(x;7.5;9.5;11.5)	gaussian(x;1;0.85;9.5)	trapezoidal(8;9;10;11)	trapezoidal(8;9;10;11)

Table 7.8 – Set 3 parameters for the “Overlap 50%” membership functions

Rating	*Severity*	*Occurrence*	*Detection*	*RPN*
1	trapezoidal(0;1;1.25;1.75)	gaussian(x;1;0.425;1)	trapezoidal(0;1;1.25;1.75)	gaussian(x;1;0.425;1)
2 or 3	trapezoidal(1;2;3;4)	gaussian(x;1;0.85;2.5)	trapezoidal(1;2;3;4)	gaussian(x;1;0.85;2.5)
4, 5 or 6	trapezoidal(3;4;6;7)	gaussian(x;1;1.275;5)	trapezoidal(3;4;6;7)	gaussian(x;1;1.275;5)
7 or 8	trapezoidal(6;7;8;9)	gaussian(x;1;0.85;7.5)	trapezoidal(6;7;8;9)	gaussian(x;1;0.85;7.5)
9 or 10	trapezoidal(8;9;10;11)	gaussian(x;1;0.85;9.5)	trapezoidal(8;9;10;11)	gaussian(x;1;0.85;9.5)

Appendix A shows the representations of each of the abovementioned sets of membership functions, concerning each of the presented parameterizations. For the Type-II fuzzy membership functions, a lower scale of 0.8 and a lower lag of 0.2 was applied, only for simplification reasons.

8. Results

In this chapter the result of the computations performed applying Fuzzy Logic are shown, and consequently, a comparison with the RPI-generated prioritization rankings is conducted. The followed approach can be illustrated by the flowchart depicted below in Figure 8.1, for better clarification and management of ideas.

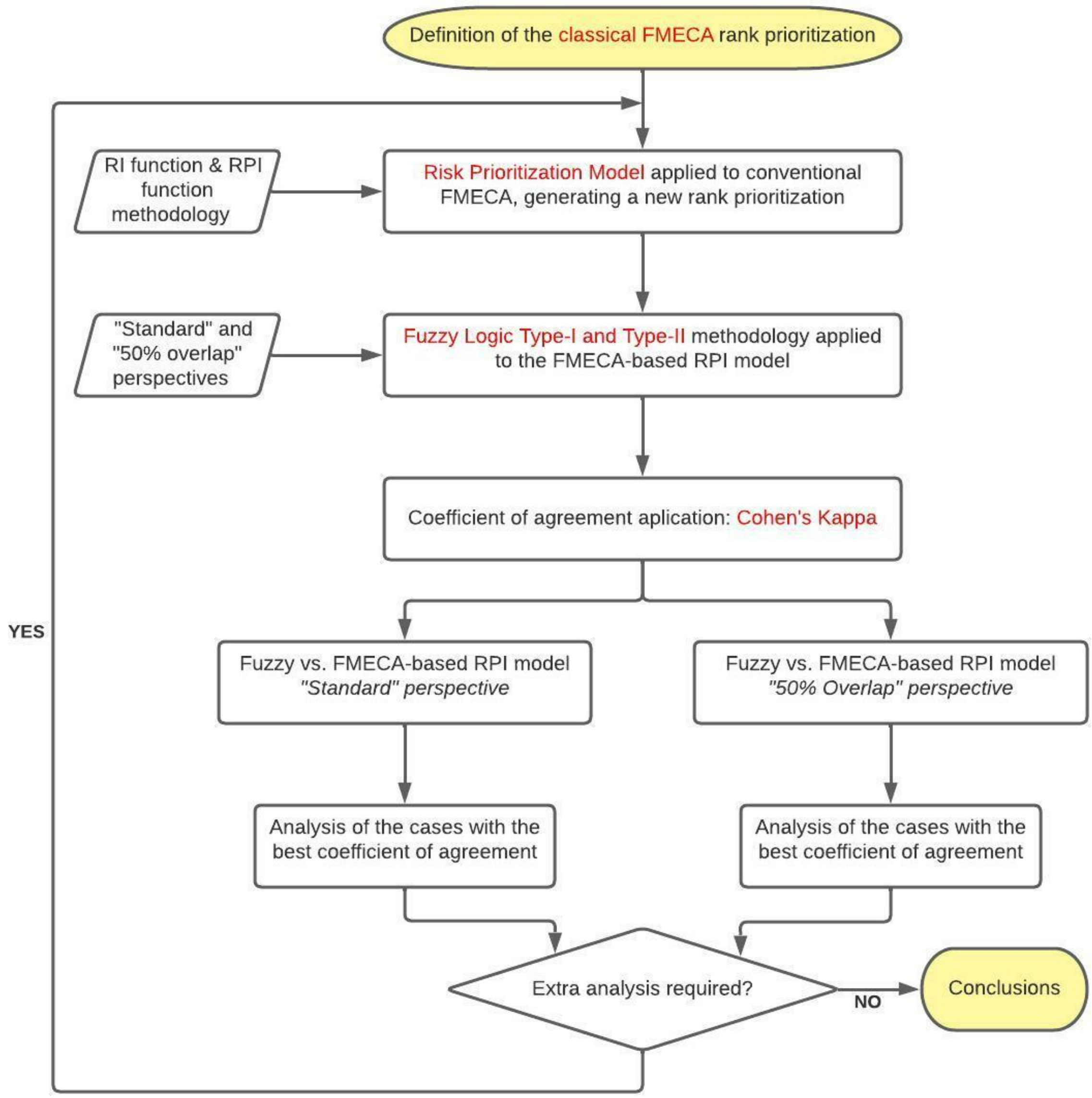

Figure 8.1 – Flowchart illustrating the followed analysis strategy

As stated in the previous chapter, the case study used for this dissertation is based on a classical FMECA conducted by the author of [97]. From that conventional FMECA analysis, a new risk prioritization model proposed by the authors of [59] was applied to this context, based on the RI and RPI functions; this new prioritization model rearranges the ranking order of the failure modes obtained by the conventional RPN computations, in accordance with the weight scenarios described in Table 4.1.

From this RPI methodology used as the reference, overcoming the shortcomings of the RPN-based FMECA rank prioritization, two of the six weighting scenarios were selected. From these two scenarios, two new failure mode rankings were created, that will serve as the reference for future analysis – denominated as “rank bases” of the RPI-based FMECA analysis.

Moreover, the Fuzzy Logic computations can be performed. With all the assumptions established throughout this dissertation, the Fuzzy reasoning receives the failure modes’ ratings defined in [97] and creates a new ranking prioritization order. In this work, there will be four Fuzzy configurations: a Type-I and a Type-II with the “Standard” parameters, in addition to a Type-I and a Type-II with the “50% Overlap” parameters. Each of these four configurations will be conducted by applying each of the three sets of membership functions described in Table 7.2, generating a total of fifteen simulations for each Fuzzy configuration – three Type-I, one for each set, plus twelve Type-II, with each of the three sets varying between a lag of 0.2 and 0.4, and a scale of 0.7 and 0.8, generating twelve combinations. Each of the fifteen simulations will generate fifteen subsequent new rank orders, that can be denominated as “rank tests”. Table 8.1 shows the fifteen fuzzy configurations computed in this work.

Table 8.1 – Fuzzy configurations considered for each of the two parameterizations

		Type-II lags and scales			
	Type-I	*0.2/0.7*	*0.4/0.7*	*0.2/0.8*	*0.4/0.8*
Set 1	T1-1	T2-1	T2-2	T2-3	T2-4
Set 2	T1-2	T2-5	T2-6	T2-7	T2-8
Set 3	T1-3	T2-9	T2-10	T2-11	T2-12

Having the “rank bases” and the “rank tests” defined, one can then apply the selected coefficient of agreement for this dissertation, the Cohen’s Kappa. Each of the fifteen “rank tests” will be compared with the two “rank bases” – the RPI chosen scenarios – to obtain the corresponding values of Kappa. Based on those, the “rank tests” with the highest Kappa values for each Fuzzy approach will be selected to be thoroughly analyzed – two Type-I and two Type-II, one of each approach – with the objective of drawing conclusions.

8.1. Risk Priority Index-based FMECA

The first step is to apply the defined Risk Prioritization Model to the classical FMECA procedure used as the basis for this dissertation. Firstly, equation (4.3) was applied to the ratings of the 43 failure modes, conducting the computations for the six possible combinations regarding the order of importance. From there a new rank order was defined for each of the combinations, so that equations (4.4), (4.5), and (4.6) can be applied, in order to obtain the delta risk drivers that compose the RPI function.

From the six suggested weight scenarios described in Table 4.1, two were selected to be adopted in this dissertation: Scenario 4 (Sc4) and 5 (Sc5), as exemplified in [59]. These scenarios were chosen as they represent the two combinations with the biggest weights for Severity and Occurrence. With the analysis conducted during this work, Detection came across as less impactful to the characterization of a failure mode than the other two risk factors. Thus, both Severity and Occurrence share the 50% and 30% weights, depending on the scenario, while the Detection is always characterized by a 20% weight.

For the application of equation (4.9), the only assumptions left to be made are the correcting factors defined by the authors in [59] which, as described previously, have the value of 10^{-3} and 10^{-2} and can be represented respectively by $1/\varepsilon^3$ and $1/\varepsilon^2$, with $\varepsilon = 10$. With all the variables defined, the RPI scores can be computed, leading to the creation of a new prioritization FMECA ranking based on the RPI model, for each of the two implemented scenarios, as demonstrated in Appendix B.

Those two new rank prioritization orders, one for scenario 4 and another for scenario 5, being theoretically an improvement from the rank defined by the RPN conventional calculations, will now serve as the “rank bases” for this dissertation’s analysis (see also Appendix B).

8.2. RPI vs Fuzzy Logic

Having defined the two selected “rank bases” to be put against the established Fuzzy simulations, which produce the “rank tests”, the Cohen’s Kappa coefficient of agreement was applied, comparing each of the scenarios’ ranks, with the ranks from the established Fuzzy systems, for each of the two parameterizations – “Standard” and “50% overlap”.

As explained previously, for each case there are fifteen comparisons, three regarding Type-I and twelve regarding Type-II, consequently generating fifteen values of the coefficient of agreement Kappa (see Appendix C for full results). From those fifteen fuzzy configurations shown in Table 8.1, the best three from each of the Fuzzy-types, I and II, are selected for a deeper analysis. In Table 8.2 and Table 8.3, the three Type-I and the three Type-II simulations with the best agreement coefficient, for each parameterization, are illustrated. In both tables, T1-1 to T1-3 correspond to the Fuzzy Type-I simulations with each of the three sets described in Table 7.2, whereas T2-1 to T2-12 correspond to the Fuzzy Type-II simulations, not only having in mind three described sets of membership functions, but their lag and scale values.

Table 8.2 – Three highest Kappa, Type-I and Type-II, for “Standard” parameterization

	Standard					
	T1-1	T1-2	T1-3	T2-3	T2-8	T2-9
Sc 4	0,710	0,711	0,711	0,708	0,710	0,711
Sc 5	0,761	0,746	0,752	0,758	0,749	0,752

Table 8.3 – Three highest Kappa, Type-I and Type-II, for “50% overlap” parameterization

	50% overlap					
	T1-1	T1-2	T1-3	T2-5	T2-7	T2-8
Sc 4	0,644	0,624	0,619	0,677	0,669	0,655
Sc 5	0,726	0,744	0,750	0,771	0,762	0,755

As one can see from the tables above, in both “Standard” and “50% overlap”, the comparisons with Sc5 present the best Cohen’s Kappa values, being better than Sc4. In other words, the Fuzzy-based methodology has a better agreement with the prioritization ranking, when the RPI model utilizes Sc5. For that reason, Sc5 will serve as the basis for a meticulous analysis regarding the verified differences between the rankings of some failure modes, in the quest of understanding which methodology – the Classical FMECA based on the RPI function or the Fuzzy reasoning – depicts the best, the real risks and threats for the grid.

