Grinding burn classification with surface Barkhausen noise measurements

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Abstract
Industrial Barkhausen noise (BN) measurements are commonly utilized for final quality control after machining operations such as grinding to point out grinding burns. Grinding burns might compromise the final use and fatigue lifetime of the ground component. The industrial BN method itself is based on a pre-determined threshold value of the BN root-mean-square value (RMS). Elevated RMS values indicate detrimental changes in the component. Usually, the evaluation of grinding burn severity is not carried out. In this study, real ground cylindrical samples were collected that were rejected based on an industrial quality control with a BN unit. A more detailed BN analysis was carried out for 41 individual grinding burn locations followed by X-ray diffraction based residual stress (RS) surface measurements and residual stress and diffraction peak full-width-at-half-maximum (FWHM) depth profiles. K-means clustering was applied to profiles to label the data points related to grinding burns of different severity. Three classes of grinding burns were identified and verified by micrographs and hardness. A linear discriminant classification model was then identified between the surface BN measurement features and labeled data points. The classification results were reasonable with about 80 % classification accuracy at worst. They showed that the classes identified can be detected with the surface BN measurements. Thus, the approach presented in this paper shows great potential in the practical use of BN measurement where grinding burns can be detected and evaluated with a surface BN measurement.

KEYWORDS: Barkhausen noise; residual stress; grinding burns

1. Introduction

Industrial Barkhausen noise (BN) measurements are commonly utilized for final quality control after machining. Such a process is for example grinding of different gear and power transmission components, where the aim is to detect possible grinding burns that might compromise the final use and fatigue lifetime of the ground component. Grinding burn can be pointed out to have an increase in tensile RS with or without associated with decrease in the surface hardness. In some cases, with high enough temperature involved, even rehardening might occur. BN measurement is a magnetic method that is based on the connection between magnetic domains, microstructure, and stress state [1]. The

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changes in the microstructure and stresses influence the magnetic domain motion during the BN measurement [1] and are the basis, why grinding burns can be detected with the method. The industrial BN method itself is based on a pre-determined threshold value of the BN root-mean-square value (RMS). Elevated RMS values indicate detrimental changes in the component and thus components with RMS values higher than the threshold are rejected. Usually, in industry, the evaluation of grinding burn severity is not carried out. Some recent studies [2], [3] have carried out more detailed characterization of the grinding burns with RS depth profiles. For example, in [2] the burns were classified in three categories and the combination of BN parameters (RMS, peak position, coercivity) were required for reliable evaluation outcome of the severity. In addition, recently the different BN measurement frequency ranges [4] are utilized for improved detection of grinding burns. This study considers grinding burn evaluation and uses real samples from an actual process. Grinding burns are clustered based on RS and FWHM profiles so that different clusters are associated with grinding burns of different severity. A classification model is then identified to study if these clusters can be distinguished based on the surface BN measurement. The details of the methods applied are not provided in this paper but instead references are provided for an interested reader.

2. Experimental methods

2.1 Materials and methods

Studied cylindrical samples were manufactured from commercial alloyed low-alloyed steel AISI/SAE L6. The samples were through hardened prior the grinding. RS and FWHM profiles together with surface BN measurements were carried out for the samples. The detailed characterization set-up and parameters are already discussed in [5] and not repeated here. For grinding burn verification, hardness measurements were carried out in this study. Vickers hardness measurements with load of 100 g were taken from cross-sectional samples with MMT-X7 (Matsuzawa Co., Japan). Micrographs were taken with scanning electron microscope (SEM, Ultraplus, Carl Zeiss AG, Germany). The SEM samples were prepared by the traditional metallographic method by grinding with 320–4000 SiC papers and then by polishing with a 3 µm diamond suspension followed by etching with 4% Nital.

2.2 Data pre-processing and data analysis

The raw data contained the surface BN measurements together with the RS and FWHM profiles of the samples. The BN measurement device provided a set of nine BN features, and they were used as such. The depths of measurements were not constant in the profiles and thus the profiles were interpolated between 0 and 100 µm depths with 2.5 µm intervals. After interpolation the dataset contained 41 RS and FWHM profiles each with 41 values from different depths. The dataset used here is the same as in [5] and a more thorough description of data processing is given there.

