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Fuzzy-FMSA: Evaluating Fault Monitoring and Detection Strategies Based on Failure Mode and Symptom Analysis and Fuzzy Logic

Failure mode and symptoms analysis (FMSA) is a relatively new and still not very much employed variation of failure modes, effects and criticality analysis (FMECA), a technique broadly used in reliability, safety, and quality engineering. While FMECA is an extension of the well-known failure mode and effects analysis (FMEA) method, primarily used when a criticality analysis is required, FMSA focuses on the symptoms produced by each considered failure mode and the selection of the most appropriate detection and monitoring techniques and strategies, maximizing the confidence level in the diagnosis and prognosis. However, in the same way as FMECA and FMEA, FMSA inherits some deficiencies, presenting somewhat biased results and uncertainties intrinsic to its development, due to its own algorithm and the dependence on knowledge-based inputs from experts. Accordingly, this article presents a fuzzy logic application as a complement to FMSA in order to mitigate such uncertainties' effects. As a practical example, the method is applied to a Kaplan turbine shaft system. The monitoring priority number (MPN) obtained through FMSA is compared to the fuzzy monitoring priority number (FMPN) resulting from fuzzy logic application, demonstrating how the proposed method improves the evaluation of detection and monitoring techniques and strategies.
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Introduction

Currently, industrial applications rely on high-performance mechanical systems that are subject to specific operating

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conditions, which require high reliability, robustness, and low operational requirements [1]. On the other hand, only through maintenance, the greater reliability of these assets can be achieved. However, maintenance costs must be optimized as well, in contrast to the safety implications of not performing any maintenance at all. To reach this goal, each industry develops its own philosophy for planning and performing maintenance activities [2] and different tools and methods are combined [3].

Considering the electricity generation industry, it is noticeable how the role of mechanical maintenance changed in the past decades, particularly for rotating machinery. In practice, with the use of modern maintenance techniques, as predictive maintenance and reliability centered maintenance (RCM), maintenance is no longer seen as the result of actions necessary to keep an equipment or component integrity, but rather as the process to determine what must be done and to ensure that any physical component continues to do whatever it was designed to do under the existing circumstances and operational conditions [4,5].

The reasons for such a change are diverse and may depend on the country where the power plant is located. They also can occur naturally or be driven by external factors such as economic or governmental issues. This is the case for many countries, including Brazil [2,6–8].

It can be said that the new forms of commercialization and the need to guarantee the energy supply has a great impact on maintenance policies in energy companies. Reducing the number of shutdowns and providing a longer interval between scheduled maintenance outings bring clear economic advantages. The use of diagnosis and prognosis tools might be the best way to achieve this goal and also minimize the probability of failure, system downtime, and maintenance costs [3,9,10].

In the Brazilian case, there was no coincidence in the fact that condition monitoring and fault diagnosis (CMFD) systems began to be seen as important tools to establish new parameters for hydrogenerator reliability just after the electricity market opening in the early nineties. However, since monitoring and diagnosis are essential to the success of predictive maintenance and RCM, the lack of knowledge in this field can compromise maintenance itself.

There are several approaches in terms of techniques and technologies to perform the instrumentation and monitoring of rotating machinery, and even more so of hydrogenerators. Some works already address this issue, focusing on the maintenance techniques that one wishes to apply to the equipment [11–17].

On the other hand, in order to provide better means to ensure the continuous operation of a piece of equipment, fault analysis techniques such as fault tree analysis (FTA), hazard and operability study (HAZOP), and failure mode and effect analysis (FMEA) are usually adopted, allowing the identification of the most critical items of a system, the investigation of the causes of failures, and the prioritization of maintenance actions.

Among all failure analysis techniques, FMEA [18–22] is probably one of the most popular and more widely applied techniques in industry. In addition, although it has been developed more than 50 years ago, there are still many ongoing researches, both from academy and industry, seeking its improvement and overcoming unsolved issues.

However, in order to go beyond the ability to analyze failures and also to be able to evaluate fault diagnosis and prognosis, failure mode and symptoms analysis (FMSA), a relatively new and not well-known technique appears to be an interesting alternative.

Failure mode and symptoms analysis focuses on the symptoms produced by each considered failure mode and in the selection of monitoring techniques and strategies that maximize the confidence level in the diagnosis and prognosis [10,23,24]. However, in the same way as failure modes, effects and criticality analysis (FMECA) and FMEA, FMSA inherits some shortcomings, with biased results and uncertainties intrinsic to its development due to its own algorithm and the dependence on knowledge-based inputs from experts.

To mitigate such uncertainties' effects, adequate modeling tools can be used, as is the case of the fuzzy set theory [25]. In such a situation, where access to accurate information is not possible, fuzzy logic can be a useful and powerful tool because it resembles human reasoning in the use of approximate information to support decision making [26,27].

The proposed method seeks to assist maintenance teams in decision making regarding asset management in two main aspects: the selection and improvement of applied maintenance techniques, including issues related to fault detection and diagnosis, and the definition of maintenance significative items. FMSA brings a more predictive feature than, for example, FMEA, as it considers the diagnosability and the prognosability of a failure, rather than the probability of failure occurrence. In other words, it is understood that predicting a fault degradation is more relevant than its occurrence rate, which directly influences the first-mentioned aspect. On the other hand, the application of fuzzy logic, in this case, allows to mitigate uncertainties inherent to the FMSA technique, resulting in a more coherent result, and assisting in the second aspect previously mentioned.

Accordingly, to assist maintenance teams in decision making regarding asset management, this article presents a method based on FMSA and fuzzy logic. Two main aspects can be refined with this method: the selection and improvement of applied maintenance techniques, including issues related to fault detection and diagnosis, and the definition of maintenance significant items.

As an example, the method is applied to a Kaplan turbine shaft system and the results of the FMSA application with and without the additional fuzzy step are discussed and compared.

FMSA: Failure Mode and Symptoms Analysis

As mentioned before, the aim of FMSA is to select monitoring technologies and strategies that maximize the confidence level in the diagnosis and prognosis of any given failure mode [10].

This process is essentially a modification of FMECA and an extension of FMEA, focusing on the symptoms produced by each failure mode identified and the subsequent selection of the most appropriate detection and monitoring techniques and strategies. Table 1 shows the FMSA worksheet with the information needed to conduct the FMSA process. Each column represents a type of information and an alphanumeric coding was used to fill in the proposed table and allow the understanding of how each column correlates with the others.

In the evaluation process, each considered component (C_i) must have at least one function (F_i) listed and several failure modes (FM_i). Every failure mode is associated with a single effect (FE_i) and one or more possible root causes (RC_i). Root causes can have several symptoms (FS_i), which can be detected by more than one different method (DM_i) associated with a location (ML_i) and a monitoring frequency (MF_i).

Next, experts must estimate the severity and likelihood of detection of each considered failure mode, considering its different root causes, symptoms, and detection methods, in addition to the confidence level of diagnoses and prognoses. The result is the monitoring priority number (MPN) obtained by the multiplication of each of the factors mentioned above.

