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Classification of Grinding Wheel Cutting Ability During Dressing via Acoustic Emission and Neural Network †

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Abstract

This study proposes a method to indicate the optimal moment to interrupt grinding wheel dressing using the counts statistics extracted from acoustic emission signals. Experiments were conducted on a surface grinding machine equipped with an aluminum oxide grinding wheel and a single-point diamond dresser. A Multilayer Perceptron neural network, trained via the Scaled Conjugate Gradient algorithm, classified the grinding wheel condition into three states: undressed, intermediate, and dressed. In three external tests not included in the training set, the model achieved an accuracy of 88.13%.

Keywords: grinding; dressing; acoustic emission; counts statistic; MLP neural network

1. Introduction

Grinding is one of the most relevant machining operations for obtaining surfaces with high dimensional accuracy and excellent surface finish [1]. However, it is also one of the most complex, owing to the multiple cutting edges with irregular geometries among the abrasive grains of the grinding wheel [2]. Throughout the process, cutting forces progressively wear these grains, compromising the quality of the ground workpiece [3].

Since grinding is typically one of the final manufacturing steps, errors at this stage lead to significant losses [2]. Therefore, grinding wheel preparation through the dressing operation is one of the most critical factors determining process performance. Dressing is a reconditioning operation that restores the grinding wheel by removing a thin layer from its surface [4], usually with a single-point diamond dresser [5]. Such is its importance that the grinding community keeps the slogan "grinding is dressing" [6].

One of the key dressing parameters is the dressing overlap ratio (U_d), defined in Equation (1) as the ratio between the effective contact width of the dresser (b_d) and the dressing feed per wheel revolution (s_d). Lower values ($2 \leq U_d \leq 3$) yield sharper grains, which are suitable for rough grinding, whereas higher overlap ratios promote surface finishes with lower roughness [3].

$$U_d = \frac{b_d}{s_d}, \tag{1}$$

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to quantify this sharpness, Coelho [7] proposed the ground disc method: a fixed cylindrical disc is pressed against the rotating grinding wheel surface under a constant normal force (F_N), and the displacement of the disc over time is recorded. This method was recently employed in the work of [8,9]. Subsequently, regression and transformation are applied by the author, and the sharpness (K of the grinding wheel, expressed in $\mathrm{mm}^3/(\mathrm{N}\cdot\mathrm{s})$, is determined by Equation (2).

$$K = \frac{2b\sqrt{8r}}{3F_N}(a_1)^{\frac{2}{3}} \tag{2}$$

where b and r are the width (thickness) and radius of the test disc, F_N is the normal force, and a_1 is the gradient of the regression line obtained from the experimental characteristic of displacement versus $(t)^{2/3}$, where t is the time of the experiment.

The volume of material removed from the grinding wheel can be estimated by the difference in diameter according to Lopes et al. [8], as expressed in Equation (3):

$$\mathrm{VMR} = \pi \cdot L_R \cdot [r^2 - (P_d \cdot a_d)^2] \tag{3}$$

where L_R is the grinding wheel width, P_d is the number of dressing passes, a_d is the dressing depth of cut, and r is the grinding wheel radius.

Despite its importance, dressing is frequently conducted empirically based on operator experience. Correctly identifying the optimal moment to interrupt the process is essential to reduce operation time, prevent premature wheel wear, and optimize costs [10]. Sensors and data acquisition systems allow indirect monitoring of this phenomenon [6], among which acoustic emission (AE) stands out for operating in a frequency range well above machine vibration and ambient noise, thereby reducing interference [11]. Its application to grinding monitoring has been well established in the literature since 1984 [12].

The counts statistic, defined as the number of times the AE signal amplitude exceeds a predefined threshold on its rising edge, has established itself as an effective parameter for dressing monitoring. Lopes et al. [8] combined the counts statistic with power spectral density to characterize AE signals during dressing. Pereira et al. [13] employed counts to track dressing evolution and detect wheel eccentricity.

The integration of machine learning and AE sensing has consolidated itself as an effective strategy for monitoring grinding wheel wear [14]. Artificial neural networks (ANNs) offer strong representation power for pattern recognition in monitoring signals, with the architecture type, activation functions, and training algorithms defined according to the nature of the problem. The Multilayer Perceptron (MLP) network is a feedforward neural model consisting of an input layer, one or more hidden layers, and an output layer. Learning occurs via the backpropagation, which adjusts the synaptic weights to minimize the error between the estimated and target outputs using gradient descent [15].