2.3 Grinding burn severity identification

The aim of this study was to find if grinding burns can be classified with surface BN measurement features. Initially, information about grinding burn severity was missing. It was then assumed that RS and FWHM profiles can be used to evaluate grinding burn severity. The profiles as such were not used but instead the following features were calculated from both profiles: minimum, lower quartile, median, upper quartile and maximum. All the possible combinations of these were subjected to k-means clustering algorithm [6] to label the data points corresponding to different levels of grinding burns.

2.4 Classification of grinding burns with BN features

To study if BN features can be used to classify grinding burns, a classification model was identified between BN features and labelled data. The identification of the classification model included BN feature selection and classification model identification. Holdout cross-validation was used with 20% of data points left out for testing to evaluate classification model's performance. For all random data splits, it was checked that training and testing datasets contained data points from all the classes. The BN feature selection was carried out with a minimum redundancy maximum relevance (mRMR) algorithm [7]. A linear discriminant classification model [8] was identified in this study.

3. Results and discussion

3.1 Grinding burn severity identification

The grinding burn severity evaluation and labelling of data points accordingly were carried out as described in 2.3. The most feasible clustering result is shown in Figure 1 where three clusters are detected based on the maximum value of RS profile and the minimum value of the FWHM profile. Figure 1 shows that the relationship between maximum RS and minimum FWHM seems to be linear and that the clustering result is logical, and clusters correspond to grinding burns with different severities.

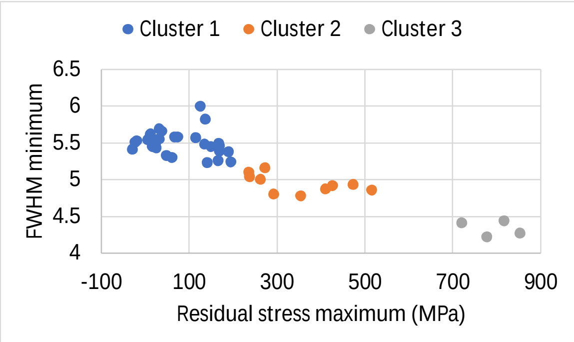

Figure 1. The clusters obtained. The number of datapoints in clusters are 28, 10 and 4 for cluster 1, 2 and 3, respectively.

3.2 Validation of different grinding burn classes

After modelling, verification of different levels of grinding damages was carried out with destructive methods. One example from every categorized class was selected to be studied more carefully. Figure 2a–d show the cross-sectional SEM micrographs taken from classes 3, 2, 1 and reference, respectively. Class 3 sample (Fig 2a) shows a modified surface layer of 4–5 µm pointed out with the arrow. The microstructure shows tempered martensite structure below the altered layer. The microhardness measurement shown for

Class 3 in Fig. 3a shows a drastic drop in the hardness value 50 µm below the surface. Class 2 (Fig 2b) and class 1 (Fig. 2c) samples show quite different microstructure than the sample in Class 3 which has been drastically tempered due to the heat generation. The exact differences in the microstructures in Class 2 and 1 are more difficult to point out compared with the reference shown in Fig. 2d, but the microhardness depth profiles (Fig. 3b) reveal more decreased hardness for Class 2 below the surface. Class 1 microhardness lies between the reference sample and Class 2 sample hardness results for the first 100 µm below the surface. Below the 100 µm distance from the surface, the hardness value saturates for samples in Class 1 and 2 to same range as the reference (Fig. 3b). The hardness depth profile for the reference has slight variation below the surface but after a mild increase in the hardness 50 µm below the surface, the hardness is rather constant. For Class 3 severe grinding burn, the decrease in the microhardness values is still visible even 300 µm below the surface. The FWHM depth profile (Fig. 3b) verifies the hardness variations between the samples in each class: Class 3 sample has the most decreased FWHM value, whereas the reference has the highest FWHM value and Class 2 and 1 are between these two (Class 3 and reference).