Furthermore, from Table 8.2 and Table 8.3, the Type-I and Type-II sets with the best coefficient of agreement, from the “Standard” and “50% overlap” parameterization, are chosen to be compared with the Sc5 ranking. The scenario ranking result of the RPI model will be used as the “rank base” put against the Fuzzy approaches conducted – the “rank tests”. For simplification reasons, the failure modes ordered by their RPN score in Table 7.1, will be defined by the number of their rank, i.e., the table is ordered from FM1 to FM43.

To perform the analysis, it was decided that only the failure modes with a difference higher than five ranks between approaches, would be thoroughly analyzed, to better understand the existing variations and have a grasp of which of the methodologies, either the reference or the tests, are more efficient. Next page, Table 8.4 depicts the comparison between Sc5 – the “rank base” – and the Fuzzy approaches T1-1 and T2-3, from Table 8.2 – the “rank tests” – regarding the “Standard” parameterization. Additionally, the differences between Fuzzy approaches T1-1 and T2-3 are almost none, as they perform a very similar rank prioritization, hence why the analysis works for both cases.

The first two main differences can be encountered in FM3, ranked 19th on Sc5 and 2nd on the Fuzzy approaches, and FM4, ranked 3rd on Sc5 and 17th on Fuzzy. On the one hand, FM3 is an operational failure in an HMI caused by human error or deficient communication between the cyber network and the HMI, which generates the loss of system monitoring and the appearance of wrong commands. This FM does not represent one of the major risks to the general operation of the grid, so one could think that the Sc5 has classified it more accurately than the Fuzzy approaches, probably because it has only a 20% weight for the Detection risk factor, and the highest rating of this FM is precisely the 10 on Detection, that influence the Fuzzy approaches. On the other hand, FM4 is a control failure in an IED, which similarly to FM3, creates the inability of applying commands and defective data, but could lead to the failure of some relevant systems. Nevertheless, despite its high ratings, FM4 is not considered as crucial for the grid’s health, leading one to be inclined to agree with the prioritization of the Fuzzy approaches.

Next on the list, comes FM13 ranked 13th on Sc 5 and 30th on Fuzzy, which is a winding overheating in a transformer. This FM usually caused by overloads leads to loss of efficiency and increase of losses, and can, in the extreme, lead to the explosion of the transformer or fire. For those reasons, it appears that the Fuzzy approaches’ classifications are not appropriate as it ranks this FM too low given the risks, hence why one would be more inclined to agree with the Sc 5 rank prioritization for this FM.

Table 8.4 – Rankings of the two best Fuzzy approaches compared to Sc5, in “Standard”

FM	Equipment	Failure Modes	Sc5	T1-1	T2-3
FM1	SV	Hardware crash	1	3	3
FM2	Transformer	Transformer explosion	2	1	1
FM3	HMI	Operational failure	19	2	2
FM4	IED	Control failure	3	17	17
FM5	Bus bar	Loss of structural integrity	7	9	9
FM6	Cable	Electrical operation failure	6	10	10
FM7	SW	Operational failure (SW blackout)	9	11	11
FM8	Bus bar	Loss of electrical continuity	4	5	5
FM9	Bus bar	Electrical disturbances	5	6	6
FM10	Transformer	Distortion, loosening or displacement of the winding	11	8	8
FM11	CB	Bushing breakdown	12	14	14
FM12	SV	Data errors	15	15	15
FM13	Transformer	Winding overheating	13	30	30
FM14	Cable	Cable integrity defect	8	22	22
FM15	CB	CB contacts degradation	21	16	16
FM16	SW	Performance decrease	22	27	28
FM17	IED	Communication failure	26	26	26
FM18	Transformer	Winding isolation degradation or breakdown	23	12	12
FM19	Transformer	Bushing breakdown	25	13	13
FM20	Transformer	Tank rupture	18	18	18
FM21	IED	Power outage	17	20	20
FM22	SV	Power outage	20	21	21
FM23	CB	Insulation failure	28	33	34
FM24	SV	Security failure	10	4	4
FM25	CB	Bushing terminal hot spot	30	28	27
FM26	IED	Security failure	16	29	29
FM27	IED	Monitoring failure	32	39	39
FM28	HMI	Security failure	14	7	7
FM29	SW	Power outage	31	19	19
FM30	SW	Network/Cyber storm	33	36	36
FM31	Transformer	Cooling system failure	27	32	33
FM32	CB	Wrong operation (Spurious opening and closure)	24	40	40
FM33	Transformer	Magnetic-Core delamination	35	37	37
FM34	Transformer	Bushing terminal hot spot	37	38	38
FM35	Transformer	Tap changer contacts degradation	36	31	32
FM36	EB	Power consumption misreading	34	34	31
FM37	HMI	Power outage	39	23	23
FM38	EB	Operation failure	40	35	35
FM39	Optical fiber link	Fracture	41	24	24
FM40	Optical fiber link	Humidity induced	42	25	25
FM41	EB	'Catastrophic' failure (burning, melting or explosion)	29	41	41
FM42	Transformer	Loss of dielectric strength in bushings	43	42	42
FM43	CB	CB mechanical failure in operating mechanism	38	43	43

FM14 ranked 8th on Sc5 and 22nd on Fuzzy, describes a cable integrity defect caused by an array of failures, which lead mainly to the decrease in power quality and general loss of efficiency. Although the grid does not operate under its optimal conditions, one could agree more with the Fuzzy reasoning of downgrading this FM, having in mind the surrounding failure modes. In comparison, the Sc5-based RPI performs an upgrade, probably based on the fact that the rating of Detection is 'Moderate' and does not carry significant weight for the RPI reasoning.

Furthermore, FM16 ranked 22nd on Sc5 and 27th/28th on Fuzzy represents a performance decrease on an SW, which can cause communications congestions and delays in data transferring that affect some systems, but do not bring a real threat to the grid's general operation when comparing to surrounding failure modes, hence why the severe downgraded performed by the Fuzzy approaches seem adequate.

FM18 (23rd on Sc5 and 12th on Fuzzy) and FM19 (25th on Sc5 and 13th on Fuzzy) represent two failure modes in a transformer: a winding isolation degradation or breakdown, and the breakdown of a bushing. Being both failure modes related to an important component of the smart grid, one could tend to agree that both should be ranked higher, as the Fuzzy approaches demonstrate. Both FMs can cause damage to the transformer, creating flashes in the windings, that lead to short circuits and a decrease in the grid's power quality. Both also have the maximum rating of Detection, meaning that the Sc5 poor ranks are associated with the low weight given to this risk factor.

Moving furtherly, ranked 28th on Sc5 and 33rd/34th on Fuzzy, FM23 is an insulation failure in a CB. It is caused by the loss of dielectric properties and leads to the failure of CBs functions, as well as possible deterioration of other components combined with a decrease in quality of operating conditions. Both methodologies downgraded this FM when compared to the classical RPN prioritization, probably due to its average ratings across the three categories of risk factors, being one more inclined to state that the Fuzzy approaches have the more accurate classification, due to the surrounding FMs.

The security failure in an SV represented by FM24 is ranked 10th on Sc5 and 4th on Fuzzy, receiving big upgrades from both methodologies, compared to the RPN. A breach in security due to a cyber-attack or malicious software can lead to the loss of integrity of the system, with data being corrupted, erased, or stolen, in addition to the risk of possible unintentional operations that could put the grid at threat. This FM has the highest rating on both Severity and Detection, and despite its 'Unlikely' Occurrence, one could be tempted to agree more with the Fuzzy approaches' classification, as Sc5 once more, does not value greatly the factor of Detection.

FM26 (16th on Sc5 and 29th on Fuzzy) and FM27 (32nd on Sc5 and 39th on Fuzzy) expose two failures on an IED: a security and a monitoring failure, respectively. On the one hand, the security failure entails a loss of integrity and applications running with fallacious data, which are perhaps more accurately classified by Sc5 which upgrades its rank. On the other hand, the monitoring failure is identical to FM4, probably deserving the downgraded performed by the Fuzzy approaches due to the not very crucial risks and not very relevant risk factors' ratings.

Furthermore, ranked 14th on Sc5 and 7th on Fuzzy, FM28 is a security failure on an HMI that entails the same risks as other security failures in components of the cyber-network – for instance, SVs and IEDs – affecting the integrity of the grid and creating unwanted operations. For these reasons, its rank should be upgraded as performed by both methodologies, with one tending to agree more with the Fuzzy approaches, as they place it in the same region of FM24, which has very similar ratings.

FM29 ranked 31st on Sc5 and 19th on Fuzzy represents a power outage on an SW, causing the failure of EMS applications and the disconnection from the rest of the grid. As with other power outages regarding network communications, one could say that this FM should also be upgraded, as performed by the Fuzzy approaches, not only for the entailing risks but also for the relatively relevant ratings, specifically on Detection.

Additionally, FM32 ranked 24th on Sc5 and 40th on Fuzzy describes a wrong operation – either spurious opening or closure – on a CB, that could lead to a wrong cut out of energy, besides a possible downstream grid disconnection and instability in the power system. Considering the surrounding failure modes one could probably agree more with the classification of the RPI Sc5 that upgrades the rank of the FM, helped by the low weight given to Detection, that in this case is 'Moderate' and has affected the Fuzzy approaches reasoning.

Moreover, ranked 39th on Sc5 and 23rd on Fuzzy, FM37 describes a power outage on an HMI, that consequently leads to its disconnection from the communication network, making it impossible to send commands or monitor the system's activity. For that reason, the Fuzzy approaches tend to rank prioritize better this FM, upgrading it to a more adequate position having into account its risks and Detection rating – which once more has an 'Almost Impossible' rating disregarded by the RPI Sc5.

Almost concluding, FM39 (41st on Sc5 and 24th on Fuzzy) and FM40 (42nd on Sc5 and 25th on Fuzzy) represent two failures in optical fiber links: a fracture and humidity-induced, respectively. Both FMs can ultimately lead to the stoppage of data transmission, corrupted signals, compromising other components and the communications network performance. Once more, the Fuzzy approaches tend to prioritize more appropriately these two FMs by upgrading them, as they represent a higher danger than the one described by their current rank.

Finally, FM41 ranked 29th on Sc5 and 41st on Fuzzy represents a catastrophic failure (burning, melting, or explosion) in an EB. In the worst-case scenario, this FM can lead to workers' injuries or even death but does not carry a substantial risk for the grid's operation, only causing degradation of some local components and a lack of information to the systems in the network. Sc5 upgrades this FM due to its greater weight associated with Severity – the FM is classified as 'Very High' – while the Fuzzy approaches maintain it in the same rank as before. Due to its low constraints on the grid's operation, one is more inclined to agree with the classifications of the Fuzzy approaches, although the origination of injuries and loss of life represents a catastrophic risk in human terms.

