Impedance-Based PZT Transducer and Fuzzy Logic to Detect Damage in Multi-point Dressers

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Abstract. Alternative techniques such as impedance-based lead zirconate titanate (PZT) transducers has emerged as an innovative approach for manufacturing monitoring process, because its flexibility of using low-cost piezoelectric diaphragms and its simple methodology in terms of apparatus by using the electromechanical impedance (EMI). In addition, this technique has been under several improvements due to the advance of artificial intelligent systems. On this point, the use of fuzzy logic systems has been reported in literature as an attractive combination to improve the process performance. Therefore, this study proposes an approach to detect damage in multi-point dresser based on EMI technique incorporating a fuzzy logic system. To this end, a fuzzy model is built considering the information obtained from representative damage indices corresponding to the different damage cases that are generated at the dresser. At the end, authors expected that the dressing operation can be optimized, preventing the operation from being performed with worn or damaged dressers and ensuring quality standards and precision to the grinding process, which have a high benefit to the manufacturing chain.

Keywords: Electromechanical impedance · PZT transducers · Fuzzy logic · Tool condition · Grinding process

1 Introduction

Grinding is one of the last steps in the machining process, i.e. a critical step in the production of high benefit and high precision parts for strategic industrial sectors such as aerospace, automotive, biomedical, among others. The success of the grinding process is highly dependent on the grinding wheel performance, which is a complicated abrasive tool with undefined geometric and random grits distribution [1, 2]. Therefore, dressing operation is periodically carried out and is responsible to recover the abrasive capacity of the wheel once excessive wear of abrasive grits has occurred. However,

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along of this operation the dressing tool (dressers) suffers damages, such as the wear throughout its use, thermal damages, shock or cracking [1]. This way, damaged dressers provide less sharpness on the grinding wheel and, consequently, an unsatisfactory grinding process. For this reason, in accordance with [3–5], the development of a monitoring and control system for the process control is of utmost importance.

To address the issue cited above, many researchers have attempted to improve the process performance based on sensor monitoring and artificial intelligent (AI) techniques. It is worth to mention in this sense, the use of artificial neural networks (ANN) combining acoustic emission [6–8] and vibration signals [9, 10], as well as fuzzy systems [11]. However, at the present paper the attention is given to the fuzzy logic (FL), which is a well-known AI technique effectively used for grinding process monitoring [12, 13]. Fuzzy tools are designed for considering uncertainty and vagueness in variables considered [14]. Fuzzy systems (FS) are based on fuzzy set theory and associated techniques pioneered by [15]. On this point, a fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. This way, a fuzzy set defines a mapping between elements in the input space and values in the interval [0, 1]. According to [12], fuzzy inference system is associated with number of names, such as fuzzy-rule-based systems, fuzzy expert system, fuzzy logic controller, fuzzy model, fuzzy associative memory and simply (and ambiguously) fuzzy system. On this point, FL may be viewed as an attempt at formalization and mechanization of two remarkable human capabilities. First, the capability to converse, reason and make rational decisions in an environment of imperfect information. Second, the capability to perform a wide variety of physical and mental tasks without any measurements and any computations.

On the other hand, impedance-based structural health monitoring (SHM) has come to the forefront in grinding operations because of its practical potential for real applications [16, 17]. For this purpose, the electromechanical impedance technique (EMI) has been considered. The basic principle of this technique is to monitor the structural integrity by exciting and sensing a piezoelectric transducer, usually a lead zirconate titanate (PZT) diaphragm bonded to the structure to be monitored and excited in a suitable frequency range. In addition, the use of PZT diaphragms has increased attention to the grinding process monitoring, following the approaches presented in [18, 19]. It is worth mentioning that an initial study to monitor the dressing operation by using EMI technique was presented in [20], however, limited to the time-domain analysis. The results indicated that representative indices were capable to extract the tool damage information and determine the level of wear. An expansion of the research presented in [20] were presented in [21, 23] by using the real part of the impedance and ANN models. The proposed approach was able to select the most damage-sensitive features based on optimal frequency band bringing improvements to the grinding process.

