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DAMAGE CLASSIFICATION IN IMPEDANCE-BASED SHM BY THE USE OF FUZZY LOGIC

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Abstract. *The majority of mechanical systems can be found in complex environments in which they are causing numerous interferences, generating wear or fractures. Therefore, the use of the Fuzzy Logic technique in the aid of the detection of damages becomes relevant, once this tool can evaluate numerous factors for the real verification of the damage. This contribution uses the eletromechanical impedance-based structural health monitoring method to develop a Fuzzy system capable of identifying structural damages in an aluminum beam. It was measured 300 signatures of impedance for the validation of the model, that presented excellent results, abstracting and identifying the proposed damage conditions.*

Keywords: *Fuzzy Logic , Detection of Damages, Impedance-based SHM*

1. INTRODUCTION

Mechanical structures are subject to wear over time, fatigue and changes in their optimal functioning. These problems can lead to major financial and human damages. Because of that methods to continuously monitor the state of integrity of structures have been developed. According to Santos *et al.* (2015) safe and robust structures are those that are well managed and monitored.

This contribution uses the eletromechanical impedance-based strutural health monitoring method, which consists in abstracting characteristics pertinent to the state of the structure based on dynamic responses gathered by sensorial elements mechanically coupled to the system Palomino *et al.* (2008).

In general, monitoring techniques use fault indices, called damage metrics, as a factor restricting the states of the structure. However, when these indices are not linearly separable, whether due to interference of climatic factors and / or factors inherent to the electronic components used in SHM techniques, the decision-making process of the useful life of the evaluated structures is characterized by a complex task Barella *et al.* (2017).

New tools capable of intelligently assisting in the identification and classification of damages in mechanical systems have been studied in recent decades, such as artificial neural networks (RNA) or techniques based on fuzzy logic. Thus, in the present work a fuzzy logic model is presented to aid the process of fault detection in mechanical systems. This model has as input variable the metric values normally used in SHM by electromechanical impedance and as a response the degree of severity of possible damages present in this system Oliveira Jr (1999); Gomide *et al.* (2002).

2. ELETROMECHANICAL IMPEDANCE

The electromechanical impedance technique was first proposed by Liang (1994). The basic concept of this technique is the monitoring of the variation of the mechanical impedance of the structure caused by the presence of damages. As the direct measurement of the mechanical impedance of the structure is a complicated task, the method uses piezoelectric materials bonded or incorporated to the structure, allowing to measure the electrical impedance. This is related to the mechanical impedance of the structure, which is affected by the presence of the damage. The Equation 1 shows the representation of the admittance measured in a 1 degree freedom structure.

$$Y(\omega) = i\omega a(\bar{\varepsilon}_{33}^{T}(1 - i\delta) - \frac{Z_s(\omega)}{Z_s(\omega) - Z_a(\omega)} d_{3x}^2 \widehat{Y}_{xx}^{E}), \tag{1}$$

where $Y(\omega)$ is the electrical admittance, Z_a the mechanical impedance of the PZT patch, Z_s the mechanical impedance of the structure, $\widehat{Y}_{xx}^{E}$ the PZT patch Young complex modulus with zero electric field, d_{3x} the coupling constant of the PZT in the direction x to the deformation 0, ε_{33}^{T} the dielectric constant at strain 0, δ the PZT patch dielectric constant and a geometry of the PZT patch.

This monitoring uses a comparison between signatures, which represent the state of the system. For the acquisition of these signatures piezoelectric ceramics are glued in the system under analysis. The role of these trandutores is to excite the structure in a frequency sweep and at each frequency step the dynamic response of the system is collected, which is related to the mechanical impedance of the structure.

There is usually a need to quantify the severity of the failures on the system, for which damage metrics are used, the most used metrics is the root mean square desviation (RMSD) proposed by Sun *et al.* (1995) according to Eq. 2.

$$RMSD = \sqrt{\sum_{i=1}^{n} \left(\frac{(Re(Z_{1,i}) - Re(Z_{2,i}))^2}{Re(Z_{1,i})^2} \right)}. \tag{2}$$

In equation 2, $Re(Z_{1,i})$ is the real part of the signal impedance of the undamaged structure (baseline), $Re(Z_{1,i})$ is the real part of the signal impedance of the structure with damage. From the Equation 2 is possible to take a quantitative analysis, that is, measure the damage occurring in the structure comparing it with the initial state.