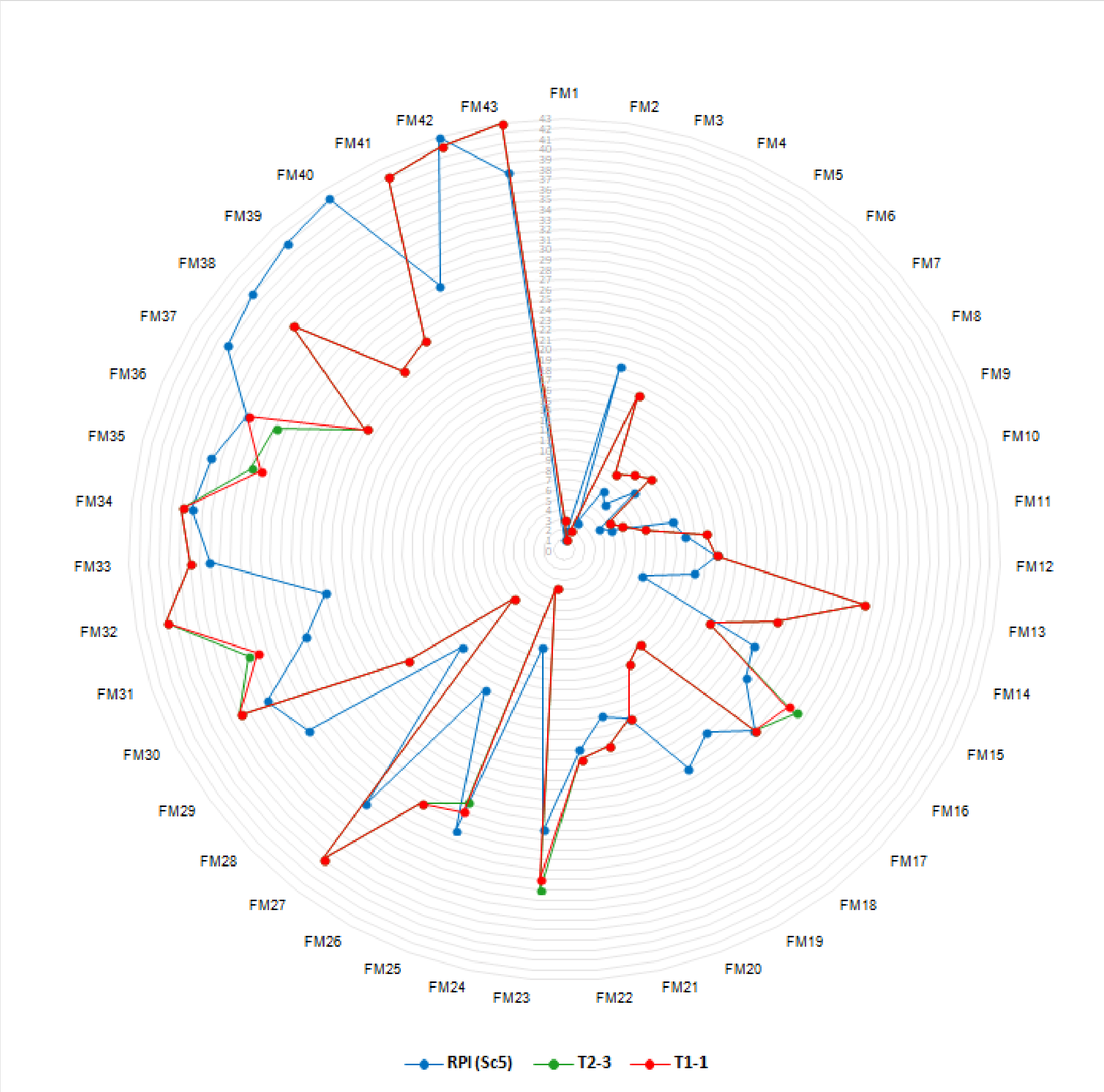

Figure 8.2 – Radar chart comparing Sc5 with Fuzzy T1-1/T2-3, "Standard" parameterization

From the comparison between the RPI Sc5 used as a reference and the two Fuzzy-based approaches, T1-1 and T2-3, a radar chart can be depicted for a better understanding of the differences found, as shown in Figure 8.2. On the one hand, the radar chart shows that there are almost no differences between the Fuzzy T1-1 and T2-3 "Standard" approaches. On the other hand, one can notice the existence of areas, where the difference between Sc5 and the Fuzzy approaches is greater than the rest, i.e. when a failure mode has two very disparate prioritizations. These "areas" are the representation of the differences between the methodologies abovementioned, serving as the basis for the analysis.

Following the same reasoning as the "Standard" parameterization, one can now analyze the differences between the RPI Sc5 and the "50% overlap" parameterizations rankings as shown in Table 8.5.

The first significant differences are found, once more, in FM3 (19th Sc5 and 3rd/5th Fuzzy) and FM4 (3rd Sc5 and 18th/20th Fuzzy), an operational failure in an HMI and a control failure in an IED, respectively. As on the first part of the analysis, Sc5 seems to prioritize better the operational failure, by downgrading it, as it does not represent a very serious risk for the grid's operation when compared to the surrounding FMs – being the Fuzzy approaches once again influenced by the high rating of Detection. In the FM4 case, the Fuzzy approaches tend to be considered more accurate in downgrading this failure mode, as a control failure does not carry substantial risk to be placed so highly, despite its ratings.

The next big difference can be encountered in FM6 ranked 6th on Sc5 and 10th/13th on Fuzzy, which represents an electrical operation failure in a cable. This failure can lead to saturation caused by heat and the loss of efficiency, affecting the operating conditions of the grid with a decrease in power quality. Despite its high rating on Detection, the real consequences that this failure mode entails, might not be sufficient to rank it as high as Sc5 does, thus one would tend to classify the Fuzzy approach T1-3 downgrade as the most acceptable.

Moreover, another relevant difference is the FM10 (11th on Sc5 and 2nd/8th on Fuzzy), which is the distortion, loosening, or displacement of the winding in a transformer, caused by short circuits that ultimately can guide to damage to the transformer, wrong power output, short circuits across the grid, and a general decrease in power quality. In this case, one can be inclined to agree with Sc5 and Fuzzy T2-5 approaches, as they both keep this FM around the same area as before, while T1-3 gives it a huge upgrade, classifying it as the second most important risk, which can be considered slightly overestimated. Furthermore, T2-5 uses a triangular membership function for Severity, theoretically more efficient due to its 50% overlap concept than the trapezoidal used by T1-3, leading to believe the T2-5 case confers more efficiency to the analysis.

Regarding transformers, FM13, FM18, and FM19 all represent failure modes that were already discussed in the first part of this analysis. As before, the winding overheating is more accurately classified by the Sc5 – that does not downgrade it on the contrary to the Fuzzy approaches –, whereas FM18 and FM19 can be considered ranked more precisely by the Fuzzy approach T2-5, as it concerns one of the most important components of the grid. The big difference between the Fuzzy approaches on these two FMs can be explained by the utilization of a triangular membership function for the Severity in T2-5, while T1-3 uses a trapezoidal membership function. FM14 and FM16, a cable integrity defect and a performance decrease on an SW, are also considered more accurately classified by the Fuzzy approaches, with a downgrade, as they do not substantially hinder the grid's normal operation.

FM20 ranked 18th on Sc5 and 10th/14th on Fuzzy is defined as a tank rupture in a transformer, that can lead not only to the damage of the transformer but also to other neighboring components, ultimately conducting to a loss of energy supply and network disconnection. These consequences bring considerable threats to the grid's operation, which guides one to believe that this FM should be upgraded in the rank order, as described by the Fuzzy approaches. Herein, lies another example of a failure mode that has a neglected high rating of Detection by Sc5.

FM21 (17th on Sc5 and 11th/18th on Fuzzy) and FM22 (20th on Sc5 and 12th/19th on Fuzzy) illustrate a power outage in an IED and in an SV, respectively. These failures, as explained before, impede communications and access to information, leading to the failure of some components in the cyber-network grid. In this case, one can say that Sc5 and Fuzzy T2-5 perform better prioritizations of the FMs,

Table 8.5 – Rankings of the two best Fuzzy approaches compared to Sc5, in “50% overlap”

FM	Equipment	Failure Modes	Sc5	T1-3	T2-5
FM1	SV	Hardware crash	1	3	2
FM2	Transformer	Transformer explosion	2	1	1
FM3	HMI	Operational failure	19	5	3
FM4	IED	Control failure	3	18	20
FM5	Bus bar	Loss of structural integrity	7	4	9
FM6	Cable	Electrical operation failure	6	13	10
FM7	SW	Operational failure (SW blackout)	9	14	11
FM8	Bus bar	Loss of electrical continuity	4	8	5
FM9	Bus bar	Electrical disturbances	5	9	6
FM10	Transformer	Distortion, loosening or displacement of the winding	11	2	8
FM11	CB	Bushing breakdown	12	15	15
FM12	SV	Data errors	15	16	16
FM13	Transformer	Winding overheating	13	27	27
FM14	Cable	Cable integrity defect	8	25	23
FM15	CB	CB contacts degradation	21	17	17
FM16	SW	Performance decrease	22	39	36
FM17	IED	Communication failure	26	31	30
FM18	Transformer	Winding isolation degradation or breakdown	23	28	12
FM19	Transformer	Bushing breakdown	25	29	13
FM20	Transformer	Tank rupture	18	10	14
FM21	IED	Power outage	17	11	18
FM22	SV	Power outage	20	12	19
FM23	CB	Insulation failure	28	32	31
FM24	SV	Security failure	10	6	4
FM25	CB	Bushing terminal hot spot	30	34	32
FM26	IED	Security failure	16	19	25
FM27	IED	Monitoring failure	32	41	41
FM28	HMI	Security failure	14	7	7
FM29	SW	Power outage	31	20	21
FM30	SW	Network/Cyber storm	33	35	33
FM31	Transformer	Cooling system failure	27	26	26
FM32	CB	Wrong operation (Spurious opening and closure)	24	30	39
FM33	Transformer	Magnetic-Core delamination	35	36	34
FM34	Transformer	Bushing terminal hot spot	37	37	35
FM35	Transformer	Tap changer contacts degradation	36	21	22
FM36	EB	Power consumption misreading	34	33	37
FM37	HMI	Power outage	39	22	24
FM38	EB	Operation failure	40	38	38
FM39	Optical fiber link	Fracture	41	23	28
FM40	Optical fiber link	Humidity induced	42	24	29
FM41	EB	'Catastrophic' failure (burning, melting or explosion)	29	40	40
FM42	Transformer	Loss of dielectric strength in bushings	43	42	42
FM43	CB	CB mechanical failure in operating mechanism	38	43	43

maintaining the ranks around the same area as before, while T1-3 overestimates and increases the priority substantially. As already discussed, this difference between the two Fuzzy approaches is explained by the use of the triangular membership function by T2-5 – theoretically more efficient – against the trapezoidal used by T1-3.

Furthermore, FM24, FM26, and FM28, all represent security failures in an SV, an IED, and an HMI, respectively. Similar to the first part of the analysis, FM26 concerning the IED can be classified more accurately by Sc5 and now by Fuzzy approach T1-3, as it upgrades it due to the high threat to the cyber network. As for FM24 and FM28, the Fuzzy approaches are more precise as they are the methodologies that upgrade the rank of this failure mode, which carries potentially substantial risk.

Additionally, FM27 and FM29 have identical outcomes to the analysis first performed. Both are more accurately classified by the Fuzzy approaches, with the monitoring failure in an IED being downgraded to the last places due to its not considerable risks and ratings, while the power outage in an SW is upgraded due to the failure risk of specific systems. By the same token, FM37 also represents a power outage, this time in an HMI, with the Fuzzy approaches being considered better, by upgrading its rank.

The wrong operation in a CB described in FM32, could lead one to be inclined to, once more, state that Sc5 attributes a more precise ranking, as well as, the Fuzzy approach T1-3, as they both slightly upgrade this FM. Moreover, a new difference can be found in FM35 (36th on Sc5 and 21st/22nd on Fuzzy), described as the contact degradation in the tap changer of a transformer. This FM created by general wear or partial discharges, possibly leads to incorrect outputs of power, as well as, hindering the operation of the power network. For that reason, plus the fact of being a transformer, the Fuzzy approaches tend to correctly rank this FM, by upgrading it due to its substantial risks to the grid.

FM39 and FM40, two failures in optical fibers register once again considerable differences between methodologies. The risks of compromising other components and the network communications systems, make one believe that the Fuzzy approaches are more precise by giving a higher priority to these FMs. Finally, FM41 can be also considered better classified by the Fuzzy approaches as seen in the first part of the analysis, despite the potentially catastrophic risk of human loss.

