Algerian Journal of Research and Technology
https://doi.org/10.58681/ajrt.22060105
A.J.R.T Volume 6 (N°1) (2022) 36 – 47
Selection and peer-review under responsibility of the scientific committee of The 1st International Symposium on INDUSTRIAL ENGINEERING, MAINTENANCE AND SAFETY IEMS'22.

Failure Mode, Effects, and Criticality Analysis Improvement Using a Fuzzy Criticality Assessment Based Approach

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Published. April 15, 2022.

DOI: https://doi.org/10.58681/ajrt.22060105

Abstract. Failure mode, effects, and criticality analysis (FMECA) is a proactive quality tool that allows the identification and prevention of the potential failure modes of a process or product. In a conventional FMECA, for each failure mode, three risk parameters, namely frequency, non-detection, and severity are evaluated and a risk priority number (RPN) is calculated by multiplying these parameters to assess one signal criticality. However, in many cases, it suffers from some shortcomings regarding the decision-making and the situation where the information provided is ambiguous or uncertain. Thus, in this paper, a fuzzy criticality assessment-based approach is used to improve the exploitation of the FMECA method. The new model is based on replacing the traditional calculation of criticality (RPN) with a fuzzy inference engine. The authors used fuzzy logic where the different parameters are shown as members of a fuzzy set, which is fuzzified by using appropriate membership functions to evaluate the criticality and then prioritizing failure causes as well preferring actions for controlling the risks of undesirable scenarios.

Keywords. Fuzzy Logic, FMECA, Criticality assessment, RPN, Failures mode.

INTRODUCTION

Industry plays a crucial role in the economies of most countries, contributing (3.8% to 4%) of annual world gross domestic product. However, various activities, complex working environments, and dangerous failures in processes, products, services, or equipment are frequently a source of challenge for any organization. Companies have evolved research methods to avoid or prevent these unexpected events. Failure mode effect and criticality analysis (FMECA) is commonly used as a proactively reliable analytical technique for identifying, ranking, and reducing these failures(Liu et al., 2019). For each failure mode, three criticality factors, namely, non-detection (ND), frequency (F), and severity (S), are evaluated, and a risk priority number (RPN) is calculated by multiplying these factors to assess the criticality value (Panchal et al., 2019).

Furthermore, it proves in a variety of applications that the FMECA still has several shortcomings. First, various combinations of S, F, and ND factors may give a similar RPN value. However, the criticality evaluation for the failure modes can be vastly dissimilar. Second, in the estimation of RPN, the relative importance of criticality parameters is not considered. Another drawback of the classical RPN is the specific evaluation of criticality parameters regarding each failure mode. However, because of limited data, time pressure, or experts' information processing abilities are limited, risk parameters cannot be specified precisely, and the criticality evaluation information may be uncertain or imprecise (Chakhrit and Chennoufi, 2021b).

To resolve the shortcomings, many improved FMECA approaches have been proposed by many researchers as a solution. (Wang et al., 2009) used the criticality parameters F, ND, and S as fuzzy values for risk evaluation and prioritization of failure modes in FMECA. (Yang et al., 2008) described a new, efficient Bayesian reasoning methodology based on fuzzy rules for ranking failures mode, which is designed to address some of the shortcomings of traditional fuzzy logic (i.e. rule-based) methods in FMECA. For assessing smart cities' information security and risks,(Li et al., 2018) proposed an FMECA approach based on the GRA approach and the trapezoidal fuzzy numbers. By using a flexible if-then rule set derived from expert knowledge and experience, (Liu et al., 2013) organized and classified the criticality assessment methodologies in FMECA to explain the relationships between criticality factors and riskiness. (Lin et al., 2014) used a fuzzy linguistic technique to transform expert subjective cognition into an information entity to obtain numeral values of criticality parameters for analyzing and constructing an evaluation model to ameliorate the safety of medical devices. In the LPG refueling station, fuzzy logic associated with the expert investigation was used to assess the basic event probability of failures mode (Rajakarunakaran et al., 2015). Fattahi and Khalilzadeh (2018) developed the fuzzy weighted RPN to rank failure modes in order of priority. At the same time, Can (2018) proposed the intuitionistic fuzzy RPN to rank corrective and preventative techniques in order of priority. Other hybrid approaches have been used to evaluate the orderings of criticality for failure modes, which used the evaluation laboratory (DEMATEL) approach, the fuzzy ordered weighted averaging (O,WA), and the decision-making trial for prioritizing the criticality of failures (Chang and Cheng, 2011). More recently, Chakhrit and Chennoufi (2021a), developed a combined criticality assessment structure integrating GRA and AHP under a fuzzy environment to evaluate and rank failure modes during the production process of a gas turbine system.