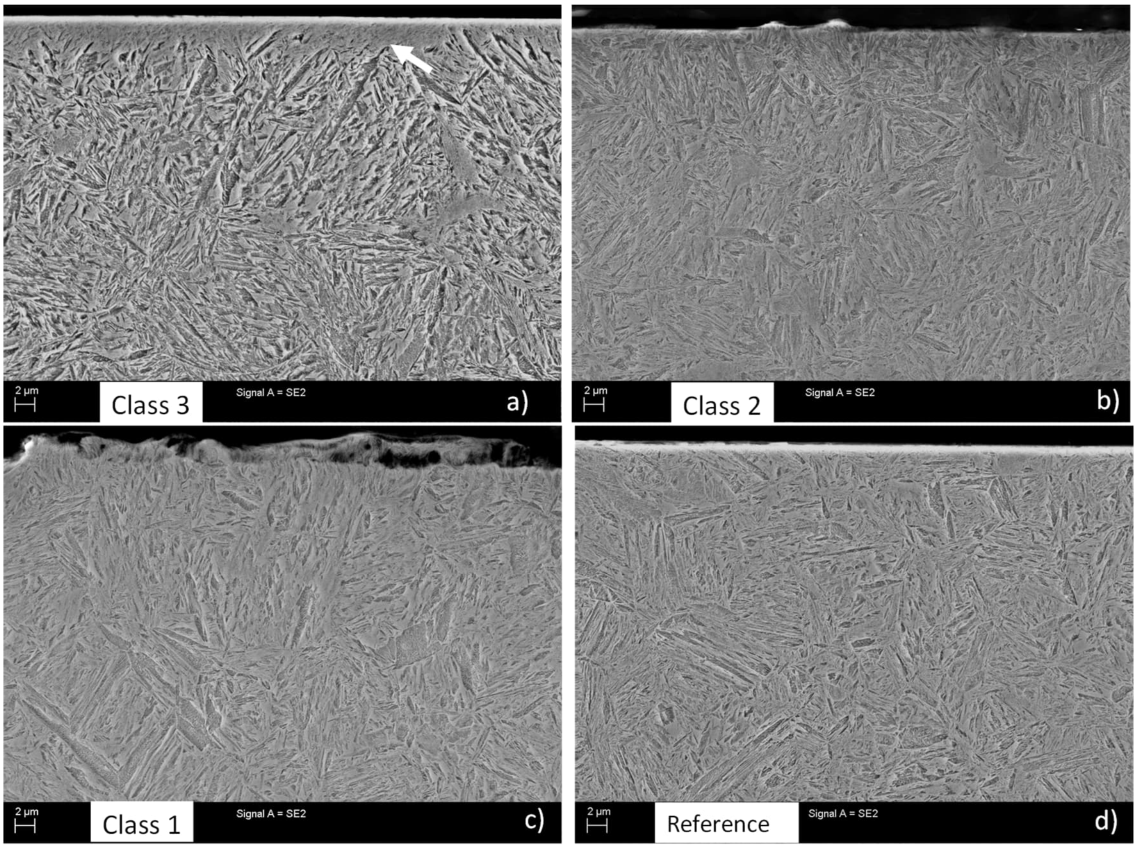

Figure 2. Micrographs taken with SEM of a) class 3, arrow showing altered layer, b) class 2, c) class 1 grinding burns and d) reference.

3.3 Classification of grinding burns with BN features

The BN features included in the classification model were selected with the mRMR algorithm as described in 2.4. Figure 4 shows the importance scores of BN features. The results are well aligned with [2] where it was suggested that grinding burn evaluation should use the RMS value and coercivity. Coercivity and peak position are almost unit correlation coefficient with each other in this dataset as was reported in [5]. Figure 4 shows that the third important feature is pulse count. That is interesting because it is seldom used in BN studies. Also [5] reports that its correlation to subsurface stress is close to zero. Thus, it is assumed that the relatively high importance score is mainly due to its low correlation to other BN features.

