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

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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.

I. Introduction

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 after the development of life conditions, electricity is nowadays a first necessity good not dispensed by a large majority of the world's population.

The concept of renewable energy was created, the first electrical vehicles appeared, 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 ground-breaking components with the most classic ones, in an attempt to face the never slowing down new world's demand, combined with the latest trends. However, with the appearance of the so-called smart grids, not only the number of components increased as well as their interdependences, but also the consequent increase of failures and 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, which required the introduction of new methodologies with the aim of improving the FMECA procedures.

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.

II. 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.

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.

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.

Dinmohammadi and Shafiee [5] 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

Perveen et al. [6] have 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.

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.

III. FMECA Methodology

Failure Mode, Effects and Criticality Analysis, vulgarly known as FMECA, is a qualitative approach method with the primary function of identifying potential system failures, analyzing their causes and consequences, and classifying them using a metric score to ultimately be able to prioritize the potential risks and subsequently create needed maintenance/mitigation plans [1,2].

Theoretically, to conduct this analysis, the first step is to gather a panel of experts that have the responsibility of identifying and characterizing said failures, whilst should also present ways of detection and recommended 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 ranking system [7,8]. This ranking system is based on three risk factors [9]:

a) *Severity (SEV): measures the impact of a failure in the system's operation, based on the worst potential consequences that may happen.*

b) *Occurrence (OCC): frequency of times a failure is likely to occur – can be related to the failure rate concept.*

c) *Detection (DET): represents the likelihood of detecting a failure before it harms the system's operation.*

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 (1):

$$RPN = SEV \times OCC \times DET \tag{1}$$

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" [3,9]. It is ambitious to represent these risk factors by single integer numbers.

The RPN score calculation is based on a simple multiplication, which also makes it highly sensitive to any variation in the risk factors assigned ratings. The three risk factors are computed with 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.

Different combinations of SEV, OCC, and DET ratings can lead to the same RPN score, which as explained can lead to a wrong ordination of 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.

For those reasons, the implementation of the Fuzzy Logic as intended by this dissertation can be a valid option and theoretically improve this process, due to its quality of manipulating human language, to then execute numerical computations as the RPN score case.

Nevertheless, before the application of the Fuzzy-based reasoning in the FMECA context, the next chapter describes a new model for risk prioritization performed by the authors of [10], where they test their discoveries in an FMECA context problem, with satisfactory results in reducing the shortcomings existing in the classical FMECA RPN-based rank prioritization. From there, one can then apply the Fuzzy-FMECA ideology not to the RPN-based classical rank method, but to an FMECA risk prioritization based on the presented new model.

IV. Risk Priority Model

Anes et al. [10], following up on the described literature, proposed a new risk prioritization model based on two functions: the risk isosurface (RI) function and the risk priority index (RPI) function. The RI function prioritizes failure modes following a given order of importance, while the RPI function performs prioritization based on weights given to each risk factor of the failure modes.

Equation (2) described below, can be used to compute the RI assuming that the given order of importance is A>B>C [10]:

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

The results of equation (2) are ranked accordingly for each combination of importance, from high to low, and with those rankings one can compute the delta risk drivers, described below in equation (3) [10], 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.

$$\delta_A = \frac{RI(A,B,C)_{A>B>C\_rating} + RI(A,B,C)_{A>C>B\_ratin}}{2} \tag{3}$$

By conducting these transformations, the delta risk drivers can then be applied to the RPI computations together with the respective weights. Equation (4) represents the general RPI formula [10]:

$$RPI = w_A\delta_A + w_B\delta_B + w_C\delta_C \quad (4)$$

Regarding the three weights to apply, one could select whichever reasonable values, if its summation corresponds to 100% (or 1). For this dissertation, six different scenarios proposed in [10] are going to be selected, as described in Table 1.

Subsequently, correcting factors need to be 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/ε^3 and 1/ε^2, with ε=10. With that in mind, equation (4.) can thus be rewritten as described below in equation (5), to then obtain the new risk prioritization [10]:

$$RPI = \left(\frac{w_A\varepsilon^3 + 1}{\varepsilon^3}\right)\delta_A + \left(\frac{w_A\varepsilon^2 + 1}{\varepsilon^2}\right)\delta_B + w_C\delta_C \quad (5)$$

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

Table.1 – Six suggested weight scenarios (from [10])

V. Fuzzy Logic 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 1, this inference system can be divided into three main phases, according to [11,12]

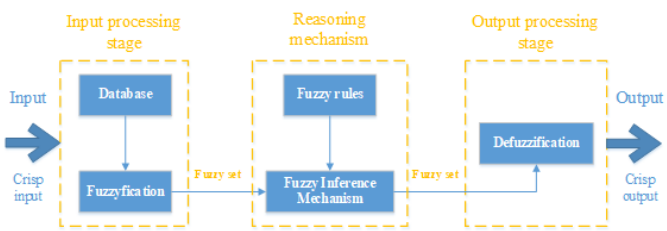

Figure 1 – FIS Type-I

Phase 1 – 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" [11]. 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".