According to the discussion cited above, the novelty and the contribution of this work are:

- To avoid the complexity and decrease the uncertainty of the judgments, for each failure mode, the authors replaced criticality calculated from the classical method with a fuzzy inference system. The latter can treat different types of ambiguities and uncertainty in assessing failure modes respectfully to the criticality factors. During modeling, by the imprecise linguistic expressions and the fuzzy inference system, human expertise is incorporated. The ability to grasp inference systems empowers users and professionals to customize them effectively.

The rest of the paper is organized as follows: In Section 2, an overview of the conventional FMECA method. The fuzzy inference methodology is presented in Section 3. Then; a case study is presented in Section 4. Finally, the results and conclusion are presented in Sections 5 and 6, respectively.

CONVENTIONAL FMECA METHOD FOR CRITICALITY EVALUATION

In FMECA, the RPN is acquired by multiplication of three inputs, frequency of occurrence (F), severity, and non-detection, as follows (Derradji and Hamzi, 2020):

$$RPN = Occurrence \times Severity \times Non\ detection \qquad (1)$$

The frequency is expressed as the probability that a precise cause will appear. Severity is an evaluation of the impact of a possible failure mode. Detection is an evaluation of the current design control's ability to detect potential failures (Khalilzadeh et al., 2020). In global, these three parameters are evaluated by FMECA. As the RPN is a measure of failures criticality, it is used for ranking failures and prioritizing actions. The latter will then be taken with priority given to the failure with the highest RPN. Tables 1–3 show the factors to which we refer. The tables show that the standard FMECA uses five scales to assess the frequency, non-detection, and severity. The failures can be minimized or decreased by prioritizing them for corrective action according to their criticality implication (Guetarni et al., 2019). As mentioned previously, the FMECA method has several drawbacks in the way computations are done, and the findings are interpreted. To overcome shortcomings and restore the traditional FMECA methodology's efficacy, a fuzzy criticality assessment-based approach is presented in Section 3.

Table 1. Probability of occurrence Scales

Probability of occurrence	**Score**	**Percentage {%}**
Remote	1	<0.01
Low	2.3	0.01 to 0.1
Moderate	4.6	0.1 to 0.5
High	7.8	0.5 to 1
very-high	9.10	>1

Table 2. Non-detectability scales

Non-detection	**Score**	**Non-detectability {%}**
Remote	1	0 to 5
Low	2	6 to15
	3	16 to 25
Moderate	4	26-35
	5	36-45
	6	46-55
	7	56-65
High	8	66-75
	9	76-85
	10	86-100
very-high		

Table 3. Severity scales

Rank	**Severity effect**	**Meaning**
1	Remote	Less MTTR greater than1 an hour
2-3	Low	MTTR greater than 1 day
4-5-6	Moderate	MTTR between 1to 4 days
7-8	High	external repair intervention
9-10	very-high	Line shut down or production loss

PROPOSED FUZZY CRITICALITY ASSESSMENT METHODOLOGY

The fuzzy criticality evaluation method is based on Zadeh's principle of fuzzy sets (Zadeh et al., 1996). Offers a more robust to evaluate criticality correlated with different failure modes, where parameters, frequency of occurrence (F), severity (S), non-detection (ND), criticality (C) used in the traditional method will be fuzzified by the use of an appropriate membership function applying of knowledge rules IF-THEN resulting from expert judgment, in which the relation: criticality = frequency _ severity _ non-detection, is turned into a rule of the following type:

"If the frequency is X, severity is Y and non-detection is Z then Criticality is C".

Where X, Y, Z, and C are the linguistic variables' qualitative descriptors of frequency, severity, nondetection, and criticality, respectively. The framework of the fuzzy approach is given in figure 1. The implementation of this fuzzy methodology based on three major modules constituting the inference system of Mamdani min-max is presented as follows.