More than one result for the MPN value can be found for each failure mode, depending on the combination of factors considered in the analysis. Thus, not only a criticality evaluation of each considered failure mode can be made but also an assessment of which different forms of monitoring would be more efficient, or which symptoms could be easier to identify for the same failure mode. In so doing, the most critical cases are associated with lower MPN values and the most favorable cases to higher values.

The likelihood of detection (DET) is rated from 1 to 5, being 1 the worst-case scenario and 5 the best-case scenario. It is designed to reflect the overall detectability of a failure mode irrespective of the following accuracy of diagnosis or prognosis. This rating must highlight failure modes that produce symptoms that are detectable but unrepeatable, undetectable, not measurable in practice, or symptoms that may be masked by other failure mode symptoms.

As a general idea, the detection grades must be given considering these guidelines:

(1) There is a remote likelihood that this failure mode will be detected;
(2) There is a low likelihood that this failure mode will be detected;
(3) There is a moderate likelihood that this failure mode will be detected;
(4) There is a high likelihood that this failure mode will be detected; and
(5) It is virtually certain that this failure mode will be detected.

The ranking for severity (SEV) will be related to any previous FMEA or FMECA analysis and is designed to rank individual failure modes by risk. This is estimated on a scale of 1–4, being 1 the best-case scenario and 4 the worst-case scenario, which is the reverse order of the one presented in the ISO standard 13379-1 [10]. In this case, the following criteria were used for ranking severity:

(1) Any event that could potentially cause the loss of primary system function(s) resulting in significant damage to the system or its environment, and/or cause the loss of life or limb;
(2) Any event that could potentially cause the loss of primary system function(s) resulting in significant damage to the said system or its environment and negligible hazard to life or limb;
(3) Any event that degrades system performance function(s) without appreciable damage to either system or life or limb; and
(4) Any event that could cause degradation of system performance function(s) resulting in negligible damage to either system or its environment, and no damage to life or limb.

The reason for that deviation from the standard was to keep the idea that the lower the MPN, the lower the confidence level for detection, diagnosis and prognosis with the technique and frequency of monitoring selected. On the other hand, the authors did not change the severity scale (ranging from 1 to 4), unlike the scales of the other factors (all ranging from 1 to 5), following the ISO standard 13379-1 [10] recommendation in this aspect.

The predicted accuracy for diagnosis (DGN) is also rated from 1 to 5, being 1 the worst-case scenario and 5 the best-case scenario. This rating is designed to identify failure modes with symptoms that are detectable but unrepeatable, unknown, or not distinguishable from other failure mode symptoms. The diagnosis rating criteria are presented below:

(1) There is a remote likelihood that this failure mode diagnosis will be accurate;
(2) There is a low likelihood that this failure mode diagnosis will be accurate;
(3) There is a moderate likelihood that this failure mode diagnosis will be accurate;
(4) There is a high likelihood that this failure mode diagnosis will be accurate; and
(5) It is virtually certain that this failure mode diagnosis will be accurate.

The predicted accuracy for the prognosis (PGN) is also rated from 1 to 5, being 1 the worst-case scenario and 5 the best-case scenario. This rating is designed to identify failure modes with detectable but unrepeatable symptoms, not sensitive to changes in degradation, unknown failure rates, or failure modes with symptoms that are not distinguishable from other failure mode symptoms. The prognosis rating criteria are presented next:

(1) There is a remote likelihood that this failure mode prognosis will be accurate;
(2) There is a low likelihood that this failure mode prognosis will be accurate;
(3) There is a moderate likelihood that this failure mode prognosis will be accurate;
(4) There is a high likelihood that this failure mode prognosis will be accurate; and
(5) It is virtually certain that this failure mode prognosis will be accurate.

Dealing With Uncertainties Using Fuzzy Logic

Several methods extensively presented in literature, such as fuzzy and stochastic modeling, can be used to mathematically quantify uncertainties [28]. The appropriate model, however, must be chosen considering the problem uncertainty characteristics and boundary conditions [29].

Usually, probabilistic models are used to deal with these uncertainties and random variables or random processes are generated for describing nondeterministic parameters. In these cases, it is determinant that prior information, whether based on models, data, or knowledge, is available to estimate the prior distributions for a Bayesian approach.

If these assumptions are not met, alternative uncertainty models may be required. In these cases, parameters should be quantified based on a few data, which may be further characterized by inaccuracies due to uncertain measurements or changes in

Table 1 FMSA worksheet

Component	Functions	Failure mode	Failure effects	Root causes	Failure symptoms	Detection methods	Measurement location	Monitoring frequency	DET	SEV	DGN	PRG	MPM
C_1	F_1	FM_1	FE_1	RC_1	FS_1	DM_1	ML_1	MF_1					
				RC_2	FS_2	DM_2	ML_2	MF_2					
						DM_3	ML_3	MF_3					
				RC_3	FS_3	DM_4	ML_4	MF_4					
					FS_4	DM_5	ML_5	MF_5					
		FM_2	FE_2	RC_4	FS_5	DM_6	ML_6	MF_6					
						DM_7	ML_7	MF_7					
				RC_5	FS_6	DM_8	ML_8	MF_8					
C_2	F_2	FM_3	FE_3	RC_6	FS_7	DM_9	ML_9	MF_9					
					FS_8	DM_{10}	ML_{10}	MF_{10}					
					FS_9	DM_{11}	ML_{11}	MF_{11}					
						DM_{12}	ML_{12}	MF_{12}					
				RC_7	FS_{10}	DM_{13}	ML_{13}	MF_{13}					
						DM_{14}	ML_{14}	MF_{14}					
C_3	F_3	FM_4	FE_4	RC_8	FS_{11}	DM_{15}	ML_{15}	MF_{15}					

reproduction conditions, for example. In addition, some specialized knowledge and language assessments should be incorporated into modeling. In so doing, the expert only has an idea about the range of values of these parameters and a vague perception about which values are most likely to occur.

To adequately model this few and imprecise available information, a nonprobabilistic uncertainty model is required, considering sets of parameter values and subjective weighting information together. For this purpose, the fuzzy set theory can be an interesting alternative that can be used to allow the theoretical modeling of uncertain parameters and, consequently, take into consideration the subjective evaluation of given elements belonging to a set by means of a membership function.

Fuzzy logic transforms the vagueness of human sense into a mathematical formula, providing meaningful representation of measurement for uncertainties and inaccurate concepts expressed in natural language, such as subjective judgment [30,31]. This offers the possibility of properly considering nonstochastic uncertainty without making artificial assumptions whose validity could not be proved.

The mathematical modeling of fuzzy concepts was presented by Zadeh in 1965 [32], and the fuzzy logic concepts and definitions are easily found in literature [33–35].

Basically, if X is a nonempty set, $X \neq \emptyset$, a fuzzy set $\tilde{A}$ in X can be characterized by its membership function, given by Eq. (1), for all pairs $(x, \mu_A(x))$. In this case, $\mu_A(x)$ can be interpreted as the degree of membership $x \in X$ in fuzzy set $\tilde{A}$.

$$\mu_A(x) : X \rightarrow [0, 1] \tag{1}$$

Considering X a finite set, given by Eq. (2), the fuzzy set $\tilde{A}$ can be given by Eq. (3), where the sum of the right-hand side of the equation represents the union of terms where μ_i is the membership degree of x_i in $\tilde{A}$.

$$X = (x_1 \ldots x_n) \tag{2}$$

$$\tilde{A} = \sum_{i=1}^{n} \frac{\mu_i}{x_i} \tag{3}$$

Therefore, a fuzzy logic system (FLS) can be defined as a nonlinear mapping of an input data vector (dataset) to a scalar output data [32,36] and consists of four main components: fuzzification process, fuzzy rules, inference engine, and defuzzification process [37].

