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Damage patterns recognition in dressing tools using PZT-based SHM and MLP networks

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Abstract

In order to promoting the optimization of the theme: "grinding-dressing", this study intends to contribute to the fill the gap of works completed with the damage diagnostic systems in dressing tools. For this purpose, this work aims to use neural models based on multilayer Perceptron networks (MLP) to improve the damage pattern recognition in diamond dressing tools based on electromechanical impedance (EMI). Thus, experimental dressing tests were performed with a single-point diamond-dressing tool and a low-cost lead zirconate titanate (PZT) transducer to acquire the impedance signatures at different dressing passes. The proposed approach was able to select the optimal frequency range in impedance signatures to determine the dressing tool condition. To achieve this, representative damage indices in several frequency bands were considered as input to the proposed intelligent system. This new approach open the door to effective implementation of future works for a broader situation in grinding process.

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Keywords: Pattern recognition; dressing monitoring; MLP networks; PZT; SHM

1. Introduction

A significant amount of research has been dedicated to attain a final solution for control and automation of the grinding process-dressing operation [1–8]. Since, grinding is a complex manufacturing process influenced by many factors, such as workpiece, machine, grinding wheel and process configuration [8, 9]. Otherwise, in the context of industry 4.0, improvements in machining monitoring systems are being promoted, which forms an opportunity to supply the purpose of the grinding process optimization. So far, the performance of the grinding process depends on dressing operation i.e., the topography and the conditions which the grinding wheel is prepared deeply influence on the quality of the grinding, which is evidenced by the cutting forces, consumed energy, temperature in the cutting zone, and often, in the finish of the workpiece [11–13].

On the other hand, impedance-based structural health monitoring (SHM) is an innovative technique to be applied in manufacturing process[14, 15], which is characterized by its flexibility of using low-cost piezoelectric transducers, such as ceramics of Lead Zirconate Titanate (PZT), and a very simple methodology for structural damage detection. In the last decades, the use of PZT patch transducers for damage diagnostic is becoming increasingly important in the SHM field [15–17]. This approach presents a great relevance for monitoring of the dressing operation because the diamond dressing tools suffer damage, such as, the wear during the process. Furthermore, the use of worn dressers can provide less sharpness to the tool, causing an increase in cutting forces and faster loss of edges of grains. For this reason, a system of damage diagnostic becomes necessary.

The application of impedance-based SHM for dressing operation is characterized by the selection of frequency bands

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in order to recognize a damage pattern in dressing tools, based on damage metrics[14, 18]. Further, a more reliable and systematic approach needs to be established for selecting the optimal frequency bands in impedance signatures, considering different dressing conditions, the type of grinding wheel and the type of dresser. Therefore, in order to improve the selection of the frequency bands most sensitive to damage in dressing tools, this study aims to use neural models based on multilayer Perceptron networks (MLP). MLP networks are a powerful computational tool, which models the basic behavior of logical thought patterns by numerical representation, using many artificial neurons, that are individual computational elements, linked to each other. Nevertheless, in this study, experimental dressing tests were performed with a single-point diamond-dressing tool and a low-cost lead zirconate titanate (PZT) transducer to acquire the impedance signatures at different dressing passes by using an EMI data acquisition system. The authors expect to bring new contributions to the theme “grinding-dressing” through the implementation of the proposed approach.

2. Material and equipment

To achieve the purpose of this study, experimental dressing tests were conducted in a surface grinding machine, model RAPH 1055, from Sulmecanica, which was equipped with an aluminum oxide grinding wheel, model 38A150L6VH (specification of hardness, grain, flange and vitrification), with the dimensions 355.6 x 25.4 x 127 mm, from NORTON. The experimental tests were conducted based on researches of [3, 14, 19]. Fig. 1 presents a diagram of the proposed approach.

A synthetic diamond (chemical vapor deposition – CVD) single-point dressing tool was used in the experiment. Each test consisted in dressing passes throughout the grinding wheel surface until the end of the grinding wheel lifespan. The main parameters were the constant dressing speed at 3.45 mm/s, the constant dressing depth of 40 µm, the overlap ratio (U_d) of 1 at the beginning of the test. The tests were carried out without application of cutting fluid in order to cause a faster wear.

2.1. Proposed approach-based data acquisition system

The data acquisition system adopted was based on the research presented in [15], and then the electromechanical impedance (EMI) technique was considered following the approach presented in [21]. Fig. 1 showed as the EMI data acquisition system was used. To this purpose, a NI USB-6221 a DAQ device was adopted, which allowed for collecting impedance signatures from a low-cost PZT transducer, mounted on the dressing tool holder, as shown in Fig. 1, at sampling rate of 250 kS/s.