Fuzzification

Development of crisp input into fuzzy values in the form of membership functions (Moreno-Cabezali et al., 2020), the latter are developed to represent inputs and output variables graphically (Fig. 2). The procedure for determining the fuzzy criticality consists of using fuzzy partitions with "Gaussian" shaped functions to describe F, S, and ND parameters used in the study as represented in tables 1–3, the illustrative expressions explaining the inputs are, remote, low, moderate, high, very high. To represent the output variable, trapezoidal and triangular membership functions are used graphically, as figure 3 illustrated.

Fuzzy inference rules

The inference engine uses the basis of linguistic rules and the fuzzy implication processes to transform the fuzzy input sets (resulting from fuzzification operation) into fuzzy output sets (Raeihagh et al., 2020). The fuzzy output is obtained using the max-min inference method, according to the following steps:

- Identification of the activation level for each rule: the truth value allocated to the "antecedent" (premise) of each rule is calculated and then applied to the "conclusion" of this rule.
- Inferencing: in the inference step, the output of rule Ri is calculated using the conjunction operator (min); therefore, the selected smallest fuzzy value from the three inputs.
- Aggregation: To obtain the system's global output, precise outputs from each rule are integrated using the operator disjunction max. All parameters and rules implemented in the Mamdani model for the generation of fuzzy inference rules are shown in Appendix.

Defuzzification

Defuzzification algorithms of various types have been established, and there is no single best algorithm for all applications. However, "the average of maximum" method and the most popular defuzzifier "centroid" is used for simplicity and speed of processing, which is defined by the following equation (Patel et al., 2019):

$$\text{Defuzzified value} = \frac{\int_i^{\mu}(x)x\,dx}{\int_i^{\mu}(x)\,dx} \qquad (2)$$

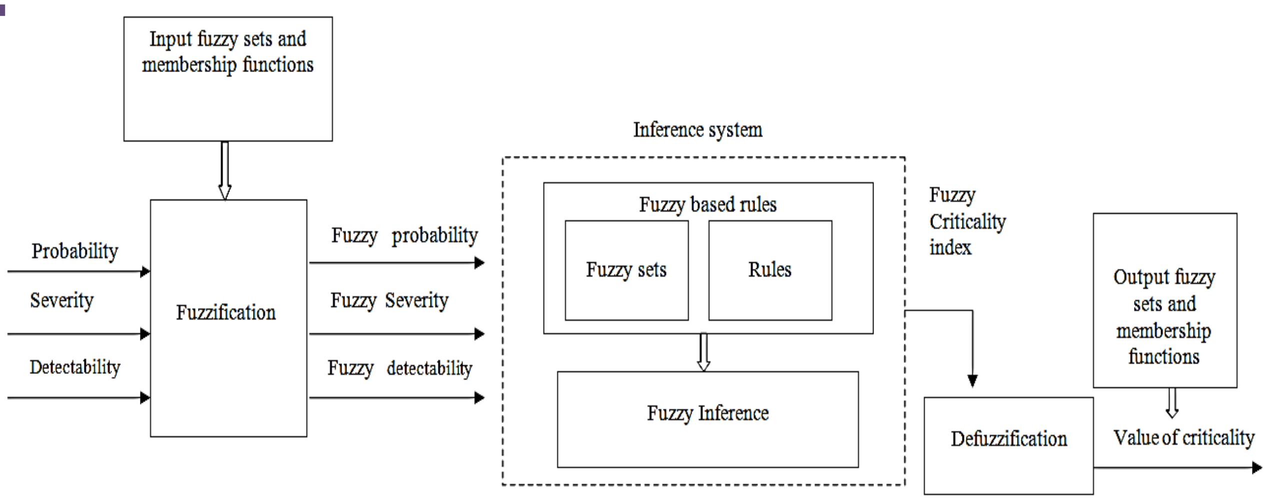

Fig.1. The procedure of the fuzzy proposed model.