Phase 2 – 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".

A. *Type-I Membership functions*

There will be five membership functions for each of the three risk categories, as demonstrated and simplified in Table 2, plus the FRPN.

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

Table 2 – Six suggested weight scenarios (from [10])

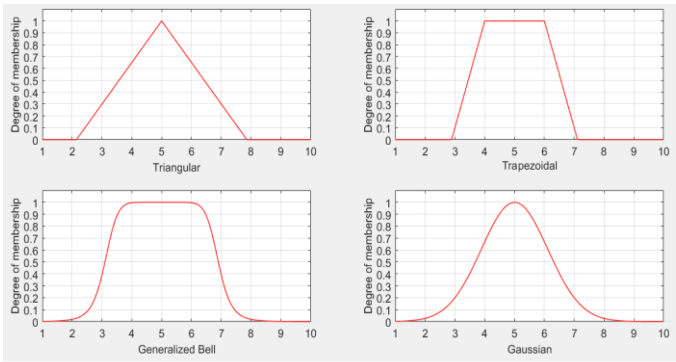

Figure 2 – Type-I possible membership functions

Each of the five can assume four possible shapes as seen in Figure 2, expressed as continuous functions and was computed based on specific parameters that define their shape [12].

The triangular membership function can be defined as equation (6), with 'a', 'b', and 'c', being the three vertexes that compose its shape:

$$triangular = \begin{cases} 0, & x < a \\ (x-a)/(b-a), & a \le x \le b \\ (c-x)/(c-b), & b \le x \le c \\ 0, & x > c \end{cases} \quad (6)$$

The trapezoidal membership is defined as in equation (7), with 'a', 'b', 'c', and 'd', being the four vertexes composing its shape:

$$trapezoidal(x, a, b, c, d) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ 1, & b \le x \le c \\ (d-x)/(d-c), & c \le x \le d \\ 0, & otherwise \end{cases} \quad (7)$$

The gaussian membership function is defined as in equation (8). 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.

$$gaussian(x, a, c, \sigma) = a.e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (8)$$

Finally, the generalized bell membership function is defined as in equation (9), with 'c' being the center of the function, as 'a' and 'b' control the width and the slopes' shape of the function.

$$bell(x, a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \quad (9)$$

VI. Fuzzy Logic Type-II

The general structure of the FIS Type-II is very similar to FIS Type-I, as shown below in Figure 3. From the three-phase description made before, 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 [13].

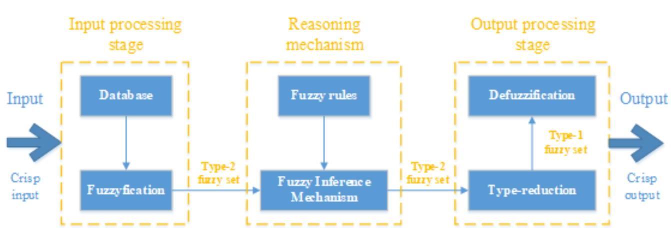

Figure 3 – FIS Type-II

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 [14]. 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 [14]. This algorithm will be applied to this study for simplification reasons and is based on the representation theorem for Type-II fuzzy sets, as establishes that the centroid for a fuzzy set is the union of the embedded Type-I fuzzy sets' centroids [15].

A. *Type-II Membership functions*

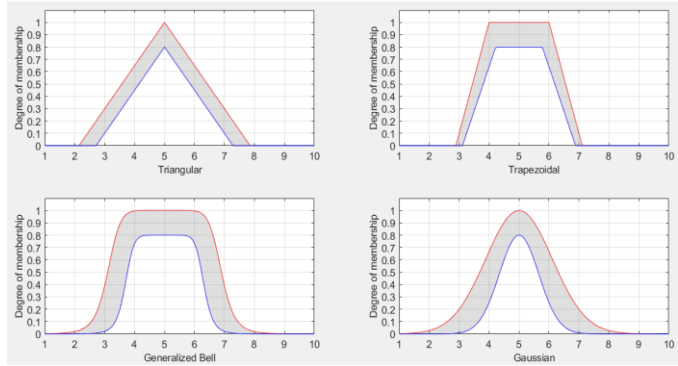

Figure 4 – Type-I possible membership functions

The four possible membership functions can also be defined as continuous functions, based on the equations from (6) to (9). 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: the "lower lag" which can be a value between 0.1 and 0.9 that defines how late does the LMF start to be created in relation to the UMF; and the "lower scale", which also can be a value between 0.1 and 0.9, defining 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 a possible statistical tool to compare the agreement between these two methodologies, hopefully obtaining better analyses and meaningful conclusions.