The first step, the fuzzification process, consists of gathering and converting a crisp set of input data to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms, and membership functions. Then, an inference is made in the light of a set of fuzzy rules. Finally, in the defuzzification process, the resulting fuzzy output is mapped to a crisp output using the corresponding membership functions.

During fuzzification, a fuzzy logic controller receives input data and analyses it according to user-defined charts called membership functions. Expert judgment and experience can be used for defining the degree of membership function for a particular variable.

The resulting fuzzy inputs are evaluated in the fuzzy inference engine, which makes use of a well-defined rule base consisting of If-Then Rules and fuzzy logic operations to determine the criticality level of a component. The fuzzy rules in the FLS are considered as the core of the inference process. The rule base describes the criticality level of a component for each combination of input variables. They are formulated in linguistic terms using two approaches: expert knowledge and expertise or a fuzzy model of the process.

The defuzzification process examines all the rule outcomes after they have been logically added and then computes a value that will be the final output of the fuzzy controller. During defuzzification, the controller converts the fuzzy output into a real-life data value [37]. It creates a fuzzy conclusion ranking that expresses the degree of risk of the item under analysis, which allows the prioritization for project revisions.

Defuzzification is performed according to the membership function of the output variable. There are different algorithms for defuzzification as well. The most popular method used in this process is the center of gravity (COG) or centroid method [35]. The centroid defuzzification method finds a point representing the center of gravity of the fuzzy set on a given interval and is the chosen approach in this work.

The Proposed Method

Figure 1 presents the proposed method framework. The process begins by collecting as much information as possible from the system under study. This information is initially used to develop a functional tree [38,39] and understand how the system and subsystems are linked. It is important to highlight that in order to perform a prognosis analysis a good knowledge of the system and of how the fault propagation process has been occurring is required.

After the functional tree development, the next step in the proposed process is the FMSA implementation. Then, the grades for diagnosis and prognosis accuracy, likelihood of detection, and degree of severity for each failure mode should be assigned to their respective columns, bearing in mind that a consistent rating throughout all analyses must be applied.

Next, in the fuzzification process each crisp input, that is, the grades for detection, severity, diagnosis, and prognosis, is converted into a membership degree representing how adequately the input belongs to the linguistically defined terms [37].

Among several other types, the triangular membership function was chosen to be applied in this work, mainly due to its simplicity. A triangular membership function, given by Eq. (4) and represented in Fig. 2, can be defined by its lower limit, a, its upper limit, b, and the modal value, m, being $a < m < b$.

$$A(x) = \begin{cases} (x-a)/(m-a) & \text{if } a < x \leq m \\ (b-x)/(b-m) & \text{if } m < x < b \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

As previously presented in the FMSA section of this work, detection (DET), diagnosis (DGN), and prognosis (PGN) have five distinct values as possible crisp inputs, while severity (SEV) has just four. Thus, for the first three cases, five linguistic terms were generated, while for the severity case, four linguistic terms were created.

The membership functions considered for the input values in this article were based on some assumptions:

(1) The knowledge of the specialists involved in this work;
(2) The fact that the choice of extreme values usually involves smaller uncertainties than the choice of intermediate values; and
(3) The fact that the core of the fuzzy numbers [40] defined by each membership function should match the grades previously considered in FMSA for severity, detection, diagnosis, and prognosis.

Figure 3 shows the generated membership functions. In the proposed approach, all membership functions were obtained from the common consensus of experts and brainstorms in meetings in which all participants were present.

The linguistic terms chosen to describe the input variables for detection (DET), diagnosis (DGN) and prognosis (PGN) are very low (VL), low (L), moderate (M), high (H), and very high (VH). On the other hand, for severity (SEV), the terms chosen to describe the input variables are very low (VL), low (L), high (H), and very high (VH).

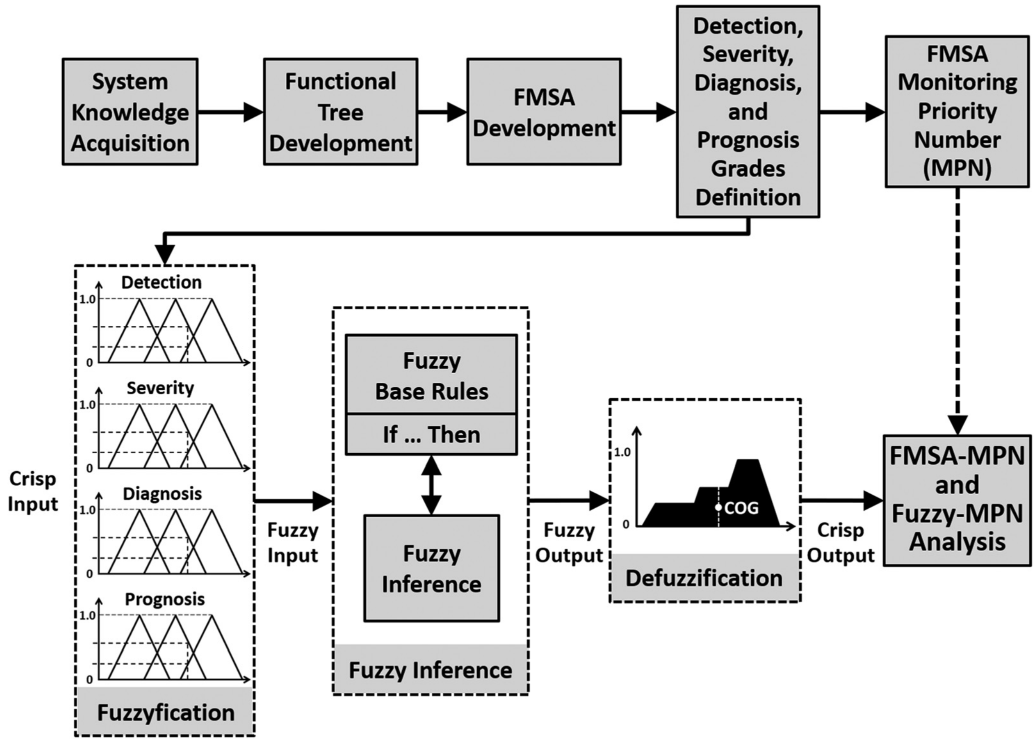

Fig. 1 Proposed method framework

The next step of the process is the fuzzy inference, in which the MPN value is defined, not by the multiplication of the SEV, DET, DGN, and PGN factors, but from the If-Then Rules. In this case, considering the number of possible values for each grade, being 4 for severity and 5 for the other factors, there is a need of five hundred rules to fully map the possible inputs and outputs of the process.