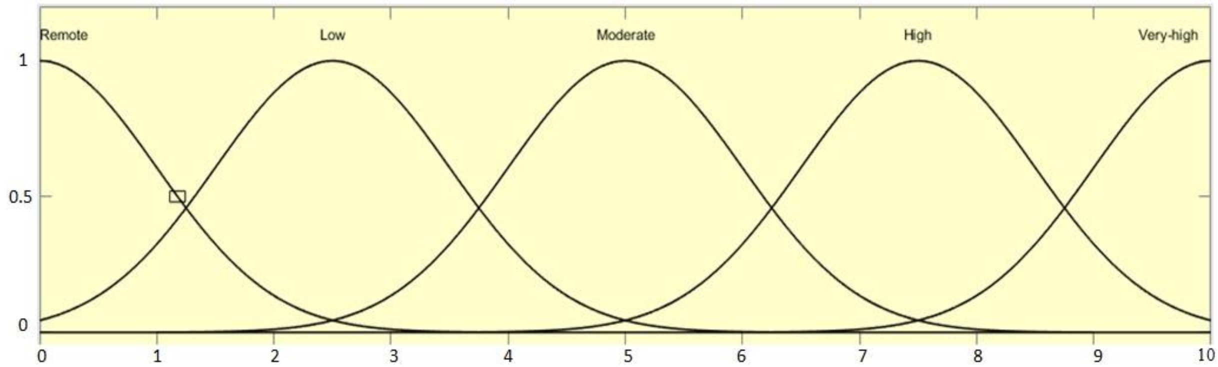

Fig.2. Membership functions are generated for, probability, severity, and detection.

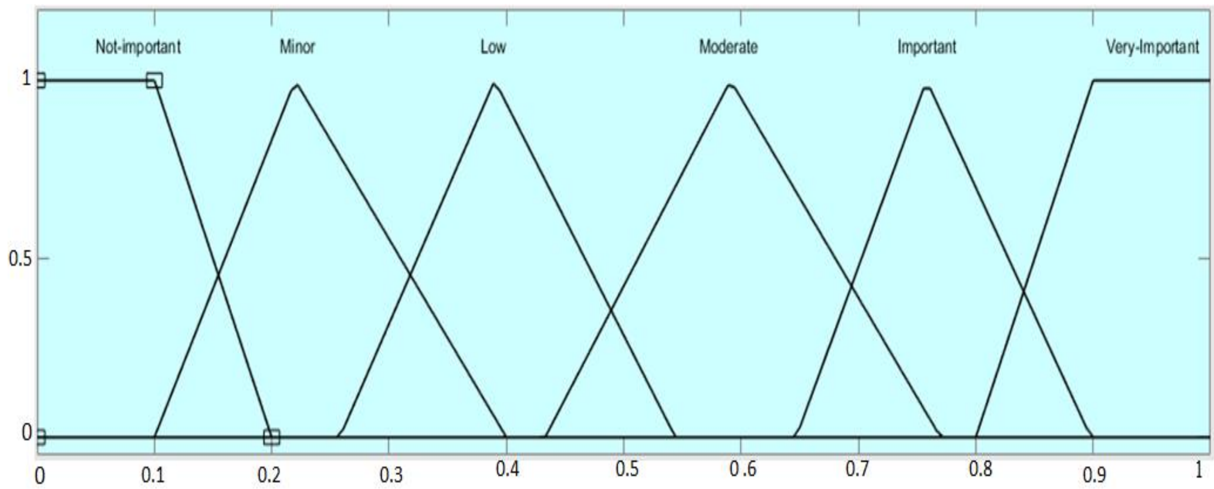

Fig. 3. Membership functions of Output variable “criticality.

ILLUSTRATIVE CASE

In this part, we suggest applying this methodology in a gas turbine system (V94.2), It is a combustion engine that can convert mechanical energy from natural gas or other liquid fuels. This energy then drives a generator that produces electrical energy. It is electrical energy that passes to homes and companies along power lines(de Araújo et al., 2020). This system is given in figure 4 and table 1. Properties of sandy soils