3. FUZZY LOGIC

Fuzzy logic was initially proposed by Zadeh (1965), like most of the revolutionary formulations of his time, was confronted with countless conflicting views of conservationist character. However, the need for modeling that permeates inaccurate reasoning, which does not achieve satisfactory results through conventional logic, it has amplified the use of this concept in the most diverse areas of research today Andrade and Jaques (2008).

In the classical set theory (classical logic), there is a relation called pertinence that refers to the fact that an element belongs or not to a given set. Thus, there are only two possible statements, or it is true that the element belongs to a sector, or the element does not belong to the sector, so it is false.

In fuzzy logic, unlike classical logic, the idea is that infinite values can be used within the range from 0 to 1, once instead of taking values of true or false (1 or 0), it is assigned to each element a degree of pertinence to express how much it belongs or not to a set. That is, it means that an element with degree of relevance of 0.5, for example, belongs to a certain set with 50% confidence.

As discussed earlier the classical set theory determines in a well-defined way, called crisp, the insertion of an element into a group. In the theory of fuzzy sets, the elements are inserted into different groups with equivalent degrees of pertinence Pourjavad and Shahin (2018).

According to Zadeh (1965) the definitions and operations on fuzzy sets is characterized as an association class between certain states, which is normalized by a membership function whose amplitude can vary from 0 to 1. This membership function is a mapping of the elements, taking as basis of a degree of associability of each of the evaluated elements in relation to this set.

The pertinence functions are continuous and can take different forms and are used according to the problem in question. Table 1 shows some pertinence functions Souza *et al.* (2018).
where μ are pertinence functions, $a, b, m, ne\sigma$ are specific parameters determined for each problem under analysis.

On the fuzzy sets, Union, Intersection and Complementary operations are commonly performed. These operations are presented by Eq. 3, 4 e 5 respectively.

$$\mu_{(A \cup B)}(u) = max\{\mu_A(u), \mu_B(u)\}, u \in U \tag{3}$$

$$\mu_{(A \cap B)}(u) = min\{\mu_A(u), \mu_B(u)\}, u \in U \tag{4}$$

$$\mu_{A'}(u) = 1 - \mu_A(u), u \in U, \tag{5}$$

where A and B are fuzzy sets, $\mu_A(u)$ and $\mu_B(u)$ are pertinence functions.

The Fuzzy process consists of steps. Initially a sampled sample of the crisp type is fuzzified. In this process, the defined variables are mapped and represented by linguistic variables of the fuzzy subsets.

Then, the inference process will be responsible for determining the output action of the fuzzy, that is, determining the set of output variables of the system. Inference is based on a set of rules determined by the fuzzy system developer. Even