Similarly, as before, from the comparison between the RPI Sc5 used as a reference, and the two Fuzzy-based approaches, T1-3 and T2-5, an additional radar chart can be depicted for a better understanding of the differences found, as one can see in Figure 8.3. In the case of this radar chart, some differences between the Fuzzy approaches can be seen, as highlighted in the analysis performed, resulting from the different prioritizations performed by Fuzzy tests with different sets of membership functions.

From the two reproduced radar charts illustrated in Figure 8.2 and Figure 8.3, some considerations can be made. The radar charts provide not only an efficient way of comparing the existing differences regarding the failure modes' ranking rater methodologies but also, of clarifying the reasoning behind the Cohen's Kappa coefficient of agreement. As explained in chapter 3, when an FMECA procedure is conducted and exists the necessity of comparing two or more rank prioritizations, that comparison is performed solely qualitatively by experts, studying each FM and its respective differences one by one.

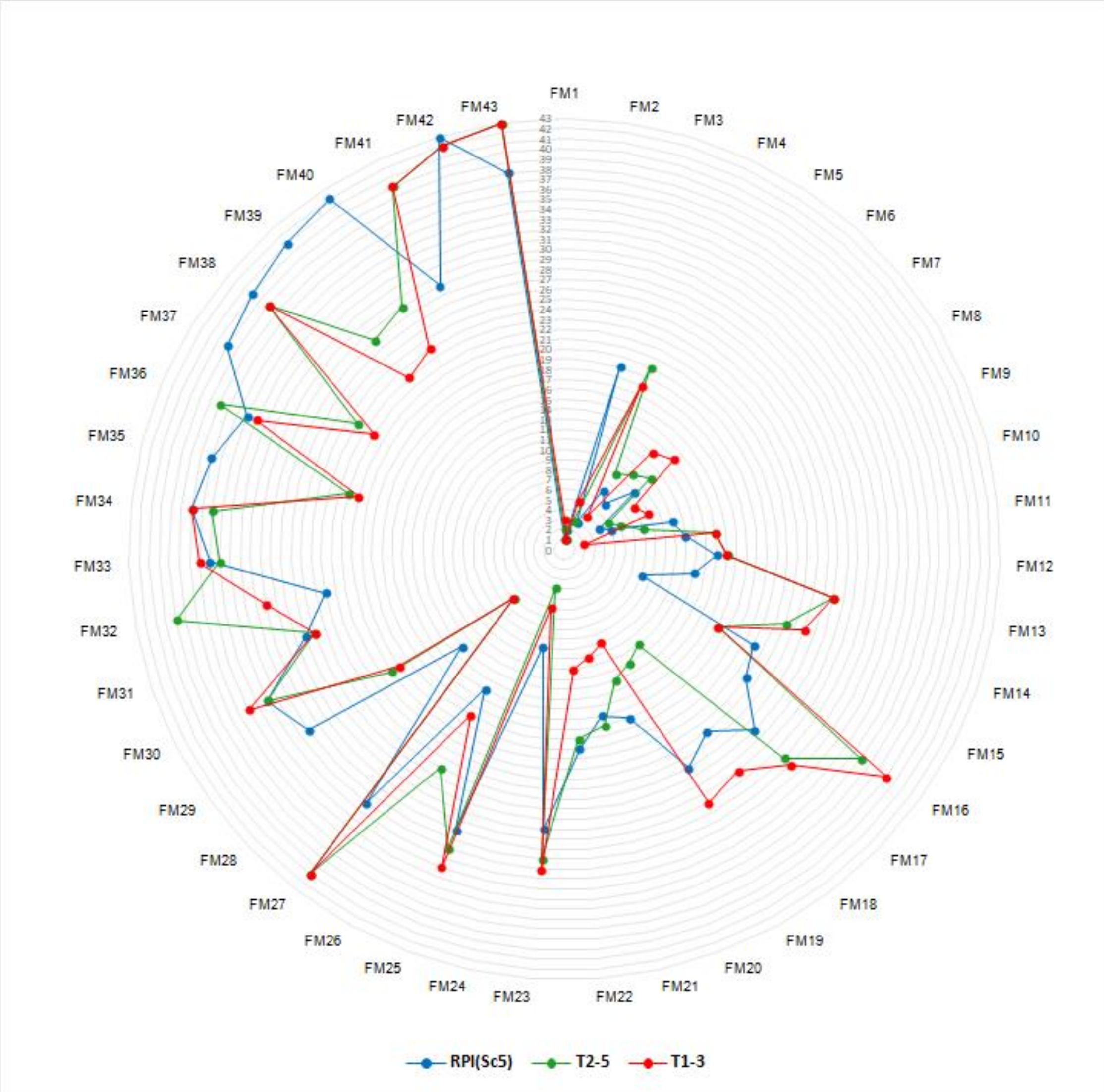

Figure 8.3 – Radar chart comparing Sc5 with Fuzzy T1-3/T2-5, "50% overlap" parameterization

This methodology can be somewhat adopted efficiently in FMECA analysis with a low number of failure modes, nevertheless, when the objects of study are systems or processes with a large number of failure modes, this process becomes very inefficient, having considerable handicaps. For instance, one of the methods to assess the agreement between rankings is to understand how many failure modes have been classified identically, as Table 8.6 shows below.

Table 8.6 – Number of identically classified failure modes for each approach

Sc5 Comparison

		Identical Ranks	*Relative %*	*Kappa*
Standard	T1-1	4	9,30%	0,761
	T2-3	3	6,98%	0,758
50% Overlap	T1-3	1	2,33%	0,750
	T2-5	1	2,33%	0,771

As one can see by the table above, it is not representative and difficult to assess the resulting agreement of the comparison of two ranks by only analyzing the perfect agreements, i.e., whenever both raters classify a failure mode with the same ranking.

For those reasons, the appearance and application of agreement coefficients in the FMECA context, namely the Cohen's Kappa, already tested with high relevance in other areas, would not only quantify but also confer the analysis with more robustness. The radar charts can be exemplificative of the Cohen's Kappa, as the coefficient not only evaluates the perfect agreements but also, and more importantly, analyzes and relies its scores on the proximities between rankings. In the case of the "Standard" parameterization T1-1, for instance, has an observed proportion of agreement $p_0 = 0.9583$, and an expected proportion of agreement by chance $p_e = 0.8254$. This type of analysis allows one to say that every comparison of rankings illustrated in Table 8.6, is considered to "Substantially Agree" with the reference, as described in Table 6.3, having quantitative frameworks as the basis, which would be not possible in the traditional FMECA ranking.

8.3. Extra Analysis

Furthermore, some extra analyses were conducted, to understand if the applied methodology to this dissertation was valid. Firstly, the classical FMECA procedure, based on the conventional RPN computations, was compared with the Fuzzy simulation from Table 8.2 and Table 8.3 with the highest Cohen's Kappa coefficient of agreement, verified in the previous analysis. The idea behind this procedure was to compare the best possible Fuzzy-based FMECA rank order observed in the simulations performed, with the classical FMECA rank prioritization, obtained by the author of [97].

The Fuzzy T2-5 from the "50% Overlap" parameterization was chosen and then compared with the classical "rank base" – ordered from FM1 to FM43 –, resulting in a coefficient of agreement Kappa equal to 0.757, i.e., 75.7%. This coefficient is lower than the value obtained when comparing the T2-5 to Sc 5 of the FMECA-based RPI methodology. In order words, the T2-5 test has a higher agreement when the FMECA uses an RPI methodology to rank and prioritize its failure modes.

This fact demonstrates the already mentioned debilities and shortcomings of the FMECA rank prioritization method based on the conventional RPN computation. By the application of a new rank prioritization model based on the RPI function, idealized by [59] and tested in this work, the FMECA procedure becomes more robust and less vague, providing better agreement results when tested against the Fuzzy-FMECA approaches.

The coefficient of agreement decreases when the classical FMECA-based RPN rank prioritization is used, due to the existence of several failure modes that were classified very differently by the two methods, having sometimes a classification difference higher than 20 ranks, as shown in Table 8.7.

Table 8.7 – The four worst ranking differences from the RPN vs. Fuzzy order comparison

FM	Equipment	Failure Modes	RPN rank	T2-5
FM4	IED	Control failure	4	20
FM16	SW	Performance decrease	16	36
FM24	SV	Security failure	24	4
FM28	HMI	Security failure	28	7

On the one hand, the first two failure modes, FM4 and FM16, despite their relevant ratings for each risk category, do not carry a substantial weight on the success of the grid's operation. They both affect some systems, causing some delays and incorrect commands, but are both ranked too highly by the FMECA-based RPN methodology, with the Fuzzy T2-5 test tending to be more accurate on the true rank for these failure modes when considering the surrounding ranks.

On the other hand, the security failures described in FM24 and FM28 can represent a serious threat to the system, as they are related to the grid's cyber-security and data protection, in addition to the avoidance of unwanted operations. Having both an 'Unlikely' Occurrence rating and despite having the highest rating possible in Severity and Detection, the RPN methodology does not confer them the adequate rank considering those risks. For that reason, the Fuzzy T2-5 test can be considered the better methodology in this case, as it is not influenced by the low Occurrence rating.

These described major differences in the rank comparison, in addition to many other cases, lower the agreement coefficient of the classical FMECA method and open the path to the introduction of new risk prioritization FMECA-based models.

Moving on, to another piece of extra analysis that can be performed, one could analyze the theoretical advantage and stability of the triangular membership functions. For that purpose, four tests – T1-1 and T2-3, from each of the parameterization rules – using set 1 of membership functions from Table 7.2, were compared with a new set of membership functions, that was composed in its totality by trapezoidal functions.

The idea was to compare the agreement coefficient's results of a membership function set with solely triangular functions, with one having only trapezoidal functions when put against the "rank base" Sc 5 used in this dissertation. Theoretically, as described by Pedrycz in [100], the triangular membership function is very satisfactory when applied to Fuzzy-based systems, especially when used an overlap of 50% between functions.

Below, in Table 8.8, the agreement coefficients generated from the comparisons with Sc 5 are illustrated. As one can see, the Cohen's Kappa values are higher for the set composed solely of trapezoidal functions, than for the triangular ones. In the "Standard" parameterization, the difference lies around 2%, whereas, in the "50% overlap" case, the differences are much larger, with the Trapezoidal tests having an "Almost Perfect Agreement" with Sc 5, based on Table 6.3.

Table 8.8 – Triangular vs. Trapezoidal Cohen's Kappa when compared to Sc5

		Comparison with Sc5	
		All Triangular	*All Trapezoidal*
Standard	T1-1	0,761	0,784
	T2-3	0,758	0,776
50% Overlap	T1-3	0,726	0,912
	T2-3	0,726	0,912

This apparent higher agreement in the case of trapezoidal functions can be explained by the shape of the function and the associated membership values. As illustrated in Figure 8.4 below, the trapezoidal function has a larger interval of ratings with a full degree of membership.

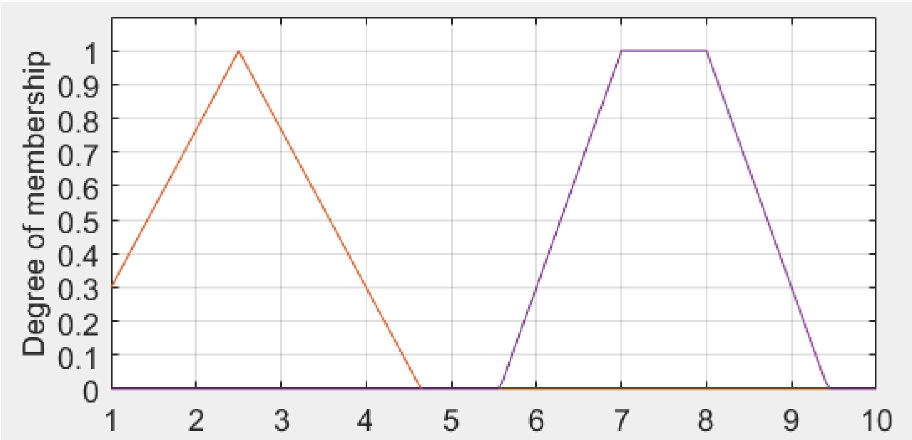

Figure 8.4 – Triangular vs. Trapezoidal functions

In order words, while the triangular function only has a single point with a full degree of membership, that corresponds to the middle of each represented risk factor's category, the trapezoidal function has the entire category's length with the full degree of membership, due to its shape. This allows the trapezoidal membership functions to better translate the human language into Fuzzy reasoning.