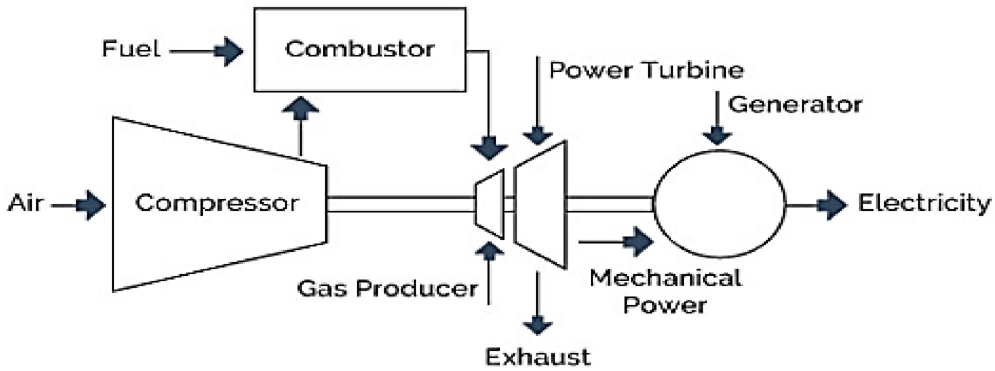

Fig.4. Gas turbine design.

Failure mode analysis by conventional FMECA method

For the gas turbine system, the FMECA analysis was performed, as shown in table 4, and the associated RPN values have been calculated. The failure modes are assessed by providing a score for the severity, frequency, and non-detection factors. For this, a ten-level score system is employed, as shown in table 1-3. An expert opinion is consulted while rating these criticality factors.

According to the FMCEA group recommendation, the RPN results allow for prioritizing actions to ensure that the gas turbine operates continuously and safely. Due to a lack of data and uncertainty, expert opinions were utilized to estimate the criticality factors.

Failure mode analysis by the fuzzy model proposed

The RPN values are calculated using the fuzzy inference technique to represent the fuzzy theory sets. As given previously, the process comprises one output and three input variables. The inference engine determines the RPN by incorporating three input factors. A Gaussian membership function is used for input variables to generate real numbers to fuzzy sets as given by equation 3. Trapezoidal and triangular membership functions are used for the output variable through equations 4 and 5

$$f(x,\sigma,c) = \exp\left(\frac{-0.5(x-c)^2}{\sigma^2}\right) \tag{3}$$

$$s(z;b1,b2,b3,b4) = \begin{cases} 0,\ldots\ldots\ldots\ldots\ldots\ldots z \le b1 \\ \dfrac{z-b1}{b2-b1}\ldots\ldots\ldots. b1 \le z \le b2 \\ 1,\ldots\ldots\ldots\ldots\ldots\ldots b2 \le z \le b3 \\ \dfrac{b4-z}{b4-b3}\ldots\ldots\ldots.. b3 \le z \le b4 \\ 0,\ldots\ldots\ldots\ldots\ldots\ldots. b4 \le z \end{cases} \tag{4}$$

$$f(z;b1,b2,b3) = \begin{cases} 0,\ldots\ldots\ldots\ldots\ldots\ldots z \le b1 \\ \dfrac{z-b1}{b2-b1}\ldots\ldots\ldots. b1 \le z \le b2 \\ \dfrac{b3-z}{b3-b2}\ldots\ldots\ldots.. b2 \le z \le b3 \\ 0,\ldots\ldots\ldots\ldots\ldots\ldots. b3 \le z \end{cases} \tag{5}$$

Five and six levels are utilized for input and output variables, respectively, as given in figures 2, and 3. Expert opinion is employed as language terms for the frequency, detection, and severity values of failures. As shown in the appendix, twenty-seven rules are used to determine criticality priority in the inference system. The Mamdani min/max approach was used for the inference process as presented in figure 5 (case for the failure causes D and G). Wile, the gravity center technique was utilized for defuzzification (see equation 1). The gravity center method is described as a centroid defuzzification method for determining the fuzzy set's center of gravity point on the fuzzy interval. The traditional and fuzzy risk priority number results are presented in table 4.

Table 4. Ranking comparison between conventional and proposed fuzzy model

Item	Failures mode	Effects	Causes	Criticality			Conventional RPN	Rank	Fuzzy RPN	Rank
				F	S	ND				
Compressor (Rotor)	Vibration	-fluctuation of speed indicators	Faulty indication of vibration (Cause A)	2	3	6	36	5	0.137	7
			Loose mount (Cause B)	7	4	1	28	6	0.478	3
			Faulty bearings (Cause C)	7	4	3	84	4	0.257	6
Compressor (Stator)	Stall	Increase in temperature + hang-up or drop-off speed indicator	Variable stator vanes binding (Cause D)	6	5	6	180	1	0.403	5
Combustion chamber	Leakage of gas	output power Reduction	Cracking of cases (Cause E)	4	6	7	168	2	0.522	1
Turbine rotor	Vibration .	-fluctuation of speed indicators	-Defective bearings (Cause F)	6	7	4	168	2	0.497	2
Turbine nozzle	Burnt of vanes	Overpressure.	over-temperature Gas (Cause G)	2	6	9	108	3	0.436	4