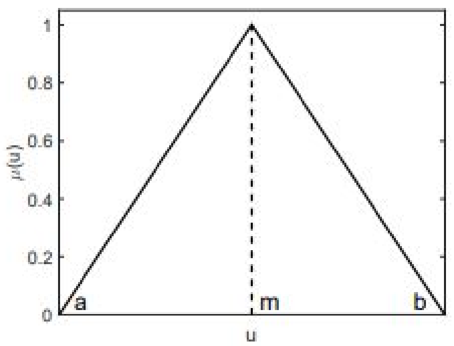
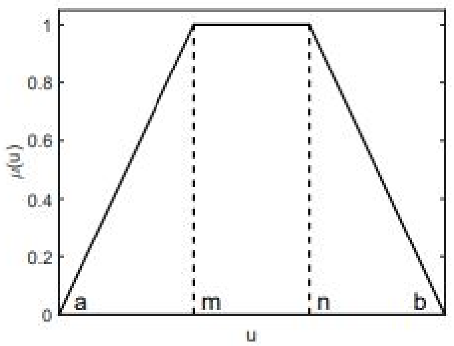
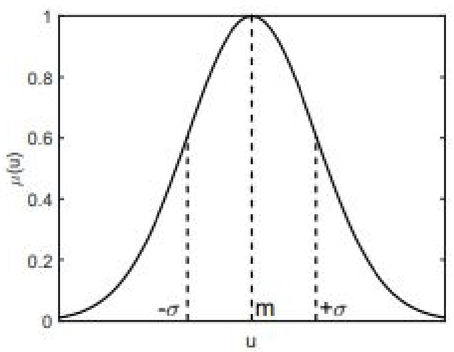
	$\mu(u,a,m,b)=\begin{cases}0, & se \quad u\le a\\ \frac{u-a}{m-a}, & se \quad u\in[a,m)\\ \frac{b-u}{b-m}, & se \quad u\in[m,b]\\ 0, & se \quad x\ge b\end{cases}$
	$\mu(u,a,m,n,b)=\begin{cases}0, & se \quad u< a\\ \frac{u-a}{m-a}, & se \quad u\in[a,m)\\ 1, & se \quad u\in[m,n)\\ \frac{b-u}{b-n} & se \quad u\in[n,b]\\ 0 & e \quad u> b\end{cases}$
	$\mu(u,m,\sigma)=\exp\left(-\frac{(u-m)^2}{\sigma^2}\right)$

Table 1. Examples of pertinence functions

in most problems it is necessary to translate the fuzzy variables into crisp variables. This process of translation is called the defuzzification.

The fuzzy inference process is based on a set of rules described and designed by a specialist. The rules are composed of antecedent and consequent linguistic variables. The antecedents are responsible for firing the rule, while the consequent ones by determining the action to be performed given a rule. Below is the structure of the rules.

IF x1 is <antecedent> **AND/OR** x2 is <antecedent> ...
THEN y1 is <consequent> **AND/OR** y1 is <consequent> ...

where xn is fuzzy input variables and yn fuzzy output variables.

The step of associating the input variables to the output variables, given a rule, is called the implication. After implication, each rule will have a resulting region. All regions generated by the list of activated rules are combined in the aggregation phase, resulting in the fuzzy output variable.

With the fuzzy output variable in place, the last step of the process is to transform it into a crisp value so that the actuation system can execute the resulting action. In the Mamdani logic, the fuzzy variable is interpreted as a region resulting from the aggregation process. Therefore, to determine the quantitative value of this area, centroid calculus techniques, medians of the maximos and center of the maximos can be used.

The architecture of the Fuzzy system used in this contribution is based on the mandami method, formulated by Ebrahim Mamdami in 1975. It is composed of 3 layers, the fuzzy entries, the evaluation and aggregation of the rule base, and finally the defuzzification Marro *et al.* (2010); Pourjavad and Mayorga (2019).

4. METODOLOGY

By means of the EVAL AD5933-EBZ board from Analog Devices Devices (2013), 300 signatures of impedance were obtained referring to an aluminum beam with the dimensions 400x25x3 mm, which represented a simple mechanical system. The PZT patch was glued to 100 mm. Figure 1 presents the beam used in the experiment.

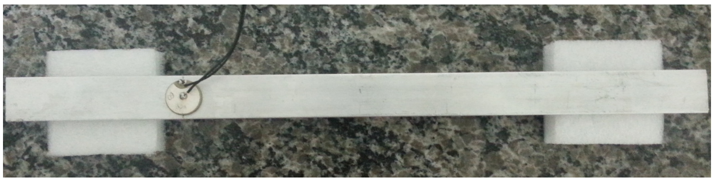


Figure 1. Bi-supported beam used in the experiment

In the aluminum beam, two damage levels were inserted through a mass addition, where the mass was 2 circular neodymium magnets of 3mm thickness per 10mm diameter. The mass addition used in the experiment is 2.3 g. The Figure 2 shows the magnets used (b) and the form of application on the specimen (a). A displacement of the mass was used to simulate an increase of the damage.