For instance, consider that an expert classifies a specific failure mode with a Severity rating of 2 or 3, classifying it with a 'Low' Severity. If the considered membership functions are triangular, ratings 2 and 3 would only have a degree of membership equal to 0.75 (consider the example in Figure 8.4), while if the functions to be applied were trapezoidal, both ratings 2 and 3 would have a full degree of membership, equal to 1. Additionally, as FMECA is based on a rating characterized by integers numbers, the trapezoidal membership functions tend to translate better the ratings attributed by the experts.

For these reasons, one can say that besides the fact of the trapezoidal functions better transform the human language into the Fuzzy methodologies, these functions also have a higher coefficient of agreement when compared with FMECA-based risk prioritization conducted by experts.

9. Conclusions

Both FMECA and Fuzzy methodologies have been applied to several other areas of interest, either individually or interconnected, showing great importance in developing processes or conferring stability and efficiency to the objects in the study.

The primary objective of this dissertation was to apply the Fuzzy-FMECA reasoning to the context of smart grids and the comparison with a well-proven FMECA method using a statistical-based ranking comparison coefficient. From the used methodology and the analyses performed, it can be established that the Fuzzy-FMECA reasoning is a valid option to analyze the failure modes and potential inherent risks that may occur in a smart grid's power and cyber networks.

The fuzzy-FMECA performance was measured quantitatively through an approach based on the Cohen's Kappa agreement coefficient. The idea of implementing a methodology based on the agreement coefficient for FMECA methods comparison was also a success. The Cohen's Kappa reveals itself as a suitable comparing metric between different FMECA methods instead of a qualitative analysis performed, ranking by ranking.

As one can see, most of the Cohen's Kappa calculated throughout this study had values comprehended between 0.6 and 0.8, meaning that the generality of the Fuzzy-FMECA comparisons had a "substantial agreement", according to Table 6.3. Consequently, the satisfactory values obtained for the performed comparisons, strengthen the argument that Fuzzy-FMECA is a valid and efficient methodology to be applied to the context of a smart grid, both qualitatively and quantitatively, when supported by a correspondent coefficient of agreement.

Nevertheless, the classical FMECA methodology based on the RPN score computations for rankings' prioritization still has its drawbacks, more precisely the ambiguity and vagueness associated with such concepts. For that reason, as described in this work, the introduction of a new prioritization model as the reference for the study is necessary. Not only it confers more robustness and less vagueness to the FMECA procedures, but also facilitates the introduction of other methodologies to be subsequently implemented.

The selection of the reference ranking becomes a crucial factor in the success of the application of these methodologies, as it serves consecutively as the basis for comparison of whichever object of analysis. For this reason, it is noteworthy that the reference ranks should be carefully selected, crucially having in mind what is the context and the objective of what is being studied. In this case, the RPI model was already previously applied to the FMECA context, conferring its suitability.

9.1. Future Work

Following the aforementioned conclusions, one can assume that there is an array of possibilities regarding future work, that eventually might have this dissertation as the basis for those studies. Some of the improvements are as follows:

- The definition of specific weights, critically reasoned, for each of the risk factors that compose the FMECA methodology.
- The utilization of another Fuzzy methodology, namely a Fuzzy FWGM, which allows for the introduction of weights in the Fuzzy reasoning, providing an additional point of influence, depending on the study that is being performed.
- The introduction of new carefully selected models to define the “rank base”, the reference rank used throughout the work to compute the desired simulations.
- The application of other coefficients of agreement that may be considered relevant for the comparison of Fuzzy-FMECA methodologies.

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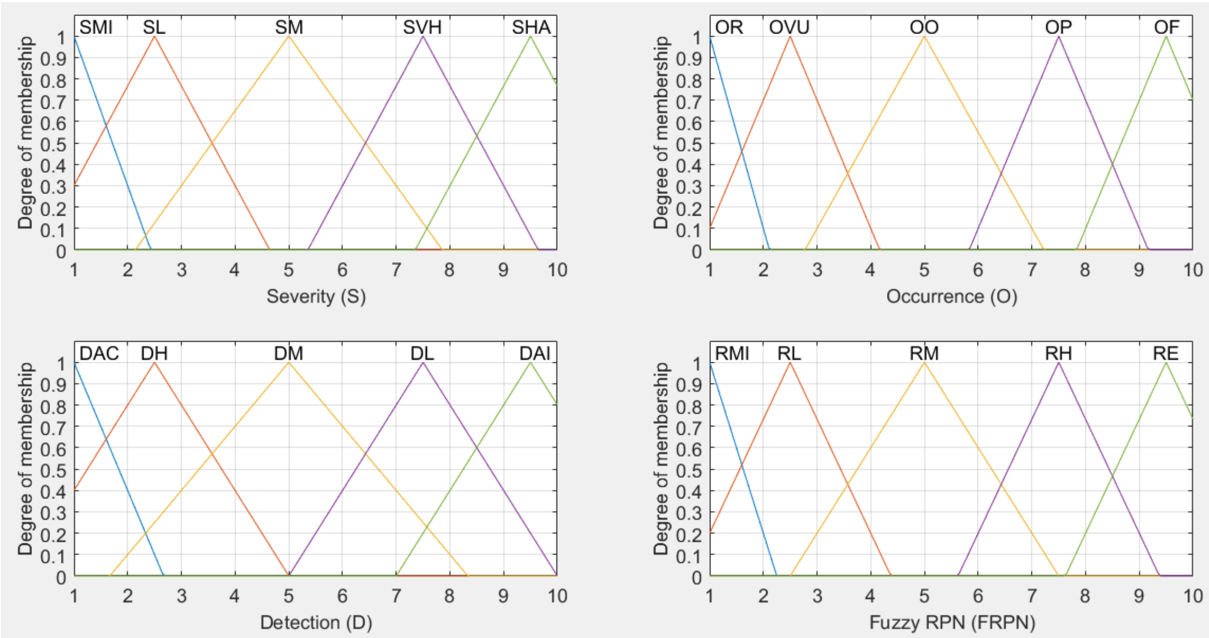
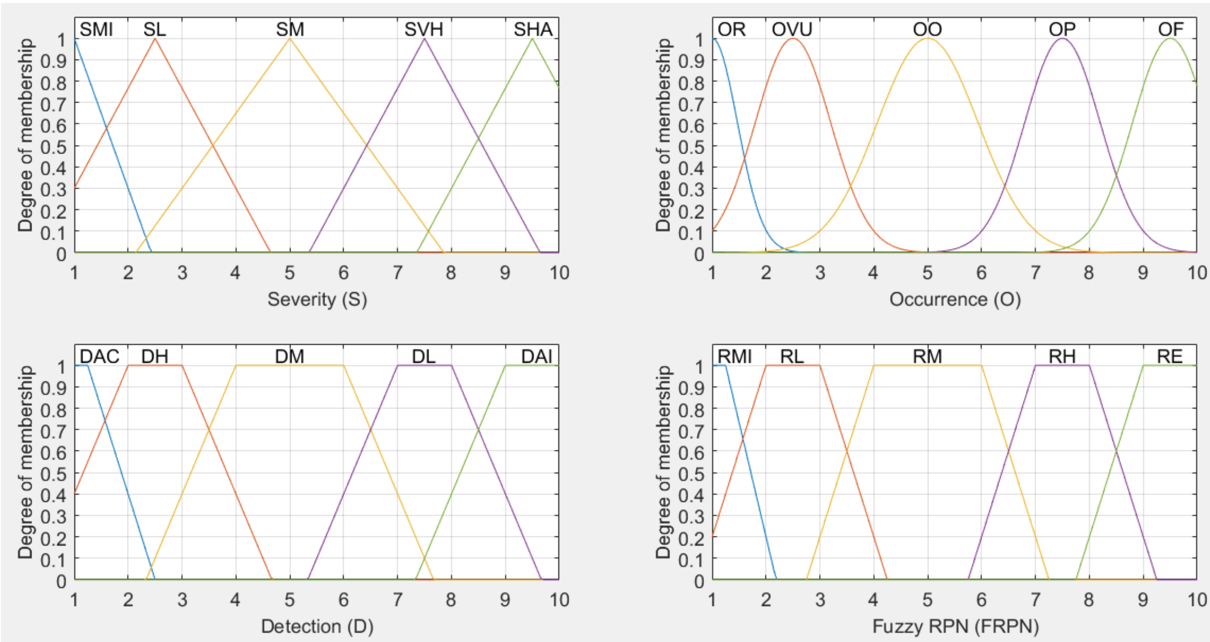
Appendix A