Once the inference rules are defined, the final stage in the proposed method is the defuzzification process. As mentioned before, the centroid defuzzification method was chosen to be applied in this article.

The center of gravity calculated in the defuzzification process represents the so-called Fuzzy Monitoring Priority Number (FMPN). FMPN follows the same principle considered for MPN, obtained with the traditional FMSA method: the lower the value, the greater the need to prioritize actions, since such a result indicates that the methods and strategies for monitoring and detecting a specific fault are not properly selected.

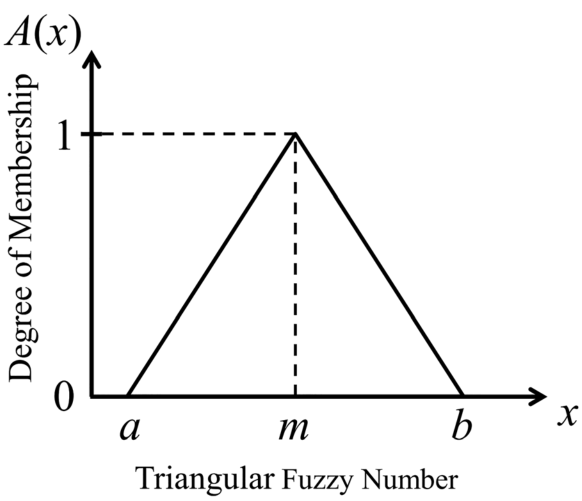

Fig. 2 Triangular fuzzy membership function

To build the membership functions for the output values, the same assumptions used for the input fuzzy sets were considered with an additional premise: the need to develop a workaround to deal with the biased result that FMSA algorithm presents, previously discussed in this article.

In this case, the fuzzy sets were defined considering ten different levels: none (N), extreme low (EL), very low (VL), low (L), moderate low (ML), moderate (M), moderate-high (MH), high (H), very high (VH), and extreme high (EH). The resulting output membership functions are presented in Fig. 4 and the corresponding rules are presented in Table 2.

The great insight to answer to the required conditions and build the output membership functions is in the support range [40] variance, as can be seen in Table 2. Lower initial values allow a better discretization of the response where the method features greater sensitivity to the algorithm bias, passing gradually to larger values, in the region where the sensitivity is not an issue and, finally, reducing the range value again, since, as previously mentioned, the values close to the edges would have a lower uncertainty than the values in the middle.

Comparing the results obtained with FMSA and fuzzy FMSA in the two-dimensional map presented in Fig. 5, it is possible to verify the discretization process that the addition of the Fuzzy algorithm brings to the final result.

Case Study

As a practical application of the proposed method, a case study will be presented considering two different hydrogenerators. Both units have Kaplan turbines and belong to run-of-the-river power plants located in the Brazilian North region. Also, they have the same layout, being supported by a guide journal bearing positioned near the turbine, two guide journal bearings near the generator (one above and one below), and one thrust journal bearing near the shaft midspan. They differ, however, in the generated power, one being a 150 MW machine and the other a 200 MW machine.

They also differ in the monitoring and diagnostic techniques adopted in their plants: the 200 MW unit has a CMFD system in addition to the usual supervisory control and data acquisition (SCADA) system, thus being aligned with the basics of condition-based maintenance (CBM) and predictive maintenance, while the 150 MW machine has only a SCADA system, and is therefore restricted to time-based maintenance (TBM) techniques [41].

Figure 6 shows a simplified representation of the analyzed hydrogenerators, including some components and online (continuous) measurements and test points (considering the 200 MW unit). In the 150 MW unit case, monitoring points 2 (vibration—proximity probes and accelerometers) and 3 (temperature sensors) are absent as they belong to the CMFD system.

The active power measurements, continuous and SCADA-related, and the nondestructive tests (NDT), performed in case of need during a scheduled shutdown of the units, are common to both analyzed units.

A functional tree was proposed for both hydrogenerators, presented in Fig. 7. Five major systems were considered: the excitation system, the generator, the shaft (including the bearings), the turbine (including suction and the draft tube), and the speed governor.

To illustrate the method, only the generator and turbine shafts will be considered (and detailed) in a joint analysis. Some typical mechanical failures related to the dynamic behavior of rotating machinery shaft were considered [42].

The FMSA spreadsheets for the turbine and generator shafts from both units are presented below, in Tables 3 and 4. The data distribution for MPN and fuzzy MPN results for both cases are presented in Fig. 8. The fuzzy analysis was conducted using FisPro 3.5 [43], an open-source portable software for fuzzy inference systems to run fuzzy models. This software is used in several articles and is therefore tested, validated, and well accepted by the scientific community.

By observing the obtained results, two important points can be highlighted: the absence of a monitoring and diagnostic system in the 150 MW unit makes the FMSA analysis much simpler and the results for both FMSA and fuzzy FMSA much more critical than in the 200 MW unit case; on the other hand, it is remarkable how in the analysis of both units the application of the fuzzy methodology significantly modifies the FMSA results.

In the case of the 150 MW unit, the inclusion of the fuzzy logic in the method resulted in cases with the same FMPN that originally had different values for MPN, considering only the FMSA analysis. In fact, the complete method clustered the results related to excessive vibration in three groups, ordering them according to fault severity. Since in the absence of a monitoring system it would not be possible to distinguish the fault root cause just by carrying out a sensory analysis of the produced noise variation of the generating unit, the result seems very plausible.

On the other hand, in the case of the 200 MW unit, the most critical cases, considering only the FMSA analysis, could be better distinguished, while the less critical cases were clustered, allowing a more accurate analysis in the general context.

It is interesting to note that the inclusion of fuzzy logic in the method does not change the results priority order. However, the method groups the results in a more logical way, considering the available information.