It is worth to emphasize that the use of AI techniques based on fuzzy logic has been related in literature for impedance-based SHM applications [22, 24, 25]. However, this approach for dressing operation monitoring has not been reported in literature yet. Therefore, this paper presents an approach to detect damages in multi-point dressers based on EMI technique. In addition, a fuzzy logic system is built to improve the damage detection performance. To validate the feasibility of the proposed approach an experimental test was carried. To this end, damages were introduced at different positions of the dresser and the electrical impedance was measured by fixing a PZT transducer at the dresser body, as well as using an alternative EMI measurement system. The fuzzy rules are extracted from the dressing tool damage information obtained from representative damage indices. Based on the proposed approach, authors expected that the dressing operation can be optimized, preventing the operation from being performed with worn or damaged dressers and ensuring quality standards and precision to the ground parts, which have a high benefit to the manufacturing chain.

2 Experimental Setup

2.1 Experimental Test and Data Acquisition System

To verify the effectiveness and reliability of the proposed approach an experimental test was carried out by using a multipoint stationary dressing tool of chemical vapor deposition (CVD) diamond (20 × 15 × 5 mm of metallic dresser body, and seven 1 × 10 mm diamond sticks), which is commonly known as fliesen dresser and is widely used by industry. The purpose of the experiment is to analyze the damage and failures in multi-point dressers (in particular at the diamond sticks that are responsible to perform the dressing operation) caused by shocks, corrosion, cracks and many more. A complete specification on procedures of the experimental test is given in Table 1. According to Table 1, in order to simulate those fault conditions mentioned above, structural damages were introduced by drilling holes with approximately 1 mm of diameter and 1 mm of depth cut at three positions (named as H1, H2 and H3) of 2.5 mm, 8.5 mm and 13.5 mm, respectively, along of the dresser surface. A schematic representation of this procedure is shown in Fig. 1.

Table 1. Description of the experimental setup.

Conditions	Damage type	Set
H1	Damage introduced at 2.50 mm from top of the dressing tool	1
H1	Damage introduced at 2.50 mm from top of the dressing tool	2
H2	Damage introduced at 8.50 mm from top of the dressing tool	1
H2	Damage introduced at 8.50 mm from top of the dressing tool	2
H3	Damage introduced at 13 mm from top of the dressing tool	1
H3	Damage introduced at 13 mm from top of the dressing tool	2

An industrial ZOCCA S30 column-drilling machine was used to introduce the damages. Each hole was made in two sets (set#1 and set#2, respectively) with 0.5 mm of depth cut, as shown in Fig. 1. The measurement of the signatures was conducted with the alternative EMI measurement system proposed by [26]. To this end, a NATIONAL NI USB-6221 multifunctional DAQ equipped with LabVIEW software was used. A MURATA 7BB 15-11 PZT diaphragm [27], was used as transducer, which was glued onto the dresser body. The transducer was excited through a chirp signal with magnitude of 1 V, a frequency ranges from 0 to 125 kHz, and a resistor of 2.2 kΩ. Its response signal was sampled at 250 kS/s. The adopted measurement system is shown in Fig. 2. At the end, six different scenarios that correspond to the impedance signatures of the dresser under damage conditions were taken for comparison purposes with the baseline signature (undamaged dresser). In order to ensure a good accuracy, an average of five measurements were taken and the process was carried out two times at every damage condition acquired.

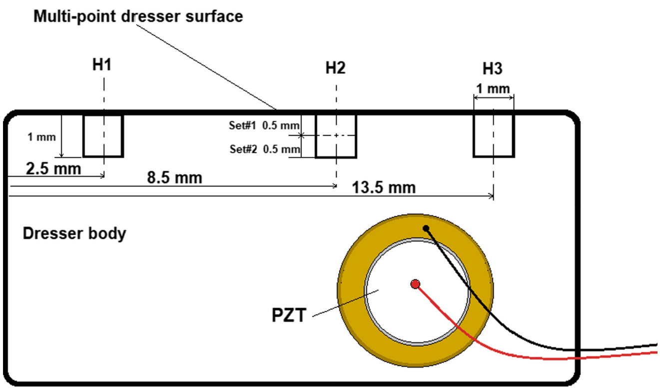

Fig. 1. Schematic representation of the experimental setup.