Moia et al. [10] applied AE statistics to an MLP network to classify the wheel surface, correlating them with sharpness measured via the ground disc method. Ferreira et al. [6] estimated the effective contact width of the dresser by combining AE and neural networks. D'Addona et al. [16] used the bandpass-filtered counts statistic (25–40 kHz), with class labels defined by sharpness measurements before and after each test.

Unlike these approaches, the present study applies the counts statistic directly to the raw AE signal, standardizes the counts vectors across all tests into a common format, and reserves complete physical tests exclusively for evaluation. Therefore, the objective of this work is to develop a Multilayer Perceptron (MLP) neural network capable of identifying, from the counts signal, the optimal moment to interrupt the dressing operation.

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2. Materials and Methods

2.1. Dressing Tests

Dressing experiments were performed on a Sulmecânica surface grinding machine model RAPH 1055 (Rio Grande do Sul, Brazil), using a single-point synthetic diamond dresser, produced via Chemical Vapor Deposition (CVD). A conventional aluminum oxide grinding wheel, model 30A.150.LVH (R150), with dimensions of 324 mm × 25.4 mm × 127 mm manufactured by NORTON (São Paulo, Brazil), was used. To monitor the contact between the dresser and the grinding wheel, an AE sensor from Sensis (São Paulo, Brazil) with operational frequency range up to 500 kHz, was attached to the tool holder, following the methodology adopted by Lopes et al. [8]. The acquired signals were amplified by a Sensis DM42 module and recorded using a Yokogawa DL850 oscilloscope (São Paulo, Brazil) at a sampling rate of 2 MHz. Figure 1 illustrates the experiment.

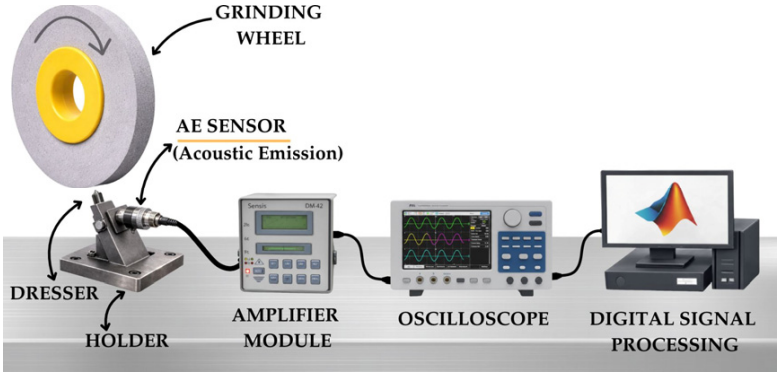


Figure 1. Test bench setup.

Prior to the experiments, a SAE 1020 steel workpiece was ground over 20 passes (depth of cut of 20 µm and cutting speed of 33 m/s) to induce wheel wear and loading. The dressing procedure comprised eight experiments, each consisting of 25 consecutive passes. Experiments 1, 2, and 3 used roughing parameters ($U_d = 2$), Experiments 4, 5, and 6 used intermediate parameters ($U_d = 3.5$), and Experiments 7 and 8 used finishing parameters ($U_d = 5.5$).

The operational parameters are presented in Table 1: wheel rotational speed (N_s), equivalent diameter (d_s), cutting speed (V_s), dressing depth of cut (a_d), dresser effective contact width (b_d), dressing time (t_d), dressing feed per revolution (s_d), dressing overlap ratio (U_d) and number of passes (P_d).

Table 1. Dressing parameters.

Experiment	N_s [RPM]	d_s[mm]	V_s [m/s]	a_d [µm]	b_d [µm]	t_d [s]	s_d [mm]	U_d	P_d
1, 2, 3	1800	324.00	30.54	10	691	2.450	0.3475	2	25
4, 5, 6	1800	321.12	30.27	10	681	4.350	0.1946	3.5	25
7, 8	1800	319.84	30.14	10	800	5.820	0.1455	5.5	25

2.2. Digital Signal Processing

The raw binary data were exported to the MATLAB R2024b environment, where digital signal processing was performed. The effective contact interval between the dresser and the grinding wheel was delimited. Consequently, both background noise and transition regions corresponding to the signal's rising and falling edges were discarded. Subsequently, the signal was segmented into time windows of 2048 samples, corresponding to intervals of 1.024 ms per segment. Within each window, the counts statistic (Figure 2) was applied

using an algorithm in the MATLAB environment. A threshold of 50 mV was adopted, based on the recommendations of Pereira et al. [13]. The counts vectors were subjected to a moving average digital filter with a 256-point non-overlapping window.