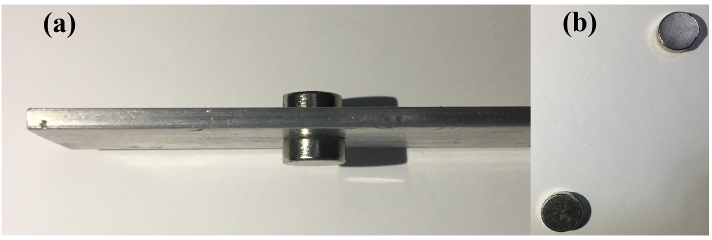


Figure 2. (a) Bi-supported beam used in the experiment (b) Addition of mass used in the experiment

The following 300 samples/signatures were obtained: 100 signatures for the pristine system, 100 signatures with the 250 mm damage and 100 signatures with the 200 mm damage. The distance used to refer to the damage represents how close the mass is to the PZT patch, i.e., damage of 250 mm is the position of the adding mass to the piezoelectric patch.

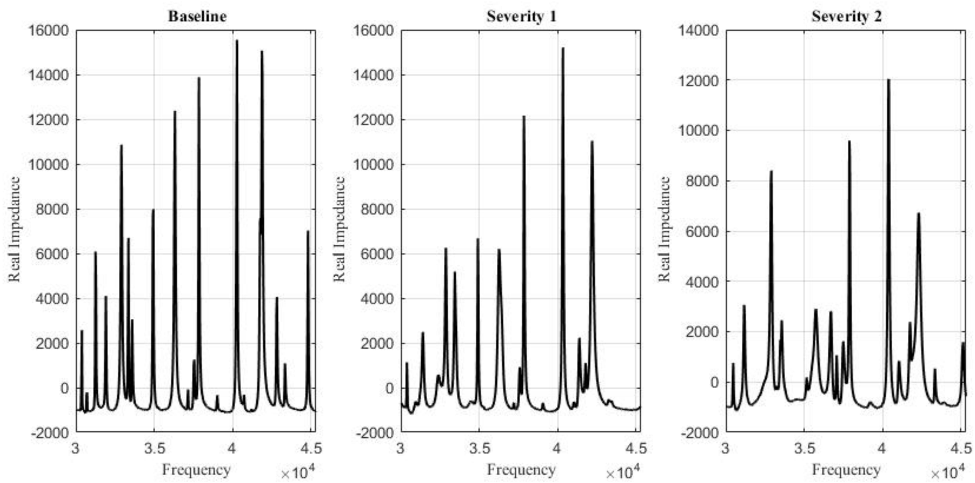


Figure 3. Signatures of 2 levels of damage and proposed baseline

To compensate for undesirable temperature and other boundary conditions in impedance signatures, the Correlation

Coefficient Deviation (CCD) method was applied Rabelo *et al.* (2017). The Equation 6 shows the CCD metric used.

$$CCD = 1 - CC = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{[Re(Z_{1,i}) - Re(\overline{Z}_{1,i})] - [Re(Z_{2,i}) - Re(\overline{Z}_{2,i})]}{S_{Z1}S_{Z2}}, \tag{6}$$

where $Re(Z_{1,i})$ is the impedance of the PZT patch measured at healthy conditions, $Re(Z_{2,i})$ is the impedance for the comparison with the baseline measurement at frequency interval i. The symbols $Re(\overline{Z}_{1,i})$ and $Re(\overline{Z}_{2,i})$ represent mean values, while S_{Z1} and S_{Z2} represent standard deviations.

Matlab was used to build the fuzzy logic system. In it, one variables of the 11 input Gaussian type with a standard deviation of 0.03 and a mean ranging from 0 to 1 with a step of 0.1 were created, which these variables had a pertinence degree varying from 0 to 1. The Fig. 4 shows the variable with its 11 pertinance functions.