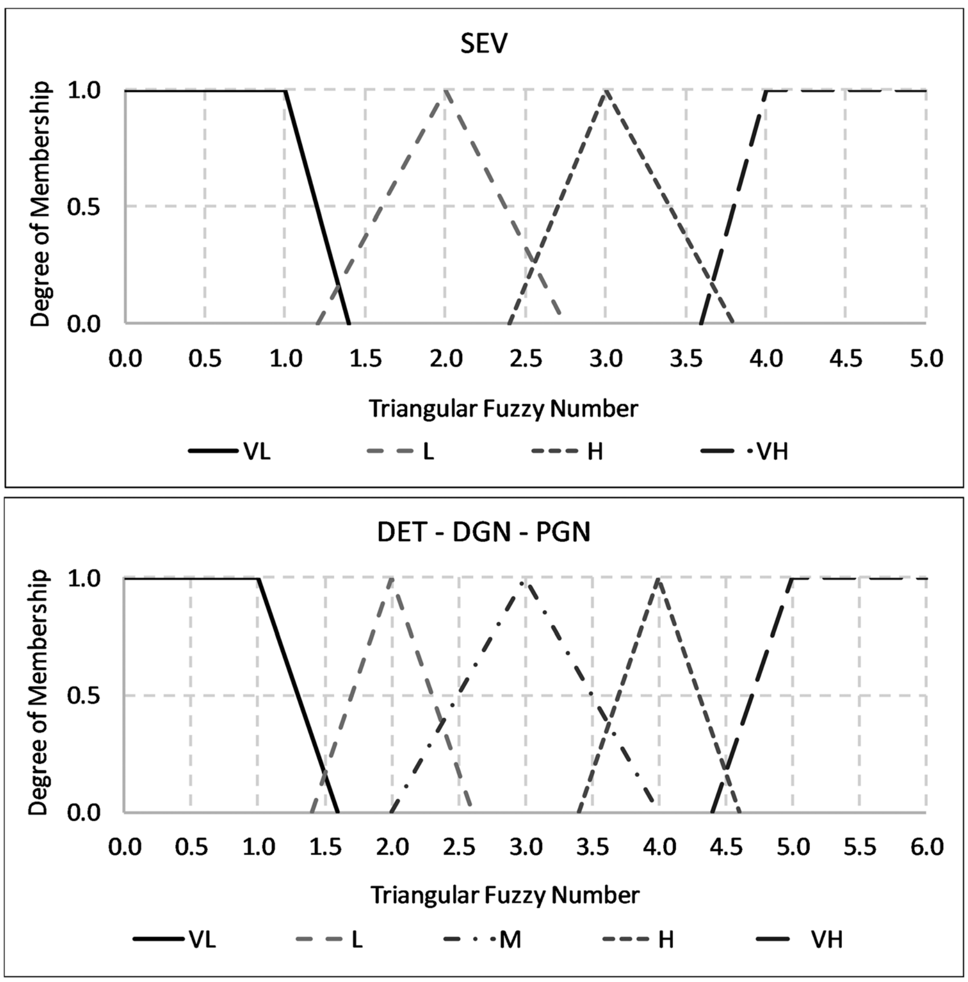

Fig. 3 Input membership functions: SEV (above) and DET, DGN, and PGN (below)

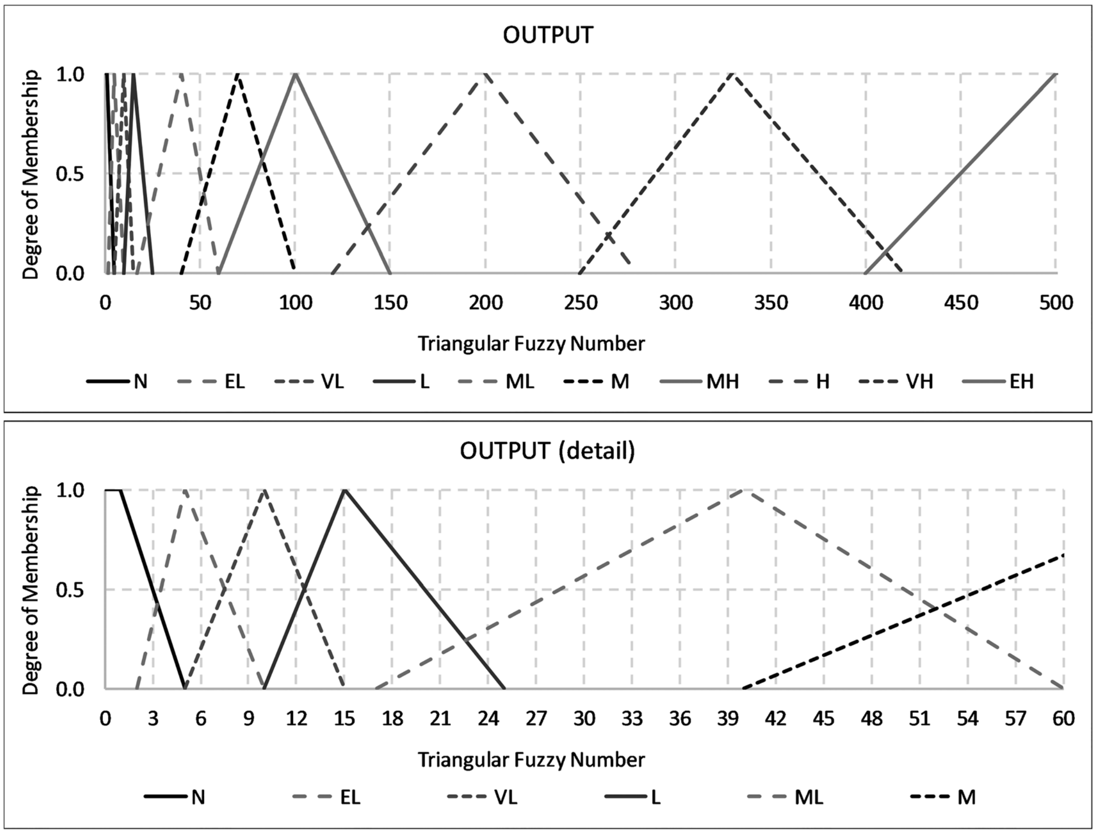

Fig. 4 Output membership functions: general view (above) and five first groups detailed view (below)

In both cases, the proposed method, which includes the application of fuzzy logic, generated more plausible results, despite the uncertainties involved.

Sensitivity Analysis

In order to verify the method robustness in relation to its sensitivity to different membership functions, variations were proposed for both fuzzification and defuzzification functions. The idea is to verify that membership functions are just a way to represent the problem's input or output data and, therefore, are dependent on the data prior knowledge.

Bearing in mind that there may be considerable uncertainty about these data, it would not be interesting if the method outcome varied significantly for different membership functions. To validate this premise, trapezoidal fuzzy numbers with different limits were considered, instead of the triangular fuzzy numbers originally considered. Figure 9 presents the new considered input membership functions, while Fig. 10 presents the new considered output membership functions and the corresponding rules are presented in Table 5. The linguistic terms chosen to describe the input and output variables are the same previously used for the triangular fuzzy numbers.

Table 6 presents the correlation between the original MPN values and the obtained results with triangular and trapezoidal Fuzzy MPN numbers considering the results presented in the case study. It is noticeable that, regardless of the membership functions and the Fuzzy MPN variations, the result regarding the clustering of the different cases analyzed does not change.

Table 2 Fuzzy and crisp values correlation for defuzzification

Linguistic variables	Fuzzy monitoring priority number limits	Support range
None	$1 \leq \text{FMPN} \leq 5$	4
Extreme low	$2 \leq \text{FMPN} \leq 10$	8
Very low	$5 \leq \text{FMPN} \leq 15$	10
Low	$10 \leq \text{FMPN} \leq 25$	15
Moderate low	$17 \leq \text{FMPN} \leq 60$	43
Moderate	$40 \leq \text{FMPN} \leq 100$	60
Moderate high	$60 \leq \text{FMPN} \leq 150$	90
High	$120 \leq \text{FMPN} \leq 280$	160
Very high	$250 \leq \text{FMPN} \leq 420$	170
Extreme high	$400 \leq \text{FMPN} \leq 500$	100