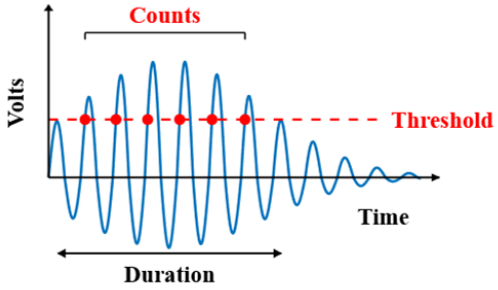


Figure 2. Schematic diagram illustrating signal counts extraction from the AE signal.

Figure 3 compares the raw AE signal (Figure 3a) and the corresponding counts statistic (Figure 3b) for the first and twenty-fifth passes of the same experiment. In Figure 3a, the undressed grinding wheel (pass 1) exhibits more irregular behavior. By contrast, in pass 25 the signal becomes more uniform, indicating full contact with the dresser [16]. This behavior directly translates into the AE counts (Figure 3b): comparing the raw signal (shaded lines) with the filtered signal (solid lines), a significant increase and stabilization in the counts level can be observed from the 1st to the 25th pass.

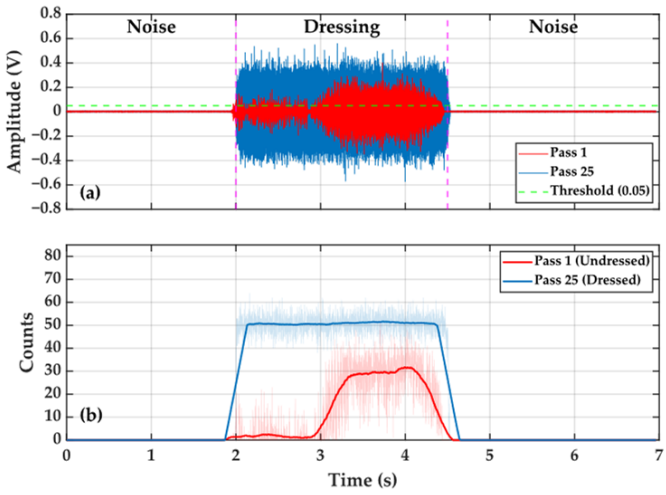


Figure 3. AE signal: (**a**) Original AE signals and the threshold used; (**b**) counts signal (light-colored lines show the raw counts, and solid lines show the filtered counts).

From the filtered counts vectors, the arithmetic mean (μ) and standard deviation (σ) of each dressing pass were extracted. These parameters, combined with the domain knowledge of an experienced dressing operator, were used to define the class labels of each pass. The three surface state conditions were established based on threshold intervals derived from these statistical metrics. The (i) undressed state was assigned when the mean counts are low ($\mu < 30.0$) and the standard deviation is high ($\sigma > 5.0$), representing low acoustic activity and irregular contact; (ii) intermediate state was assigned when the mean counts is below 50 or when the standard deviation lies in an intermediate range ($2.0 \leq \sigma \leq 5.0$); (iii) dressed state was assigned when the mean counts reach a high level ($\mu \approx 50$) and the standard deviation remains low ($\sigma < 2.0$). Future studies will define class labels using measured sharpness for each pass.

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2.3. Multilayer Perceptron (MLP) Network

The neural network used in this work was an MLP implemented in MATLAB (patternnet), with a single hidden layer of 64 neurons, trained using the Scaled Conjugate Gradient Backpropagation algorithm (trainscg) with a cross-entropy loss function. The architecture was defined empirically by observing the training error; a systematic hyperparameter search is left for future work. The network input corresponds to the counts vector of each pass, resampled via linear interpolation to 3000 samples, ensuring a fixed input dimension across passes. The output, one-hot encoded, represents the three grinding wheel condition classes (Undressed, Intermediate, Dressed). Class labels were defined from the arithmetic mean and standard deviation of the counts statistic of each pass, combined with the domain knowledge of an experienced dressing operator.