The PZT transducer used was the model 7BB-20-6 low-cost diaphragm type, from MURATA [23], which is constructed of a circular bronze disc with a diameter of 20 mm and thickness of 0.20 mm. For the present measurement system, this transducer was excited through a resistor of 2.2 kΩ by a chirp signal with magnitude of 1 V and frequency from 0 to 125 kHz. The mean value for three measurements was calculated, ensuring a satisfactory accuracy, based on the recommendations of [21, 24, 25]. A computer equipped with LABVIEW software was used to acquire the impedance signatures from DAQ system. For the structural damage detection, the impedance measurements were taken at 300 and 600 dressing passes, respectively.

The damage conditions defined at the present study were: damage1 (D1) at 300 dressing passes, and damage 2 (D2) at 600 dressing passes, compared with the baseline signal which indicates the dresser with healthy diamond (H). Fig. 2 shows the real part of impedance signatures for each one of the conditions. The healthy condition was established for the dresser diamonds before the dressing passes. In addition, to analyse the results, the root mean square deviation (RMSD) damage index was computed. The RMSD is one of the most employed metrics in SHM applications, according to [25], which is presented in Eq. (1). The results are shown in Fig. 3.

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

3. Damage pattern recognition using MLP networks

According to Table 1, the RMSD metric was computed to four sub-frequency bands, considering over a wide frequency of 0-100 kHz, with each frequency band spanning 25 kHz. The indices were computed every 50 Hz for each sub-frequency bands. Therefore, 500 patterns for each frequency band was considered as input to the neural models. This approach was based on concept of the sub-range of frequency most sensitive selection, presented by [27].

A neural network model was constructed based on [3], where the multi-layer perceptron neural network (MLP) was considered. The scope was to selecting the optimal frequency band to determine dressing tool damage pattern. To this end, the neural training process was carried out by considering four inputs, which corresponding at each frequency band previously selected. Fig. 4 presents general structure of the proposed pattern recognition system.

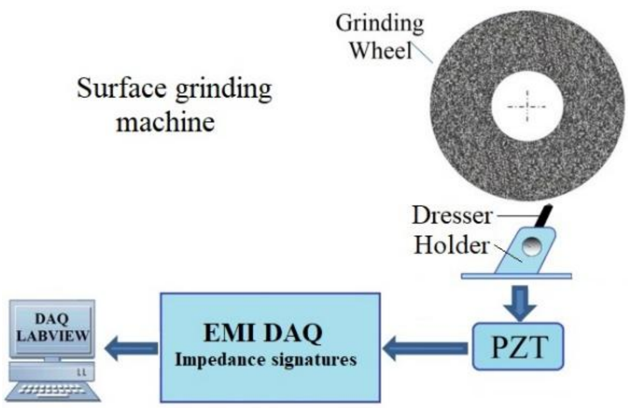

Fig. 1. Experimental test bench and DAQ system

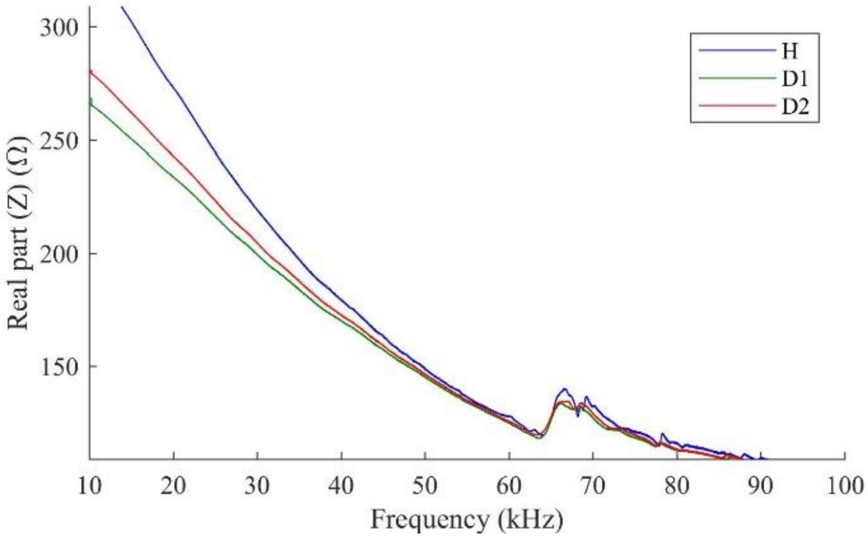

Fig. 2. Real part of the impedance signature for dressing tool conditions

An input pattern for the neural model was considered by varying each one of the chosen frequency bands, in order to obtain the best sub frequency range, which is able to determine the dressing tool condition. The neural network was trained in MATLAB by using the *Levenberg-marquardt* backpropagation algorithm and 10 % of the input data was separated for experimental validation purpose. The experimental validation step was based on confusion matrices and cross validation theory, reported by [28, 29].