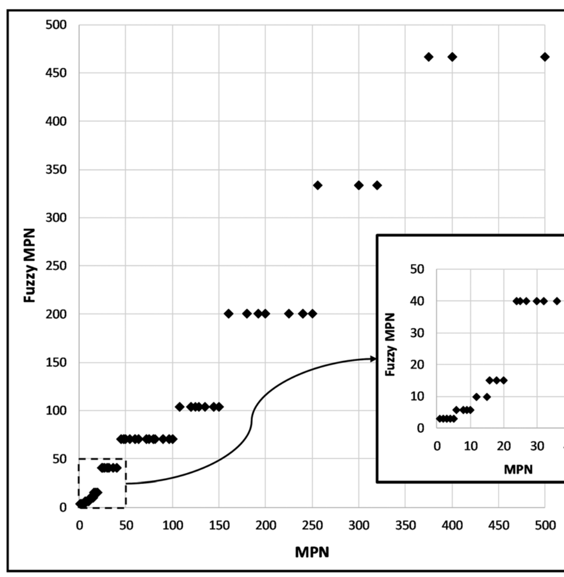

Fig. 5 MPN versus FMPN mapping

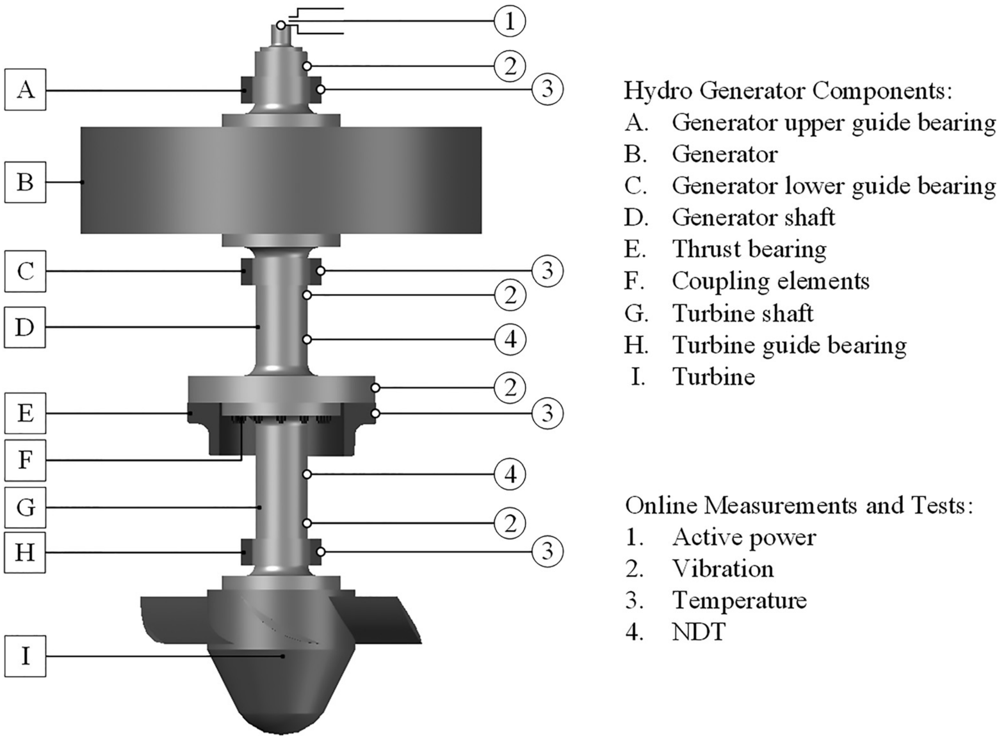

Fig. 6 Hydro-generator components and measuring points

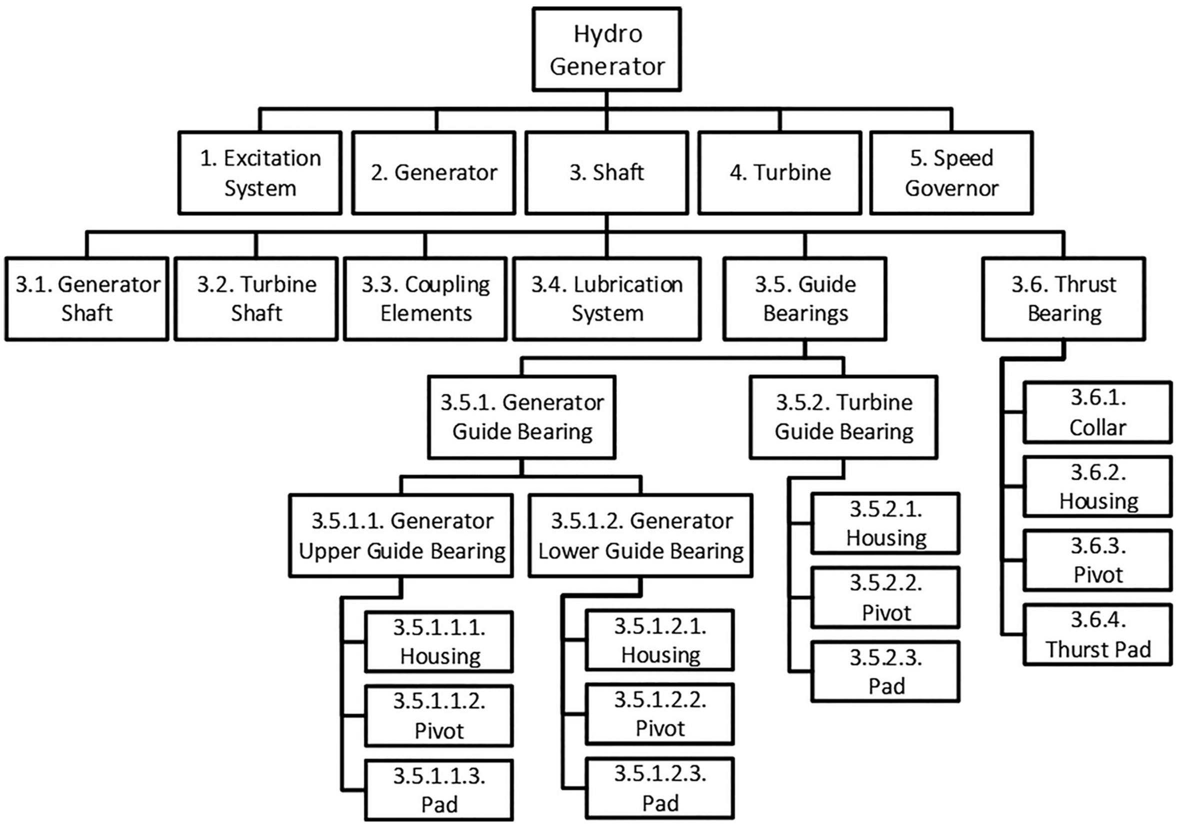

Fig. 7 Hydro-generator functional tree

Conclusions

This article proposed a method based on FMSA and fuzzy logic to evaluate fault monitoring and detection strategies. The method exploits FMSA's potential to analyze different failure modes from its symptoms and to select the most appropriate detection and monitoring techniques and strategies to maximize the confidence level in fault diagnosis and prognosis. At the same time, the method seeks with the introduction of fuzzy logic to overcome some issues intrinsic to FMSA, such as the natural biased results and uncertainties intrinsic to its development due to its dependence on knowledge-based inputs from experts.