The training dataset consisted of the passes from Experiments (Exp) 1, 2, 4, 5 and 8 (Table 2), with Experiment 2 reserved entirely for internal validation. Generalization was evaluated externally on the complete, unseen Experiments 3, 6, and 7 (Table 3). To assess result stability and mitigate the risk of overfitting given the high input dimensionality, the network was trained over ten random initializations, with early stopping (patience of six epochs) based on the validation cross-entropy loss.

Table 2. Distribution of grinding wheel condition classes for the training dataset.

Experiment	Undressed	Intermediate	Dressed
Exp 1	Passes 1–2	Passes 3–10	Passes 11–25
Exp 2	Passes 1–2	Passes 3–7	Passes 8–25
Exp 4	-	Passes 1–5	Passes 6–25
Exp 5	Passes 1–2	Pass 3	Passes 4–25
Exp 8	Passes 1–4	Passes 5–11	Passes 12–25

Table 3. Distribution of grinding wheel condition classes for the testing dataset.

Experiment	Undressed	Intermediate	Dressed
Exp 3	Passes 1–2	Passes 3–5	Passes 6–25
Exp 6	Pass 1	Passes 2–6	Passes 7–25
Exp 7	Passes 1–3	Passes 4–10	Passes 11–25

2.4. Grinding Wheel Sharpness

To evaluate the grinding wheel sharpness, the ground disc method was used at four dressing test moments for Experiments 3, 6 and 7. For each experiment, measurements were taken at passes 0, 5, 10, and 25, recording displacement over time at three equidistant points on the wheel surface to compute the mean curve and calculate standard deviations. A normal force (F_N) of 1.02N was applied at one end of a balance scale, pressing a stationary SAE 1020 steel disc (24 mm outer diameter, 7.8 mm inner diameter, and 2 mm thickness) against the grinding wheel. The displacement was measured using a TESATRONIC TT60 instrument Tesa Technology (Renens, Switzerland), with data acquired via serial communication in MATLAB R2024b. The volume of material removed from the grinding wheel was based on the difference in diameter [8].

The experimental setup is presented in Figure 4 and consists of: (a) grinding wheel; (b) sharpness measurement device; (c) displacement sensor; (d) SAE 1020 steel disc; (e) load application system; and (f) TESATRONIC TT60 digital indicator. Figure 5 illustrates the dressing effect on the wheel surface: the undressed condition (a) shows embedded chips and an irregular surface, whereas the dressed condition (b) is uniform.

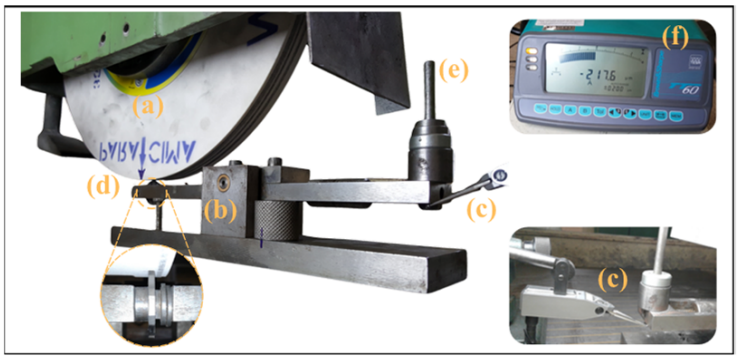


Figure 4. Experimental setup for sharpness measurement: (**a**) grinding wheel; (**b**) sharpness measurement device; (**c**) displacement sensor; (**d**) SAE 1020 steel disc; (**e**) load application system; (**f**) TESATRONIC TT60 digital indicator.

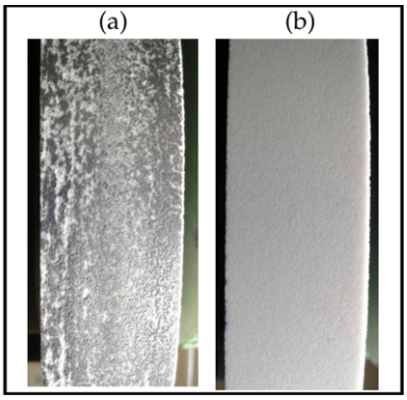


Figure 5. Grinding wheel: (**a**) Undressed. (**b**) Dressed condition.

3. Results and Discussion

3.1. MLP Performance Evaluation

To prevent the validation set from containing passes correlated with the training experiments, the internal split was redefined so that Experiment 2 was held out entirely for validation, while Experiments 1, 4, 5, and 8 were used for training. The network was trained ten times with different random initializations. For the best run, training converged after 18 epochs (cross-entropy loss decreasing from 0.38 to 0.03), with the training and validation loss curves remaining close throughout, showing no divergence.