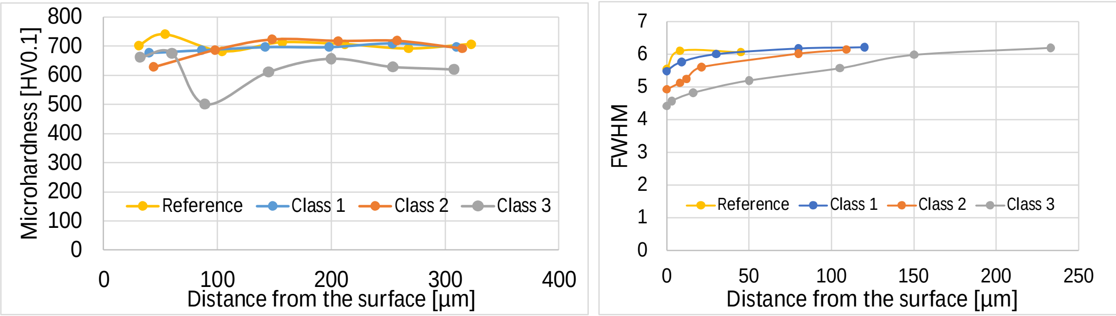

Figure 3. a) Microhardness cross-sectional profiles and b) FWHM depth profiles of samples in class 1, 2, 3 and reference.

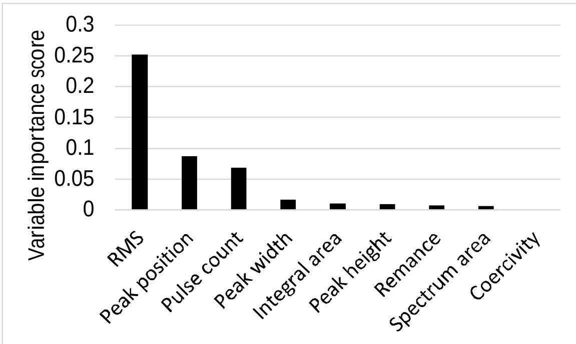

Figure 4. Variable importance score based on the mRMR algorithm.

According to the ranking in Figure 4, features were added to the classification model. The suitable number of features was evaluated based on the average misclassification rates. It was observed that one variable (the RMS value) is not enough for classifying the data. Especially class 3 corresponding to the most severe grinding burns was not classified correctly. It was also noticed that increasing the number of features beyond 2 did not improve the model significantly. Thus, a classifier with two BN features (the RMS value and peak position) was studied in more detail.

The confusion matrix with two feature classifier is shown in Table 1. The table shows the average results for training and testing datasets obtained through about 1000 repetitions of holdout cross-validation. It is seen that the classification result for class 1 is very good; only 3.7% of datapoints are misclassified into class 2. The accuracy is the same for training and testing datasets. For class 2, the classification accuracy is about 80% and the accuracy is the same for training and testing datasets. The misclassified datapoints are classified as class 1. The classification accuracy of class 3 is very good for the training dataset but for testing dataset it drops to 78.1%.

Overall, the results were reasonable and showed that the proposed approach is applicable to grinding burn classification. The lower classification accuracy for classes 2 and 3 may arise from many sources. First, the dataset used was quite small and majority of the datapoints (28 out of 41) belonged to class 1. More datapoints are needed especially for class 3 because it only had 4 datapoints. Another reason for lower classification accuracy is the methods applied. The methods applied are linear and nonlinear methods may lead to better classification result. Also, methods compensating for data unbalance can be applied. Finally, the classification model was identified so that it tried to identify all the classes simultaneously. A better approach could be to use two sequential classifiers where the first one distinguishes between class 1 and other classes and the second one tries to separate classes 2 and 3.

Table 1. The confusion matrix for average classifier performance. The values are presented for training / testing data sets.

		Predicted class		
		1	2	3
True class	1	96.4% / 96.3%	3.6% / 3.7%	0% / 0%
	2	20.1% / 20.0%	80.0% / 80.1%	0% / 0%
	3	0% / 0.4%	2.8% / 21.5%	97.2% / 78.1%

4. Conclusions

The main conclusions of this study are as follows. Clustering of the grinding burns with k-means algorithm was successful and verified by micrographs and hardness profiles. The classification results showed that grinding burns can be classified with surface BN features. The results indicated that two BN features (the RMS value and peak position) should be used.

Acknowledgements

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