Table 3 150 MW machine FMSA spreadsheet results

Item	Failure mode	Root causes	Failure symptoms	Primary technique	Monitoring location	Monitoring frequency	DET	SEV	DGN	PGN	MPN	FMPN
Turbine and generator shafts	Fracture	Cracks propagation due to mechanical fatigue or overload	Noise, excessive vibration and loss of synchronism	Active power	Phase bus	Continuous	2	1	4	5	40	39
				Noise	Local	Inspection round	1	1	4	5	20	16.7
	Excessive vibration	Bearings lubrication failure (lack or loss of oil properties)	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	2	3	1	6	5.67
		Mechanical unbalance	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	3	2	2	12	10
		Electromagnetic imbalance	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	3	2	2	12	10
		Shaft misalignment	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	3	1	1	3	2.33
		Misalignment between bearings	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	3	1	1	3	2.33
		Shaft bow	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	3	1	1	3	2.33
		Cracks propagation in the shaft	Excessive bearing vibration and temperature, noise	Noise	Local	Inspection round	1	1	1	1	1	2.33

Table 4 200 MW machine FMSA spreadsheet results

Item	Failure mode	Root causes	Failure symptoms	Primary technique	Monitoring location	Monitoring frequency	DET	SEV	DGN	PGN	MPN	FMPN
Turbine and generator shafts	Fracture	Cracks propagation due to mechanical fatigue or overload	Noise, excessive vibration and loss of synchronism	Active power and vibration measurements	Phase bus and shaft	Continuous	3	1	4	5	60	70
	Excessive vibration	Bearings lubrication failure (lack or loss of oil properties)	Excessive bearing vibration and temperature	Vibration and oil temperature measurements	Shaft and bearings	Continuous	3	2	3	2	36	39
		Mechanical unbalance	Excessive vibration in 1× rotation	Vibration measurements	Shaft	Continuous	4	3	4	3	144	103
		Electromagnetic imbalance	Excessive vibration in 1× rotation and 120 Hz	Vibration measurements	Shaft	Continuous	4	3	4	3	144	103
		Shaft misalignment	Excessive vibration in 1×, 2×, and 3× rotation	Vibration measurements	Shaft	Continuous	3	3	3	3	81	70
		Misalignment between bearings	Excessive vibration in 1×, 2×, and 3× rotation	Vibration measurements	Shaft	Continuous	2	3	3	3	54	70
		Shaft bow	Excessive vibration in 1× rotation	Vibration measurements	Shaft	Continuous	3	3	3	3	81	70
		Cracks propagation in the shaft	Excessive vibration at several frequencies	Vibration measurements	Shaft	Continuous	2	1	2	4	16	16.7
			Presence of cracks in the shaft	NDTs	Shaft	Scheduled	3	1	5	3	45	70

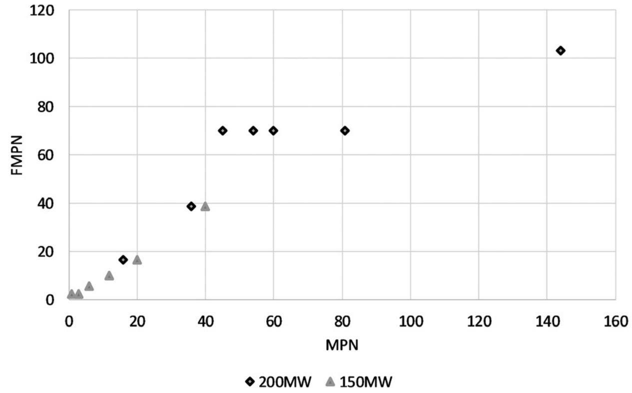

Fig. 8 Comparison between MPN and fuzzy MPN results from both units

In complex systems, it is very difficult to have a complete knowledge about all involved parameters a priori. Thus, such uncertainties may propagate to the results of any performed analyzes considering the available data. The introduction of the fuzzy set theory in the method to overcome these limitations proved to be a useful approach for dealing with the vagueness and fuzziness of the traditional FMSA.

The work is divided into two steps: in the first one, the proposed method was presented and analyzed from a generalized condition. In the second stage, the method was applied to a real case where two hydrogenerating units were considered. In this application, it became evident how the application of linguistic terms allows experts to provide more reasonable and meaningful information for FMSA input parameters, at the same time fuzzy rules allow more realistic and logical rules in the defuzzification process to be built.

If historical data are not available, it is highly recommended that information from experts with substantial experience be considered when generating the membership functions. However, it is important to bear in mind that there is not a most appropriate method to deal with uncertainties and that the best attainable solution will depend on the context in question. Likewise, increasing the complexity of the chosen approach will not necessarily bring greater accuracy to results.

Considering that the authors sought to apply in the best possible way the simplest form to represent the input and output data, as well as their uncertainties, the method had to deal with these uncertainties regardless of the specificities of the membership functions information. In fact, the performed sensitive analysis shows no changes in the method response regarding the chosen membership functions.

In the presented case study, the membership functions and fuzzy rules were obtained from the common consensus of experts and brainstorms in meetings, avoiding this way conflicting assumptions in the design process. Also, the sensitivity analysis presented in the article shows how the method deals with input and output data uncertainties regardless of the specificities of the membership functions information.

The authors concluded that the fuzzy logic-based approach overcomes the limitations associated with the traditional FMSA method in MPN evaluation. The comparison between both approaches recommended the implementation of FMSA integrated with the fuzzy logic approach.