The performance of the MLP network was evaluated exclusively on the 75 passes from Experiments 3, 6, and 7, which were kept completely out of training. Across the ten runs, the external test accuracy averaged 88.13% ± 0.93%. The confusion matrix (Figure 6) shows that 67 of the 75 passes were correctly classified. Table 4 and Figure 6 report the run with the highest external test accuracy among the ten initializations (89.3%; macro F1-score 79.03%, AUC 0.9651), versus a mean of 88.13% ± 0.93% across all runs.

Table 4. Performance metrics of the MLP classification model on the external test set.

Class	Precision	Recall	F1-Score	AUC
Undressed	100.00%	50.00%	66.67%	0.9638
Intermediate	70.59%	80.00%	75.00%	0.9467
Dressed	94.55%	96.30%	95.41%	0.9850
Macro average	88.38%	75.43%	79.03%	0.9651



Figure 6. Test confusion matrix.

The Dressed class was recognized most reliably (recall 96.30%, F1-score 95.41%). The Undressed class, with only six test passes, obtained precision 100% but a lower recall (50%) due to the small class support. The Intermediate class showed the lowest precision (70.59%), mainly due to confusion with the Dressed class.

3.2. Grinding Wheel Sharpness Analysis

Figure 7 presents the evolution of removed material volume and calculated sharpness at passes 0, 5, 10, and 25 for the Experiments 3, 6, and 7. In all cases, the removed volume increases along the dressing process, whereas sharpness rises rapidly between passes 0 and 5, when the grinding wheel transitions from a loaded state to exposing sharp grains, and tends to stabilize between passes 10 and 25, indicating that most of the sharpness gain occurs within this interval. Experiment 3 ($U_d = 2$) reaches higher sharpness values (up to 1.46 mm^3/N · s) than Experiments 6 and 7 ($U_d = 3.5$ and 5.5) which is consistent with expectations for lower overlap ratios that yield sharper abrasive grains.

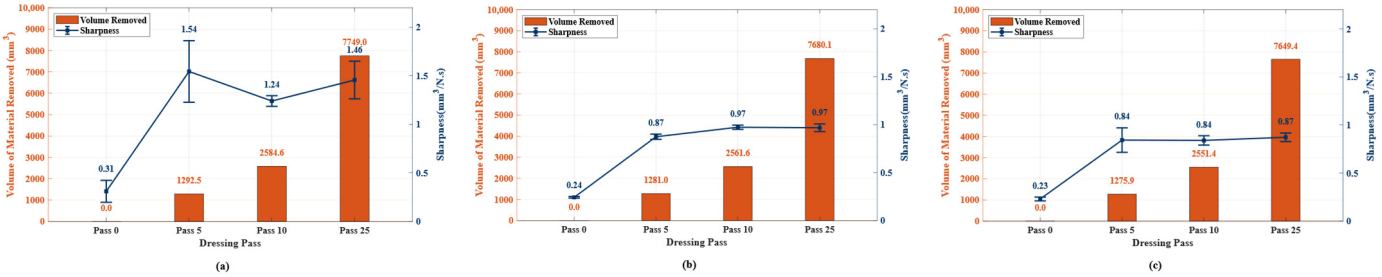


Figure 7. Sharpness and volume of material removed: (**a**) Test 3 ($U_d = 2$); (**b**) Test 6 ($U_d = 3.5$); (**c**) Test 7 ($U_d = 5.5$).

Error bars representing the standard deviation across the three equidistant peripheral measurements have been added to Figure 7a–c.

4. Conclusions

This work developed an MLP neural network to classify the grinding wheel condition during dressing, based on the counts statistic extracted from AE signals, with labels assigned from the mean and standard deviation of the counts signal combined with the operator's process knowledge. To avoid validation passes correlated with the training

experiments, one complete experimental run was reserved exclusively for validation, and the network was trained over ten random initializations. Evaluation on three unseen experimental runs yielded a mean accuracy of 88.13% $\pm$ 0.93% and an AUC above 0.94 for all classes, with training and validation loss curves remaining close throughout. The results confirm the method's capacity to indicate the appropriate moment for process termination.

Future work should include a systematic hyperparameter search and an expanded test dataset, particularly for the Undressed class, as well as new experimental runs under different dressing conditions.

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