Fig. 2. Measurement system used in the experiment.

A MINIPA MT455 digital thermometer equipped with a type K thermocouple was used to measure the temperature, in order to ensure all impedance measured at the same temperature of 27.5 °C. The thermocouple was fixed in the dresser body during the impedance measurements.

To analyze the signals, the real part of the impedance was used for calculation. In addition, it has been well known in SHM that the damages are identified by comparing the measured electrical impedance in an initial condition (healthy), with the impedance measured after the structure underwent a damage. To this end, the root mean square deviation (RMSD) and the correlation coefficient deviation metric (CCDM) were used to compute damage indices in this paper. The RMSD is based on Euclidean distance between two impedance signatures, as given by (1), which was used in [28]. The CCDM is based on the correlation coefficient between the two impedance signatures, as given by (2), [16, 29].

$$\mathrm{RMSD} = \sum_{k=\omega_I}^{\omega_F} \sqrt{\frac{\left[\mathrm{Re}\left(Z_{E,D}(k)\right) - \mathrm{Re}\left(Z_{E,H}(k)\right)\right]^2}{\mathrm{Re}^2\left(Z_{E,H}(k)\right)}} \tag{1}$$

$$\mathrm{CCDM} = 1 - C_c \tag{2}$$

In Eq. (1), the subscripts H and D represents the healthy and damaged conditions, respectively, while $Re\left(Z_{E,H}(k)\right)$ and $Re\left(Z_{E,D}(k)\right)$ are the real part of the electrical impedance signatures of the structure under healthy and damaged conditions, respectively, which are measured at a frequency k that ranges from ω_1 (the initial frequency) to ω_F (the final frequency). In Eq. (2), C_c is the correlation coefficient, calculated using the real part of the electrical impedance signatures for the structure under healthy and damaged conditions at the frequency range previously defined.

Therefore, the representative damage indices RMSD and CCDM were computed at the frequency band of 40–50 kHz, which was experimentally determined as the best range according to the situation that is covered by this paper. The results of the calculation are shown in Fig. 3.

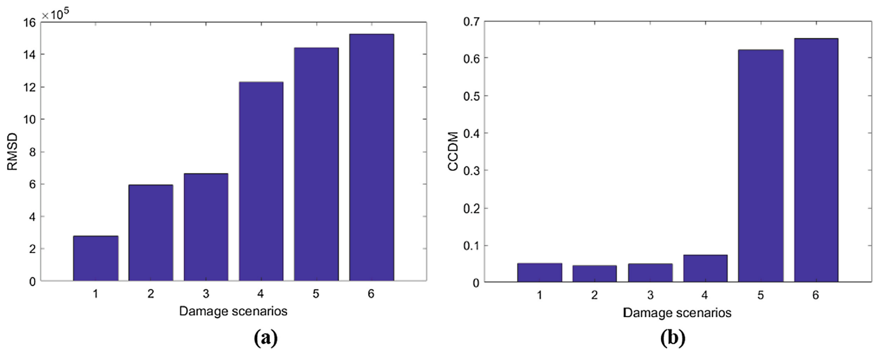

Fig. 3. Representative damage indices calculation: RMSD (a), CCDM (b).