Table 1. Frequency bands defined

Frequency bands	Range
#a	0-25 kHz
#b	25-50 kHz
#c	50-75 kHz
#d	75-100kHz

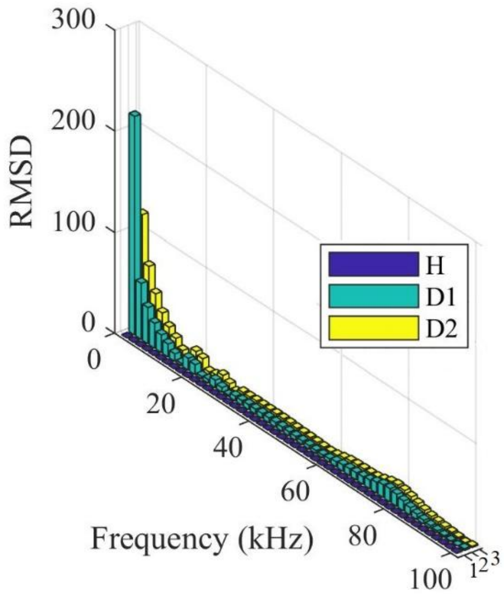

Fig. 3. RMSD index for the defined dressing tool conditions

4. Neural models results

This section presents the configurations resulting from the training performed with the MLP neural network for the proposed pattern recognition system. Mean features of the neural model are presented in the Table 2, where the first column shows the considered parameters in the training and in the feature extraction process, such as, input patterns, layers and neurons structure, training function, and percentage errors of the each input pattern. The second column indicates respective specifications for those parameters.

According to results, the input pattern that obtained the best percentage errors was the *#c* with an error of 1.4 %, which used the frequency band of 50-75 kHz, and a simple structure of 3-10 neurons, with only two hidden layers. Otherwise, the input pattern *#d*, which has used frequency band of 75-100 kHz also presented good results with an error of 2.3 % and a structure only one hidden layer with 19 neurons.

On the other hand, the input pattern #b, and, in particular, the input pattern #a, showed errors of 4.9% and 11.2 %, respectively, by fixing the frequency bands of 0-25 kHz and 25-50 kHz. Thus, this input pattern has not proved attractive for implementation because their overall errors were too high when compared to the other input patterns of the neural model.

In order to verify the recognizing success of the proposed approach to achieve the optimal frequency band, confusion matrices and region classifier graphics based on cross validation process were considered for the best-input pattern.

Table 2. Mean features of the neural models

Parameters	**Specification**			
Input pattern	***#a***	***#b***	***#c***	***#d***
Range	0-25 kHz	25-50 kHz	50-75 kHz	75-100 kHz
Structure	1-8-5-5-2	1-15-15-3	1-3-10-0-2	1-19-0-0-2
Algorithm	LVM Backpropagation			
Error	11.2 %	4.9 %	1.4 %	2.3 %

These graphics are presented in Fig. 5 (a) and Fig. 5 (b), respectively, which shows only the results of the input pattern #c, which used the frequency band of 50-75 kHz.

According to results of the confusion matrix, which is shown in Fig. 5 (a), the network presented 97.8 % of predictive capacity and 99.5 % of sensitivity for D1 condition, with occurrence of false positive. In D2 condition, the predictive capacity of the neural model was 99.4 % and the sensitivity was 97.7 %, corresponding to the occurrence of only one false negative diagnostic. The overall accuracy rate of the network for this input pattern was 98.3%, which is attractive for implementation.

Fig. 5 (b) shows the region graph based on pattern recognition system proposed in this study, where the data of both damage condition D1 and D2 are located and classified by regions. The points on the map correspond to space location of the values used at the model input. It is possible to verify the errors indicated by arrows, which occurred in the patterns located closer to the boundaries of the damage classes. Thus, it is possible to see the patterns which were classified wrong, i.e., one pattern pertaining to D1 class that were classified as D21, also some patterns pertaining to D2 class that were classified as D1.