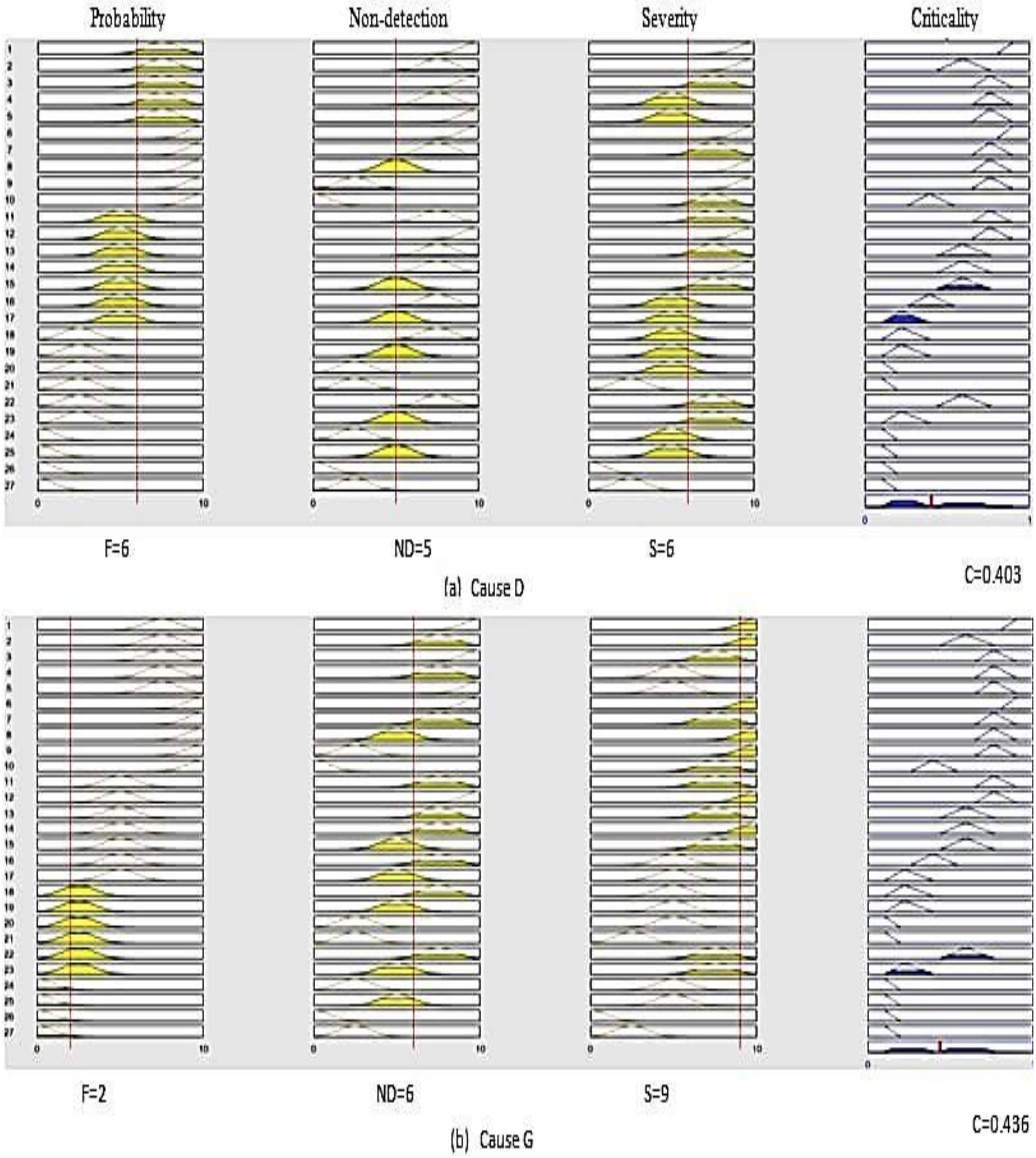

Fig.5. Fuzzy inference process for cause D and G.