VII. Coefficient of Agreement: Cohen's Kappa

Let po be the "observed" proportion of agreement between experts. This proportion does not take into consideration the "agreement obtained by chance" [16]. For that reason, the proportion of agreement result of chance, designated by pe, must be taken into account and represents the probability of both experts categorize a failure with the same ranking by pure chance. Both po and pe can be expressed as shown by equations (10) and (11) [17,18].

$$p_0 = \sum_{i=1}^{k} p_{ii} \quad (10)$$

$$p_e = \sum_{i=1}^{k} (p_{i+} \cdot p_{+i}) \quad (11)$$

From those two concepts, one can define the Cohen's Kappa coefficient as described in equation 12 [17,18,19]:

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{10}$$

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 [16]. By the same token, 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 [19], 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 [20].

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

Table 3 – Strengths of agreement

For this dissertation, the objective was that the null hypothesis H0 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 H0 rejected, with an associated level of significance of 0.05

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.

VIII. Study Case

An FMECA analysis applied to the electrical network introduced in [21] is used to test the proposed fuzzy-based FMECA approach and the comparison approach for the FMECA methods; in [21] the author conducts a classical FMECA analysis to identify and prioritize the failure modes in a specific smart grid test system.

The Fuzzy Logic parameters chosen to perform the needed computations will be presented, with both serving as a base for the future discussion between the classical and Fuzzy FMECA analysis.

Figure 4 shows the basic architecture of the smart grid test system analyzed in [21]. This grid can be divided into two subsystems: the power network and the cyber network.

Table 4 shows three sets of membership functions selected for the applications. Both Type-I and Type-II fuzzy system will. use the same set of membership functions to help maintain coherency in the results

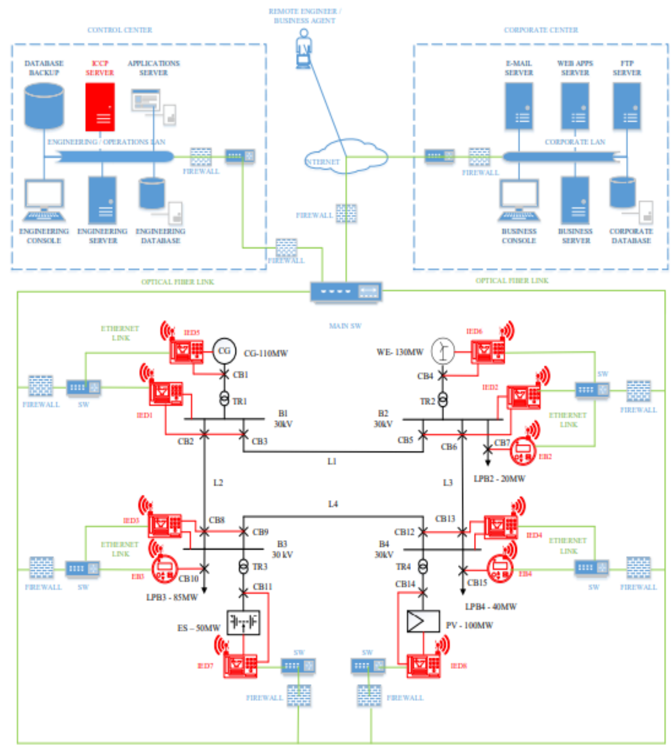

Figure 5 – Study case smart grid

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

Table 4 – Three sets for the Fuzzy Logic reasoning

Moreover, there are two parameterization rules: the first one is denoted as "Standard", where this perspective 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' 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 its attributed percentage due to the lack of data regarding this risk factor category.

The other parameterization rule is the Pedrycz's view – denoted as "50% overlap". This perspective is based on [22], 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.