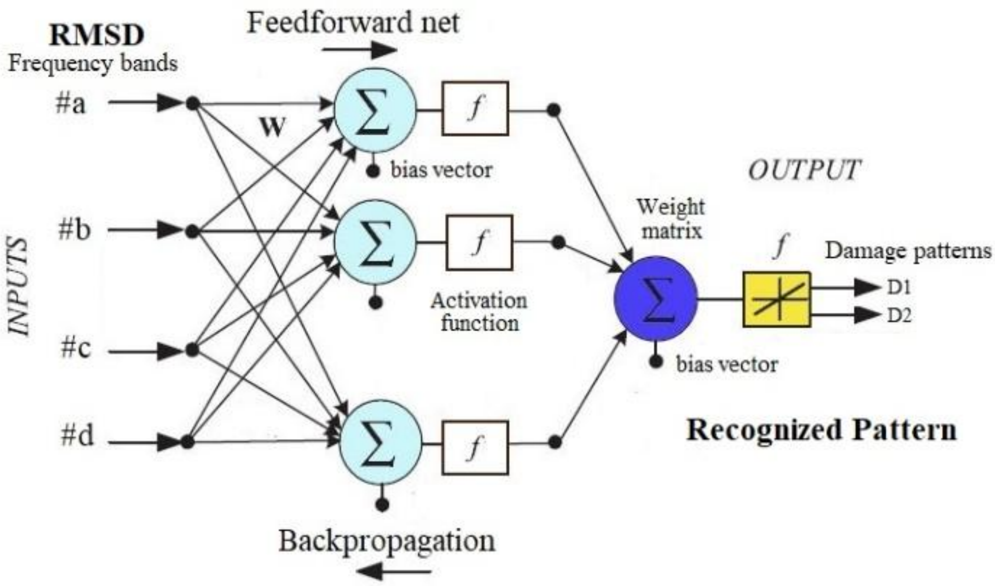

Fig. 4. Proposed pattern recognition system using MLP networks

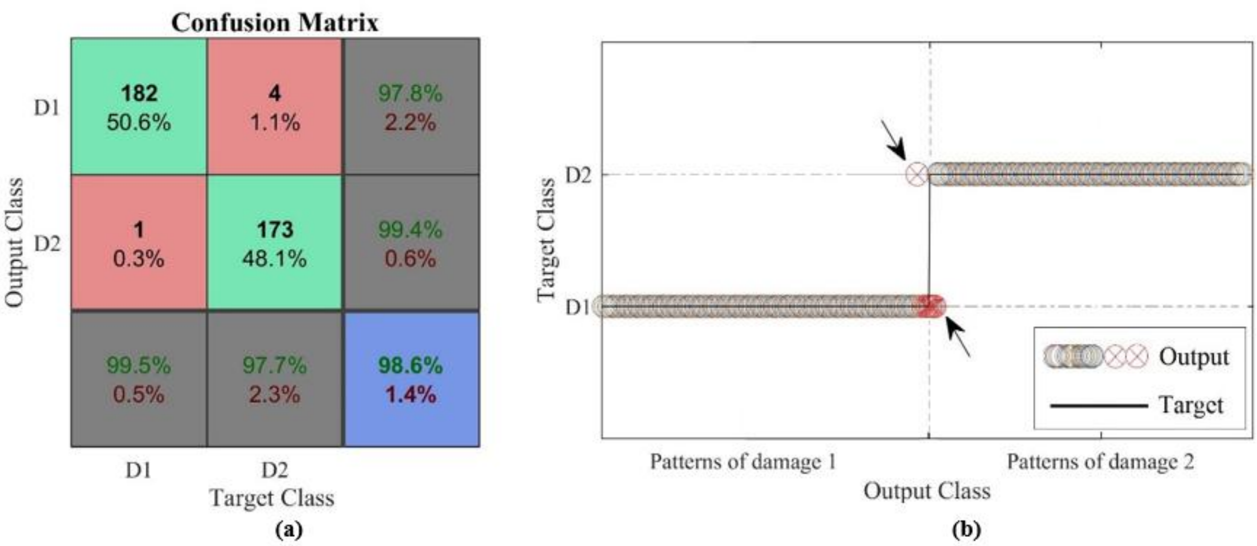

Fig. 5. Confusion matrix for optimal frequency band achieved by neural (a); region graph for the optimal frequency band achieved by neural model

5. Conclusions

Artificial neural networks has recently emerged as a promising tool to improve the damage diagnostic in SHM applications. Therefore, this study presented this respective approach for the dressing operation monitoring, incorporating MLP neural models, in order to promoting a damage pattern recognition system in dressing tools. To this end, a neural model was built considering as input the damage metric RMSD by fixing different frequency bands. The proposed intelligent system was an efficient technique to improve the damage diagnostic in the dressing operation. Since, as result, the pattern recognition system was able to determine the frequency band most sensitive to damage, which was the range of 50-75 kHz. Further, the proposed approach presented a general average error of 1.4 % to determine the damage severity D1, D2 in the single-point dressing tool. Finally, this paper presented a new approach to monitoring the dressing operation, bringing improvements to the grinding process.

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