2.2 Proposed Fuzzy Logic System

Once the representative damage indices were computed, the construction of the metamodel based on fuzzy logic system could be started. The architecture of the metal model is illustrated in Fig. 4. Then, the inputs to the system was consisted of RSMD and CCDM average values and the fuzzy models were implemented by using the fuzzy logic toolbox of the MATLAB. The inference system was established based on the Mamdani method given in [30] and the centroid approach was considered for deffuzification purpose. The trapezoidal type of membership functions were used to the fuzzy system (*trapmf*), which were experimentally defined based on the conditions considered in this paper. The terms linguistic Low, Medium and High were used to represent the membership functions. These terms were defined considering the values minimum and maximum of the RMSD and CCDM in each one of the six-damage conditions. Figure 4 also illustrates the membership functions and the adopted concepts.

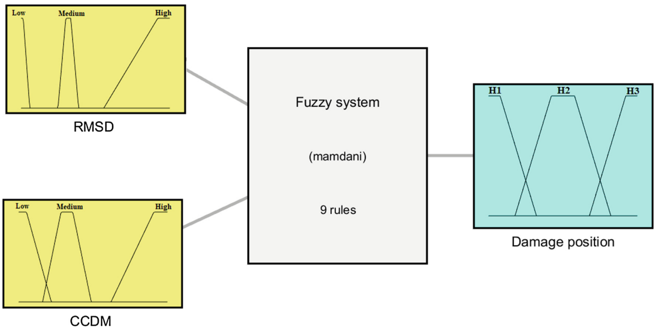

Fig. 4. Proposed fuzzy logic system: membership function and the adopted concepts (Low, Medium, High, H1, H2, and H3).

Regarding the system output, namely the position of the damage (H1, H2, and H3), it is classified according to the three sets of linguistic variables (Low, Medium, and High). To this end, the system should be capable to classify two damage types to each position (i.e. set#1 and set#2, as given in Table 1). Therefore, to manipulate the linguistic data, nine rules were generated as given in Table 2. In addition, the adopted ranges to the membership functions by considering the RMSD and CCDM values are given in Table 3.

Table 2. Set of rules.

Input	Set of rules (tool damage position)			
RMSD and CCDM (40–50 kHz)		Low	Medium	High
	Low	H1	H1	H2
	Medium	H1	H2	H3
	High	H2	H3	H3

Table 3. Adopted ranges to the membership functions

RMSD			CCDM			Output (mm)		
MF1	MF2	MF3	MF1	MF2	MF3	MF1*	MF2*	MF3*
[1.2 * 10^5 2.4 * 10^5]	[3.41 * 10^5 1.7342 * 10^6]	[5 * 10^5 3.0105 * 10^6]	[0.0441 0.392]	[0.0518 0.6021]	[0.111 1.1290]	[1.9 2.5]	[1.9 8.5]	[1.9 13.5]

MF1 – membership function ‘Low’
MF2 – membership function ‘Medium’
MF3 – membership function ‘High’
MF1* – membership function ‘Position 1’
MF2* – membership function ‘Position 2’
MF3* – membership function ‘Position 3’

3 Results and Discussions

In order to observe the input and output effects of the fuzzy model, the 3D surfaces, shown in Fig. 5, were generated. According to Fig. 5, the regions corresponding to the clusters H1, H2, and H3 are well defined at different areas and colors based on the prior elaboration of fuzzy rules. In addition, it is possible to confirm that the combined inputs resulted in different influences on the damage position in dresser. Furthermore, according to the rules surface, when the RMSD and CCDM have a low value, the damage cases reach the H1. On the other hand, when the RMSD and CCDM have intermediate values, the damage cases reach the H2. Similarity, when the RMSD has an intermediate value and CCDM has a high value, the damage cases also reach the H2. Finally, when the RMSD and CCDM have high and very high values, the damage case reach the H3. This fuzzy model, however, presents some discontinuities and abrupt transitions at the boundaries of the areas, which occurs due to the range of values of the damage metrics RMSD and CCDM corresponding to the frequency band of 40–50 kHz. In addition, this result is in agreement with [11], where authors used acoustic emission and vibration signals incorporating fuzzy logic to predict the wear in single-point dressers. According to 3D surface results, the combined inputs result in different influences on the final wear prediction. Based on the set of rules extracted by authors, if the statistical values were high, a percentage of wear was estimated on the ordinate axis.