Membership functions for the “Standard” Parameterization

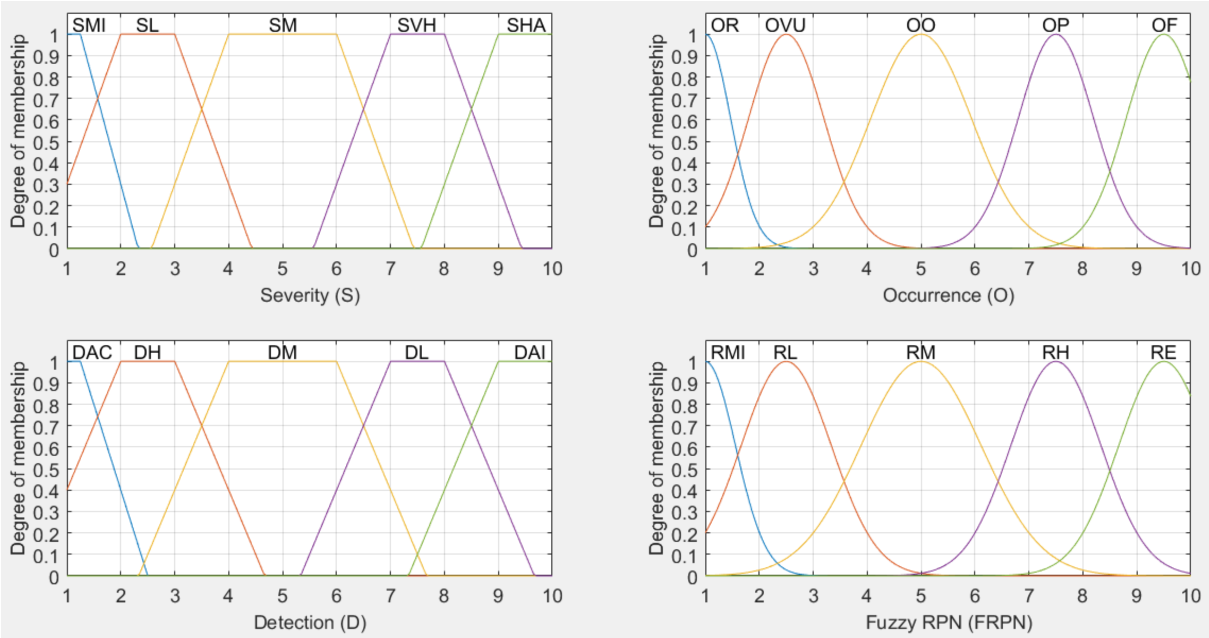
Set1 Type-I



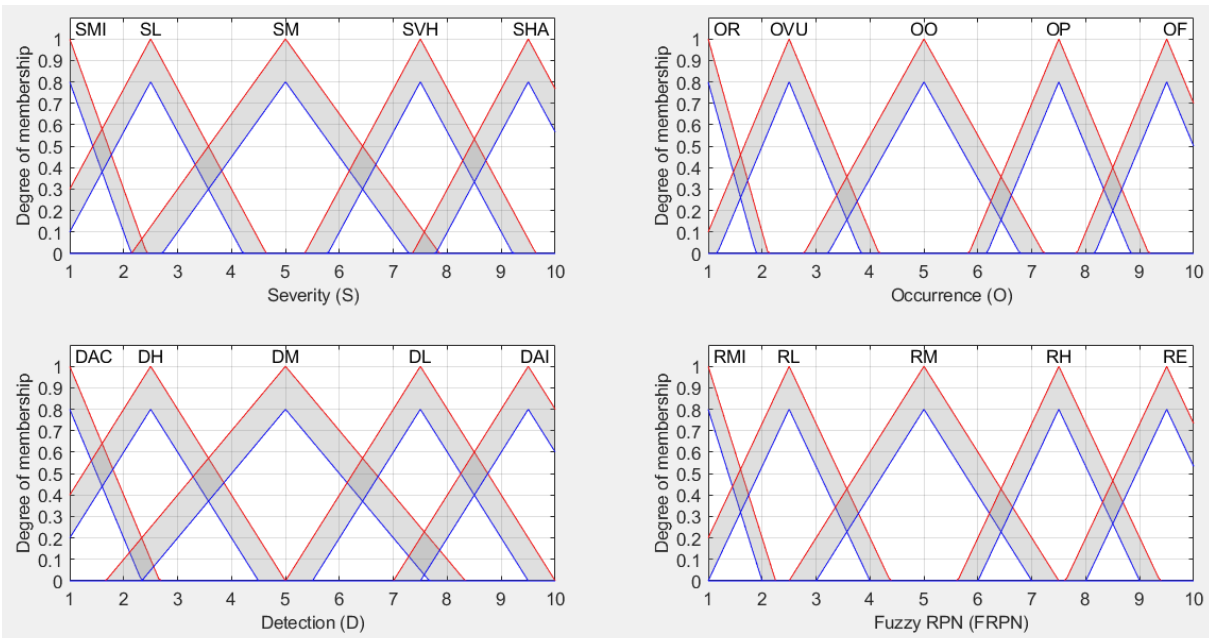
Set2 Type-I



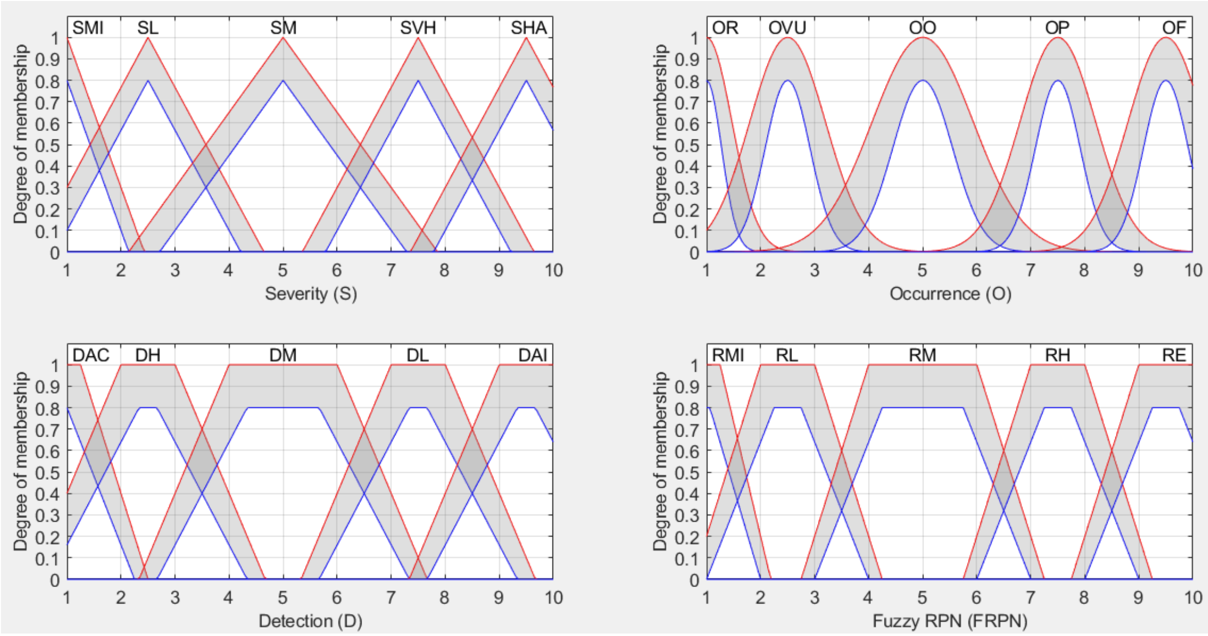
Set3 Type-I



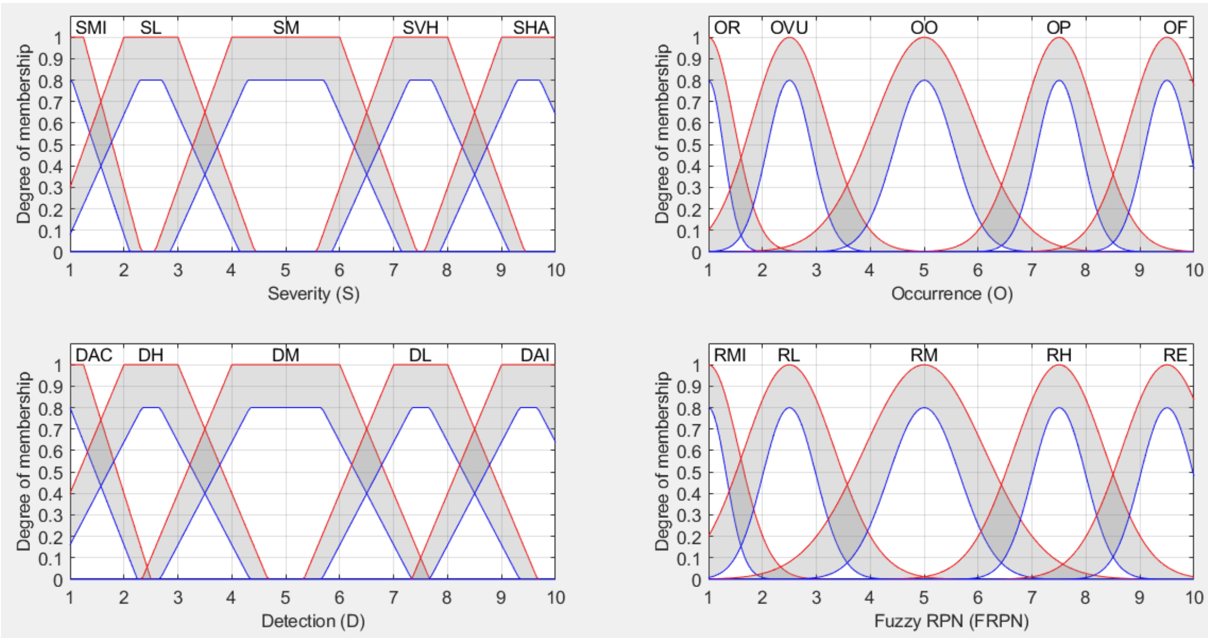
Set1 Type-II



Set2 Type-II

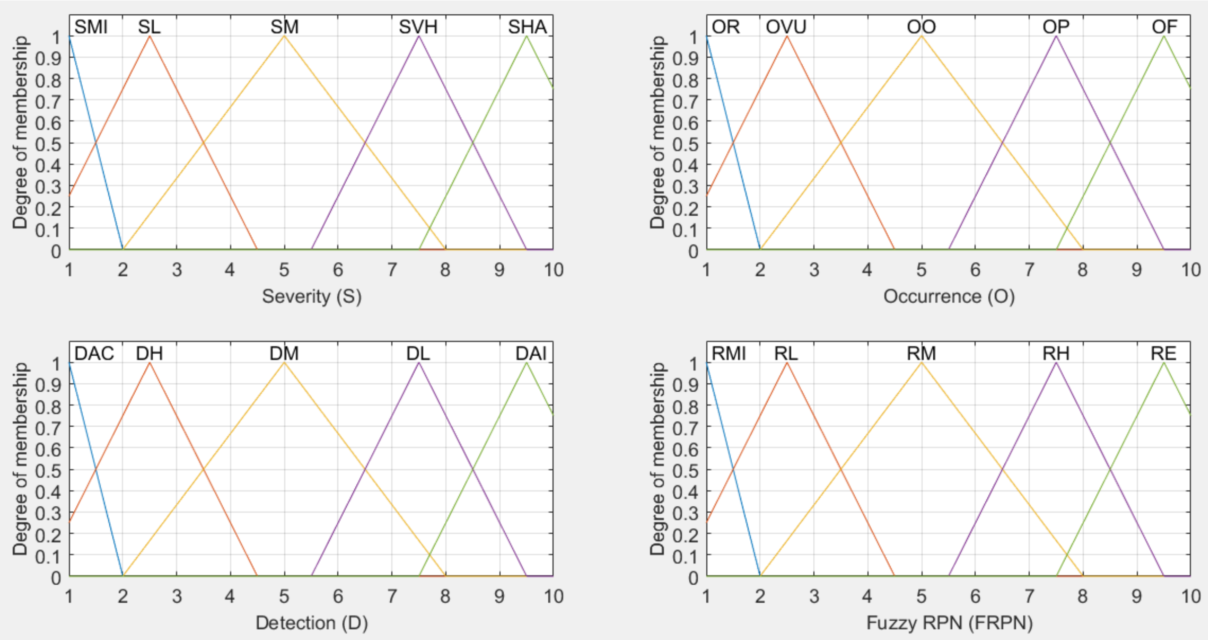


Set 3 Type-II



Membership functions for the “50% Overlap” Parameterization

Set1 Type-I



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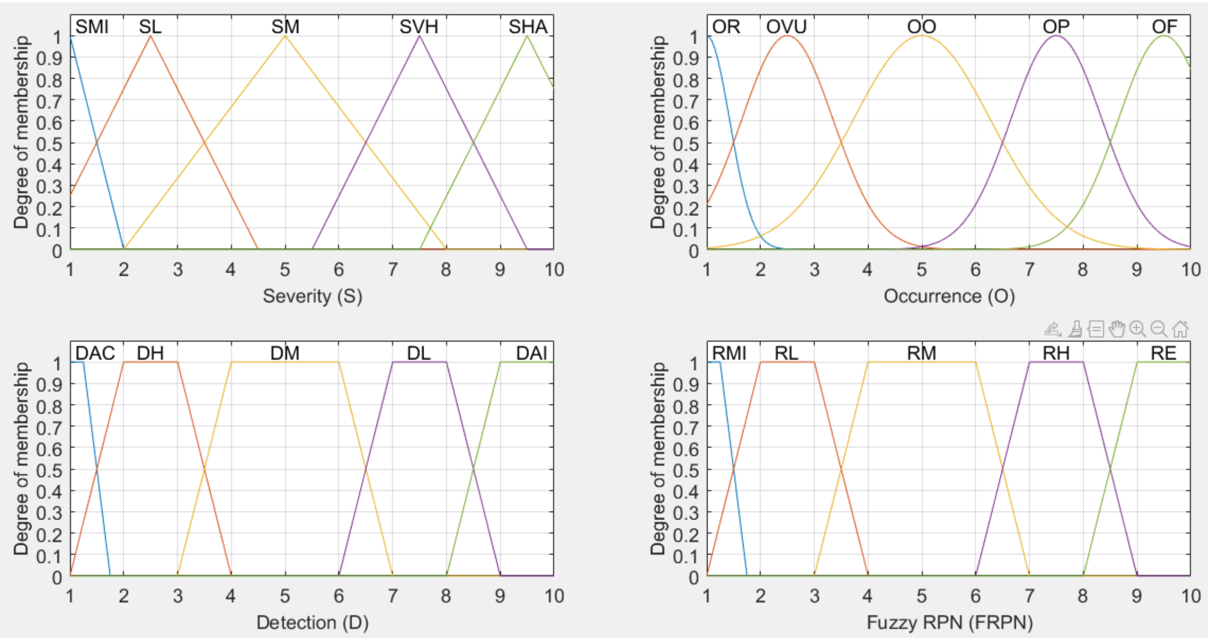