For each parameterization one will have fifteen simulations as described in Table 5

	Type-I	Type-II lags and scales			
		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

Table 5 – All combinations used in the Fuzzy Logic reasoning

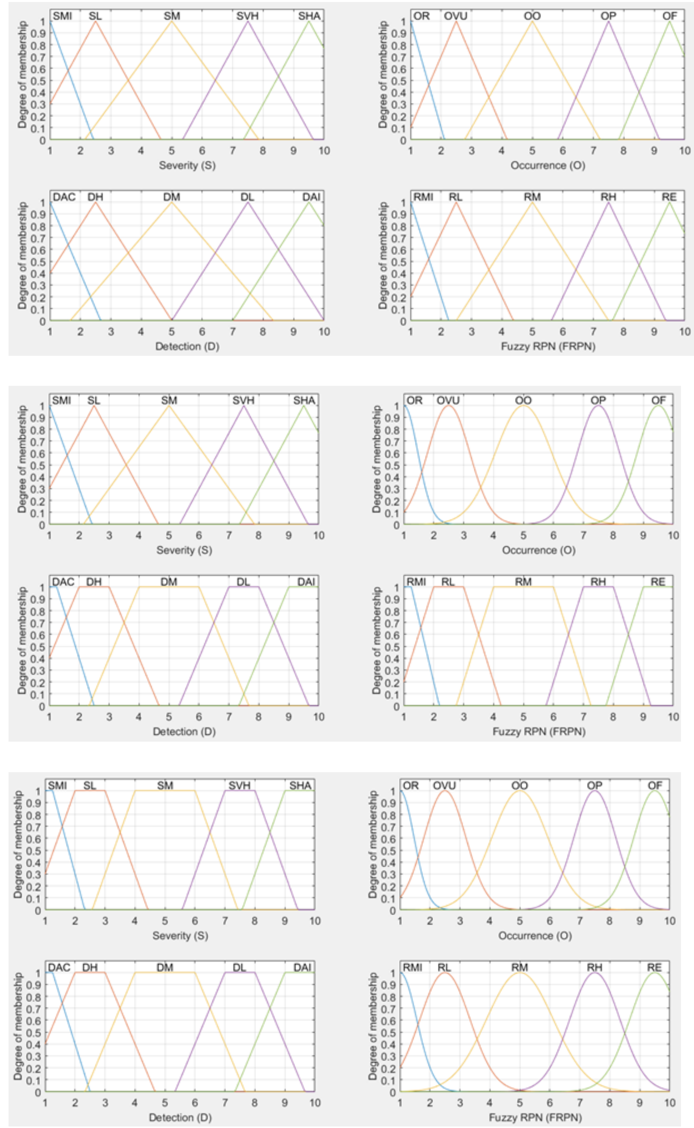

Figure 6 –The 3 sets represented for T1-1,T1-2,T1-3

IX. Results: Classical vs Fuzzy FMECA

The case study used for this dissertation is based on a classical FMECA procedure conducted by the author of [21]. From that conventional FMECA analysis, a new risk prioritization model presented by the authors of [10] 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 RPN conventional computations, in accordance with the weight scenarios described in Table 1. In the course of time, two of the six presented 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 FMECA-based RPI 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 [21] and creates a new ranking prioritization order. In this work, there will be four Fuzzy approaches: 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 approaches will be conducted by applying each of the three sets of membership functions described in Table 7.2, generating in total fifteen simulations for each Fuzzy approach – 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" (see Table 4).

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" of the four Fuzzy approaches, 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.

A. Classical FMECA based on RPI function

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 (2) 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 equation (3) can be applied, in order to obtain the delta risk drivers that compose the RPI function.

From the six suggested weight scenarios described in 1, two were selected to be adopted in this dissertation: Scenario 4 and 5 – as exemplified in [10]. 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% weight, depending on the scenario, while the Detection is always characterized by a 20% weight.

For the application of equation 5, the only assumptions left to be made are the correcting factors defined by the authors in [10], 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.

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

B. Classical 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 system, 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. From those fifteen obtained results, the best three from each of the Fuzzy-types, I and II, are selected for a deeper analysis. In Table 6 and 7, the three Type-I and the three Type-II simulations with the best agreement coefficient are illustrated, for each parameterization. In both tables, T1-1 to T1-3 correspond to the Fuzzy Type-I simulations with each of the three sets described in Table 4, 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 its lag and scale values.

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 6 – Three highest Kappa, Type-I and Type-II, for "Standard" 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

Table 7 – Three highest Kappa, Type-I and Type-II, for "50% overlap" parameterization

From the analysis with all the 43 failure modes regarded for this dissertation, 2 radar charts can be drawn. From the two reproduced radar charts illustrated in Figure 7, 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. In this dissertation, with the tool of the Cohen's Kappa, a thorough analysis of the methodologies (reference vs Fuzzy) was made to gather an opinion on which would represent better the rank prioritization needed in the context of a smart grid.