In addition, considering a database that was not presented to the fuzzy system before, the process of defuzzification could be initiated in order to verify the effectiveness and robustness of the proposed fuzzy logic system. The result is shown in Fig. 6. The matrix has three distinct regions that represent those three clusters H1, H2 and H3, respectively. The result indicates high assertiveness with only one case for test (corresponding to D3 damage case) that was misclassified, as indicated by arrow, i.e. the fuzzy system classified the damage position as H1 while it is in fact a damage that was induced at position H2. On the other hand, the error case corresponding to the validation database, however, is located very close from the border. In accordance with [9, 31] it is not a serious error in practical applications, since, when the system scores damage near the line corresponding to the real region, it is reasonable to assume that the error is asymptotically normal due to distribution based on process uncertainty. In addition, it is important to point out that this defuzzification was acceptable in terms of

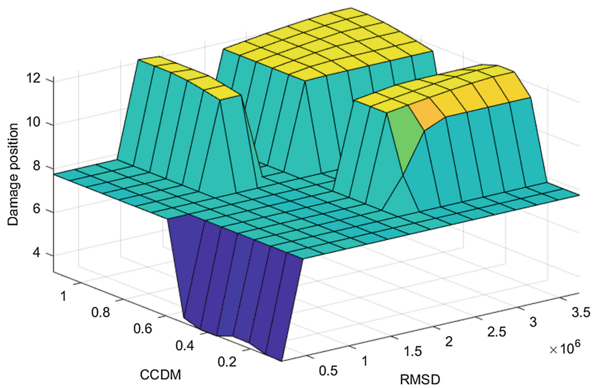

Fig. 5. 3D surface generated to the fuzzy model corresponding to 40–50 kHz (H1in blue, H2 in green and H3 in yellow).

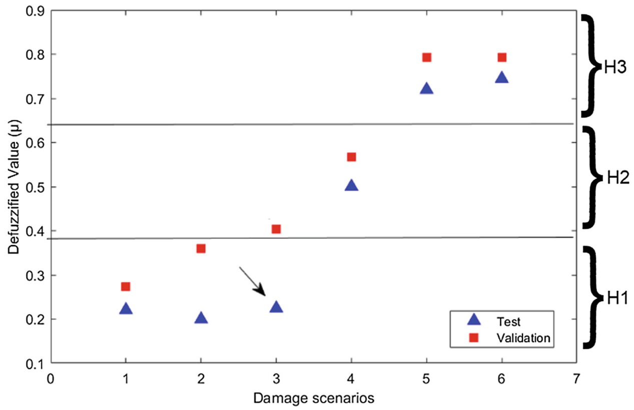

Fig. 6. Validation results considering the fuzzy model corresponding to 40–50 kHz.

accuracy rate taking into account possible cases with not clear symptoms, i.e. those damage cases that present high similarity between their values and limits.

4 Conclusion

This paper presented an approach to detect damage in multi-point dressers based on EMI technique and fuzzy logic. The experiments were conducted on a multipoint stationary dressing tool of CVD diamond and six different damage cases were obtained. The proposed approach considered the real part of the impedance, which was acquired from a PZT attached to the dresser body and an EMI measurement system. A fuzzy model was developed and implemented considered the dressing tool damage information extracted from the representative damage indices RMSD and CCDM at the frequency band of 40–50 kHz. The results indicated high assertiveness to determine the damage positions H1, H2 and H3, respectively, with a minimum number of errors that are acceptable in terms of accuracy rate taking into account possible cases with not clear symptoms. The proposed approach contributes to the grinding community in view of the simplicity of the EMI technique and its use of inexpensive PZT transducers, as well as the simplified fuzzy model that proved to be effective and easier to implement. Future analysis will go deeper on the robustness of the fuzzy models. That is, the combination of different frequency bands is suggested so that the proposed approach will be conducted to a broader situation.

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