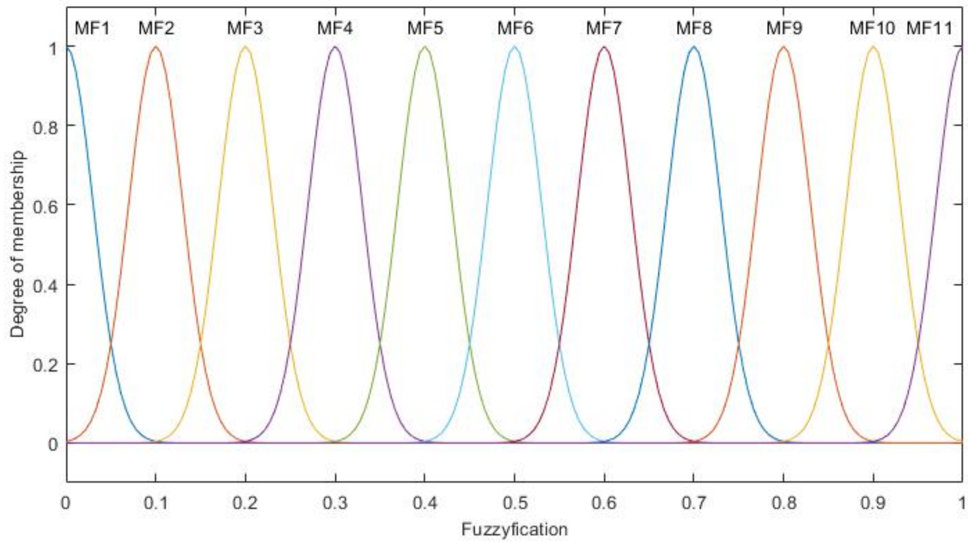


Figure 4. Input pertinance functions used to build fuzzy logic model

Other output variables were also created with 11 output of Gaussian pattern with a standard deviation of 4 and averages ranging from 10 to 65 with a pitch of 5, where these variables have a degree of pertinence ranging from 0 to 100. The Fig. 5 shows the variable with its 11 pertinance functions.

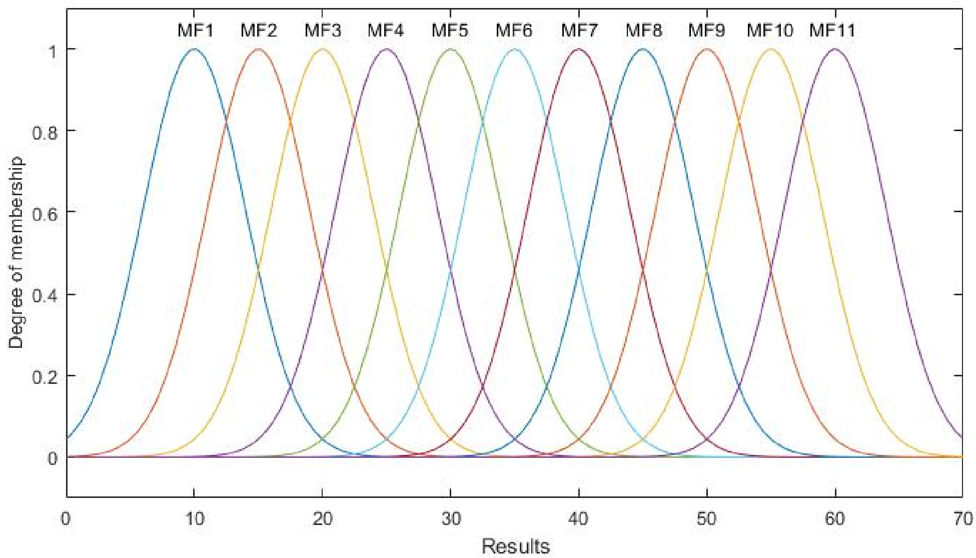


Figure 5. Output pertinance functions used to build fuzzy logic model

For the process of construction of the base of rules was used the principle that the value of metric is proportional to the severity of the fault found in the structure. In this way, the used rule set can be observed in Tab. 4.

Number of Pertinece Function	Variable	Rule Weight	Operador OR(2) AND(1)
1	1	1	1
2	2	1	1
3	3	1	1
4	4	1	1
5	5	1	1
6	6	1	1
7	7	1	1
8	8	1	1
9	9	1	1
10	10	1	1
11	11	1	1

Table 2. Rule base used in the fuzzy logic model

Table 4. represents the damage evaluation simulation of a given structure. Basically, for a given input value, there is a relative metric region of evaluation, which allows to establish the severity of the damage through the study of the output of the model.