The appearance and application of agreement coefficients in the FMECA context, 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 on its scores on the proximities between rankings

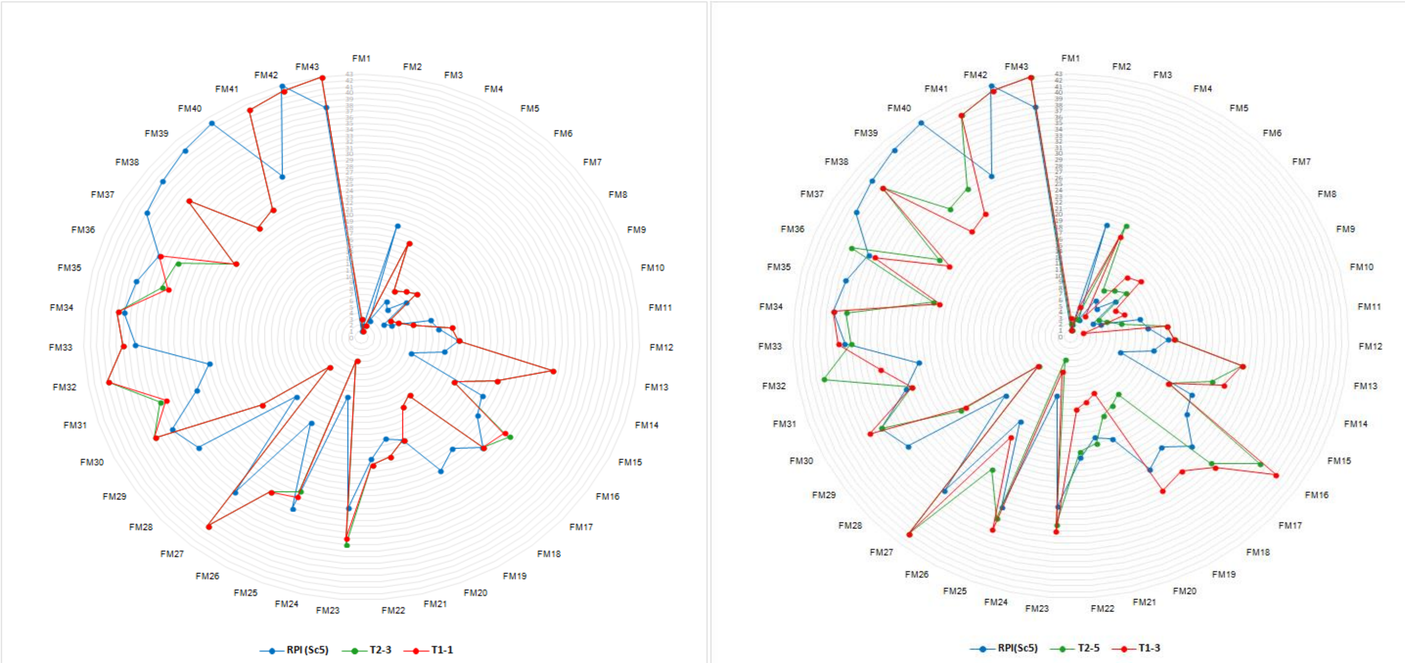

Figure 7 – 2 radar charts for a better clarification of the differences between methodologies

X. Extra Analysis

A. *Best Fuzzy case with RPN classical prioritization*

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 Sc5 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 [10] 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. These 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.

B. *Triangular vs. Trapezoidal membership functions*

An analysis of the theoretical advantage and stability of the triangular membership functions. For that purpose, four tests – T1-1 and T2-3, from each parameterization – using the set 1 of membership functions, 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" Sc5 used in this dissertation. Theoretically, as described by Pedrycz in [22], 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 6 the agreement coefficients generated from the comparisons with Sc5 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 Sc5, a classification based in Table 3

Table 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: the trapezoidal function has a larger interval of ratings with a full degree of membership.

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, the ratings 2 and 3 would only have a degree of membership equal to 0.75, while if the functions to be applied were trapezoidal, both ratings 2 and 3 would have a full degree of membership, equal to 1.

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.

XI. 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 the smart grids. 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 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 2 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 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 whichever the object of the analysis. In this case, the RPI model was already previously applied to the FMECA context, conferring its suitability.

A. *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:

a) *The definition of specific weights, critically reasoned, for each of the risk factors that compose the FMECA methodology.*

b) *The utilization of other 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 what study is being performed.*

c) *The introduction of new models, carefully selected, to define the "rank base", the reference rank used throughout the work to compute the desired simulations.*

d) *The application of other coefficients of agreement that may be considered relevant for the comparison of Fuzzy-FMECA methodologies.*

XII. References

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