RESULTS AND DISCUSSION

Table 4 represents the results of the various methods of analysis for the gas turbine system. As seen previously in the conventional FMECA method, the RPN number is estimated by multiplying each failure mode's factor scores. The system FMECA assists us in producing prevention both at the functioning levels and system conception to prevent the failure mode criticality. Then, a similar strategy is used for other elements and sub-systems. According to the findings, safety amelioration activities at various stages of processes were proposed.

As shown in table 4 the ranking of causes acquired from the classical FMECA is changed (cause D > cause E, F >cause G > cause C> cause A> cause B), For instance, Cause D is the major critical cause regarding RPN however, after using fuzzy criticality evaluation it classifies at the 5th with a value of 0.403. At the same time, Cause E is the farthest critical with an overall value of 0.522, the arrangement of failure caused by a fuzzy method is (Cause E >Cause F>Cause B >Cause G >Cause D >Cause C>Cause A).

Comparing classical results of FMECA with the fuzzy approach the limitations associated with traditional FMECA can be observed, the most critical drawback of the conventional FMECA is that the different combinations of three-parameter ratings generate an identical RPN value; however, the criticality representations can be different, For instance, the failure cause E and F have the same RPN of 168; while the criticality consequences of any of these events can not exactly be the same, but the fuzzy inference differs in those and it would help define priority on those causes. The second constraint of the classical method: ignores the importance between F, Nd, and S. The three inputs should be of equal importance but the relative importance between the inputs exists in real applications; for example, a cause G with a low probability, very high severity, and moderate detection (2,6,9) with a lower RPN of 108 than one with all parameters moderate as a failure cause D (6,5,6) with RPN 180. Conversely, the fuzzy system model can be shown that cause G has a higher value than cause D 0.436,0.403 respectively as shown in figure 5, and so will have a higher priority for corrective-preventive action.

CONCLUSION

The FMECA method was widely identified as a normalized engineering process for identifying ranking potential failures mode in processes and products. The conventional RPN method was widely criticized for its disadvantage, particularly in assessing failure modes and RPN calculations. In this study, new criticality ranking models for evaluating the risk of failures in FMECA are suggested.

Compared with tare conventional method, the merits of fuzzy-based criticality assessment methodology allow experts to more flexibly and objectively combine the frequency, undetectability, and severity of failures mode by using their judgment to overcome the difficulties arising in performing the standard FMECA procedure.

A case study of a gas turbine system showed the applicability of the fuzzy proposed approach by providing encouraging results regarding the estimation of criticality and then prioritizing failure causes of the system for taking corrective or preventive actions, this latter will then be taken with priority given to the failure with the highest criticality value to eliminate or reduce the probability of occurrence and the severity of the undesirable scenarios.

Our future research continues to work on defining an algorithm to optimize the number of inference rules. Neural networks are recommended in this context.

APPENDIX

Rules of a combination of criticality parameters

Rules	Probability	Non-detection	Severity	Criticality
1	High	Very-High	Very-High	Very-important
2	High	High	Very-High	Moderate
3	High	Very-High	High	important
4	High	High	Moderate	important
5	High	Very-High	Moderate	important
6	Very-High	Very-High	Very-High	Very-important
7	Very-High	High	High	important
8	Very-High	Moderate	Very-High	important
9	Very-High	Low	Very-High	important
10	Very-High	Remote	High	Low
11	Moderate	High	High	important
12	Moderate	Very-High	Very-High	important
13	Moderate	High	High	Moderate
14	Moderate	High	Very-High	Moderate
15	Moderate	Moderate	High	Moderate
16	Moderate	High	Moderate	Low
17	Moderate	Moderate	Moderate	Minor
18	Low	High	Moderate	Minor
19	Low	Moderate	Moderate	Minor
20	Low	Low	Moderate	Not-important
21	Low	Low	Low	Not-important
22	Low	High	High	Moderate
23	Low	Moderate	High	Minor
24	Remote	Low	Moderate	Not-important
25	Remote	Moderate	Moderate	Not-important
26	Remote	Remote	Remote	Not-important
27	Remote	Low	Low	Not-important

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