Each RMSD metric value ranging from 0 to 1 is associated with one or more membership functions. These functions by the set of rules are related by determining the degree of damage in the structure. With the fuzzy model created, the 300 values of the metrics previously calculated by Eq. 2 are then evaluated. Finally after the evaluation the data are then defuzzified.

5. RESULTS AND DESCUSSION

By implementing the fuzzy model it is possible to verify the severity of damage on the system under analysis. The values of the metrics are passed as parameters, and the model shows the degree of severity of the system. Fig 6 presents the results obtained from the model together with the fuzzy model's pertinence output functions.

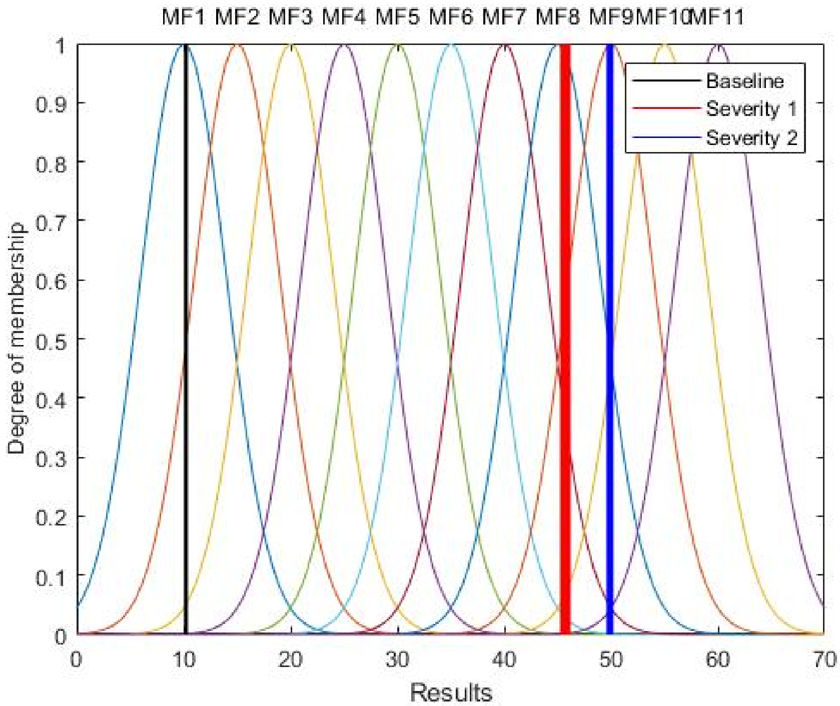


Figure 6. Result of fuzzy logic model

The result obtained in the model presents 11 probabilities of damage represented by membership functions (MFs), in which the baseline was classified as level 10, the damage of 200 mm as 50 and the damage of 250 mm as 60, it's highlights the separability and damage classification capacity.

Once fuzzy models are commonly used for applications in complex and variable systems, it is possible to use the value of the metrics to quantify the damage as well as to use other parameters, which will be treated in the rules of the model in question to obtain the result of the problem under analysis.

6. CONCLUSION

This contribution aims to approach and apply fuzzy logic theory in structural integrity analysis, focused on obtaining alternative method for the quantification of damage besides providing an increase in the signal abstraction to improve the results obtained with the analysis. This Fuzzy model leads to the process of fault inference in mechanical structures. For this, RMSD damage metrics of a bi-supported beam were obtained experimentally by the electromechanical impedance technique.

Although the results demonstrated that the formulation of the proposed model was simple, it was able to efficiently delineate the severity of the damages considered in the experimental procedure. Thus, it is intended to apply this model aided to other tools of integrity analysis already developed by the authors in order to develop a low-cost structural model of monitoring and easy instrumentation.

In conclusion, the steps to construct the fuzzy model, the determination of its input variables and the best relevance function for the data set, the model output and the best functions for the defuzzification and finally the definition of the rules in the fuzzified dataset, are approached with the purpose of presenting an alternative and robust model for prediction and identification of structural damages.

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9. RESPONSIBILITY NOTICE

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