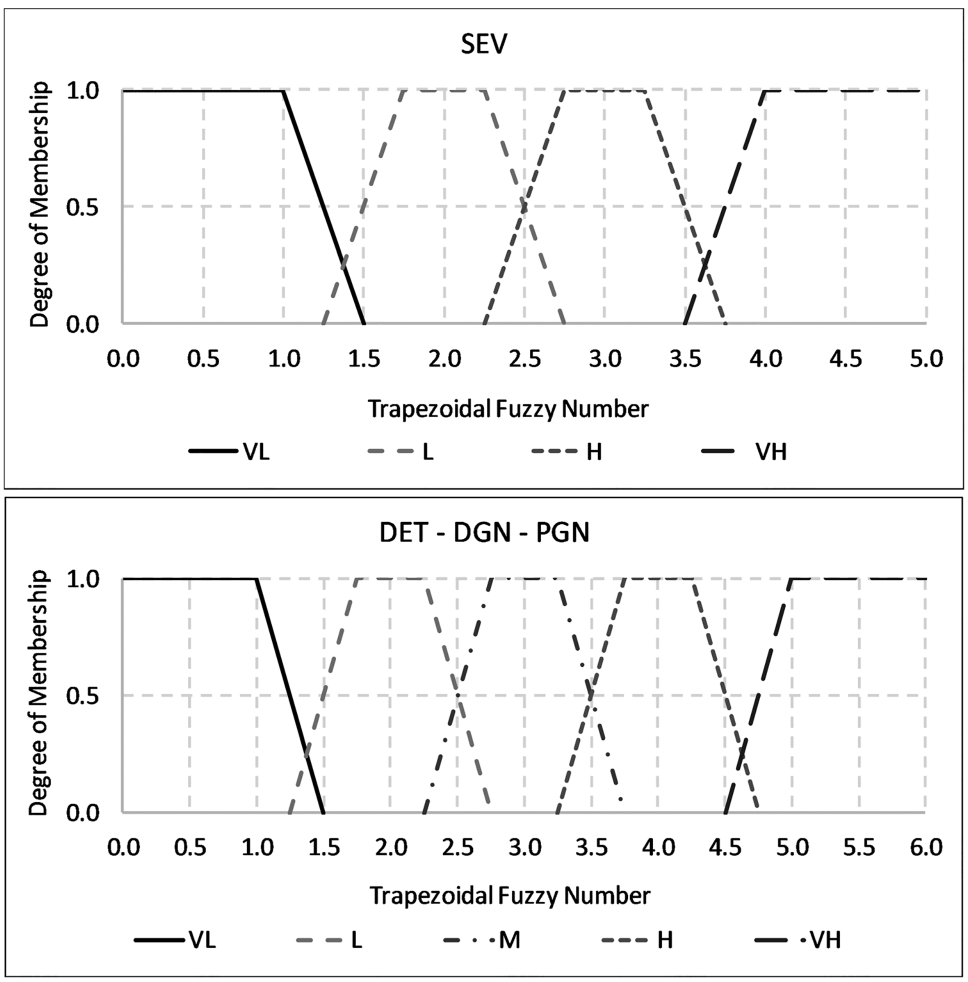

Fig. 9 New input membership functions: SEV (above) and DET, DGN, and PGN (below)

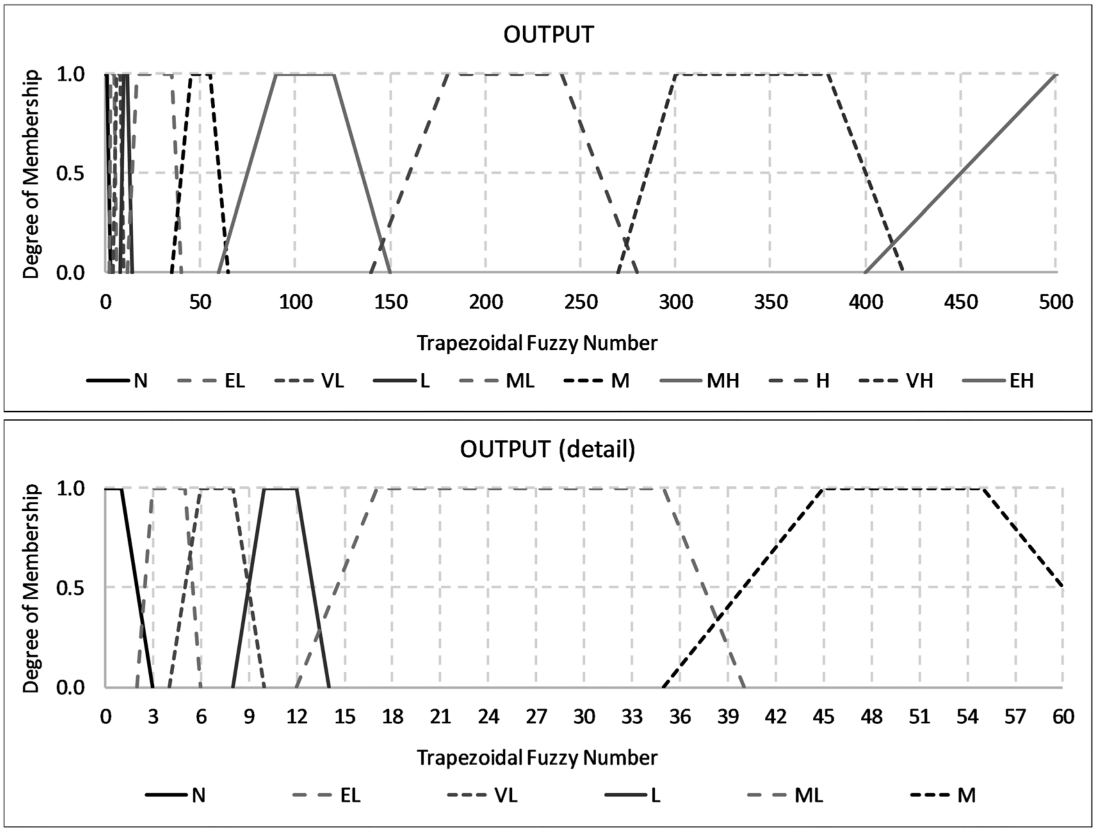

Fig. 10 New output membership functions: general view (above) and five first groups detailed view (below)

Table 5 New fuzzy and crisp values correlation for defuzzification

Linguistic variables	Fuzzy monitoring priority number limits	Support range
None	$1 \leq$ FMPN ≤ 5	4
Extreme low	$2 \leq$ FMPN ≤ 10	8
Very low	$5 \leq$ FMPN ≤ 15	10
Low	$10 \leq$ FMPN ≤ 25	15
Moderate low	$17 \leq$ FMPN ≤ 60	43
Moderate	$40 \leq$ FMPN ≤ 100	60
Moderate high	$60 \leq$ FMPN ≤ 150	90
High	$120 \leq$ FMPN ≤ 280	160
Very high	$250 \leq$ FMPN ≤ 420	170
Extreme high	$400 \leq$ FMPN ≤ 500	100

Table 6 Correlation between MPN, triangular fuzzy MPN, and trapezoidal fuzzy MPN values

MPN	Triangular fuzzy MPN	Trapezoidal fuzzy MPN
1	2.33	2.33
3	2.33	2.33
6	5.67	4
12	10	7
16	16.7	11
20	16.7	11
36	39	26
40	39	26
45	70	50
54	70	50
60	70	50
81	70	50
144	103	105

In addition, the fuzzy rule base can also be revised or updated when more precise information is available. In so doing, a more accurate ordering of the FMPN values is generated.

The only drawback observed in relation to the proposed method is the fact that, like FMEA, FMSA does not predict the occurrence of dependent failure modes. Moreover, two failure modes with distinct and known symptoms can generate a third symptom in the event of a simultaneous or dependent occurrence, which may bring a limitation to the method application. This issue should be investigated and proposals to work around it may be presented in future works.

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Nomenclature

C_i = component
CBM = condition based maintenance
CMFD = condition monitoring and fault diagnosis
COG = center of gravity
DET = detectability
DGN = diagnosability
DM_i = detection method

EH = extremely high
EL = extremely low
F_i = function
FE_i = failure effect
FLS = fuzzy logic system
FM_i = failure mode
FMEA = failure modes and effects analysis
FMECA = failure modes, effects and criticality analysis
FMPN = fuzzy monitoring priority number
FMSA = failure mode and symptoms analysis
FS_i = failure symptom
FTA = fault tree analysis
H = high
HAZOP = hazard and operability study
L = low
M = moderate
MF_i = monitoring frequency
MH = moderate high
ML = moderate low
ML_i = measurement location
MPN = monitoring priority number
N = none
NDT = non-destructive tests
PGN = prognosability
RC_i = root cause
RCM = reliability centered maintenance
SEV = severity
TBM = time-based maintenance
VH = very high
VL = very low

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