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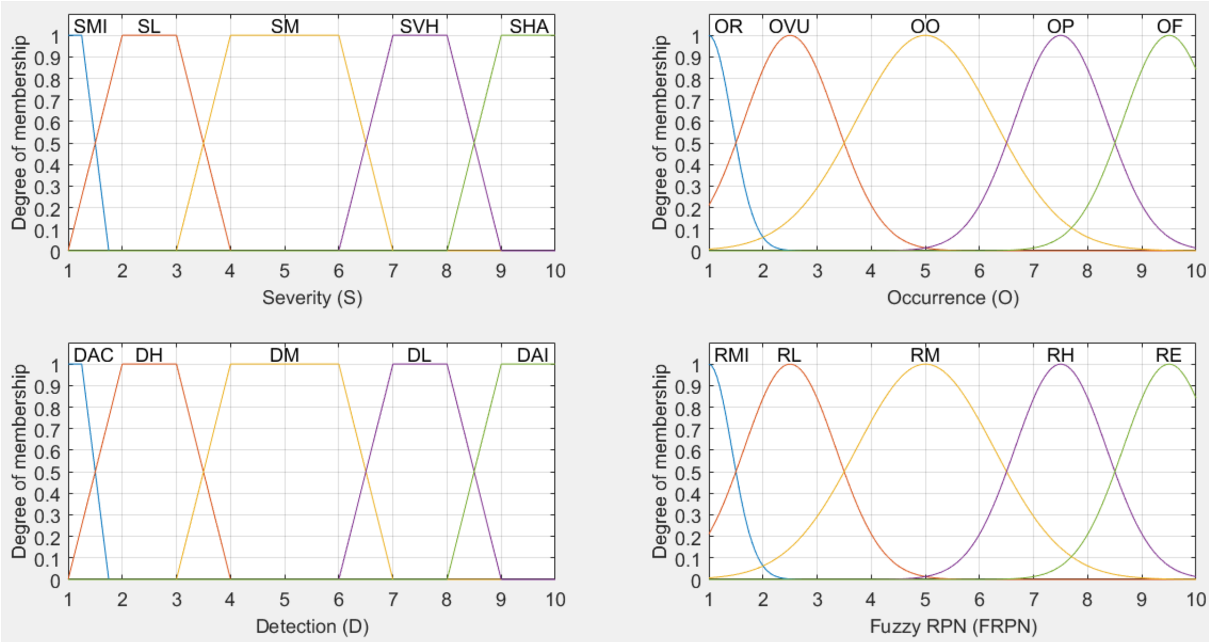
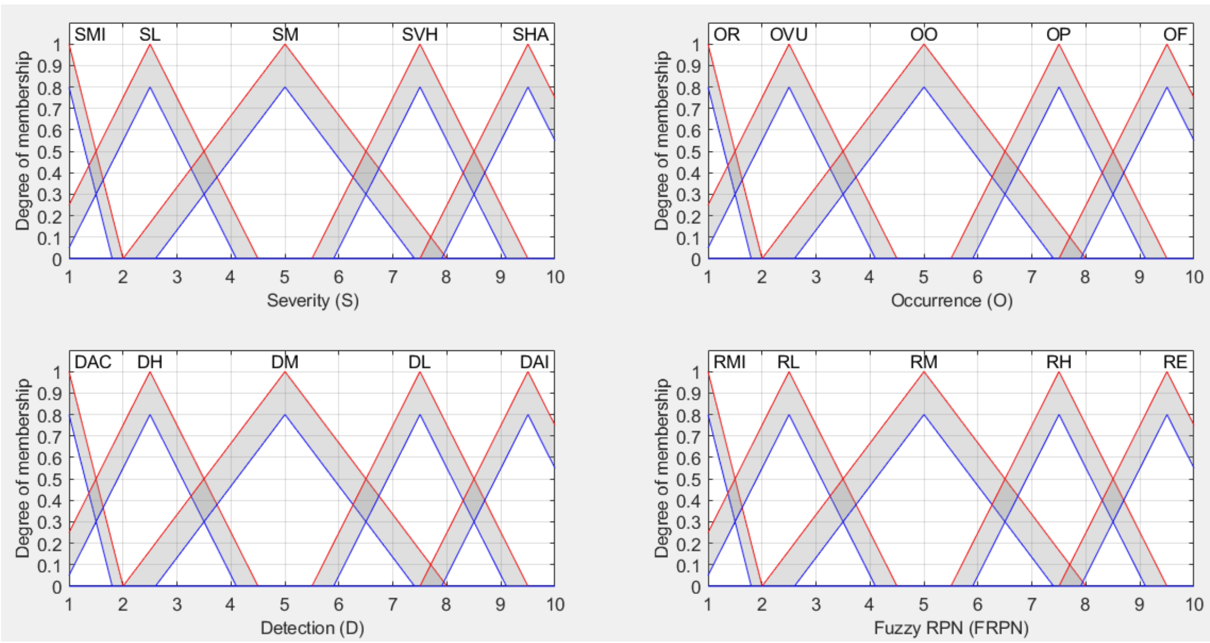


Set1 Type-II



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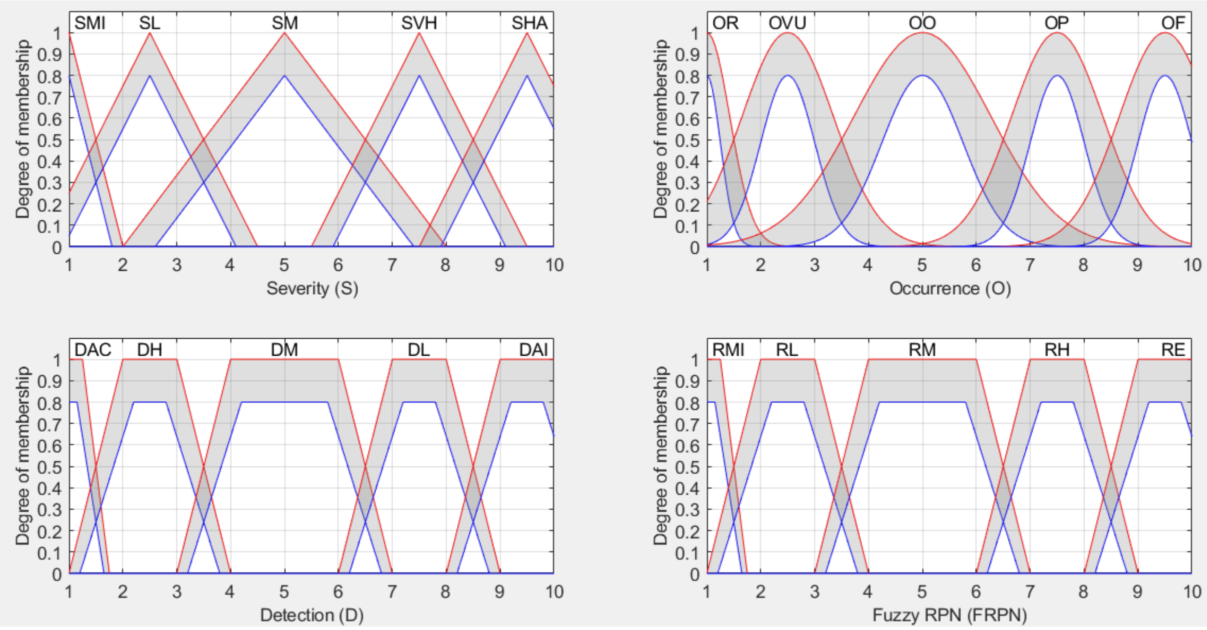

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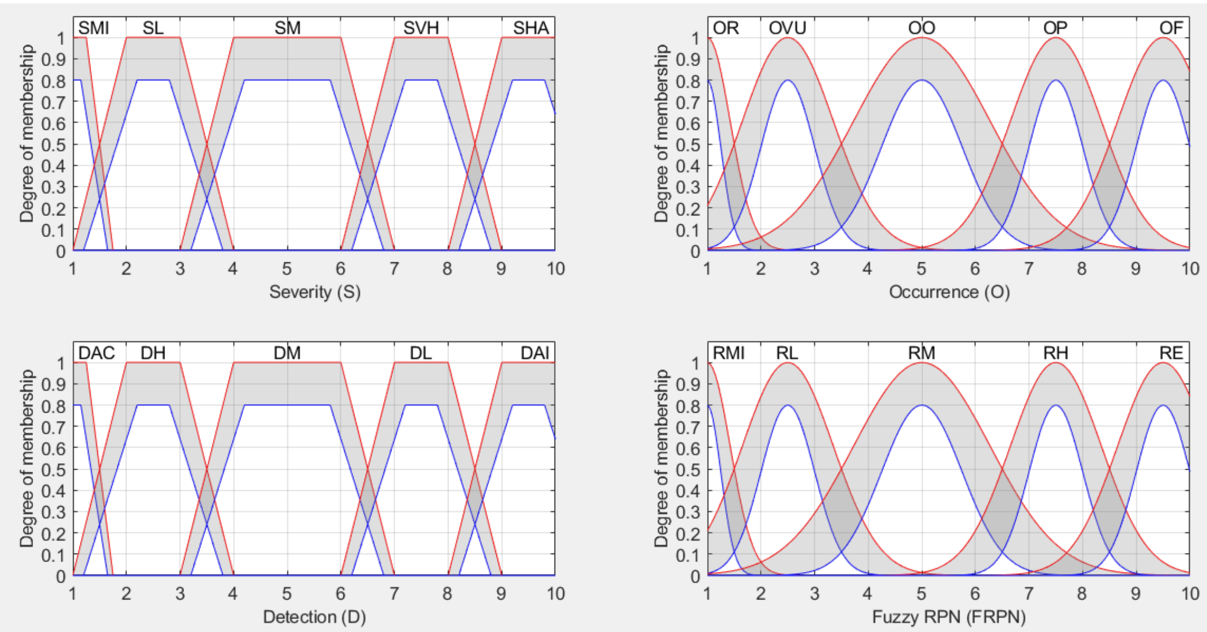

Appendix B

Following equation (4.3), the six orders of importance can be computed:

Rank	S	O	D	RPN	***SOD***	***SDO***	***OSD***	***ODS***	***DSO***	***DOS***
1	8	6	10	480	210	226	170	178	266	258
2	9	5	10	450	230	250	150	154	270	254
3	5	8	10	400	145	153	205	225	253	265
4	8	7	7	392	212	212	192	188	192	188
5	7	6	9	378	184	196	164	172	236	232
6	6	6	10	360	160	176	160	176	256	256
7	6	6	10	360	160	176	160	176	256	256
8	8	4	10	320	200	224	120	128	264	248
9	8	4	10	320	200	224	120	128	264	248
10	7	5	9	315	179	195	139	147	235	227
11	6	5	10	300	155	175	135	151	255	251
12	6	5	10	300	155	175	135	151	255	251
13	7	6	7	294	182	186	162	162	186	182
14	8	7	5	280	210	202	190	178	142	138
15	6	5	9	270	154	170	134	146	230	226
16	6	7	6	252	161	157	181	181	157	161
17	6	5	8	240	153	165	133	141	205	201
18	6	4	10	240	150	174	110	126	254	246
19	6	4	10	240	150	174	110	126	254	246
20	8	3	9	216	194	218	94	98	238	218
21	7	3	10	210	170	198	90	102	258	242
22	7	3	10	210	170	198	90	102	258	242
23	6	5	7	210	152	160	132	136	180	176
24	10	2	10	200	240	272	80	80	272	240
25	6	4	8	192	148	164	108	116	204	196
26	9	3	7	189	217	233	97	89	193	169
27	6	5	6	180	151	155	131	131	155	151
28	9	2	10	180	215	247	75	79	267	239
29	6	3	10	180	145	173	85	101	253	241
30	6	4	7	168	147	159	107	111	179	171
31	8	3	7	168	192	208	92	88	188	168
32	7	6	4	168	179	171	159	147	111	107
33	6	4	7	168	147	159	107	111	179	171
34	6	4	7	168	147	159	107	111	179	171
35	6	3	9	162	144	168	84	96	228	216
36	4	5	8	160	103	115	123	139	195	199
37	5	3	10	150	120	148	80	100	248	240
38	4	4	8	128	98	114	98	114	194	194
39	4	3	10	120	95	123	75	99	243	239
40	4	3	10	120	95	123	75	99	243	239
41	8	3	4	96	189	193	89	73	113	93
42	6	4	4	96	144	144	104	96	104	96
43	6	5	3	90	148	140	128	116	80	76

Attributing ranks for each of the orders of importance:

Rank	S	O	D	***SOD***	***SDO***	***OSD***	***ODS***	***DSO***	***DOS***
1	8	6	10	6	5	5	4	4	2
2	9	5	10	2	2	11	10	2	5
3	5	8	10	35	36	1	1	15	1
4	8	7	7	5	9	2	2	30	29
5	7	6	9	13	14	6	8	21	20
6	6	6	10	20	18	8	6	9	3
7	6	6	10	21	19	9	7	10	4
8	8	4	10	8	6	21	20	5	8
9	8	4	10	9	7	22	21	6	9
10	7	5	9	15	15	12	13	22	21
11	6	5	10	22	20	13	11	11	6
12	6	5	10	23	21	14	12	12	7
13	7	6	7	14	17	7	9	32	30
14	8	7	5	7	11	3	5	39	39
15	6	5	9	24	26	15	15	23	22
16	6	7	6	19	34	4	3	37	37
17	6	5	8	25	28	16	16	25	25
18	6	4	10	28	22	23	22	13	10
19	6	4	10	29	23	24	23	14	11
20	8	3	9	10	8	32	36	20	23
21	7	3	10	17	12	34	30	7	12
22	7	3	10	18	13	35	31	8	13
23	6	5	7	26	30	17	18	33	31
24	10	2	10	1	1	39	41	1	15
25	6	4	8	30	29	25	24	26	27
26	9	3	7	3	4	31	39	29	35
27	6	5	6	27	35	18	19	38	38
28	9	2	10	4	3	41	42	3	17
29	6	3	10	36	24	37	32	16	14
30	6	4	7	32	31	26	27	34	32
31	8	3	7	11	10	33	40	31	36
32	7	6	4	16	25	10	14	41	40
33	6	4	7	33	32	27	28	35	33
34	6	4	7	34	33	28	29	36	34
35	6	3	9	37	27	38	37	24	24
36	4	5	8	40	42	20	17	27	26
37	5	3	10	39	37	40	33	17	16
38	4	4	8	41	43	30	26	28	28
39	4	3	10	42	40	42	34	18	18
40	4	3	10	43	41	43	35	19	19
41	8	3	4	12	16	36	43	40	42
42	6	4	4	38	38	29	38	42	41
43	6	5	3	31	39	19	25	43	43

And then obtaining the delta risk drivers, to be applied to the RPI formula:

Rank	S	O	D	***δS***	***δO***	***δD***
1	8	6	10	5,5	4,5	3
2	9	5	10	2	10,5	3,5
3	5	8	10	35,5	1	8
4	8	7	7	7	2	29,5
5	7	6	9	13,5	7	20,5
6	6	6	10	19	7	6
7	6	6	10	20	8	7
8	8	4	10	7	20,5	6,5
9	8	4	10	8	21,5	7,5
10	7	5	9	15	12,5	21,5
11	6	5	10	21	12	8,5
12	6	5	10	22	13	9,5
13	7	6	7	15,5	8	31
14	8	7	5	9	4	39
15	6	5	9	25	15	22,5
16	6	7	6	26,5	3,5	37
17	6	5	8	26,5	16	25
18	6	4	10	25	22,5	11,5
19	6	4	10	26	23,5	12,5
20	8	3	9	9	34	21,5
21	7	3	10	14,5	32	9,5
22	7	3	10	15,5	33	10,5
23	6	5	7	28	17,5	32
24	10	2	10	1	40	8
25	6	4	8	29,5	24,5	26,5
26	9	3	7	3,5	35	32
27	6	5	6	31	18,5	38
28	9	2	10	3,5	41,5	10
29	6	3	10	30	34,5	15
30	6	4	7	31,5	26,5	33
31	8	3	7	10,5	36,5	33,5
32	7	6	4	20,5	12	40,5
33	6	4	7	32,5	27,5	34
34	6	4	7	33,5	28,5	35
35	6	3	9	32	37,5	24
36	4	5	8	41	18,5	26,5
37	5	3	10	38	36,5	16,5
38	4	4	8	42	28	28
39	4	3	10	41	38	18
40	4	3	10	42	39	19
41	8	3	4	14	39,5	41
42	6	4	4	38	33,5	41,5
43	6	5	3	35	22	43

Using equation (4.9) with the weights from Table 4.1, one can compute the RPI and respective ranks:

	RPI score (the lowest the score the higher the rank)						*RPI-based prioritization Rank*					
Rank	**Sc1**	**Sc2**	**Sc3**	**Sc4**	**Sc5**	**Sc6**	**Sc1**	**Sc2**	**Sc3**	**Sc4**	**Sc5**	**Sc6**
FM1	4,6005	4,2555	4,0005	4,5505	4,7505	4,2505	2	1	1	1	1	1
FM2	4,257	6,702	5,407	6,657	4,957	5,257	1	2	2	2	2	2
FM3	20,3955	10,0355	11,4455	12,7955	19,6955	14,1955	20	4	6	8	19	8
FM4	12,777	11,257	16,777	9,027	10,027	14,527	6	6	12	3	3	11
FM5	14,3835	12,3635	15,1335	11,7335	13,0335	14,4335	10	7	10	6	7	9
FM6	12,789	9,119	8,989	10,489	12,889	10,289	7	3	3	4	6	3
FM7	13,8	10,12	10	11,5	13,9	11,3	9	5	4	5	9	5
FM8	9,762	13,607	11,012	13,862	11,162	11,062	3	9	5	9	4	4
FM9	10,773	14,608	12,023	14,873	12,173	12,073	4	11	7	11	5	6
FM10	16,59	15,715	17,64	15,19	15,69	16,99	12	13	14	13	11	13
FM11	15,591	12,771	12,191	14,141	15,941	13,441	11	8	8	10	12	7
FM12	16,602	13,772	13,202	15,152	16,952	14,452	13	10	9	14	15	10
FM13	18,7455	16,4155	21,0955	14,9455	16,4455	19,5455	19	14	20	12	13	18
FM14	17,049	15,509	22,549	12,549	13,549	19,549	15	12	21	7	8	19
FM15	22,425	19,275	20,925	19,675	21,675	21,175	23	16	19	16	21	21
FM16	25,1115	18,1765	24,9115	17,1615	21,7615	23,8615	27	15	25	15	22	24
FM17	24,1365	20,8265	22,7865	21,1365	23,2365	22,9365	25	19	22	18	26	23
FM18	20,7	19,725	17,75	21,3	21,8	19,1	21	17	15	19	23	17
FM19	21,711	20,726	18,761	22,311	22,811	20,111	22	18	18	21	25	20
FM20	18,099	25,259	23,099	24,349	19,349	21,849	17	26	23	26	18	22
FM21	16,8345	21,7645	17,5845	22,5845	19,0845	18,0845	14	20	13	22	17	15
FM22	17,8455	22,7655	18,5955	23,5955	20,0955	19,0955	16	23	17	23	20	16
FM23	27,303	23,978	27,053	23,753	25,853	26,653	29	24	27	24	28	28
FM24	11,301	22,601	16,601	22,301	14,501	15,901	5	22	11	20	10	12
FM25	27,8745	26,1295	26,7745	26,6745	27,6745	27,0745	31	28	26	29	30	29
FM26	18,7035	27,8035	27,5535	25,3035	19,0035	24,7035	18	31	30	27	16	25
FM27	30,816	26,881	30,966	26,366	28,866	30,266	32	29	36	28	32	33
FM28	13,4685	24,4535	18,5685	24,2185	16,6185	17,9185	8	25	16	25	14	14
FM29	26,775	27,78	24,225	29,625	28,725	25,725	28	30	24	32	31	26
FM30	31,2465	29,4815	31,0465	29,5965	30,5965	30,8965	34	32	37	33	33	35
FM31	22,9755	30,4105	30,1755	28,4755	23,2755	27,8755	24	33	35	31	27	30
FM32	24,9405	22,2705	28,0905	20,3905	22,0905	26,0905	26	21	31	17	24	27
FM33	32,2575	30,4825	32,0575	30,6075	31,6075	31,9075	36	34	39	35	35	37
FM34	33,2685	31,4835	33,0685	31,6185	32,6185	32,9185	38	38	40	36	37	41
FM35	31,107	32,382	30,057	33,557	32,457	30,857	33	39	34	40	36	34
FM36	32,376	25,441	27,226	27,076	31,576	28,676	37	27	29	30	34	31
FM37	31,653	30,838	27,203	33,353	33,653	29,353	35	35	28	37	39	32
FM38	35,322	30,842	31,122	32,522	35,322	32,522	42	36	38	38	40	39
FM39	33,921	32,641	29,021	35,321	35,921	31,321	39	40	32	41	41	36
FM40	34,932	33,642	30,032	36,332	36,932	32,332	40	41	33	42	42	38
FM41	27,609	34,864	35,559	32,559	27,459	32,859	30	42	42	37	29	40
FM42	38,523	36,838	38,773	36,823	37,723	38,423	43	43	43	43	43	43
FM43	35,055	30,935	35,355	30,355	32,955	34,555	41	37	41	34	38	42

Appendix C

Standard Parameterization comparison results

Kappa	Sc4	Sc5
T1-1	0,710	0,761
T1-2	0,710	0,744
T1-3	0,711	0,752
T2-1	0,699	0,749
T2-2	0,702	0,752
T2-3	0,708	0,758
T2-4	0,694	0,745
T2-5	0,704	0,748
T2-6	0,707	0,748
T2-7	0,704	0,748
T2-8	0,710	0,749
T2-9	0,711	0,752
T2-10	0,708	0,745
T2-11	0,709	0,752
T2-12	0,709	0,746

"50% Overlap" Parameterization comparison results

Kappa	Sc4	Sc5
T1-1	0,644	0,726
T1-2	0,624	0,744
T1-3	0,619	0,750
T2-1	0,644	0,726
T2-2	0,631	0,714
T2-3	0,644	0,726
T2-4	0,643	0,724
T2-5	0,677	0,771
T2-6	0,631	0,731
T2-7	0,669	0,762
T2-8	0,655	0,755
T2-9	0,619	0,750
T2-10	0,578	0,720
T2-11	0,619	0,750
T2-12	0,570	0,715